# Signal Processing Tool box 

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Computation

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User's Guide
Version 5

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## Signal Processing Tool box User's Guide

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## Preface

Overview ..... xvi
What Is the Signal Processing Toolbox? ..... xvii
R12 Related Products List ..... xviii
How to Use This Manual ..... xxi
If You Are a New User ..... xxi
If Y ou Are an Experienced Tool box User ..... xxii
All Tool box Users ..... xxii
Installing the Signal Processing Toolbox ..... xxiii
Technical Conventions ..... xxiv
Typographical Conventions ..... xxv
Signal Processing Basics
1
Overview ..... 1-2
Signal Processing Toolbox Central Features ..... 1-3
Filtering and FFTs ..... 1-3
Signals and Systems ..... 1-3
Key Areas: Filter Design and Spectral Analysis ..... 1-3
Interactive Tools: SPTool and FDATool ..... 1-4
Extensibility ..... 1-4
Representing Signals ..... 1-5
Vector Representation ..... 1-5
Waveform Generation: Time Vectors and Sinusoids ..... 1-7
Common Sequences: Unit Impulse, Unit Step, and Unit Ramp ..... 1-8
Multichannel Signals ..... 1-8
Common Periodic Waveforms ..... 1-9
Common Aperiodic Waveforms ..... 1-10
The pulstran Function ..... 1-11
The Sinc Function ..... 1-12
The Dirichlet Function ..... 1-13
Working with Data ..... 1-14
Filter Implementation and Analysis ..... 1-15
Convolution and Filtering ..... 1-15
Filters and Transfer Functions ..... 1-16
Filter Coefficients and Filter Names ..... 1-16
Filtering with the filter F unction ..... 1-17
The filter Function ..... 1-18
Other Functions for Filtering ..... 1-20
Multirate Filter Bank Implementation ..... 1-20
Anti-Causal, Zero-Phase Filter Implementation ..... 1-21
Frequency Domain Filter Implementation ..... 1-23
Impulse Response ..... 1-24
Frequency Response ..... 1-25
Digital Domain ..... 1-25
Analog Domain ..... 1-27
Magnitude and Phase ..... 1-27
Delay ..... 1-29
Zero-Pole Analysis ..... 1-31
Linear System Models ..... 1-33
Discrete-Time System M odels ..... 1-33
Transfer Function ..... 1-33
Zero-Pole-Gain ..... 1-34
State-Space ..... 1-35
Partial Fraction Expansion (Residue Form) ..... 1-36
Second-Order Sections (SOS) ..... 1-38
Lattice Structure ..... 1-38
Convolution Matrix ..... 1-41
Continuous-Time System M odels ..... 1-42
Linear System Transformations ..... 1-43
Discrete Fourier Transform ..... 1-45
Selected Bibliography ..... 1-48
Filter Design
2
Overview ..... 2-2
Filter Requirements and Specification ..... 2-3
IIR Filter Design ..... 2-5
Classical IIR Filter Design Using Analog Prototyping ..... 2-7
Complete Classical IIR Filter Design ..... 2-7
Designing IIR Filters to Frequency Domain Specifications ..... 2-8
Comparison of Classical IIR Filter Types ..... 2-9
Butterworth Filter ..... 2-9
Chebyshev Type I Filter ..... 2-10
Chebyshev Type II Filter ..... 2-11
Elliptic Filter ..... 2-11
Bessel Filter ..... 2-12
Direct IIR Filter Design ..... 2-14
Generalized Butterworth Filter Design ..... 2-15
FIR Filter Design ..... 2-17
Linear Phase Filters ..... 2-18
Windowing Method ..... 2-19
Standard Band FIR Filter Design: fir1 ..... 2-21
Multiband FIR Filter Design: fir2 ..... 2-22
Multiband FIR Filter Design with Transition Bands ..... 2-23
Basic Configurations ..... 2-23
The Weight Vector ..... 2-26
Anti-Symmetric Filters / Hilbert Transformers ..... 2-26
Differentiators ..... 2-27
Constrained Least Squares FIR Filter Design ..... 2-28
Basic Lowpass and Highpass CLS Filter Design ..... 2-29
Multiband CLS Filter Design ..... 2-30
Weighted CLS Filter Design ..... 2-31
Arbitrary-Response Filter Design ..... 2-32
Multiband Filter Design ..... 2-33
Filter Design with Reduced Delay ..... 2-35
Special Topics in IIR Filter Design ..... 2-38
Analog Prototype Design ..... 2-39
Frequency Transformation ..... 2-39
Filter Discretization ..... 2-42
Impulse Invariance ..... 2-42
Bilinear Transformation ..... 2-43
Selected Bibliography ..... 2-46
Statistical Signal Processing
3
Overview ..... 3-2
Correlation and Covariance ..... 3-3
Bias and Normalization ..... 3-4
Multiple Channels ..... 3-5
Spectral Analysis ..... 3-6
Spectral Estimation Method Overview ..... 3-8
Nonparametric Methods ..... 3-10
The Periodogram ..... 3-10
Performance of the Periodogram 3-12
The Modified Periodogram ..... 3-18
Welch's Method ..... 3-20
Bias and Normalization in Welch's Method ..... 3-23
Multitaper Method ..... 3-24
Cross-Spectral Density Function ..... 3-27
Confidence Intervals ..... 3-27
Transfer Function Estimate ..... 3-28
Coherence Function ..... 3-29
Parametric Methods ..... 3-30
Yule-Walker AR Method ..... 3-32
Burg Method ..... 3-33
Covariance and Modified Covariance Methods ..... 3-36
MUSIC and Eigenvector Analysis Methods ..... 3-36
Eigenanalysis Overview ..... 3-37
Selected Bibliography ..... 3-39
Special Topics
4
Overview ..... 4-2
Windows ..... 4-3
Basic Shapes ..... 4-3
Generalized Cosine Windows ..... 4-5
Kaiser Window ..... 4-6
Kaiser Windows in FIR Design ..... 4-8
Chebyshev Window ..... 4-10
Parametric Modeling ..... 4-12
Time-Domain Based Modeling ..... 4-14
Linear Prediction ..... 4-14
Prony's Method (ARMA M odeling) ..... 4-15
Steiglitz-McBride Method (ARMA M odeling) ..... 4-17
Frequency-Domain Based Modeling ..... 4-19
Resampling ..... 4-22
Cepstrum Analysis ..... 4-25
Inverse Complex Cepstrum ..... 4-27
FFT-Based Time-Frequency Analysis ..... 4-29
Median Filtering ..... 4-30
Communications Applications ..... 4-31
Deconvolution ..... 4-35
Specialized Transforms ..... 4-36
Chirp z-Transform ..... 4-36
Discrete Cosine Transform ..... 4-38
Hilbert Transform ..... 4-40
Selected Bibliography ..... 4-42
Filter Design and Analysis Tool
5
Overview ..... 5-2
Filter Design Methods ..... 5-3
Using the Filter Design and Analysis Tool ..... 5-4
Analyzing Filter Responses ..... 5-4
Filter Design and Analysis Tool Modes ..... 5-4
Getting Help ..... 5-5
Opening the Filter Design and Analysis Tool ..... 5-6
Choosing a Filter Type ..... 5-7
Choosing a Filter Design Method ..... 5-8
Setting the Filter Design Specifications ..... 5-9
Bandpass Filter Frequency Specifications ..... 5-9
Bandpass Filter Magnitude Specifications ..... 5-10
Filter Order ..... 5-11
Computing the Filter Coefficients ..... 5-12
Analyzing the Filter ..... 5-13
Converting the Filter Structure ..... 5-15
Importing a Filter Design ..... 5-17
Filter Structures ..... 5-18
Direct Form ..... 5-18
Direct Form II (Second-Order Sections) ..... 5-19
State-Space ..... 5-19
Lattice ..... 5-19
Quantized Filter (Qfilt Object) ..... 5-20
Exporting a Filter Design ..... 5-21
Exporting Filter Coefficients to the Workspace ..... 5-21
Exporting Filter Coefficients to a Text File ..... 5-22
Exporting to a C Header File ..... 5-22
Saving and Opening Filter Design Sessions ..... 5-25
SPTool: A Signal Processing GUI Suite
6
Overview ..... 6-2
SPTool: An Interactive Signal Processing Environment ..... 6-3
SPTool Data Structures ..... 6-3
Opening SPTool ..... 6-5
Getting Help ..... 6-7
Context-Sensitive Help: The What's This? Button ..... 6-7
Overview of the Signal Browser: Signal Analysis ..... 6-8
Opening the Signal Browser ..... 6-8
Overview of the Filter Designer: Filter Design ..... 6-11
Filter Types ..... 6-11
FIR Filter Methods ..... 6-11
IIR Filter Methods ..... 6-11
Pole/Zero Editor ..... 6-12
Spectral Overlay Feature ..... 6-12
Opening the Filter Designer ..... 6-12
Overview of the Filter Viewer: Filter Analysis ..... 6-14
Opening the Filter Viewer ..... 6-14
Overview of the Spectrum Viewer: Spectral Analysis ..... 6-17
Opening the Spectrum Viewer ..... 6-17
Using SPTool: Filtering and Analysis of Noise ..... 6-20
Importing a Signal into SPTool ..... 6-20
Designing a Filter ..... 6-22
Opening the Filter Designer ..... 6-22
Specifying the Bandpass Filter ..... 6-22
Applying a Filter to a Signal ..... 6-24
Analyzing Signals: Opening the Signal Browser ..... 6-26
Playing a Signal ..... 6-27
Printing a Signal ..... 6-27
Spectral Analysis in the Spectrum Viewer ..... 6-28
Creating a PSD Object From a Signal ..... 6-29
Opening the Spectrum Viewer with Two Spectra ..... 6-29
Printing the Spectra ..... 6-30
Exporting Signals, Filters, and Spectra ..... 6-32
Opening the Export Dialog Box ..... 6-32
Exporting a Filter to the MATLAB Workspace ..... 6-33
Accessing Filter Parameters ..... 6-34
Accessing Filter Parameters in a Saved Filter ..... 6-34
The tf Field: Accessing Filter Coefficients ..... 6-34
The Fs Field: Accessing Filter Sample F requency ..... 6-34
The specs Field: Accessing other Filter Parameters ..... 6-35
Accessing Parameters in a Saved Spectrum ..... 6-37
Importing Filters and Spectra into SPTool ..... 6-39
Importing Filters ..... 6-39
Importing Spectra ..... 6-41
Loading Variables from the Disk ..... 6-43
Selecting Signals, Filters, and Spectra in SPTool ..... 6-44
Editing Signals, Filters, or Spectra in SPTool ..... 6-45
Designing a Filter with the Pole/Zero Editor ..... 6-46
Positioning Poles and Zeros ..... 6-47
Redesigning a Filter Using the Magnitude Plot ..... 6-49
Setting Preferences ..... 6-50
Making Signal Measurements: Using Markers ..... 6-52
Function Reference
7
Function Category List ..... 7-3
Alphabetical List of Functions ..... 20
abs ..... 7-26
ac2poly ..... 7-27
ac2rc ..... 7-28
angle ..... 7-29
arburg ..... 7-30
arcov ..... 7-31
armcov ..... 7-32
aryule ..... 7-33
barthannwin ..... 7-34
bartlett ..... 7-36
besselap ..... 7-38
besself ..... 7-39
bilinear ..... 7-42
bitrevorder ..... 7-47
blackman ..... 7-49
blackmanharris ..... 7-51
bohmanwin ..... 7-53
buffer ..... 7-55
buttap ..... 7-64
butter ..... 7-65
buttord ..... 7-70
cceps ..... 7-75
cell2sos ..... 7-77
cheblap ..... 7-78
cheblord ..... 7-79
cheb2ap ..... 7-83
cheb2ord ..... 7-84
chebwin ..... 7-89
cheby1 ..... 7-90
cheby2 ..... 7-95
chirp ..... 7-100
cohere ..... 7-106
conv ..... 7-110
conv2 ..... 7-111
convmtx ..... 7-113
corrcoef ..... 7-115
corrmtx ..... 7-116
cov ..... 7-119
cplxpair ..... 7-120
cremez ..... 7-121
csd ..... 7-129
czt ..... 7-133
dct ..... 7-136
decimate ..... 7-138
deconv ..... 7-141
demod ..... 7-142
dftmtx ..... 7-144
diric ..... 7-145
downsample ..... 7-146
dpss ..... 7-148
dpssclear ..... 7-151
dpssdir ..... 7-152
dpssload ..... 7-153
dpsssave ..... 7-154
ellip ..... 7-155
ellipap ..... 7-161
ellipord ..... 7-162
eqtflength ..... 7-167
fdatool ..... 7-168
fft ..... 7-170
fft2 ..... 7-173
fftfilt ..... 7-174
fftshift ..... 7-176
filter ..... 7-177
filter2 ..... 7-180
filternorm ..... 7-181
filtfilt ..... 7-183
filtic ..... 7-184
fir1 ..... 7-186
fir2 ..... 7-190
fircls ..... 7-193
fircls1 ..... 7-196
firls ..... 7-199
firrcos ..... 7-204
freqs ..... 7-206
freqspace ..... 7-208
freqz ..... 7-209
freqzplot ..... 7-213
fvtool ..... 7-216
gauspuls ..... 7-220
gausswin ..... 7-222
gmonopuls ..... 7-224
goertzel ..... 7-226
grpdelay ..... 7-231
hamming ..... 7-234
hann ..... 7-236
hilbert ..... 7-238
icceps ..... 7-242
idct ..... 7-243
ifft ..... 7-244
ifft2 ..... 7-245
impinvar ..... 7-246
impz ..... 7-248
interp ..... 7-251
intfilt ..... 7-253
invfreqs ..... 7-255
invfreqz ..... 7-259
is2rc ..... 7-262
kaiser ..... 7-263
kaiserord ..... 7-265
lar2rc ..... 7-270
latc2tf ..... 7-271
latcfilt ..... 7-272
levinson ..... 7-274
lp2bp ..... 7-276
Ip2bs ..... 7-279
lp2hp ..... 7-281
Ip2lp ..... 7-283
Ipc ..... 7-285
Isf2poly ..... 7-289
maxflat ..... 7-290
medfilt1 ..... 7-292
modulate ..... 7-293
nuttallwin ..... 7-296
pburg ..... 7-299
pCOV ..... 7-304
peig ..... 7-309
periodogram ..... 7-316
pmcov ..... 7-321
pmtm ..... 7-326
pmusic ..... 7-331
poly2ac ..... 7-339
poly2lsf ..... 7-340
poly2rc ..... 7-341
polyscale ..... 7-343
polystab ..... 7-344
prony ..... 7-345
psdplot ..... 7-347
pulstran ..... 7-349
pwelch ..... 7-353
pyulear ..... 7-359
rc2ac ..... 7-364
rc2is ..... 7-365
rc2lar ..... 7-366
rc2poly ..... 7-367
rceps ..... 7-368
rectpuls ..... 7-369
rectwin ..... 7-370
remez ..... 7-371
remezord ..... 7-378
resample ..... 7-381
residuez ..... 7-384
rlevinson ..... 7-387
rooteig ..... 7-390
rootmusic ..... 7-393
sawtooth ..... 7-396
schurrc ..... 7-397
seqperiod ..... 7-398
sgolay ..... 7-400
sgolayfilt ..... 7-404
sinc ..... 7-406
sos2cell ..... 7-408
sos2ss ..... 7-409
sos2tf ..... 7-411
sos2zp ..... 7-413
sosfilt ..... 7-415
specgram ..... 7-416
sptool ..... 7-420
square ..... 7-425
ss2sos ..... 7-426
ss2tf ..... 7-430
ss2zp ..... 7-431
stmcb ..... 7-433
strips ..... 7-436
tf2latc ..... 7-438
tf2sos ..... 7-439
tf2ss ..... 7-442
tf2zp ..... 7-444
tfe ..... 7-447
triang ..... 7-451
tripuls ..... 7-453
tukeywin ..... 7-454
udecode ..... 7-456
uencode ..... 7-459
unwrap ..... 7-462
upfirdn ..... 7-463
upsample ..... 7-467
VCO ..... 7-469
window ..... 7-471
xcorr ..... 7-473
xcorr2 ..... 7-477
xCOV ..... 7-478
yulewalk ..... 7-481
zp2sos ..... 7-483
zp2ss ..... 7-487
zp2tf ..... 7-488
zplane ..... 7-489

## Preface

Overview ..... xvi
What Is the Signal Processing Toolbox? ..... xvii
R12 Related Products List ..... xviii
How to Use This Manual ..... xxi
If Y ou Are a New User ..... xxi
If Y ou Are an Experienced Toolbox User ..... xxii
All Toolbox Users ..... xxii
Installing the Signal Processing Toolbox ..... xxiii
Technical Conventions ..... xxiv
Typographical Conventions ..... XXV

## Overview

This chapter provides an introduction to the Signal Processing Tool box and the documentation. It contains the following sections:

- "What Is the Signal Processing Toolbox?"
- "R12 Related Products List"
- "How to Use This Manual"
- "Installing the Signal Processing Toolbox"
- "Technical Conventions"
- "Typographical Conventions"


## What Is the Signal Processing Toolbox?

The Signal Processing Tool box is a collection of tools built on the MATLAB ${ }^{\circledR}$ numeric computing environment. The tool box supports a wide range of signal processing operations, from waveform generation to filter design and implementation, parametric modeling, and spectral analysis. The tool box provides two categories of tools:

- Signal processing command line functions
- A suite of graphical user interfaces for:
- Interactive filter design
- Signal plotting and analysis
- Spectral analysis
- Filtering signals
- Analyzing filter designs


## R12 Related Products List

The MathWorks provides several products that are especially relevant to the kinds of tasks you can perform with the Signal Processing Tool box.

For more information about any of these products, see either:

- The online documentation for that product if it is installed or if you are reading the documentation from the CD
- TheMathWorks Web site, at http: / /www.mathworks. com; seethe"products" section

Note The tool boxes listed below all include functions that extend MATLAB's capabilities. The blocksets all include blocks that extend Simulink's capabilities.

| Product | Description |
| :--- | :--- |
| Communications <br> Blockset | Simulink block libraries for modeling the <br> physical layer of communications systems |
| Communications Tool box | MATLAB functions for modeling the physical <br> layer of communications systems |
| Data Acquisition Toolbox | MATLAB functions for direct access to live, <br> measured data from MATLAB |
| Database Tool box | Tool for connecting to, and interacting with, <br> most ODBC/J DBC databases from within <br> MATLAB |

$\left.\begin{array}{ll}\hline \text { Product } & \text { Description } \\ \hline \begin{array}{l}\text { Developer's Kit for Texas } \\ \text { Instruments'm DSP }\end{array} & \begin{array}{l}\text { Developer's kit that unites MATLAB, } \\ \text { Simulink, and Real-Time Workshop code } \\ \text { generation with the Texas Instruments Code } \\ \text { Composer Studio }\end{array} \\ \text { systems architects with suite of tools for DSP } \\ \text { development, from simulating signal } \\ \text { processing algorithms to optimizing and } \\ \text { running code on Texas Instruments DSPs }\end{array}\right\}$

| Product | Description |
| :--- | :--- |
| Simulink | Interactive, graphical environment for <br> modeling, simulating, and prototyping <br> dynamic systems |
| Statistics Tool box | Tool for analyzing historical data, modeling <br> systems, developing statistical algorithms, and <br> learning and teaching statistics |
| System Identification <br> Tool box | Tool for building accurate, simplified models of <br> complex systems from noisy time-series data |
| Wavelet Tool box | Tool for signal and image analysis, <br> compression, and de-noising |

## How to Use This Manual

This section explains how to use the documentation to get hel p about the Signal Processing Tool box. Read the topic that best fits your skill level:

- "If You Area New User"
- "If Y ou Are an Experienced Tool box User"
- "All Toolbox Users"


## If You Are a New User

Begin with Chapter 1, "Signal Processing Basics." This chapter introduces the MATLAB signal processing environment through the tool box functions. It describes the basic functions of the Signal Processing Tool box, reviewing its use in basic waveform generation, filter implementation and analysis, impulse and frequency response, zero-pole analysis, linear system models, and the discrete Fourier transform.

When you feel comfortable with the basic functions, move on to Chapter 2 and Chapter 3 for a more in-depth introduction to using the Signal Processing Toolbox:

- Chapter 2, "Filter Design," for a detailed explanation of using the Signal Processing Tool box in infinite impulse response (IIR) and finite impulse response (FIR) filter design and implementation, including special topics in IIR filter design.
- Chapter 3, "Statistical Signal Processing," for how to use the correlation, covariance, and spectral analysis tools to estimate important functions of discrete random signals.

Once you understand the general principles and applications of the toolbox, learn how to use the interactive tools:

- Chapter 5, "Filter Design and Analysis Tool," and Chapter 6, "SPTool: A Signal Processing GUI Suite," for an overview of the interactive GUI environments and examples of how to use them for signal exploration, filter design and implementation, and spectral analysis.

Finally, see the following chapter:

- Chapter 4, "Special Topics," for specialized functions, including filter windows, parametric modeling, resampling, cepstrum analysis, time-dependent Fourier transforms and spectrograms, median filtering, communications applications, deconvolution, and specialized transforms.


## If You Are an Experienced Toolbox User

See Chapter 5, "Filter Design and Analysis Tool," and Chapter 6, "SPTool: A Signal Processing GUI Suite," for an overview of the interactive GUI environments and examples of how to usethem for signal viewing, filter design and implementation, and spectral analysis.

## All Toolbox Users

Use Chapter 7, "F unction Reference," for locating information on specific functions. Reference descriptions include a synopsis of the function's syntax, as well as a complete explanation of options and operations. Many reference descriptions also include helpful examples, a description of the function's algorithm, and references to additional reading material.

Use this manual in conjunction with the software to learn about the powerful features that MATLAB provides. Each chapter provides numerous examples that apply the tool box to representative signal processing tasks.

Some examples use MATLAB's random number generation function randn. In these cases, to duplicate the results in the example, type
randn('state',0)
before running the example.

## Installing the Signal Processing Toolbox

To determine if the Signal Processing Tool box is installed on your system, type this command at the MATLAB prompt.
ver
When you enter this command, MATLAB displays information about the version of MATLAB you are running, including a list of all tool boxes installed on your system and their version numbers.
For information about installing the tool box, see the MATLAB Installation Guidefor your platform.

## Technical Conventions

This manual and the Signal Processing Tool box functions use the following technical notations.

| Nyquist frequency | One-half the sampling frequency. Some <br> toolbox functions normalize this value to 1. |
| :--- | :--- |
| $\mathrm{x}(1)$ | The first element of a data sequence or <br> filter, corresponding to zero lag. |
| $\Omega$ or $w$ | Analog frequency in radians per second. |
| $\omega$ or $w$ | Digital frequency in radians per sample. |
| f | Digital frequency in hertz. |
| $[\mathrm{x}, \mathrm{y})$ | The interval from x to y, including x but not <br> including y. |
| $\ldots$ | Ellipses in the argument list for a given <br> syntax on a function reference page <br> indicate all possible argument lists for that <br> function appearing prior to the given <br> syntax are valid. |

## Typographical Conventions

This manual uses some or all of these conventions.

| Item | Convention Used | Example |
| :--- | :--- | :--- |
| Example code | Monospace font | To assign the value 5 to A, <br> enter <br> A $=5$ |
| Function names/syntax | Monospace font | The cos function finds the <br> cosine of each array element. <br> Syntax line example is <br> MLGetVar ML_var_name |
| Keys | Boldface with an initial capital <br> letter | Press the Return key. |
| Literal strings (in syntax <br> descriptions in reference <br> chapters) | Monospace bold for literals | f = freqspace (n, 'whole ') |

## Signal Processing Basics

Overview1-2Signal Processing Toolbox Central Features ..... 1-3
Representing Signals ..... 1-5
Waveform Generation: Time Vectors and Sinusoids ..... 1-7
Working with Data ..... 1-14
Filter Implementation and Analysis ..... 1-15
The filter Function ..... 1-18
Other Functions for Filtering ..... 1-20
Impulse Response ..... 1-24
Frequency Response ..... 1-25
Zero-Pole Analysis ..... 1-31
Linear System Models ..... 1-33
Discrete Fourier Transform ..... 1-45
Selected Bibliography ..... 1-48

## Overview

This chapter describes how to begin using MATLAB and the Signal Processing Toolbox for your signal processing applications. It assumes a basic knowledge and understanding of signals and systems, including such topics as filter and linear system theory and basic Fourier analysis. The chapter covers the following topics:

- "Signal Processing Tool box Central Features"
- "Representing Signals"
- "Waveform Generation: Time Vectors and Sinusoids"
- "Working with Data"
- "Filter Implementation and Analysis"
- "The filter Function"
- "Other Functions for Filtering"
- "Impulse Response"
- "Frequency Response"
- "Zero-Pole Analysis"
- "Linear System Models"
- "Discrete Fourier Transform"
- "Selected Bibliography"

Many examples throughout the chapter demonstrate how to apply tool box functions. If you are not already familiar with MATLAB's signal processing capabilities, use this chapter in conjunction with the software to try examples and learn about the powerful features available to you.

## Signal Processing Toolbox Central Features

The Signal Processing Tool box functions are algorithms, expressed mostly in M -files, that implement a variety of signal processing tasks. These tool box functions are a specialized extension of the MATLAB computational and graphical environment.

## Filtering and FFTs

Two of the most important functions for signal processing are not in the Signal Processing Tool box at all, but are built-in MATLAB functions:

- filter applies a digital filter to a data sequence.
- fft calculates the discrete F ourier transform of a sequence.

The operations these functions perform are the main computational workhorses of classical signal processing. Both are described in this chapter. The Signal Processing Tool box uses many other standard MATLAB functions and language features, including polynomial root finding, complex arithmetic, matrix inversion and manipulation, and graphics tools.

## Signals and Systems

The basic entities that tool box functions work with are signals and systems. The functions emphasize digital, or discrete, signals and filters, as opposed to analog, or continuous, signals. The principal filter type the toolbox supports is the linear, time-invariant digital filter with a single input and a single output. You can represent linear time-invariant systems using one of several models (such as transfer function, state-space, zero-pole-gain, and second-order section) and convert between representations.

## Key Areas: Filter Design and Spectral Analysis

In addition toits corefunctions, thetool box provides rich, customizablesupport for the key areas of filter design and spectral analysis. It is easy to implement a design technique that suits your application, design digital filters directly, or create analog prototypes and discretize them. Tool box functions also estimate power spectral density and cross spectral density, using either parametric or nonparametric techniques. "Filter Design" on page 2-1 and "Statistical Signal Processing" on page 3-1, respectively detail tool box functions for filter design and spectral analysis.

Some filter design and spectral analysis functions included in the tool box are

- computation and graphical display of frequency response
- system identification
- generating signals
- discrete cosine, chirp-z, and Hilbert transforms
- lattice filters
- resampling
- timefrequency analysis
- basic communication systems simulation


## Interactive Tools: SPTool and FDATool

The power of the Signal Processing Tool box is greatly enhanced by its easy-to-use interactive tools. SPTool provides a rich graphical environment for signal viewing, filter design, and spectral analysis. The Filter Design and Analysis Tool (FDATool) provides a more comprehensive collection of features for addressing the problem of filter design. The FDATool also offers seamless access to the additional filter design methods and quantization features of the Filter Design Tool box when that product is installed.

## Extensibility

Perhaps the most important feature of the MATLAB environment is that it is extensible: MATLAB lets you create your own M-files to meet numeric computation needs for research, design, or engineering of signal processing systems. Simply copy the M-files provided with the Signal Processing Tool box and modify them as needed, or create new functions to expand the functionality of the tool box.

## Representing Signals

The central data construct in MATLAB is the numeric array, an ordered collection of real or complex numeric data with two or more dimensions. The basic data objects of signal processing (one-dimensional signals or sequences, multichannel signals, and two-dimensional signals) are all naturally suited to array representation.

## Vector Representation

MATLAB represents ordinary one-dimensional sampled data signals, or sequences, as vectors. Vectors are 1-by-n or n-by-1 arrays, where n is the number of samples in the sequence. One way to introduce a sequence into MATLAB is to enter it as a list of elements at the command prompt. The statement
$x=\left[\begin{array}{lllll}4 & 3 & 7 & -9 & 1\end{array}\right]$
creates a simple five-element real sequence in a row vector. Transposition turns the sequence into a column vector

$$
x=x^{\prime}
$$

resulting in
$x=$
4
3
7
-9
1
Column orientation is preferable for single channel signals because it extends naturally to the multichannel case. F or multichannel data, each column of a matrix represents one channel. Each row of such a matrix then corresponds to a sample point. A three-channel signal that consists of $x, 2 x$, and $x / \pi$ is

$$
y=[x \quad 2 * x \quad x / p i]
$$

This results in

| $y=$ |  |  |
| :---: | :---: | :---: |
| 4.0000 | 8.0000 | 1.2732 |
| 3.0000 | 6.0000 | 0.9549 |
| 7.0000 | 14.0000 | 2.2282 |
| -9.0000 | -18.0000 | -2.8648 |
| 1.0000 | 2.0000 | 0.3183 |

## Waveform Generation: Time Vectors and Sinusoids

A variety of tool box functions generate waveforms. Most require you to begin with a vector representing a time base. Consider generating data with a 1000 Hz sample frequency, for example. An appropriate time vector is

$$
t=(0: 0.001: 1)^{\prime} ;
$$

where MATLAB's colon operator creates a 1001-element row vector that represents time running from zero to one second in steps of one millisecond. The transpose operator (' ) changes the row vector into a column; the semicolon (;) tells MATLAB to compute but not display the result.

Given t you can create a sample signal y consisting of two sinusoids, one at 50 Hz and one at 120 Hz with twice the amplitude.

```
y = sin(2*pi*50*t) + 2*sin(2*pi*120*t);
```

The new variable $y$, formed from vector $t$, is also 1001 elements long. Y ou can add normally distributed white noise to the signal and graph the first fifty points using

```
randn('state',0);
yn = y + 0.5*randn(size(t));
plot(t(1:50),yn(1:50))
```



## Common Sequences: Unit Impulse, Unit Step, and Unit Ramp

Since MATLAB is a programming language, an endless variety of different signals is possible. Here are some statements that generate several commonly used sequences, including the unit impulse, unit step, and unit ramp functions.

```
t = (0:0.001:1)';
y = [1; zeros(99,1)]; % impulse
y = ones(100,1); % step (filter assumes 0 initial cond.)
y = t; % ramp
y = t.^2;
y = square(4*t);
```

All of these sequences are column vectors. The last three inherit their shapes from $t$.

## Multichannel Signals

Use standard MATLAB array syntax to work with multichannel signals. For example, a multichannel signal consisting of the last three signals generated above is

```
z = [t t.^2 square(4*t)];
```

You can generate a multichannel unit samplefunction using the outer product operator. F or example, a six-element column vector whosefirst element is one, and whose remaining five elements are zeros, is

```
a = [1 zeros(1,5)]';
```

To duplicate column vector a into a matrix without performing any multiplication, use MATLAB's col on operator and the ones function.

```
c = a(:,ones(1,3));
```


## Common Periodic Waveforms

The tool box provides functions for generating widely used periodic waveforms:

- sawtooth generates a sawtooth wave with peaks at $\pm 1$ and a period of $2 \pi$. An optional width parameter specifies a fractional multiple of $2 \pi$ at which the signal's maximum occurs.
- square generates a square wave with a period of $2 \pi$. An optional parameter specifies duty cycle, the percent of the period for which the signal is positive.

To generate 1.5 seconds of a 50 Hz sawtooth wave with a sample rate of 10 kHz and plot 0.2 seconds of the generated waveform, use

```
fs = 10000;
t = 0:1/fs:1.5;
x = sawtooth(2*pi*50*t);
plot(t,x), axis([0 0.2 -1 1])
```



## Common Aperiodic Waveforms

The toolbox also provides functions for generating several widely used aperiodic waveforms:

- gauspuls generates a Gaussian-modulated sinusoidal pulse with a specified time, center frequency, and fractional bandwidth. Optional parameters return in-phase and quadrature pulses, the RF signal envelope, and the cutoff time for the trailing pulse envel ope.
- chirp generates a linear swept-frequency cosine signal. An optional parameter specifies alternative sweep methods. An optional parameter phi allows initial phase to be specified in degrees.

To compute 2 seconds of a linear chirp signal with a sample rate of 1 kHz , that starts at DC and crosses 150 Hz at 1 second, use

```
t = 0:1/1000:2;
y = chirp(t,0,1,150);
```

To plot the spectrogram, use
specgram(y, 256, 1000, 256,250)


## The pulstran Function

The pulstran function generates pulse trains from either continuous or sampled prototype pulses. The following example generates a pulse train consisting of the sum of multiple delayed interpolations of a Gaussian pulse. The pulse train is defined to have a sample rate of 50 kHz , a pulse train length of 10 ms , and a pulse repetition rate of 1 kHz ; D specifies the delay to each pulse repetition in column 1 and an optional attenuation for each repetition in column 2. The pulse train is constructed by passing the name of the gauspuls function to pulstran, along with additional parameters that specify a 10 kHz Gaussian pulse with 50\% bandwidth.

```
T = 0:1/50E3:10E-3;
D = [0:1/1E3:10E-3;0.8.^(0:10)]';
Y = pulstran(T,D,'gauspuls',10E3,0.5);
plot(T,Y)
```



## The Sinc Function

The sinc function computes the mathematical sinc function for an input vector or matrix $x$. The sinc function is the continuous inverse F ourier transform of the rectangular pulse of width $2 \pi$ and height 1 .

The sinc function has a value of 1 where $x$ is zero, and a value of

$$
\frac{\sin (\pi x)}{\pi x}
$$

for all other elements of $x$.
To plot the sinc function for a linearly spaced vector with values ranging from -5 to 5 , use the following commands.

```
x = linspace(-5,5);
y = sinc(x);
plot(x,y)
```



## The Dirichlet Function

The tool box function diric computes the Dirichlet function, sometimes called the periodic sinc or aliased sinc function, for an input vector or matrix $x$. The Dirichlet function is

$$
\operatorname{diric}(x)=\left\{\begin{array}{cl}
-1^{k(n-1)} & x=2 \pi k, k=0, \pm 1, \pm 2, \ldots \\
\frac{\sin (n x / 2)}{n \sin (x / 2)} & \text { otherwise }
\end{array}\right.
$$

where n is a user-specified positive integer. For n odd, the Dirichlet function has a period of $2 \pi$; for $n$ even, its period is $4 \pi$. The magnitude of this function is $(1 / n)$ times the magnitude of the discrete-time Fourier transform of the n-point rectangular window.
To plot the Dirichlet function over the range 0 to $4 \pi$ for $n=7$ and $n=8$, use

```
x = linspace(0,4*pi,300);
plot(x,diric(x,7))
plot(x,diric(x,8))
```




## Working with Data

The examples in the preceding sections obtain data in one of two ways:

- By direct input, that is, entering the data manually at the keyboard
- By using a MATLAB or toolbox function, such as sin, cos, sawtooth, square, or sinc

Some applications, however, may need to import data from outside MATLAB. Depending on your data format, you can do this in the following ways:

- Load data from an ASCII file or MAT-file with MATLAB's load command.
- Read the data into MATLAB with a low-level fileI/O function, such as fopen, fread, and fscanf.
- Develop a MEX-file to read the data.

Other resources are also useful, such as a high-level language program (in Fortran or C, for example) that converts your data into MAT-file format - see the MATLAB External Interfaces/API Reference for details. MATLAB reads such files using the load command.

Similar techniques are available for exporting data generated within MATLAB. See the MATLAB documentation for more details on importing and exporting data.

## Filter Implementation and Analysis

This section describes how to filter discrete signals using MATLAB's filter function and other functions in the Signal Processing Tool box. It al so discusses how to use the tool box functions to analyze filter characteristics, including impulse response, magnitude and phase response, group delay, and zero-pole locations.

## Convolution and Filtering

The mathematical foundation of filtering is convolution. MATLAB's conv function performs standard one-dimensional convolution, convolving one vector with another.

```
conv([[11 1 1}][,[\begin{array}{lll}{1}&{1}&{1}\end{array}]
ans =
    1 2 3 1 % 
```

Note Convolve rectangular matrices for two-dimensional signal processing using the conv2 function.

A digital filter's output $y(k)$ is related to its input $x(k)$ by convolution with its impulse response $h(k)$.

$$
\mathrm{y}(\mathrm{k})=\mathrm{h}(\mathrm{k}) * x(\mathrm{k})=\sum_{\mathrm{I}=-\infty}^{\infty} \mathrm{h}(\mathrm{k}-\mathrm{l}) \mathrm{x}(\mathrm{l})
$$

If a digital filter's impulse response $h(k)$ is finite length, and the input $x(k)$ is al so finitelength, you can implement thefilter using conv. Storex(k) in a vector $x, h(k)$ in a vector $h$, and convolve the two.

```
x = randn(5,1); % A random vector of length 5
h = [11 1 1 1 1]/4; % Length 4 averaging filter
y = conv(h,x);
```


## Filters and Transfer Functions

In general, the z-transform $Y(z)$ of a digital filter's output $y(n)$ is related to the $z$-transform $X(z)$ of the input by

$$
Y(z)=H(z) X(z)=\frac{b(1)+b(2) z^{-1}+\cdots+b(n+1) z^{-n}}{a(1)+a(2) z^{-1}+\cdots+a(m+1) z^{-m}} X(z)
$$

where $\mathrm{H}(\mathrm{z})$ is the filter's transfer function. Here, the constants $\mathrm{b}(\mathrm{i})$ and $\mathrm{a}(\mathrm{i})$ are the filter coefficients and the order of the filter is the maximum of $n$ and $m$.

Note The filter coefficients start with subscript 1, rather than 0 . This reflects MATLAB's standard indexing scheme for vectors.

MATLAB stores the coefficients in two vectors, one for the numerator and one for the denominator. By convention, MATLAB uses row vectors for filter coefficients.

## Filter Coefficients and Filter Names

Many standard names for filters reflect the number of $a$ and $b$ coefficients present:

- When $\mathrm{n}=0$ (that is, b is a scalar), the filter is an Infinite Impulse Response (IIR), all-pole, recursive, or autoregressive (AR) filter.
- When $\mathrm{m}=0$ (that is, a is a scalar), the filter is a Finite Impulse Response (FIR), all-zero, nonrecursive, or moving average (MA) filter.
- If both $n$ and $m$ are greater than zero, thefilter is an IIR, pole-zero, recursive, or autoregressive moving average (ARMA) filter.

The acronyms AR, MA, and ARMA are usually applied to filters associated with filtered stochastic processes.

## Filtering with the filter Function

It is simple to work back to a difference equation from thez-transform relation shown earlier. Assume that $a(1)=1$. Move the denominator to the left-hand side and take the inverse z-transform.
$y(k)+a_{2} y(k-1)+\cdots+a_{m+1} y(k-m)=b_{1} x(k)+b_{2} x(k-1)+\cdots+b_{n+1} x(k-m)$
In terms of current and past inputs, and past outputs, $\mathrm{y}(\mathrm{n})$ is

$$
y(k)=b_{1} x(k)+b_{2} x(k-1)+\cdots+b_{n+1} x(k-n)-a_{2} y(k-1)-\cdots-a_{m+1} y(k-n)
$$

This is the standard time-domain representation of a digital filter, computed starting with $\mathrm{y}(1)$ and assuming zero initial conditions. This representation's progression is

$$
\begin{aligned}
y(1) & =b_{1} \mathrm{x}(1) \\
\mathrm{y}(2) & =\mathrm{b}_{1} \mathrm{x}(2)+b_{2} \mathrm{x}(1)-\mathrm{a}_{2} \mathrm{y}(1) \\
\mathrm{y}(3) & =\mathrm{b}_{1} \mathrm{x}(3)+\mathrm{b}_{2} \mathrm{x}(2)+\mathrm{b}_{3} \mathrm{x}(1)-\mathrm{a}_{2} \mathrm{y}(2)-\mathrm{a}_{3} \mathrm{y}(1) \\
\vdots & =\vdots
\end{aligned}
$$

A filter in this form is easy to implement with the filter function. For example, a simple single-pole filter (lowpass) is

```
b = 1; % Numerator
a = [1 -0.9]; % Denominator
```

where the vectors b and a represent the coefficients of a filter in transfer function form. To apply this filter to your data, use

```
y = filter(b,a,x);
```

filter gives you as many output samples as there are input samples, that is, the length of $y$ is the same as the length of $x$. If the first element of a is not 1 , filter divides the coefficients by a(1) before implementing the difference equation.

## The filter Function

filter is implemented as the transposed direct-form II structureshown below, where $\mathrm{n}-1$ is the filter order. This is a canonical form that has the minimum number of delay elements.


At sample m, filter computes the difference equations

$$
\begin{aligned}
y(m) & =b(1) x(m)+z_{1}(m-1) \\
z_{1}(m) & =b(2) x(m)+z_{2}(m-1)-a(2) y(m) \\
\vdots & =\vdots \\
z_{n-2}(m) & =b(n-1) x(m)+z_{n-1}(m-1)-a(n-1) y(m) \\
z_{n-1}(m) & =b(n) x(m)-a(n) y(m)
\end{aligned}
$$

In its most basic form, filter initializes the delay outputs $z_{i}(1), i=1, \ldots, n-1$ to 0 . This is equivalent to assuming both past inputs and outputs are zero. Set the initial delay outputs using a fourth input parameter to filter, or access the final delay outputs using a second output parameter.

```
[y,zf] = filter(b,a,x,zi)
```

Access to initial and final conditions is useful for filtering data in sections, especially if memory limitations are a consideration. Suppose you have collected data in two segments of 5000 points each.

```
x1 = randn(5000,1); % Generate two random data sequences.
x2 = randn(5000,1);
```

Perhaps the first sequence, $x 1$, corresponds to the first 10 minutes of data and the second, $x 2$, to an additional 10 minutes. The whole sequence is $x=[x 1 ; x 2]$. If there is not sufficient memory to hold the combined sequence, filter the
subsequences $x 1$ and $x 2$ one at a time. To ensure continuity of the filtered sequences, use the final conditions from $x 1$ as initial conditions to filter $\times 2$.

```
[y1,zf] = filter(b,a,x1);
y2 = filter(b,a,x2,zf);
```

The filtic function generates initial conditions for filter. filtic computes the delay vector to make the behavior of the filter reflect past inputs and outputs that you specify. To obtain the same output delay values zf as above using filtic, use

```
zf = filtic(b,a,flipud(y1),flipud(x1));
```

This can be useful when filtering short data sequences, as appropriate initial conditions help reduce transient startup effects.

## Other Functions for Filtering

In addition to filter, several other functions in the Signal Processing Tool box perform the basic filtering operation. These functions include upfirdn, which performs FIR filtering with resampling, filtfilt, which eliminates phase distortion in the filtering process, fftfilt, which performs the FIR filtering operation in the frequency domain, and latcfilt, which filters using a lattice implementation.

## Multirate Filter Bank Implementation

The function upfirdn alters the sampling rate of a signal by an integer ratio P/Q. It computes the result of a cascade of three systems that performs the following tasks:

- U psampling (zero insertion) by integer factor $p$
- Filtering by FIR filter h
- Downsampling by integer factor q


For example, to changethe sample rate of a signal from 44.1 kHz to 48 kHz , we first find the smallest integer conversion ratio p/q. Set

```
d = gcd(48000,44100);
p = 48000/d;
q = 44100/d;
```

In this example, $p=160$ and $q=147$. Sample rate conversion is then accomplished by typing

```
y = upfirdn(x,h,p,q)
```

This cascade of operations is implemented in an efficient manner using polyphase filtering techniques, and it is a central concept of multirate filtering (see reference[1] for details on multiratefilter theory). Note that the quality of the resampling result relies on the quality of the FIR filter $h$.

Filter banks may be implemented using upfirdn by allowing the filter $h$ to be a matrix, with one FIR filter per column. A signal vector is passed independently through each FIR filter, resulting in a matrix of output signals.

Other functions that perform multirate filtering (with fixed filter) include resample, interp, and decimate.

## Anti-Causal, Zero-Phase Filter Implementation

In the case of FIR filters, it is possible to design linear phase filters that, when applied to data (using filter or conv), simply delay the output by a fixed number of samples. For IIR filters, however, the phase distortion is usually highly nonlinear. The filtfilt function uses the information in the signal at points before and after the current point, in essence "looking into the future," to eliminate phase distortion.

To see how filtfilt does this, recall that if the z-transform of a real sequence $x(n)$ is $X(z)$, the $z$-transform of the time reversed sequence $x(n)$ is $X(1 / z)$. Consider the processing scheme


When $|\mathrm{z}|=1$, that is $z=\mathrm{e}^{\mathrm{j} \omega}$, the output reduces to $X\left(\mathrm{e}^{\mathrm{j}}\right)\left|\mathrm{H}\left(\mathrm{e}^{\mathrm{j}}\right)\right|^{2}$. Given all the samples of the sequence $x(n)$, a doubly filtered version of $x$ that has zero-phase distortion is possible.

For example, a 1-second duration signal sampled at 100 Hz , composed of two sinusoidal components at 3 Hz and 40 Hz , is

```
fs = 100;
t = 0:1/fs:1;
x = sin(2*pi*t*3)+.25*sin(2*pi*t*40);
```

Now create a 10-point averaging FIR filter, and filter x using both filter and filtfilt for comparison.

```
b = ones(1,10)/10; % 10 point averaging filter
y = filtfilt(b,1,x); % Noncausal filtering
yy = filter(b,1,x); % Normal filtering
plot(t,x,t,y,'--',t,yy,':')
```



Both filtered versions eliminate the 40 Hz sinusoid evident in the original, solid line. The plot also shows how filter and filtfilt differ; the dashed (filtfilt) line is in phase with the original 3 Hz sinusoid, while the dotted (filter) line is delayed by about five samples. Also, the amplitude of the dashed line is smaller due to the magnitude squared effects of filtfilt.
filtfilt reduces filter startup transients by carefully choosing initial conditions, and by prepending onto the input sequence a short, reflected piece of the input sequence. For best results, make sure the sequence you are filtering has length at least three times the filter order and tapers to zero on both edges.

## Frequency Domain Filter Implementation

Duality between the time domain and the frequency domain makes it possible to perform any operation in either domain. Usually one domain or the other is more convenient for a particular operation, but you can always accomplish a given operation in either domain.

To implement general IIR filtering in the frequency domain, multiply the discreteF ourier transform (DFT) of the input sequence with thequotient of the DFT of the filter.

```
n = length(x);
y = ifft(fft(x).*fft(b,n)./fft(a,n));
```

This computes results that are identical to filter, but with different startup transients (edge effects). For long sequences, this computation is very inefficient because of the large zero-padded FFT operations on the filter coefficients, and because the FFT algorithm becomes less efficient as the number of points $n$ increases.

For FIR filters, however, it is possible to break longer sequences into shorter, computationally efficient FFT lengths. The function

```
y = fftfilt(b,x)
```

uses the overlap add method (see reference [1] at the end of this chapter) to filter a long sequence with multiple medium-length FFTs. Its output is equivalent to filter (b, $1, x$ ).

## Impulse Response

The impulse response of a digital filter is the output arising from the unit impulse input sequence defined as

$$
x(n)= \begin{cases}1, & n=1 \\ 0, & n \neq 1\end{cases}
$$

In MATLAB, you can generate an impulse sequence a number of ways; one straightforward way is

```
imp = [1; zeros(49,1)];
```

The impulse response of the simple filter $b=1$ and $a=\left[\begin{array}{ll}1 & -0.9\end{array}\right]$ is

```
h = filter(b,a,imp);
```

The impz function in the tool box simplifies this operation, choosing the number of points to generate and then making a stem plot (using the stem function).

```
impz(b,a)
```

The plot shows the exponential decay $h(n)=0.9 n$ of the single pole system.


## Frequency Response

The Signal Processing Tool box enables you to perform frequency domain analysis of both analog and digital filters.

## Digital Domain

freqz uses an FFT-based algorithm to calculate the z-transform frequency response of a digital filter. Specifically, the statement

$$
[h, w]=\operatorname{freqz}(b, a, p)
$$

returns the p-point complex frequency response, $\mathrm{H}\left(\mathrm{e}^{\mathrm{j} \omega}\right)$, of the digital filter.

$$
H\left(e^{\mathrm{j} \omega}\right)=\frac{b(1)+b(2) e^{-j \omega}+\cdots+b(n+1) e^{-j \omega(n)}}{a(1)+a(2) e^{-j \omega}+\cdots+a(m+1) e^{-j \omega(m)}}
$$

In its simplest form, freqz accepts the filter coefficient vectors band a, and an integer $p$ specifying the number of points at which to calculate the frequency response. freqz returns the complex frequency response in vector $h$, and the actual frequency points in vector w in rad/s.
freqz can accept other parameters, such as a sampling frequency or a vector of arbitrary frequency points. The example below finds the 256-point frequency response for a 12th-order Chebyshev Typel filter. The call to freqz specifies a sampling frequency fs of 1000 Hz .

```
[b,a] = cheby1(12,0.5,200/500);
[h,f] = freqz(b,a,256,1000);
```

Because the parameter list includes a sampling frequency, freqz returns a vector f that contains the 256 frequency points between 0 and $\mathrm{fs} / 2$ used in the frequency response calculation.

Frequency Normalization This tool box uses the convention that unit frequency is the Nyquist frequency, defined as half the sampling frequency. The cutoff frequency parameter for all basic filter design functions is normalized by the Nyquist frequency. For a system with a 1000 Hz sampling frequency, for example, 300 Hz is $300 / 500=0.6$. To convert normalized frequency to angular frequency around the unit circle, multiply by $\pi$. To convert normalized frequency back to hertz, multiply by half the sample frequency.

If you call freqz with no output arguments, it automatically plots both magnitude versus frequency and phase versus frequency. For example, a ninth-order Butterworth lowpass filter with a cutoff frequency of 400 Hz , based on a 2000 Hz sampling frequency, is

$$
[b, a]=\operatorname{butter}(9,400 / 1000) ;
$$

Now calculate the 256-point complex frequency responsefor this filter, and plot the magnitude and phase with a call to freqz.

freqz can also accept a vector of arbitrary frequency points for use in the frequency response calculation. For example,

$$
\begin{aligned}
& \mathrm{w}=\operatorname{linspace}(0, \mathrm{pi}) \\
& \mathrm{h}=\operatorname{freqz}(\mathrm{b}, \mathrm{a}, \mathrm{w})
\end{aligned}
$$

calculates the complex frequency response at the frequency points in w for the filter defined by vectors $b$ and $a$. The frequency points can range from 0 to $2 \pi$. To specify a frequency vector that ranges from zero to your sampling frequency, include both the frequency vector and the sampling frequency value in the parameter list.

## Analog Domain

freqs evaluates frequency response for an analog filter defined by two input coefficient vectors, b and a. Its operation is similar to that of freqz; you can specify a number of frequency points to use, supply a vector of arbitrary frequency points, and plot the magnitude and phase response of the filter.

## Magnitude and Phase

MATLAB provides functions to extract magnitude and phase from a frequency response vector $h$. The function abs returns the magnitude of the response; angle returns the phase angle in radians. To extract and plot the magnitude and phase of a Butterworth filter.

```
[b,a] = butter(6,300/500);
[h,w] = freqz(b,a,512,1000);
m = abs(h); p = angle(h);
semilogy(w,m); title('Magnitude');
figure; plot(w,p*180/pi); title('Phase');
```




The unwrap function is also useful in frequency analysis. unwrap unwraps the phase to make it continuous across $360^{\circ}$ phase discontinuities by adding multiples of $\pm 360^{\circ}$, as needed. To see how unwrap is useful, design a 25 th-order lowpass FIR filter.

```
h = fir1(25,0.4);
```

Obtain the filter's frequency response with freqz, and plot the phase in degrees.

```
[H,f] = freqz(h,1,512,2);
plot(f,angle(H)*180/pi); grid
```



It is difficult to distinguish the $360^{\circ}$ jumps (an artifact of the arctangent function inside angle) from the $180^{\circ}$ jumps that signify zeros in the frequency response.

Use unwrap to eliminate the $360^{\circ}$ jumps.
plot(f,unwrap(angle(H))*180/pi); grid


## Delay

The group delay of a filter is a measure of the average delay of the filter as a function of frequency. It is defined as the negative first derivative of a filter's phase response. If the complex frequency response of a filter is $H\left(e^{\omega \omega}\right)$, then the group delay is

$$
\tau_{g}(\omega)=-\frac{d \theta(\omega)}{d \omega}
$$

where $\theta$ is the phase angle of $H\left(e^{j \omega}\right)$. Compute group delay with

$$
[g d, w]=\operatorname{grpdelay}(b, a, n)
$$

which returns the $n$-point group delay, $\tau_{g}(\omega)$, of the digital filter specified by $b$ and $a$, evaluated at the frequencies in vector $w$.
The phase delay of a filter is the negative of phase divided by frequency

$$
\tau_{p}(\omega)=-\frac{\theta(\omega)}{\omega}
$$

To plot both the group and phase delays of a system on the same graph, type

```
[b,a] = butter(10,200/1000);
gd = grpdelay(b,a,128);
[h,f] = freqz(b,a,128,2000);
pd = -unwrap(angle(h))*(2000/(2*pi))./f;
plot(f,gd,'-',f,pd,'--')
axis([0 1000 -30 30])
legend('Group Delay','Phase Delay')
```



## Zero-Pole Analysis

The zplane function plots poles and zeros of a linear system. For example, a simple filter with a zero at $-1 / 2$ and a complex pole pair at $0.9 \mathrm{e}^{\mathrm{j} 2 \pi(0.3)}$ and $0.9 \mathrm{e}^{-\mathrm{j} 2 \pi(0.3)}$ is

```
zer = -0.5;
pol = 0.9*exp(j*2*pi*[-0.3 0.3]');
```

The zero-pole plot for the filter is

```
zplane(zer,pol)
```



For a system in zero-pole form, supply column vector arguments $z$ and $p$ to zplane.

```
zplane(z,p)
```

For a system in transfer function form, supply row vectors b and a as arguments to zplane.

```
zplane(b,a)
```

In this case zplane finds the roots of $b$ and a using the roots function and plots the resulting zeros and poles.

See "Linear System M odels" on page 1-33 for details on zero-pole and transfer function representation of systems.

## Linear System Models

The Signal Processing Tool box provides several models for representing linear time-invariant systems. This flexibility lets you choose the representational scheme that best suits your application and, within the bounds of numeric stability, convert freely to and from most other models. This section provides a brief overview of supported linear system models and describes how to work with these models in MATLAB.

## Discrete-Time System Models

The discrete-time system models are representational schemes for digital filters. MATLAB supports several discrete-time system models, which are described in the following sections:

- "Transfer Function"
- "Zero-Pole-Gain"
- "State-Space"
- "Partial Fraction Expansion (Residue Form)"
- "Second-Order Sections (SOS)"
- "Lattice Structure"
- "Convolution Matrix"


## Transfer Function

The transfer function is a basic z-domain representation of a digital filter, expressing the filter as a ratio of two polynomials. It is the principal discrete-time model for this tool box. The transfer function model description for the z-transform of a digital filter's difference equation is

$$
Y(z)=\frac{b(1)+b(2) z^{-1}+\cdots+b(n+1) z^{-n}}{a(1)+a(2) z^{-1}+\cdots+a(m+1) z^{-m}} X(z)
$$

Here, the constants $b(i)$ and $a(i)$ are the filter coefficients, and the order of the filter is the maximum of $n$ and $m$. In MATLAB, you store these coefficients in two vectors (row vectors by convention), one row vector for the numerator and one for the denominator. See "Filters and Transfer Functions" on page 1-16 for more details on the transfer function form.

## Zero-Pole-Gain

The factored or zero-polegain form of a transfer function is

$$
H(z)=\frac{q(z)}{p(z)}=k \frac{(z-q(1))(z-q(2)) \cdots(z-q(n))}{(z-p(1))(z-p(2)) \cdots(z-p(n))}
$$

By convention, MATLAB stores polynomial coefficients in row vectors and polynomial roots in column vectors. In zero-pole-gain form, therefore, the zero and pole locations for the numerator and denominator of a transfer function reside in column vectors. The factored transfer function gain $k$ is a MATLAB scalar.

The poly and roots functions convert between polynomial and zero-pole-gain representations. For example, a simple IIR filter is

```
b = [2 3 4];
a = [11 3 3 1];
```

The zeros and poles of this filter are

```
q = roots(b)
q =
    -0.7500 + 1.1990i
    -0.7500 - 1.1990i
p = roots(a)
p =
    -1.0000
    -1.0000 + 0.0000i
    -1.0000 - 0.0000i
k = b(1)/a(1)
k =
    2
```

Returning to the original polynomials,

```
bb = k*poly(q)
bb =
    2.0000 3.0000 4.0000
```

```
aa = poly(p)
aa =
    1.0000 3.0000 3.0000 1.0000
```

Note that b and a in this case represent the transfer function

$$
H(z)=\frac{2+3 z^{-1}+4 z^{-2}}{1+3 z^{-1}+3 z^{-2}+z^{-3}}=\frac{2 z^{3}+3 z^{2}+4 z}{z^{3}+3 z^{2}+3 z+1}
$$

For $b=\left[\begin{array}{lll}2 & 3 & 4\end{array}\right]$, the roots function misses the zero for $z$ equal to 0 . In fact, it misses poles and zeros for z equal to 0 whenever the input transfer function has more poles than zeros, or vice versa. This is acceptable in most cases. To circumvent the problem, however, simply append zeros to make the vectors the same length before using the roots function; for example, $b=\left[\begin{array}{ll}b & 0\end{array}\right]$.

## State-Space

It is always possible to represent a digital filter, or a system of difference equations, as a set of first-order difference equations. In matrix or statespace form, you can write the equations as

$$
\begin{aligned}
x(n+1) & =A x(n)+B u(n) \\
y(n) & =C x(n)+D u(n)
\end{aligned}
$$

where u is the input, x is the state vector, and y is the output. F or single-channel systems, $A$ is an m-by-m matrix where $m$ is the order of the filter, $B$ is a column vector, $C$ is a row vector, and $D$ is a scalar. State-space notation is especially convenient for multichannel systems where input $u$ and output y become vectors, and $B, C$, and $D$ become matrices.

State-space representation extends easily to the MATLAB environment. In MATLAB, A, B, C, and D are rectangular arrays; MATLAB treats them as individual variables.

Taking thez-transform of the state-space equations and combining them shows the equivalence of state-space and transfer function forms.

$$
Y(z)=H(z) U(z), \quad \text { where } H(z)=C(z l-A)^{-1} B+D
$$

Don't be concerned if you are not familiar with the state-space representation of linear systems. Some of the filter design al gorithms use state-space form internally but do not require any knowledge of state-space concepts to use them
successfully. If your applications use state-space based signal processing extensively, however, consult the Contr ol System Tool box for a comprehensive library of state-space tools.

## Partial Fraction Expansion (Residue Form)

Each transfer function also has a corresponding partial fraction expansion or residueform representation, given by

$$
\frac{b(z)}{a(z)}=\frac{r(1)}{1-p(1) z^{-1}}+\cdots+\frac{r(n)}{1-p(n) z^{-1}}+k(1)+k(2) z^{-1}+\cdots+k(m-n+1) z^{-(m-n)}
$$

provided $\mathrm{H}(\mathrm{z})$ has no repeated poles. Here, n is the degree of the denominator polynomial of the rational transfer function $b(z) / a(z)$. If $r$ is a pole of multiplicity $\mathrm{s}_{\mathrm{r}}$, then $\mathrm{H}(\mathrm{z})$ has terms of the form

$$
\frac{r(j)}{1-p(j) z^{-1}}+\frac{r(j+1)}{\left(1-p(j) z^{-1}\right)^{2}}+\cdots+\frac{r\left(j+s_{r}-1\right)}{\left(1-p(j) z^{-1}\right)^{s_{r}}}
$$

The residuez function in the Signal Processing Tool box converts transfer functions to and from the partial fraction expansion form. The " $z$ " on the end of residuez stands for z-domain, or discrete domain. residuez returns the poles in a column vector $p$, the residues corresponding to the poles in a column vector $r$, and any improper part of the original transfer function in a row vector k. residuez determines that two poles are the same if the magnitude of their difference is smaller than 0.1 percent of either of the poles' magnitudes.

Partial fraction expansion arises in signal processing as one method of finding the inversez-transform of a transfer function. For example, the partial fraction expansion of

$$
H(z)=\frac{-4+8 z^{-1}}{1+6 z^{-1}+8 z^{-2}}
$$

is

```
b = [-4 8];
a = [1 6 8];
[r,p,k] = residuez(b,a)
```

$$
\begin{aligned}
& r= \\
& \text {-12 } \\
& 8 \\
& p= \\
& \text {-4 } \\
& \text {-2 } \\
& \mathrm{k}= \\
& \text { [] }
\end{aligned}
$$

which corresponds to

$$
H(z)=\frac{-12}{1+4 z^{-1}}+\frac{8}{1+2 z^{-1}}
$$

Tofind the inversez-transform of $\mathrm{H}(\mathrm{z})$, find the sum of theinversez-transforms of the two addends of $\mathrm{H}(\mathrm{z})$, giving the causal impulse response

$$
h(n)=-12(-4)^{n}+8(-2)^{n}, \quad n=0,1,2, \ldots
$$

To verify this in MATLAB, type
imp = [10 0 0 0];
resptf = filter(b,a,imp)
resptf =
$\begin{array}{lllll}-4 & 32 & -160 & 704 & -2944\end{array}$
respres $=$ filter(r(1),[1 -p(1)],imp) + filter(r(2),[1-p(2)],imp)
respres =
$\begin{array}{lllll}-4 & 32 & -160 & 704 & -2944\end{array}$

## Second-O rder Sections (SOS)

Any transfer function $\mathrm{H}(\mathrm{z})$ has a second-order sections representation

$$
H(z)=\prod_{k=1}^{L} H_{k}(z)=\prod_{k=1}^{L} \frac{b_{0 k}+b_{1 k^{\prime}} z^{-1}+b_{2 k} z^{-2}}{a_{0 k}+a_{1 k^{\prime}} z^{-1}+a_{2 k} z^{-2}}
$$

where $L$ is the number of second-order sections that describe the system. MATLAB represents the second-order section form of a discrete-time system as an L-by-6 array sos. E ach row of sos contains a single second-order section, where the row elements are the three numerator and three denominator coefficients that describe the second-order section.

$$
\operatorname{sos}=\left[\begin{array}{cccccc}
b_{01} & b_{11} & b_{21} & a_{01} & a_{11} & a_{21} \\
b_{02} & b_{12} & b_{22} & a_{02} & a_{12} & a_{22} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
b_{0 L} & b_{1 L} & b_{2 L} & a_{0 L} & a_{1 L} & a_{2 L}
\end{array}\right]
$$

There are an uncountable number of ways to represent a filter in second-order section form. Through careful pairing of the pole and zero pairs, ordering of the sections in the cascade, and multiplicative scaling of the sections, it is possible to reduce quantization noise gain and avoid overflow in some fixed-point filter implementations. The functions zp2sos and ss2sos, described in "Linear System Transformations" on page 1-43, perform pole-zero pairing, section scaling, and section ordering.

Note In the Signal Processing Tool box, all second-order section transformations apply only to digital filters.

## Lattice Structure

For a discrete Nth order all-pole or all-zero filter described by the polynomial coefficients $a(n), n=1,2, \ldots, N+1$, there are $N$ corresponding lattice structure coefficients $k(n), n=1,2, \ldots, N$. The parameters $k(n)$ are al so called the reflection coefficients of the filter. Given these reflection coefficients, you can implement a discrete filter as shown below.


For a general polezeroIIR filter described by polynomial coefficients $a$ and $b$, there are both lattice coefficients $k(n)$ for the denominator a and ladder coefficients $v(n)$ for the numerator $b$. The lattice/ladder filter may be implemented as


The tool box function tf2latc accepts an FIR or IIR filter in polynomial form and returns the corresponding reflection coefficients. An exampleFIR filter in polynomial form is
b $=[1.0000$
0.6149
0.9899
0.0000
$0.0031-0.0082]$;

This filter's lattice (reflection coefficient) representation is

$$
\begin{aligned}
\mathrm{k}= & \text { tf2latc }(\mathrm{b}) \\
\mathrm{k}= & \\
& 0.3090 \\
& 0.9801 \\
& 0.0031 \\
& 0.0081 \\
& -0.0082
\end{aligned}
$$

For IIR filters, the magnitude of the reflection coefficients provides an easy stability check. If all the reflection coefficients corresponding to a polynomial have magnitude less than 1, all of that polynomial's roots are inside the unit circle. For example, consider an IIR filter with numerator polynomial b from above and denominator polynomial

$$
a=\left[\begin{array}{lll}
1 & 1 / 2 & 1 / 3
\end{array}\right] ;
$$

The filter's lattice representation is

```
[k,v] = tf2latc(b,a)
k =
        0.3750
        0.3333
            0
            0
            0
v =
    0.6252
    0.1212
    0.9879
    -0.0009
    0.0072
    -0.0082
```

Because abs (k) <1 for all reflection coefficients in k, the filter is stable.

The function latc2tf calculates the polynomial coefficients for a filter from its lattice (reflection) coefficients. Given the reflection coefficient vector k (above), the corresponding polynomial form is

```
b = latc2tf(k)
b =
    1.0000 0.6149 0.9899 -0.0000 0.0031 -0.0082
```

The lattice or lattice/ladder coefficients can be used to implement the filter using the function latcfilt.

## Convolution Matrix

In signal processing, convolving two vectors or matrices is equivalent to filtering one of the input operands by the other. This relationship permits the representation of a digital filter as a convolution matrix.

Given any vector, thetoolbox function convmtx generates a matrix whose inner product with another vector is equivalent to the convolution of the two vectors. The generated matrix represents a digital filter that you can apply to any vector of appropriate length; the inner dimension of the operands must agree to compute the inner product.

The convolution matrix for a vector $b$, representing the numerator coefficients for a digital filter, is

```
b = [1 2 3]; x = randn(3,1);
C = convmtx(b',3)
C =
    1 0}
    2 0
    3 2 1
    0 3 2
    0 0 3
```

Two equivalent ways to convolve $b$ with $x$ are as follows.

```
y1 = C*x;
y2 = conv(b,x);
```


## Continuous-Time System Models

The continuous-time system models are representational schemes for analog filters. Many of the discrete-time system models described earlier are also appropriate for the representation of continuous-time systems:

- State-space form
- Partial fraction expansion
- Transfer function
- Zero-pole-gain form

It is possible to represent any system of linear time-invariant differential equations as a set of first-order differential equations. In matrix or statespace form, you can express the equations as

$$
\begin{aligned}
& \dot{x}=A x+B u \\
& y=C x+D u
\end{aligned}
$$

where $u$ is a vector of nu inputs, $x$ is an $n x$-element state vector, and $y$ is a vector of ny outputs. In MATLAB, store A, B, C, and D in separate rectangular arrays.
An equivalent representation of the state-space system is the Laplace transform transfer function description

$$
\mathrm{Y}(\mathrm{~s})=\mathrm{H}(\mathrm{~s}) \mathrm{U}(\mathrm{~s})
$$

where

$$
H(s)=C(s l-A)^{-1} B+D
$$

For single-input, single-output systems, this form is given by

$$
H(s)=\frac{b(s)}{a(s)}=\frac{b(1) s^{n}+b(2) s^{n-1}+\cdots+b(n+1)}{a(1) s^{m}+a(2) s^{m-1}+\cdots+a(m+1)}
$$

Given the coefficients of a Laplace transform transfer function, residue determines the partial fraction expansion of the system. See the description of residue in the MATLAB documentation for details.

The factored zero-pole-gain form is

$$
H(s)=\frac{z(s)}{p(s)}=k \frac{(s-z(1))(s-z(2)) \cdots(s-z(n))}{(s-p(1))(s-p(2)) \cdots(s-p(n))}
$$

As in the discrete-time case, MATLAB stores polynomial coefficients in row vectors in descending powers of $s$. MATLAB stores polynomial roots, or zeros and poles, in column vectors.

## Linear System Transformations

The Signal Processing Tool box provides a number of functions that convert between the various linear system models; see Chapter 7, F unction Reference for a complete description of each. You can use the following chart to find an appropriate transfer function: find the row of the model to convert from on the left side of the chart and the column of the model to convert to on the top of the chart and read the function name(s) at the intersection of the row and column.

|  | Transfer <br> function | State- <br> space | Zero- <br> pole- <br> gain | Partial <br> fraction | Lattice <br> filter | Second- <br> order <br> sections | Convolution <br> matrix |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Transfer <br> function |  | tf2ss | tf2zp <br> roots | residuez <br> residue | tf2latc |  | convmtx |
| State-space | ss2tf |  | ss2zp |  |  | ss2sos |  |
| Zero-pole- <br> gain | zp2tf <br> poly | zp2ss |  |  |  | zp2sos |  |
| Partial <br> fraction | residuez <br> residue |  |  |  |  |  |  |
| Lattice filter | latc2tf |  |  |  |  |  |  |
| SOS | sos2tf | sos2ss | sos2zp |  |  |  |  |
| Convolution |  |  |  |  |  |  |  |
| matrix |  |  |  |  |  |  |  |

Note Converting from one filter structure or model to another may produce a result with different characteristics than the original. This is due to the computer's finite-precision arithmetic and the variations in the conversion's round-off computations.

> Many of the tool box filter design functions use these functions internally. For example, the zp2ss function converts the poles and zeros of an analog prototype into the state-space form required for creation of a Butterworth, Chebyshev, or elliptic filter. Once in state-space form, thefilter design function performs any required frequency transformation, that is, it transforms the initial lowpass design into a bandpass, highpass, or bandstop filter, or a lowpass filter with the desired cutoff frequency. See the descriptions of the individual filter design functions in Chapter 7, "F unction Reference," for more details.

Note In the Signal Processing Tool box, all second-order section transformations apply only to digital filters.

## Discrete Fourier Transform

The discrete F ourier transform, or DFT, is the primary tool of digital signal processing. The foundation of the Signal Processing Tool box is the fast Fourier transform (FFT), a method for computing the DFT with reduced execution time. Many of the tool box functions (including z-domain frequency response, spectrum and cepstrum analysis, and some filter design and implementation functions) incorporate the FFT.

MATLAB provides thefunctions fft and ifft to compute the discrete Fourier transform and its inverse, respectively. For the input sequence $x$ and its transformed version $X$ (the discrete-time Fourier transform at equally spaced frequencies around the unit circle), the two functions implement the relationships

$$
\begin{aligned}
& X(k+1)=\sum_{n=0}^{N-1} x(n+1) W_{n}^{k n} \\
& x(n+1)=\frac{1}{N} \sum_{k=0}^{N-1} X(k+1) W_{n}^{-k n}
\end{aligned}
$$

In these equations, the series subscripts begin with 1 instead of 0 because of MATLAB's vector indexing scheme, and

$$
W_{N}=e^{-j\left(\frac{2 \pi}{N}\right)}
$$

Note MATLAB uses a negativej for the fft function. This is an engineering convention; physics and pure mathematics typically use a positive $j$.
fft, with a single input argument $x$, computes the DFT of the input vector or matrix. If x is a vector, fft computes the DFT of the vector; if x is a rectangular array, fft computes the DFT of each array column.

For example, create a time vector and signal.

```
t = (0:1/100:10-1/100); % Time vector
x = sin(2*pi*15*t) + sin(2*pi*40*t); % Signal
```

The DFT of the signal, and the magnitude and phase of the transformed sequence, are then

```
y = fft(x); % Compute DFT of x
m = abs(y); p = unwrap(angle(y)); % Magnitude and phase
```

To plot the magnitude and phase, type the following commands.

```
f = (0:length(y)-1)*99/length(y); % Frequency vector
plot(f,m); title('Magnitude');
set(gca,'XTick',[15 40 60 85]);
figure; plot(f,p*180/pi); title('Phase');
set(gca,'XTick',[15 40 60 85]);
```




A second argument to fft specifies a number of points $n$ for the transform, representing DFT length.

$$
y=f f t(x, n) ;
$$

In this case, fft pads the input sequence with zeros if it is shorter than $n$, or truncates the sequence if it is longer than $n$. If $n$ is not specified, it defaults to the length of the input sequence. Execution time for fft depends on the length, $n$, of the DFT it performs; see the fft reference page in the MATLAB documentation for details about the algorithm.

The inverse discrete Fourier transform function ifft also accepts an input sequence and, optionally, the number of desired points for the transform. Try the example bel ow; the original sequence $x$ and the reconstructed sequence are identical (within rounding error).

```
t = (0:1/255:1);
x = sin(2*pi*120*t);
y = real(ifft(fft(x)));
```

This tool box also includes functions for the two-dimensional FFT and its inverse, fft2 and ifft2. Thesefunctions are useful for two-dimensional signal or image processing. The goertzel function, which is another algorithm to compute the DFT, also is included in the tool box. This function is efficient for computing the DFT of a portion of a long signal. Seethedescriptions in Chapter 7, "F unction Reference," for details.

It is sometimes convenient to rearrange the output of the fft or fft2 function so the zerofrequency component is at the center of the sequence. The MATLAB function fftshift moves the zero frequency component to the center of a vector or matrix.

## Selected Bibliography

Algorithm development for the Signal Processing Tool box has drawn heavily upon the references listed below. All are recommended to the interested reader who needs to know more about signal processing than is covered in this manual.
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## Filter Design

Overview ..... 2-2
Filter Requirements and Specification ..... 2-3
IIR Filter Design ..... 2-5
Classical IIR Filter Design Using Analog Prototyping ..... 2-7
Comparison of Classical IIR Filter Types ..... 2-9
FIR Filter Design ..... 2-17
Linear Phase Filters ..... 2-18
Windowing Method ..... 2-19
Multiband FIR Filter Design with Transition Bands ..... 2-23
Constrained Least Squares FIR Filter Design ..... 2-28
Arbitrary-Response Filter Design ..... 2-32
Special Topics in IIR Filter Design ..... 2-38
Analog Prototype Design ..... 2-39
Frequency Transformation ..... 2-39
Filter Discretization ..... 2-42
Selected Bibliography ..... 2-46

## Overview

The Signal Processing Tool box provides functions that support a range of filter design methodologies. The following sections explain how to apply the filter design tools to Infinite I mpulse Response (IIR) and Finite Impulse Response (FIR) filter design problems:

- "Filter Requirements and Specification"
- "IIR Filter Design"
- "FIR Filter Design"
- "Special Topics in IIR Filter Design"
- "Selected Bibliography"


## Filter Requirements and Specification

The goal of filter design is to perform frequency dependent alteration of a data sequence. A possible requirement might be to remove noise above 30 Hz from a data sequence sampled at 100 Hz . A more rigorous specification might call for a specific amount of passband ripple, stopband attenuation, or transition width. A very precise specification could ask to achieve the performance goals with the minimum filter order, or it could call for an arbitrary magnitude shape, or it might require an FIR filter.

Filter design methods differ primarily in how performance is specified. For "loosely specified" requirements, as in the first case above, a Butterworth IIR filter is often sufficient. To design a fifth-order 30 Hz lowpass Butterworth filter and apply it to the data in vector $x$,

```
[b,a] = butter(5,30/50);
y = filter(b,a,x);
```

The second input argument to butter specifies the cutoff frequency, normalized to half the sampling frequency (the Nyquist frequency).


#### Abstract

Frequency Normalization in the Signal Processing Toolbox All of the filter design functions operate with normalized frequencies, so they do not require the system sampling rate as an extra input argument. This tool box uses the convention that unit frequency is the Nyquist frequency, defined as half the sampling frequency. The normalized frequency, therefore, is always in the interval $0 \leq f \leq 1$. For a system with a 1000 Hz sampling frequency, 300 Hz is $300 / 500=0.6$. To convert normalized frequency to angular frequency around the unit circle, multiply by $\pi$. To convert normalized frequency back to hertz, multiply by half the sample frequency.


M ore rigorous filter requirements traditionally include passband ripple (Rp, in decibels), stopband attenuation (Rs, in decibels), and transition width (Ws-Wp, in hertz).


You can design Butterworth, Chebyshev Type I, Chebyshev Type II, and elliptic filters that meet this type of performance specification. The tool box order selection functions estimate the minimum filter order that meets a given set of requirements.

To meet specifications with more rigid constraints like linear phase or arbitrary filter shape, use the FIR and direct IIR filter design routines.

## IIR Filter Design

The primary advantage of IIR filters over FIR filters is that they typically meet a given set of specifications with a much lower filter order than a corresponding FIR filter. Although IIR filters have nonlinear phase, data processing within MATLAB is commonly performed "off-line," that is, the entire data sequence is available prior to filtering. This allows for a noncausal, zero-phase filtering approach (via the filtfilt function), which eliminates the nonlinear phase distortion of an IIR filter.

The classical IIR filters, Butterworth, Chebyshev Types I and II, elliptic, and Bessel, all approximate the ideal "brick wall" filter in different ways. This tool box provides functions to create all thesetypes of classical IIR filters in both the analog and digital domains (except Bessel, for which only the analog case is supported), and in lowpass, highpass, bandpass, and bandstop configurations. For most filter types, you can also find the lowest filter order that fits a given filter specification in terms of passband and stopband attenuation, and transition width(s).

The direct filter design function yulewalk finds a filter with magnitude response approximating a desired function. This is one way to create a multiband bandpass filter.
You can also use the parametric modeling or system identification functions to design IIR filters. These functions are discussed in "Parametric Modeling" on page 4-12.

The generalized Butterworth design function maxflat is discussed in the section "Generalized Butterworth Filter Design" on page 2-15.
The following table summarizes the various filter methods in the toolbox and lists the functions available to implement these methods.

| Method | Description | Functions |
| :--- | :--- | :--- |
| Analog <br> Prototyping | Using the poles and zeros of <br> a dassical lowpass <br> prototype filter in the <br> continuous (Laplace) <br> domain, obtain a digital <br> filter through frequency <br> transformation and filter <br> discretization. | Complete design functions: <br> besself, butter, cheby1, cheby2, ellip <br> Order estimation functions: <br> buttord, cheb1ord, cheb2ord, ellipord |
| Lowpass analog prototype functions: |  |  |
| Direct Design | Design digital filter directly <br> in the discretetime-domain <br> by approximating a <br> piecewise linear magnitude <br> response. | ellipap |
| Design lowpass <br> Butterworth filters with <br> more zeros than poles. | Frequency transformation functions: |  |
| lp2bp, lp2bs, lp2hp, lp2lp |  |  |

## Classical IIR Filter Design Using Analog Prototyping

The principal IIR digital filter design technique this tool box provides is based on the conversion of classical lowpass analog filters to their digital equivalents. The following sections describe how to design filters and summarize the characteristics of the supported filter types. See "Special Topics in IIR Filter Design" on page 2-38 for detailed steps on the filter design process.

## Complete Classical IIR Filter Design

You can easily create a filter of any order with a lowpass, highpass, bandpass, or bandstop configuration using the filter design functions.

| Filter Type | Design Function |
| :---: | :---: |
| Bessel (analog only) | $\begin{aligned} & [\mathrm{b}, \mathrm{a}]=\text { besself( } \mathrm{n}, \text { Wn,options }) \\ & [\mathrm{z}, \mathrm{p}, \mathrm{k}]=\text { besself( } \mathrm{n}, \text { Wn,options }) \\ & {[\mathrm{A}, \mathrm{~B}, \mathrm{C}, \mathrm{D}]=\operatorname{besself}(\mathrm{n}, \text { Wn,options })} \end{aligned}$ |
| Butterworth | $\begin{aligned} & {[\mathrm{b}, \mathrm{a}]=\operatorname{butter}(\mathrm{n}, \text { Wn, options })} \\ & {[\mathrm{z}, \mathrm{p}, \mathrm{k}]=\operatorname{butter}(\mathrm{n}, \text { Wn, options })} \\ & {[\mathrm{A}, \mathrm{~B}, \mathrm{C}, \mathrm{D}]=\operatorname{butter}(\mathrm{n}, \text { Wn, options })} \end{aligned}$ |
| Chebyshev Type I | $\begin{aligned} & {[b, a]=\text { cheby1 }(\mathrm{n}, \mathrm{Rp}, \text { Wn,options })} \\ & [\mathrm{z}, \mathrm{p}, \mathrm{k}]=\text { cheby1( } \mathrm{n}, \mathrm{Rp}, \text { Wn,options }) \\ & {[\mathrm{A}, \mathrm{~B}, \mathrm{C}, \mathrm{D}]=\operatorname{cheby} 1(\mathrm{n}, \mathrm{Rp}, \text { Wn, options })} \end{aligned}$ |
| Chebyshev Type II | $\begin{aligned} & [\mathrm{b}, \mathrm{a}]=\text { cheby2( } \mathrm{n}, \mathrm{Rs}, \mathrm{Wn}, \text { options }) \\ & [\mathrm{z}, \mathrm{p}, \mathrm{k}]=\text { cheby2( } \mathrm{n}, \mathrm{Rs}, \text { Wn,options }) \\ & {[\mathrm{A}, \mathrm{~B}, \mathrm{C}, \mathrm{D}]=\operatorname{cheby2} 2(\mathrm{n}, \text { Rs }, \text { Wn, options })} \end{aligned}$ |
| Elliptic | $\begin{aligned} & {[\mathrm{b}, \mathrm{a}]=\operatorname{ellip}(\mathrm{n}, \mathrm{Rp}, \mathrm{Rs}, \text { Wn,options })} \\ & {[\mathrm{z}, \mathrm{p}, \mathrm{k}]=\operatorname{ellip}(\mathrm{n}, \mathrm{Rp}, \mathrm{Rs}, \text { Wn,options })} \\ & {[\mathrm{A}, \mathrm{~B}, \mathrm{C}, \mathrm{D}]=\operatorname{ellip}(\mathrm{n}, \mathrm{Rp}, \mathrm{Rs}, \text { Wn,options })} \end{aligned}$ |

By default, each of these functions returns a lowpass filter; you need only specify the desired cutoff frequency Wn in normalized frequency (Nyquist frequency $=1 \mathrm{~Hz}$ ). F or a highpass filter, append the string ' high ' to the function's parameter list. F or a bandpass or bandstop filter, specify Wn as a two-element vector containing the passband edge frequencies, appending the string 'stop' for the bandstop configuration.

Here are some example digital filters.

```
[b,a] = butter(5,0.4); % Lowpass Butterworth
[b,a] = cheby1(4,1,[0.4 0.7]); % Bandpass Chebyshev Type I
[b,a] = cheby2(6,60,0.8,'high'); % Highpass Chebyshev Type II
[b,a] = ellip(3,1,60,[0.4 0.7],'stop'); % Bandstop elliptic
```

To design an analog filter, perhaps for simulation, use a trailing 's ' and specify cutoff frequencies in rad/s.

```
[b,a] = butter(5,.4,'s'); % Analog Butterworth filter
```

All filter design functions return a filter in the transfer function, zero-pole-gain, or state-space linear system model representation, depending on how many output arguments are present.

Note All classical IIR lowpass filters are ill-conditioned for extremely low cut-off frequencies. Therefore, instead of designing a lowpass IIR filter with a very narrow passband, it can be better to design a wider passband and decimate the input signal.

## Designing IIR Filters to Frequency Domain Specifications

This tool box provides order selection functions that calculate the minimum filter order that meets a given set of requirements.

| Filter Type | Order Estimation Function |
| :--- | :--- |
| Butterworth | $[n, W n]=$ buttord $(W p, W s, R p, R s)$ |
| Chebyshev Type I | $[n, W n]=$ cheb1ord $(W p, W s, R p, R s)$ |
| Chebyshev Type II | $[n, W n]=$ cheb2ord $(W p, W s, R p, R s)$ |
| Elliptic | $[n, W n]=$ ellipord $(W p, W s, R p, R s)$ |

These are useful in conjunction with the filter design functions. Suppose you want a bandpass filter with a passband from 1000 to 2000 Hz , stopbands starting 500 Hz away on either side, a 10 kHz sampling frequency, at most 1 dB
of passband ripple, and at least 60 dB of stopband attenuation. You can meet these specifications by using the butter function as follows.

```
[n,Wn] = buttord([1000 2000]/5000,[500 2500]/5000,1,60)
n =
    1 2
Wn =
        0.1951 0.4080
[b,a] = butter(n,Wn);
```

An elliptic filter that meets the same requirements is given by

```
[n,Wn] = ellipord([1000 2000]/5000,[500 2500]/5000,1,60)
n =
    5
Wn =
    0.2000 0.4000
[b,a] = ellip(n,1,60,Wn);
```

Thesefunctions also work with the other standard band configurations, as well as for analog filters; see Chapter 7, "F unction Reference," for details.

## Comparison of Classical IIR Filter Types

The tool box provides five different types of classical IIR filters, each optimal in some way. This section shows the basic analog prototype form for each and summarizes major characteristics.

## Butterw orth Filter

The Butterworth filter provides the best Taylor Series approximation to the ideal lowpass filter response at analog frequencies $\Omega=0$ and $\Omega=\infty$; for any order N , the magnitude squared response has $2 \mathrm{~N}-1$ zero derivatives at these locations (maximally flat at $\Omega=0$ and $\Omega=\infty$ ). Response is monotonic overall, decreasing smoothly from $\Omega=0$ to $\Omega=\infty$. $|\mathrm{H}(\mathrm{j} \Omega)|=\sqrt{1 / 2}$ at $\Omega=1$.


## Chebyshev Type I Filter

The Chebyshev Type I filter minimizes the absolute difference between the ideal and actual frequency response over the entire passband by incorporating an equal ripple of Rp dB in the passband. Stopband response is maximally flat. The transition from passband to stopband is more rapid than for the Butterworth filter. $|\mathrm{H}(\mathrm{j} \Omega)|=10^{-\mathrm{R}} / 20$ at $\Omega=1$.


## Chebyshev Type II Filter

The Chebyshev Type II filter minimizes the absolute difference between the ideal and actual frequency response over the entire stopband by incorporating an equal ripple of Rs dB in the stopband. Passband response is maximally flat.

The stopband does not approach zero as quickly as the type I filter (and does not approach zero at all for even-valued filter order $n$ ). The absence of ripplein the passband, however, is often an important advantage. $|\mathrm{H}(\mathrm{j} \Omega)|=10^{-}$ at $\Omega=1$.


## Elliptic Filter

Elliptic filters are equiripple in both the passband and stopband. They generally meet filter requirements with the lowest order of any supported filter type. Given a filter order $n$, passband rippleRp in decibels, and stopband ripple Rs in decibels, elliptic filtersminimizetransition width. $|\mathrm{H}(\mathrm{j} \Omega)|=10^{-\mathrm{Rp} / 20}$ at $\Omega=1$.


## Bessel Filter

Analog Bessel lowpass filters have maximally flat group delay at zero frequency and retain nearly constant group delay across the entire passband. Filtered signals therefore maintain their waveshapes in the passband frequency range. Frequency mapped and digital Bessel filters, however, do not have this maximally flat property; this tool box supports only the analog case for the complete Bessel filter design function.

Bessel filters generally require a higher filter order than other filters for satisfactory stopband attenuation. $|\mathrm{H}(\mathrm{j} \Omega)|<1 / \sqrt{2}$ at $\Omega=1$ and decreases as filter order n increases.


Note The lowpass filters shown above were created with the analog prototype functions besselap, buttap, cheb1ap, cheb2ap, and ellipap. These functions find the zeros, poles, and gain of an order $n$ anal og filter of the appropriate type with cutoff frequency of $1 \mathrm{rad} / \mathrm{s}$. The complete filter design functions (besself, butter, cheby1, cheby2, and ellip) call the prototyping functions as a first step in the design process. See "Special Topics in IIR Filter Design" on page 2-37 for details.

To create similar plots, use $\mathrm{n}=5$ and, as needed, $\mathrm{Rp}=0.5$ and $\mathrm{Rs}=20$. For example, to create the elliptic filter plot

```
[z,p,k] = ellipap(5,0.5,20);
w = logspace(-1,1,1000);
h = freqs(k*poly(z),poly(p),w);
semilogx(w,abs(h)), grid
```


## Direct IIR Filter Design

This tool box uses the term direct methods to describe techniques for IIR design that find a filter based on specifications in the discrete domain. Unlike the analog prototyping method, direct design methods are not constrained to the standard lowpass, highpass, bandpass, or bandstop configurations. Rather, these functions design filters with an arbitrary, perhaps multiband, frequency response. This section discusses the yulewalk function, which is intended specifically for filter design; "Parametric M odeling" on page 4-12 discusses other methods that may also be considered direct, such as Prony's method, Linear Prediction, the Steiglitz-McBride method, and inverse frequency design.

The yulewalk function designs recursivelIR digital filters by fitting a specified frequency response. yulewalk's name reflects its method for finding the filter's denominator coefficients: it finds the inverse FFT of the ideal desired power spectrum and solves the "modified Yule-Walker equations" using the resulting autocorrelation function samples. The statement

$$
[b, a]=\operatorname{yulewalk}(n, f, m)
$$

returns row vectors $b$ and a containing the $n+1$ numerator and denominator coefficients of the order n IIR filter whose frequency-magnitude characteristics approximate those given in vectors $f$ and $m$. $f$ is a vector of frequency points ranging from 0 to 1 , where 1 represents the $N$ yquist frequency. $m$ is a vector containing the desired magnitude response at the points in f. $f$ and $m$ can describe any piecewise linear shape magnitude response, including a multiband response. The FIR counterpart of this function is fir2, which also designs a filter based on an arbitrary piecewise linear magnituderesponse. See "FIR Filter Design" on page 2-16 for details.

Note that yulewalk does not accept phase information, and no statements are made about the optimality of the resulting filter.
Design a multiband filter with yulewalk, and plot the desired and actual frequency response.

```
m = [0 0
f = [0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 1];
[b,a] = yulewalk(10,f,m);
[h,w] = freqz(b,a,128);
plot(f,m,w/pi,abs(h))
```



## Generalized Butterworth Filter Design

The tool box function maxflat enables you to design generalized Butterworth filters, that is, Butterworth filters with differing numbers of zeros and poles. This is desirable in some implementations where poles are more expensive computationally than zeros. maxflat is just like the butter function, except that it you can specify two orders (one for the numerator and one for the denominator) instead of just one. These filters are maxi mally flat. This means that the resulting filter is optimal for any numerator and denominator orders, with the maximum number of derivatives at 0 and the Nyquist frequency $\omega=\pi$ both set to 0 .

For example, when the two orders are the same, maxflat is the same as butter.

```
[b,a] = maxflat(3,3,0.25)
b =
    0.0317 0.0951 0.0951 0.0317
a =
    1.0000 -1.4590 0.9104 -0.1978
```

```
[b,a] = butter(3,0.25)
b =
    0.0317 0.0951 0.0951 0.0317
a =
    1.0000 -1.4590 0.9104 -0.1978
```

However, maxflat is more versatile because it allows you to design a filter with more zeros than poles.

```
[b,a] = maxflat(3,1,0.25)
b =
    0.0950 0.2849 0.2849 0.0950
    a =
        1.0000 -0.2402
```

The third input to maxflat is the half-power frequency, a frequency between 0 and 1 with a desired magnitude response of $1 / \sqrt{2}$.

You can also design linear phase filters that have the maximally flat property using the 'sym' option.

```
maxflat(4,'sym',0.3)
ans =
    0.0331 0.2500 0.4337 0.2500 0.0331
```

F or complete details of the maxflat algorithm, see Selesnick and Burrus [2].

## FIR Filter Design

Digital filters with finite-duration impulse response (all-zero, or FIR filters) have both advantages and disadvantages compared to infinite-duration impulse response (IIR) filters.

FIR filters have the following primary advantages:

- They can have exactly linear phase.
- They are always stable.
- The design methods are generally linear.
- They can be realized efficiently in hardware.
- The filter startup transients have finite duration.

The primary disadvantage of FIR filters is that they often require a much higher filter order than IIR filters to achieve a given level of performance. Correspondingly, the delay of these filters is often much greater than for an equal performance IIR filter.

| Method | Description | Functions |
| :--- | :--- | :--- |
| Windowing | Apply window to truncated <br> inverse Fourier transform of <br> desired "brick wall" filter | fir1, fir2, <br> kaiserord |
| Multiband with <br> Transition <br> Bands | Equiripple or least squares <br> approach over sub-bands of the <br> frequency range | firls, remez, <br> remezord |
| Constrained <br> Least Squares | Minimize squared integral <br> error over entire frequency <br> range subject to maximum <br> error constraints | fircls, fircls1 |
| Arbitrary <br> Response | Arbitrary responses, including <br> nonlinear phase and complex <br> filters | cremez |
| Raised Cosine | Lowpass response with <br> smooth, sinusoidal transition | firrcos |

## Linear Phase Filters

Except for cremez, all of the FIR filter design functions design linear phase filters only. The filter coefficients, or "taps," of such filters obey either an even or odd symmetry relation. Depending on this symmetry, and on whether the order n of the filter is even or odd, a linear phase filter (stored in length $\mathrm{n}+1$ vector b) has certain inherent restrictions on its frequency response.

| Linear Phase Filter Type | Filter Order | Symmetry of Coefficients | $\begin{aligned} & \text { Response } H(f), \\ & f=0 \end{aligned}$ | Response H(f), f = 1 (Nyquist) |
| :---: | :---: | :---: | :---: | :---: |
| Type I | Even | even:$b(k)=b(n+2-k), \quad k=1, \ldots, n+1$ | No restriction | No restriction |
| Type II | Odd |  | No restriction | $\mathrm{H}(1)=0$ |
| Type III | Even | odd:$b(k)=-b(n+2-k), \quad k=1, \ldots, n+1$ | $\mathrm{H}(0)=0$ | $\mathrm{H}(1)=0$ |
| Type IV | Odd |  | $\mathrm{H}(0)=0$ | No restriction |

The phase delay and group delay of linear phase FIR filters are equal and constant over the frequency band. For an order n linear phase FIR filter, the group delay is $\mathrm{n} / 2$, and the filtered signal is simply delayed by $\mathrm{n} / 2$ time steps (and the magnitude of its F ourier transform is scaled by the filter's magnitude response). This property preserves the wave shape of signals in the passband; that is, there is no phase distortion.

The functions fir1, fir2, firls, remez, fircls, fircls1, and firrcos all design type I and II linear phase FIR filters by default. Both firls and remez design type III and IV linear phase FIR filters given a 'hilbert' or 'differentiator' flag. cremez can design any type of linear phase filter, and nonlinear phase filters as well.

Note Because the frequency response of a typell filter is zero at the $N$ yquist frequency ("high" frequency), fir1 does not design type II highpass and bandstop filters. For odd-valued $n$ in these cases, fir1 adds 1 to the order and returns a type I filter.

## Windowing Method

Consider the ideal, or "brick wall," digital lowpass filter with a cutoff frequency of $\omega_{0} \mathrm{rad} / \mathrm{s}$. This filter has magnitude 1 at all frequencies with magnitude less than $\omega_{0}$, and magnitude 0 at frequencies with magnitude between $\omega_{0}$ and $\pi$. Its impulse response sequence $h(n)$ is

$$
h(n)=\frac{1}{2 \pi} \int_{-\pi}^{\pi} H(\omega) \mathrm{e}^{\mathrm{j} \omega \mathrm{n}} \mathrm{~d} \omega=\frac{1}{2 \pi} \int_{-\omega_{0}}^{\omega_{0}} \mathrm{e}^{\mathrm{j} \omega \mathrm{n}} \mathrm{~d} \omega=\frac{\omega_{0}}{\pi} \operatorname{sinc}\left(\frac{\omega_{0}}{\pi} n\right)
$$

This filter is not implementable since its impulse response is infinite and noncausal. To create a finite-duration impulse response, truncate it by applying a window. By retaining the central section of impulse response in this truncation, you obtain a linear phase FIR filter. F or example, a length 51 filter with a lowpass cutoff frequency $\omega_{0}$ of $0.4 \pi \mathrm{rad} / \mathrm{s}$ is

$$
b=0.4^{*} \operatorname{sinc}\left(0.4^{*}(-25: 25)\right) ;
$$

The window applied here is a simple rectangular window. By Parseval's theorem, this is the length 51 filter that best approximates the ideal lowpass filter, in the integrated least squares sense. The following commands display the filter's frequency response.

```
[H,w] = freqz(b,1,512,2);
s.xunits = 'rad/sample';
s.yunits = 'squared';
s.plot = 'mag'; % Plot magnitude only.
freqzplot(H,w,s)
title('Truncated Sinc Lowpass FIR Filter');
```



Note the ringing and ripples in the response, especially near the band edge. This "Gibbs effect" does not vanish as the filter length increases, but a nonrectangular window reduces its magnitude. Multiplication by a window in the time domain causes a convolution or smoothing in the frequency domain. Apply a length 51 Hamming window to the filter.

```
b = 0.4*sinc(0.4*(-25:25));
b = b.*hamming(51)';
[H,w] = freqz(b,1,512,2);
s.xunits = 'rad/sample';
s.yunits = 'squared';
s.plot = 'mag';
freqzplot(H,w,s)
title('Hamming-Windowed Truncated Sinc LP FIR Filter');
```



As you can see, this greatly reduces the ringing. This improvement is at the expense of transition width (the windowed version takes longer to ramp from passband to stopband) and optimality (the windowed version does not minimize the integrated squared error).

The functions fir1 and fir2 are based on this windowing process. Given a filter order and description of an ideal desired filter, these functions return a windowed inverse F ourier transform of that ideal filter. Both use a Hamming window by default, but they accept any window function. See "Overview" on page 4-2 for an overview of windows and their properties.

## Standard Band FIR Filter Design: fir1

fir1 implements the classical method of windowed linear phase FIR digital filter design. It resembles thelIR filter design functions in that it is formulated to design filters in standard band configurations: lowpass, bandpass, highpass, and bandstop.

The statements

```
n = 50;
Wn = 0.4;
b = fir1(n,Wn);
```

create row vector b containing the coefficients of the order n Hamming-windowed filter. This is a lowpass, linear phaseFIR filter with cutoff frequency Wn . Wn is a number between 0 and 1 , where 1 corresponds to the Nyquist frequency, half the sampling frequency. (Unlike other methods, here Wn corresponds to the 6 dB point.) F or a highpass filter, simply append the string 'high' to the function's parameter list. F or a bandpass or bandstop filter, specify $W n$ as a two-element vector containing the passband edge frequencies; append the string 'stop' for the bandstop configuration.
b = fir1( $\mathrm{n}, \mathrm{Wn}$, window) usesthe window specified in column vector window for the design. The vector window must be $n+1$ elements long. If you do not specify a window, fir1 applies a Hamming window.

Kaiser Window Order Estimation. The kaiserord function estimates the filter order, cutoff frequency, and Kaiser window beta parameter needed to meet a given set of specifications. Given a vector of frequency band edges and a corresponding vector of magnitudes, as well as maximum allowable ripple, kaiserord returns appropriate input parameters for the fir1 function.

## Multiband FIR Filter Design: fir2

The fir2 function also designs windowed FIR filters, but with an arbitrarily shaped piecewise linear frequency response. This is in contrast to fir1, which only designs filters in standard lowpass, highpass, bandpass, and bandstop configurations.

The commands

```
n = 50;
f = [0 .4 .5 1];
m = [\begin{array}{llll}{1}&{1}&{0}&{0}\end{array}];
b = fir2(n,f,m);
```

return row vector b containing the $\mathrm{n}+1$ coefficients of the order n FIR filter whose frequency-magnitude characteristics match those given by vectors $f$ and $m$. $f$ is a vector of frequency points ranging from 0 to 1 , where 1 represents the Nyquist frequency. $m$ is a vector containing the desired magnitude response at the points specified in f. (The IIR counterpart of this function is yulewalk, which also designs filters based on arbitrary piecewise linear magnitude responses. See "IIR Filter Design" on page 2-5 for details.)

## Multiband FIR Filter Design with Transition Bands

The firls and remez functions provide a more general means of specifying the ideal desired filter than the fir1 and fir2 functions. These functions design Hilbert transformers, differentiators, and other filters with odd symmetric coefficients (type III and type IV linear phase). They also let you include transition or "don't care" regions in which the error is not minimized, and perform band dependent weighting of the minimization.
The firls function is an extension of the fir1 and fir2 functions in that it minimizes theintegral of the square of the error between the desired frequency response and the actual frequency response.

The remez function implements the Parks-McClellan algorithm, which uses the Remez exchange al gorithm and Chebyshev approximation theory to design filters with optimal fits between the desired and actual frequency responses. The filters are optimal in the sense that they minimize the maximum error between the desired frequency response and the actual frequency response; they are sometimes called minimax filters. Filters designed in this way exhibit an equiripple behavior in their frequency response, and hence are also known as equiripplefilters. The Parks-McClellan FIR filter design algorithm is perhaps the most popular and widely used FIR filter design methodology.
The syntax for firls and remez is the same; the only difference is their minimization schemes. The next example shows how filters designed with firls and remez reflect these different schemes.

## Basic Configurations

The default mode of operation of firls and remez is to design type I or type II linear phase filters, depending on whether the order you desire is even or odd, respectively. A lowpass example with approximate amplitude 1 from 0 to 0.4 Hz , and approximate amplitude 0 from 0.5 to 1.0 Hz is

```
n = 20; % Filter order
f = [0 0.4 0.5 1]; % Frequency band edges
a = [1 1 1 0 0]; % Desired amplitudes
b = remez(n,f,a);
```

From 0.4 to 0.5 Hz , remez performs no error minimization; this is a transition band or "don't care" region. A transition band minimizes the error more in the bands that you do care about, at the expense of a slower transition rate. In this
way, these types of filters have an inherent trade-off similar to FIR design by windowing.

To compare least squares to equiripple filter design, use firls to create a similar filter. Type

```
bb = firls(n,f,a);
```

and compare their frequency responses.

```
[H,w] = freqz(b);
[HH,w] = freqz(bb);
plot(w/pi,abs(H),w/pi,abs(HH),'--'), grid
```



You can see that the filter designed with remez exhibits equiripple behavior. Also note that the firls filter has a better response over most of the passband and stopband, but at the band edges ( $f=0.4$ and $f=0.5$ ), the response is further away from the ideal than the remez filter. This shows that the remez filter's maximum error over the passband and stopband is smaller and, in fact, it is the smallest possible for this band edge configuration and filter length.

Think of frequency bands as lines over short frequency intervals. remez and firls use this scheme to represent any piecewise linear desired function with any transition bands. firls and remez design lowpass, highpass, bandpass, and bandstop filters; a bandpass example is

```
f}=[\begin{array}{llllll}{0}&{0.3}&{0.4}&{0.7}&{0.8}&{1}\end{array}]; % Band edges in pair
a = [lllllll}00010 0 0 % % Bandpass filter amplitude
```

Technically, these $f$ and a vectors define five bands:

- Two stopbands, from 0.0 to 0.3 and from 0.8 to 1.0
- A passband from 0.4 to 0.7
- Two transition bands, from 0.3 to 0.4 and from 0.7 to 0.8

Example highpass and bandstop filters are


An example multiband bandpass filter is

```
f}=[\begin{array}{lllllllllllllllll}{0}&{0.1}&{0.15}&{0.25}&{0.3}&{0.4}&{0.45}&{0.55}&{0.6}&{0.7}&{0.75}&{0.85}&{0.9 1];}
a =[[11 1 0 0 0 0 1 1 1 0
```

Another possibility is a filter that has as a transition region the line connecting the passband with the stopband; this can help control "runaway" magnitude response in wide transition regions.

```
f = [llllllll}
a = [llllllll}10.0.8 0.2 0 0 % Passband,linear transition, stopband
```


## The Weight Vector

Both firls and remez allow you to place more or less emphasis on minimizing the error in certain frequency bands relative to others. To do this, specify a weight vector following the frequency and amplitude vectors. An example lowpass equiripple filter with 10 times less ripple in the stopband than the passband is

```
n = 20; % Filter order
f = [0 0.4 0.5 1]; % Frequency band edges
a = [1 1 1 0 0]; % Desired amplitudes
w = [1 10]; % Weight vector
b = remez(n,f,a,w);
```

A legal weight vector is always half thelength of the f and a vectors; there must be exactly one weight per band.

## Anti-Symmetric Filters / Hilbert Transformers

When called with a trailing ' $h$ ' or 'Hilbert' option, remez and firls design FIR filters with odd symmetry, that is, type III (for even order) or type IV (for odd order) linear phase filters. An ideal Hilbert transformer has this anti-symmetry property and an amplitude of 1 across the entire frequency range. Try the following approximate Hilbert transformers.

```
b = remez(21,[0.05 1],[1 1],'h'); % Highpass Hilbert
bb = remez(20,[0.05 0.95],[1 1],'h'); % Bandpass Hilbert
```



You can find the delayed Hilbert transform of a signal x by passing it through these filters.

```
fs = 1000; % Sampling frequency
t = (0:1/fs:2)'; % Two second time vector
x = sin(2*pi*300*t); % 300 Hz sine wave example signal
xh = filter(bb,1,x); % Hilbert transform of x
```

The analytic signal corresponding to x is the complex signal that has x as its real part and the Hilbert transform of $x$ as its imaginary part. For this FIR method (an alternative to the hilbert function), you must delay $x$ by half the filter order to create the analytic signal.

```
xd = [zeros(10,1); x(1:length(x)-10)]; % Delay 10 samples
xa = xd + j*xh; % Analytic signal
```

This method does not work directly for filters of odd order, which require a noninteger delay. In this case, the hilbert function, described in "Specialized Transforms" on page 4-36, estimates the analytic signal. Alternatively, use the resample function to delay the signal by a noninteger number of samples.

## Differentiators

Differentiation of a signal in the time domain is equivalent to multiplication of the signal's F ourier transform by an imaginary ramp function. That is, to differentiate a signal, pass it through a filter that has a response $H(\omega)=j \omega$. Approximate the ideal differentiator (with a delay) using remez or firls with a 'd' or 'differentiator' option.
b = remez(21,[0 1],[0 pi*fs],'d');
To obtain the correct derivative, scaleby pi *fs rad/s, where fs is the sampling frequency in hertz. For a type III filter, the differentiation band should stop short of the Nyquist frequency, and the amplitude vector must reflect that change to ensure the correct slope.

```
bb = remez(20,[0 0.9],[0 0.9*pi*fs],'d');
```

In the ' d' mode, remez weights the error by $1 / \omega$ in nonzero amplitude bands to minimize the maximum relative error. firls weights the error by $(1 / \omega)^{2}$ in nonzero amplitude bands in the 'd ' mode.

The following plots show the magnitude response for the differentiators above.


## Constrained Least Squares FIR Filter Design

The Constrained Least Squares (CLS) FIR filter design functions implement a technique that enables you to design FIR filters without explicitly defining the transition bands for the magnitude response. The ability to omit the specification of transition bands is useful in several situations. F or example, it may not be clear where a rigidly defined transition band should appear if noise and signal information appear together in the same frequency band. Similarly, it may make sense to omit the specification of transition bands if they appear only to control the results of Gibbs phenomena that appear in the filter's response. See Selesnick, Lang, and Burrus [2] for discussion of this method.

Instead of defining passbands, stopbands, and transition regions, the CLS method accepts a cutoff frequency (for the highpass, lowpass, bandpass, or bandstop cases), or passband and stopband edges (for multiband cases), for the desired response. In this way, the CLS method defines transition regions implicitly, rather than explicitly.
The key feature of the CLS method is that it enables you to define upper and lower thresholds that contain the maximum allowable ripple in the magnitude response. Given this constraint, the technique applies the least square error minimization technique over the frequency range of the filter's response, instead of over specific bands. The error minimization includes any areas of
discontinuity in the ideal, "brick wall" response. An additional benefit is that the technique enables you to specify arbitrarily small peaks resulting from Gibbs' phenomena.
There are two tool box functions that implement this design technique.

| Description | Function |
| :--- | :--- |
| Constrained least square multiband FIR filter design | fircls |
| Constrained least square filter design for lowpass and <br> highpass linear phase filters | fircls1 |

F or details on the calling syntax for these functions, see their reference descriptions in Chapter 7, "Function Reference."

## Basic Lowpass and Highpass CLS Filter Design

The most basic of the CLS design functions, fircls1, uses this technique to design lowpass and highpass FIR filters. As an example, consider designing a filter with order 61 impulse response and cutoff frequency of 0.3 (normalized). Further, define the upper and lower bounds that constrain the design process as:

- Maximum passband deviation from 1 (passband ripple) of 0.02.
- Maximum stopband deviation from 0 (stopband ripple) of 0.008 .


To approach this design problem using fircls1, use the following commands.

```
n = 61;
wo = 0.3;
dp = 0.02;
ds = 0.008;
h = fircls1(n,wo,dp,ds,'plot');
```



## Multiband CLS Filter Design

fircls uses the same technique to design FIR filters with a desired piecewise constant magnitude response. In this case, you can specify a vector of band edges and a corresponding vector of band amplitudes. In addition, you can specify the maximum amount of ripple for each band.

F or example, assume the specifications for a filter call for:

- From 0 to 0.3 (normalized): amplitude 0, upper bound 0.005 , lower bound -0.005
- From 0.3 to 0.5 : amplitude 0.5, upper bound 0.51 , lower bound 0.49
- From 0.5 to 0.7: amplitude 0, upper bound 0.03 , lower bound -0.03
- From 0.7 to 0.9 : amplitude 1, upper bound 1.02, lower bound 0.98
- From 0.9 to 1: amplitude 0, upper bound 0.05, lower bound -0.05

Design a CLS filter with impulse response order 129 that meets these specifications.

```
n = 129;
f = [l0 0.3 0.5 0.7 0.9 1];
a = [0 0.5 0 1 0];
up = [0.005 0.51 0.03 1.02 0.05];
```

```
lo = [-0.005 0.49 -0.03 0.98 -0.05];
h = fircls(n,f,a,up,lo,'plot');
```



## Weighted CLS Filter Design

Weighted CLS filter design lets you design lowpass or highpass FIR filters with relative weighting of the error minimization in each band. The fircls 1 function enables you to specify the passband and stopband edges for the least squares weighting function, as well as a constant $k$ that specifies the ratio of the stopband to passband weighting.
For example, consider specifications that call for an FIR filter with impulse response order of 55 and cutoff frequency of 0.3 (normalized). Also assume maximum allowable passband ripple of 0.02 and maximum allowable stopband ripple of 0.004 . In addition, add weighting requirements:

- Passband edge for the weight function of 0.28 (normalized)
- Stopband edge for the weight function of 0.32
- Weight error minimization 10 times as much in the stopband as in the passband

To approach this using fircls1, type

```
n = 55;
wo = 0.3;
dp = 0.02;
ds = 0.004;
wp = 0.28;
ws = 0.32;
k = 10;
h = fircls1(n,wo,dp,ds,wp,ws,k,'plot');
```



## Arbitrary-Response Filter Design

The cremez filter design function provides a tool for designing FIR filters with arbitrary complex responses. It differs from the other filter design functions in how the frequency response of the filter is specified: it accepts the name of a function which returns the filter response cal culated over a grid of frequencies. This capability makes cremez a highly versatile and powerful technique for filter design.

This design technique may be used to produce nonlinear-phase FIR filters, asymmetric frequency-response filters (with complex coefficients), or more symmetric filters with custom frequency responses.

The design algorithm optimizes the Chebyshev (or minimax) error using an extended Remez-exchange algorithm for an initial estimate. If this exchange method fails to obtain the optimal filter, the algorithm switches to an ascent-descent algorithm that takes over to finish the convergence to the optimal solution.

## Multiband Filter Design

Consider a multiband filter with the following special frequency-domain characteristics.
$\left.\begin{array}{l|l|l}\hline \text { Band } & \text { Amplitude } & \begin{array}{l}\text { Optimization } \\ \text { Weighting }\end{array} \\ \hline[-1-0.5] & {[51]} & 1 \\ \hline[-0.4+0.3] & {[22} & 2]\end{array}\right] 109 .\left[\begin{array}{ll}{[+0.4+0.8]} & 1]\end{array}\right.$

A linear-phase multiband filter may be designed using the predefined frequency-response function multiband, as follows.

```
b = cremez(38, [ -1 -0.5 -0.4 0.3 0.4 0.8], ...
    {'multiband', [\begin{array}{llll}{5}&{2}&{2}&{2}\end{array}1]},[\begin{array}{lll}{1}&{10}&{5}\end{array}]);
```

For the specific case of a multiband filter, we can use a shorthand filter design notation similar to the syntax for remez.

```
b = cremez(38,[ -1 -0.5 -0.4 0.3 0.4 0.8], ...
    [5 1 1 2 2 2 1], [11 10 5]);
```

As with remez, a vector of band edges is passed to cremez. This vector defines the frequency bands over which optimization is performed; note that there are two transition bands, from -0.5 to -0.4 and from 0.3 to 0.4 .

In either case, the frequency response is obtained and plotted using linear scale.

```
[h,w] = freqz(b,1,512,'whole');
plot(w/pi-1,fftshift(abs(h))); grid;
xlabel('Normalized Frequency');
ylabel('Magnitude Response');
```

Note that the frequency response has been calculated over the entire normalized frequency range[ $-1+1$ ] by passing the option 'whole' to freqz. In order to plot the negative frequency information in a natural way, theresponse has been "wrapped," just as FFT data is, using fftshift.


The filter response for this multiband filter is complex, which is expected because of the asymmetry in the frequency domain.


## Filter Design with Reduced Delay

Consider the design of a 62-tap lowpass filter with a half-N yquist cutoff. If we specify a negative offset value to the lowpass filter design function, the group delay offset for the design is significantly less than that obtained for a standard linear-phase design. This filter design may be computed as follows.

```
b = cremez(61,[0 0.5 0.55 1],{'lowpass',-16});
```

The resulting magnitude response is

```
[h,w] = freqz(b,1,512,'whole');
plot(w/pi-1,fftshift(abs(h))); grid;
xlabel('Normalized Frequency');
ylabel('Magnitude Response');
```



The group delay of the filter reveals that the offset has been reduced from N/2 to N/2-16 (i.e., from 30.5 to 14.5). Now, however, the group delay is nolonger flat in the passband region (plotted over the normalized frequency range 0 to 0.5 for clarity).


If we compare this nonlinear-phase filter to a linear-phase filter that has exactly 14.5 samples of group delay, the resulting filter is of order $2 * 14.5$, or 29. Using b = cremez(29,[0 0.5 0.55 1],'lowpass'), the passband and stopband ripple is much greater for the order 29 filter. These comparisons can assist you in deciding which filter is more appropriate for a specific application.

## Special Topics in IIR Filter Design

The classic IIR filter design techniquefinds an analog lowpass filter with cutoff frequency of 1, translates this "prototype" filter to the desired band configuration, then transforms the filter to the digital domain. The tool box provides functions for each step of this process.


The butter, cheby1, cheby2, and ellip functions are sufficient for many design problems, and the lower level functions are generally not needed. But if you do have an application where you need to transform the band edges of an analog filter, or discretize a rational transfer function, this section describes the tools with which to do so.

## Analog Prototype Design

This tool box provides a number of functions to create lowpass anal og prototype filters with cutoff frequency of 1 , the first step in the classical approach to IIR filter design. The table below summarizes the analog prototype design functions for each supported filter type; plots for each type are shown in "IIR Filter Design" on page 2-5.

| Filter Type | Analog Prototype Function |
| :--- | :--- |
| Bessel | $[z, p, k]=\operatorname{besselap}(n)$ |
| Butterworth | $[z, p, k]=\operatorname{buttap}(n)$ |
| Chebyshev Type I | $[z, p, k]=\operatorname{cheb} 1 a p(n, R p)$ |
| Chebyshev Type II | $[z, p, k]=\operatorname{cheb} 2 a p(n, R s)$ |
| Elliptic | $[z, p, k]=\operatorname{ellipap}(n, R p, R s)$ |

## Frequency Transformation

The second step in the analog prototyping design technique is the frequency transformation of a lowpass prototype. The tool box provides a set of functions to transform analog lowpass prototypes (with cutoff frequency of 1 rad/s) into bandpass, highpass, bandstop, and lowpass filters of the desired cutoff frequency.

| Freq. Transformation | Transformation Function |
| :---: | :---: |
| Lowpass to lowpass $s^{\prime}=s / \omega_{0}$ | $\begin{aligned} {[\text { numt }, \text { dent }] } & =\operatorname{lp2lp}(\text { num }, \text { den, Wo }) \\ {[A t, B t, C t, D t] } & =\operatorname{lp} 2 l p(A, B, C, D, \text { Wo }) \end{aligned}$ |
| Lowpass to highpass $s^{\prime}=\frac{\omega_{0}}{s}$ | $\begin{aligned} {[\text { numt }, \text { dent }] } & =\operatorname{lp2hp}(\text { num }, \text { den, Wo }) \\ {[A t, B t, C t, D t] } & =\operatorname{lp2hp}(A, B, C, D, W o) \end{aligned}$ |
| Lowpass to bandpass $s^{\prime}=\frac{\omega_{0}}{B_{\omega}} \frac{\left(\mathrm{s} / \omega_{0}\right)^{2}+1}{\mathrm{~s} / \omega_{0}}$ | $\begin{array}{ll} {[\text { numt }, \text { dent] }} & =\operatorname{lp2bp}(\text { num }, \text { den, Wo }, \mathrm{Bw}) \\ {[\mathrm{At}, \mathrm{Bt}, \mathrm{Ct}, \mathrm{Dt}]} & =\operatorname{lp2bp}(\mathrm{A}, \mathrm{~B}, \mathrm{C}, \mathrm{D}, \mathrm{Wo}, \mathrm{Bw}) \end{array}$ |
| Lowpass to bandstop $s^{\prime}=\frac{B_{\omega}}{\omega_{0}} \frac{s / \omega_{0}}{\left(s / \omega_{0}\right)^{2}+1}$ | $\begin{array}{ll} {[\text { numt }, \text { dent }]} & =\text { lp2bs (num, den, Wo, Bw }) \\ {[A t, B t, C t, D t]} & =l p 2 b s(A, B, C, D, W o, B w) \end{array}$ |

As shown, all of the frequency transformation functions can accept two linear system models: transfer function and state-space form. For the bandpass and bandstop cases

$$
\omega_{0}=\sqrt{\omega_{1} \omega_{2}}
$$

and

$$
B_{\omega}=\omega_{2}-\omega_{1}
$$

where $\omega_{1}$ is the lower band edge and $\omega_{2}$ is the upper band edge.
The frequency transformation functions perform frequency variable substitution. In the case of lp2bp and lp2bs, this is a second-order substitution, so the output filter is twice the order of the input. For lp2lp and lp2hp, the output filter is the same order as the input.
To begin designing an order 10 bandpass Chebyshev Type I filter with a value of 3 dB for passband ripple, enter

$$
[z, p, k]=\operatorname{cheb} 1 a p(5,3) ;
$$

Outputs z, p, and k contain the zeros, poles, and gain of a lowpass analog filter with cutoff frequency $\Omega_{c}$ equal to $1 \mathrm{rad} / \mathrm{s}$. Use the 1p2bp function to transform this lowpass prototype to a bandpass analog filter with band edges $\Omega_{1}=\pi / 5$ and $\Omega_{2}=\pi$. First, convert the filter to state-space form so the lp2bp function can accept it.

```
[A,B,C,D] = zp2ss(z,p,k); % Convert to state-space form.
```

Now, find the bandwidth and center frequency, and call lp2bp.

```
u1 = 0.1*2*pi; u2 = 0.5*2*pi; % In radians per second
Bw = u2-u1;
Wo = sqrt(u1*u2);
[At,Bt,Ct,Dt] = lp2bp(A,B,C,D,Wo,Bw);
```

Finally, calculate the frequency response and plot its magnitude.

```
[b,a] = ss2tf(At,Bt,Ct,Dt); % Convert to TF form.
w = linspace(0.01,1,500)*2*pi; %Generate frequency vector.
h = freqs(b,a,w); % Compute frequency response.
semilogy(w/2/pi,abs(h)), grid % Plot log magnitude vs. freq.
xlabel('Frequency (Hz)');
```



## Filter Discretization

The third step in the analog prototyping technique is the transformation of the filter to the discrete-time domain. The tool box provides two methods for this: the impulse invariant and bilinear transformations. Thefilter design functions butter, cheby1, cheby2, and ellip use the bilinear transformation for discretization in this step.

| Analog to Digital <br> Transformation | Transformation Function |
| :--- | :--- |
| Impulse invariance | $[$ numd, dend $]=$ impinvar (num, den, fs$)$ |
| Bilinear transform | $[\mathrm{zd}, \mathrm{pd}, \mathrm{kd}]=$ bilinear $(\mathrm{z}, \mathrm{p}, \mathrm{k}, \mathrm{fs}, \mathrm{Fp})$ <br> $[$ numd, dend $=$ bilinear $(\mathrm{num}, \mathrm{den}, \mathrm{fs}, \mathrm{Fp})$ <br> $[\mathrm{Ad}, \mathrm{Bd}, \mathrm{Cd}, \mathrm{Dd}]=$ bilinear $(\mathrm{At}, \mathrm{Bt}, \mathrm{Ct}, \mathrm{Dt}, \mathrm{fs}, \mathrm{Fp})$ |

## Impulse Invariance

The tool box function impinvar creates a digital filter whose impulse response is the samples of the continuous impulse response of an analog filter. This function works only on filters in transfer function form. For best results, the analog filter should have negligible frequency content above half the sampling frequency, because such high frequency content is aliased into lower bands upon sampling. Impulse invariance works for some lowpass and bandpass filters, but is not appropriate for highpass and bandstop filters.

Design a Chebyshev Type I filter and plot its frequency response.

```
[bz,az] = impinvar(b,a,2);
[H,w] = freqz(bz,az);
freqzplot(H,w)
```



Impulse invariance retains the cutoff frequencies of 0.1 Hz and 0.5 Hz .

## Bilinear Transformation

The bilinear transformation is a nonlinear mapping of the continuous domain to the discrete domain; it maps the s-plane into the z-plane by

$$
H(z)=\left.H(s)\right|_{s=k \frac{z-1}{z+1}}
$$

Bilinear transformation maps the $\mathrm{j} \Omega$-axis of the continuous domain to the unit circle of the discrete domain according to

$$
\omega=2 \tan ^{-1}\left(\frac{\Omega}{\mathrm{k}}\right)
$$

The tool box function bilinear implements this operation, where the frequency warping constant $k$ is equal to twice the sampling frequency ( 2 *fs) by default, and equal to $2 \pi f_{p} / \tan \left(\pi f_{p} / f_{s}\right)$ if you give bilinear a trailing argument that represents a "match" frequency Fp. If a match frequency Fp (in hertz) is present, bilinear maps the frequency $\Omega=2 \pi \mathrm{f}_{\mathrm{p}}$ (in rad/s) to the same frequency in the discrete domain, normalized to the sampling rate: $\omega=2 \pi f_{p} / f_{s} \quad$ (in rad/sample).

The bilinear function can perform this transformation on three different linear system representations: zero-pole-gain, transfer function, and state-space form. Try calling bilinear with the state-space matrices that describe the Chebyshev Type I filter from the previous section, using a sampling frequency of 2 Hz , and retaining the lower band edge of 0.1 Hz .

```
[Ad,Bd,Cd,Dd] = bilinear(At,Bt,Ct,Dt,2,0.1);
```

The frequency response of the resulting digital filter is

```
[bz,az] = ss2tf(Ad,Bd,Cd,Dd); % convert to TF
freqz(bz,az)
```




The lower band edge is at 0.1 Hz as expected. Notice, however, that the upper band edge is slightly less than 0.5 Hz , although in the analog domain it was exactly 0.5 Hz . This illustrates the nonlinear nature of the bilinear transformation. To counteract this nonlinearity, it is necessary to create analog domain filters with "prewarped" band edges, which map tothe correct locations upon bilinear transformation. Here the prewarped frequencies u1 and u2 generate Bw and wo for the lp2bp function.

```
fs = 2; % Sampling frequency (hertz)
u1 = 2*fs*tan(0.1*(2*pi/fs)/2); % Lower band edge (rad/s)
u2 = 2*fs*tan(0.5*(2*pi/fs)/2); % Upper band edge (rad/s)
Bw = u2 - u1; % Bandwidth
Wo = sqrt(u1*u2); % Center frequency
[At,Bt,Ct,Dt] = lp2bp(A,B,C,D,Wo,Bw);
```

A digital bandpass filter with correct band edges 0.1 and 0.5 times the N yquist frequency is

$$
[A d, B d, C d, D d]=\text { bilinear(At,Bt,Ct,Dt,fs); }
$$

The example bandpass filters from the last two sections could also be created in one statement using the complete IIR design function cheby1. For instance, an analog version of the example Chebyshev filter is

```
[b,a] = cheby1(5,3,[0.1 0.5]*2*pi,'s');
```

Note that the band edges are in rad/s for analog filters, whereas for the digital case, frequency is normalized.

```
[bz,az] = cheby1(5,3,[0.1 0.5]);
```

All of the complete design functions call bilinear internally. They prewarp the band edges as needed to obtain the correct digital filter. See Chapter 7, "F unction Reference," for more on these functions.

## Selected Bibliography

[1] Karam, L.J ., and J.H. McClellan. "Complex Chebyshev Approximation for FIR Filter Design." IEEE Trans. on Circuits and Systems II. March 1995.
[2] Selesnick, I.W., and C.S. Burrus. "Generalized Digital Butterworth Filter Design." Proceedings of theIEEE Int. Conf. Acoust., Speech, Signal Processing. Vol. 3 (May 1996).
[3] Selesnick, I.W., M. Lang, and C.S. Burrus. "Constrained Least Square Design of FIR Filters without Specified Transition Bands." Proceedings of the IEEE Int. Conf. Acoust., Speech, Signal Processing. Vol. 2 (May 1995). Pgs. 1260-1263.

## Statistical Signal Processing

Overview ..... 3-2
Correlation and Covariance ..... 3-3
Bias and Normalization ..... 3-4
Multiple Channels ..... 3-5
Spectral Analysis ..... 3-6
Spectral Estimation Method Overview ..... 3-8
Nonparametric Methods ..... 3-10
Parametric Methods ..... 3-30
Selected Bibliography ..... 3-39

## Overview

The Signal Processing Tool box provides tools for estimating important functions of random signals. In particular, there are tools to estimate correlation and covariance sequences and spectral density functions of discrete signals. Thefollowing sections explain the correlation and covariancefunctions and discuss the mathematically related functions for estimating the power spectrum:

- "Correlation and Covariance"
- "Spectral Analysis"
- "Selected Bibliography"


## Correlation and Covariance

The functions xcorr and xcov estimate the cross-correlation and cross-covariance sequences of random processes. They also handle autocorrelation and autocovariance as special cases.

The true cross-correlation sequence is a statistical quantity defined as

$$
R_{x y}(m)=E\left\{x_{n+m} y^{*} n\right\}=E\left\{x_{n} y^{*} n-m\right\}
$$

where $\mathrm{x}_{\mathrm{n}}$ and $\mathrm{y}_{\mathrm{n}}$ are stationary random processes, $-\infty<\mathrm{n}<\infty$, and $\mathrm{E}\}$ is the expected value operator. The covariance sequence is the mean-removed cross-correlation sequence

$$
C_{x y}(m)=E\left\{\left(x_{n+m}-\mu_{x}\right)\left(y_{n}-\mu_{y}\right)^{*}\right\}
$$

or, in terms of the cross-correlation,

$$
C_{x y}(m)=R_{x y}(m)-\mu_{x} \mu^{*} y
$$

In practice, you must estimate these sequences, because it is possibleto access only a finite segment of theinfinite-length random process. A common estimate based on $N$ samples of $x_{n}$ and $y_{n}$ is the deterministic cross-correlation sequence (also called the time-ambiguity function)

$$
\hat{R}_{x y}(m)= \begin{cases}\sum_{n=0}^{N-m-1} x_{n}+m y_{n}^{*} & m \geq 0 \\ \hat{R}_{y x(-m)}^{*} & m<0\end{cases}
$$

where we assume for this discussion that $x_{n}$ and $y_{n}$ are indexed from 0 to $N-1$, and $\mathrm{Rxy}_{\mathrm{xy}}(\mathrm{m})$ from $-(\mathrm{N}-1)$ to $\mathrm{N}-1$. The xcorr function evaluates this sum with an efficient FFT-based algorithm, given inputs $x_{n}$ and $y_{n}$ stored in length $N$ vectors $x$ and $y$. Its operation is equivalent to convolution with one of the two subsequences reversed in time.

For example,

$$
\begin{aligned}
& \mathrm{x}=\left[\begin{array}{lllll}
1 & 1 & 1 & 1 & 1
\end{array}\right]^{\prime} ; \\
& \mathrm{y}=\mathrm{x} ;
\end{aligned}
$$

```
\(x y c=x \operatorname{cor}(x, y)\)
xyc =
    1.0000
    2.0000
    3.0000
    4.0000
    5.0000
    4.0000
    3.0000
    2.0000
    1.0000
```

Notice that the resulting sequence length is one less than twice the length of the input sequence. Thus, the Nth element is the correlation at lag 0 . Also notice the triangular pulse of the output that results when convolving two square pulses.

The xcov function estimates autocovariance and cross-covariance sequences. This function has the same options and evaluates the same sum as xcorr, but first removes the means of $x$ and $y$.

## Bias and Normalization

An estimate of a quantity is biased if its expected value is not equal to the quantity it estimates. The expected value of the output of xcorr is

$$
E\left\{\hat{R}_{x y}(m)\right\}=\sum_{n=0}^{|v-|m|-\perp} E\left\{x_{n+m} y^{*} n\right\}=(N-|m|) R_{x y}(m)
$$

xcorr provides the unbiased estimate, dividing by $\mathrm{N}-|\mathrm{m}|$, when you specify an ' unbiased ' flag after the input sequences.

```
xcorr(x,y,'unbiased')
```

Although this estimate is unbiased, the end points (near -(N-1) and N-1) suffer from large variance because xcorr computes them using only a few data points. A possible trade-off is to simply divide by N using the 'biased ' flag.

```
xcorr(x,y,'biased')
```

With this scheme, only the sample of the correlation at zerolag (theNth output element) is unbiased. This estimate is often more desirable than the unbiased one because it avoids random large variations at the end points of the correlation sequence.
xcorr provides one other normalization scheme. The syntax
$x \operatorname{corr}(x, y, ' \operatorname{coeff} ')$
divides the output by norm ( $x$ ) *norm ( $y$ ) so that, for autocorrelations, the sample at zero lag is 1 .

## Multiple Channels

For a multichannel signal, xcorr and xcov estimate the autocorrelation and cross-correlation and covariance sequences for all of the channels at once. If s is an M -by- N signal matrix representing N channels in its columns, xcorr ( S ) returns a ( $2 \mathrm{M}-1$ )-by- $\mathrm{N}^{2}$ matrix with the autocorrelations and cross-correlations of the channels of S in its $\mathrm{N}^{2}$ columns. If S is a three-channel signal

```
S = [s1 s2 s3]
```

then the result of $\operatorname{xcorr}(\mathrm{S})$ is organized as

```
R = [Rs1s1 Rs1s2 Rs1s3 Rs2s1 Rs2s2 Rs2s3 Rs3s1 Rs3s2 Rs3s3]
```

Two related functions, cov and corrcoef, are available in the standard MATLAB environment. They estimate covariance and normalized covariance respectively between the different channels at lag 0 and arrange them in a square matrix.

## Spectral Analysis

The goal of spectral estimation is to describe the distribution (over frequency) of the power contained in a signal, based on a finite set of data. Estimation of power spectra is useful in a variety of applications, including the detection of signals buried in wide-band noise.

The power spectrum of a stationary random process $x_{n}$ is mathematically related to the correlation sequence by the discrete-time F ourier transform. In terms of normalized frequency, this is given by

$$
S_{x x}(\omega)=\sum_{m=-\infty} R_{x x}(m) e^{-j \omega m}
$$

This can be written as a function of physical frequency $f$ (e.g., in hertz) by using the relation $\omega=2 \pi f / f_{s}$, where $f_{s}$ is the sampling frequency.

$$
S_{x x}(f)=\sum_{m=-\infty}^{\infty} R_{x x}(m) e^{-2 \pi j f m / f_{s}}
$$

The correlation sequence can be derived from the power spectrum by use of the inverse discrete-time F ourier transform.

$$
R_{x x}(m)=\int_{-\pi}^{\pi} \frac{S_{x x}(\omega) e^{j \omega m}}{2 \pi} d \omega=\int_{-f_{s} / 2}^{f_{s} / 2} \frac{S_{x x}(f) e^{2 \pi j f m / f_{s}}}{f_{s}} d f
$$

The average power of the sequence $x_{n}$ over the entire $N$ yquist interval is represented by

$$
R_{x x}(0)=\int_{-\pi}^{\pi} \frac{S_{x x}(\omega)}{2 \pi} d \omega=\int_{-f_{s} / 2}^{f_{s} / 2} \frac{S_{x x}(f)}{f_{s}} d f
$$

The quantities

$$
P_{x x}(\omega)=\frac{S_{x x}(\omega)}{2 \pi} \quad \text { and } \quad P_{x x}(f)=\frac{S_{x x}(f)}{f_{s}}
$$

from the above expression are defined as the power spectral density (PSD) of the stationary random signal $\mathrm{x}_{\mathrm{n}}$.

The average power of a signal over a particular frequency band $\left[\omega_{1}, \omega_{2}\right]$, $0 \leq \omega_{1}<\omega_{2} \leq \pi$, can be found by integrating the PSD over that band.

$$
\bar{P}_{\left[\omega_{1}, \omega_{2}\right]}=\int_{\omega_{1}}^{\omega_{2}} P_{x x}(\omega) d \omega+\int_{-\omega_{2}}^{-\omega_{1}} P_{x x}(\omega) d \omega
$$

You can seefrom the above expression that $P_{x x}(\omega)$ represents the power content of a signal in an infinitesimal frequency band, which is why we call it the power spectral density.

The units of the PSD are power (e.g., watts) per unit of frequency. In the case of $P_{x x}(\omega)$, this is watts/rad/sample or simply watts/rad. In the case of $P_{x x}(f)$, the units are watts/hertz. Integration of the PSD with respect to frequency yields units of watts, as expected for the average power $\overline{\mathrm{P}}_{\left[\omega_{1}, \omega_{2}\right]}$.
For real signals, the PSD is symmetric about DC, and thus $\mathrm{P}_{\mathrm{xx}}(\omega)$ for $0 \leq \omega<\pi$ is sufficient to completely characterize the PSD. However, in order to obtain the average power over the entire Nyquist interval it is necessary to introduce the concept of the one-sided PSD.

The one-sided PSD is given by

$$
\mathrm{P}_{\text {onesided }}(\omega)=\left\{\begin{array}{lr}
0, & -\pi \leq \omega<0 \\
2 \mathrm{P}_{\mathrm{xx}}(\omega), & 0 \leq \omega<\pi
\end{array}\right.
$$

Theaverage power of a signal over the frequency band $\left[\omega_{1}, \omega_{2}\right], 0 \leq \omega_{1}<\omega_{2} \leq \pi$, can be computed using the one-sided PSD as

$$
\overline{\mathrm{P}}_{\left[\omega_{1}, \omega_{2}\right]}=\int_{\omega_{1}}^{\omega_{2}} \mathrm{P}_{\text {onesided }}(\omega) \mathrm{d} \omega
$$

## Spectral Estimation Method Overview

The various methods of spectrum estimation available in the Signal Processing Toolbox can be categorized as follows:

- Nonparametric methods
- Parametric methods
- Subspace methods

Nonparametric methods are those in which the estimate of the PSD is made directly from the signal itself. The simplest such method is the periodogram. An improved version of the periodogram is Welch's method [8]. A more modern nonparametric technique is the multitaper method (MTM).

Parametric methods are those in which the signal whose PSD we want to estimate is assumed to be output of a linear system driven by white noise. Examples are the YuleWalker autoregressive (AR) method and the Burg method. These methods estimate the PSD by first estimating the parameters (coefficients) of the linear system that hypothetically "generates" the signal. They tend to produce better results than classical nonparametric methods when the data length of the available signal is relatively short.

Subspace methods, also known as high-resolution methods or super-resolution methods, generate frequency component estimates for a signal based on an eigenanalysis or eigendecomposition of the correlation matrix. Examples are the multiplesignal classification (MUSIC) method or the eigenvector (EV) method. These methods are best suited for line spectra - that is, spectra of sinusoidal signals - and are effective in the detection of sinusoids buried in noise, especially when the signal to noise ratios are low.

All three categories of methods are listed in the table below with the corresponding tool box function names. More information about each function is on the corresponding function reference page. See "Parametric M odeling" on page 4-12 for details about lpc and other parametric estimation functions.

| Method | Description | Functions |
| :--- | :--- | :--- |
| Periodogram | Power spectral density estimate | periodogram |
| Welch | Averaged periodograms of <br> overlapped, windowed signal sections | pwelch, csd, <br> tfe, cohere |
| Multitaper) | Spectral estimate from combination <br> of multiple orthogonal windows (or <br> "tapers") | pmtm |
| Yule-Walker <br> AR | Autoregressive (AR) spectral <br> estimate of a time-series from its <br> estimated autocorrelation function | pyulear |
| Burg | Autoregressive (AR) spectral <br> estimation of a time-series by <br> minimization of linear prediction <br> errors | pburg |
| Covariance | Autoregressive (AR) spectral <br> estimation of a time-series by <br> minimization of the forward <br> prediction errors | pcov |
| Modified | Autoregressive (AR) spectral <br> estimation of a time-series by <br> minimization of the forward and <br> backward prediction errors | pmcov |
| Covariance | Multiple signal classification | pmusic |
| MUSIC | Pseudospectrum estimate | peig |

## Nonparametric Methods

The following sections discuss the periodogram, modified periodogram, Welch, and multitaper methods of nonparametric estimation, along with the related CSD function, transfer function estimate, and coherence function.

## The Periodogram

One way of estimating the power spectrum of a process is to simply find the discrete-time F ourier transform of the samples of the process (usually done on a grid with an FFT) and take the magnitude squared of the result. This estimate is called the periodogram.

The periodogram estimate of the PSD of a length-L signal $x_{L}[n]$ is

$$
\hat{P}_{x x}(f)=\frac{\left|X_{L}(f)\right|^{2}}{f_{s} L}
$$

where

$$
X_{L}(f)=\sum_{n=0} X_{L}[n] e^{-2 \pi j f n / f_{s}}
$$

The actual computation of $X_{L}(f)$ can be performed only at a finite number of frequency points, N , and usually employs the FF . In practice, most implementations of the periodogram method compute the N-point PSD estimate

$$
\hat{P}_{\mathrm{xx}}\left[\mathrm{f}_{\mathrm{k}}\right]=\frac{\left|\mathrm{X}_{\mathrm{L}}\left[\mathrm{f}_{\mathrm{k}}\right]\right|^{2}}{\mathrm{f}_{\mathrm{s}} \mathrm{~L}}, \quad \mathrm{f}_{\mathrm{k}}=\frac{\mathrm{kf}}{\mathrm{~N}}, \quad \mathrm{k}=0,1, \ldots, \mathrm{~N}-1
$$

where

$$
X_{L}\left[f_{k}\right]=\sum_{n=0}^{N-1} x_{L}[n] e^{-2 \pi j k n / N}
$$

It is wise to choose $N>L$ so that $N$ is the next power of two larger than L. To evaluate $X_{L}\left[f_{k}\right]$, we simply pad $x_{L}[n]$ with zeros to length $N$. If $L>N$, we must wrap $x_{L}[n]$ modulo-N prior to computing $X_{L}\left[f_{k}\right]$.

As an example, consider the following 1001-element signal xn , which consists of two sinusoids plus noise.

```
randn('state',0);
fs = 1000; % Sampling frequency
t = (0:fs)/fs; % One second worth of samples
A = [1 2]; % Sinusoid amplitudes (row vector)
f = [150;140]; % Sinusoid frequencies (column vector)
xn = A*sin(2*pi*f*t) + 0.1*randn(size(t));
```

Note The three last lines illustrate a convenient and general way to express the sum of sinusoids. Together they are equivalent to

```
xn = sin(2*pi*150*t) + 2*sin(2*pi*140*t) + 0.1*randn(size(t));
```

The periodogram estimate of the PSD can be computed by

```
Pxx = periodogram(xn,[],'twosided',1024,fs);
```

and a plot of the estimate can be displayed by simply omitting the output argument, as below.

```
periodogram(xn,[],'twosided',1024,fs);
```



The average power can be computed by approximating the integral with the following sum.

```
Pow = (fs/length(Pxx)) * sum(Pxx)
Pow =
    2.5028
```

You can also compute the average power from the onesided PSD estimate.

```
Pxxo = periodogram(xn,[],1024,fs);
Pow = (fs/(2*length(Pxxo))) * sum(Pxxo)
Pow =
    2.4979
```


## Performance of the Periodogram

The following sections discuss the performance of the periodogram with regard to the issues of leakage, resolution, bias, and variance.

Spectral Leakage. Consider the power spectrum or PSD of a finite-length signal $x_{L}[n]$, as discussed in "The Periodogram" on page 3-10. It is frequently useful to interpret $x_{L}[n]$ as the result of multiplying an infinite signal, $x[n]$, by a finitelength rectangular window, $w_{R}[n]$.

$$
x_{L}[n]=x[n] \cdot w_{R}[n]
$$

Because multiplication in the time domain corresponds to convolution in the frequency domain, the F ourier transform of the expression above is

$$
X_{L}(f)=\frac{1}{f_{S}} \int_{-f_{s} / 2}^{f_{s} / 2} X(\rho) W_{R}(f-\rho) d \rho
$$

The expression developed earlier for the periodogram,

$$
\hat{P}_{x x}(f)=\frac{\left|X_{L}(f)\right|^{2}}{f_{s} L}
$$

illustrates that the periodogram is also influenced by this convolution.

The effect of the convolution is best understood for sinusoidal data. Suppose that $x[n]$ is composed of a sum of $M$ complex sinusoids.

$$
x[n]=\sum_{k=1}^{M} A_{k} e^{j \omega_{k} n}
$$

Its spectrum is

$$
X(f)=f_{s} \sum_{k=1}^{M} A_{k} \delta\left(f-f_{k}\right)
$$

which for a finite-length sequence becomes

$$
X_{L}(f)=\int_{-f_{s} / 2}^{f_{s} / 2}\left(\sum_{k=1}^{M} A_{k} \delta\left(\rho-f_{k}\right)\right) W_{R}(f-\rho) d \rho=\sum_{k=1}^{M} A_{k} W_{R}\left(f-f_{k}\right)
$$

So in the spectrum of the finite-length signal, the Dirac deltas have been replaced by terms of the form $W_{R}\left(f-f_{k}\right)$, which corresponds to the frequency response of a rectangular window centered on the frequency $f_{k}$.

The frequency response of a rectangular window has the shape of a sinc signal, as shown below.


The plot displays a main lobe and several side lobes, the largest of which is approximately 13.5 dB below the mainlobe peak. These lobes account for the effect known as spectral leakage. While the infinite-length signal has its power concentrated exactly at the discrete frequency points $f_{k}$, the windowed (or truncated) signal has a continuum of power "leaked" around the discrete frequency points $f_{k}$.

Becausethefrequency response of a short rectangular window is a much poorer approximation to the Dirac delta function than that of a longer window, spectral leakage is especially evident when data records areshort. Consider the following sequence of 100 samples.

```
randn('state',0)
fs = 1000; % Sampling frequency
t = (0:fs/10)/fs; % One-tenth of a second worth of samples
A = [1 2]; % Sinusoid amplitudes
f = [150;140]; % Sinusoid frequencies
xn = A*sin(2*pi*f*t) + 0.1*randn(size(t));
periodogram(xn,[],1024,fs);
```



It is important to note that the effect of spectral leakage is contingent solely on the length of the data record. It is not a consequence of the fact that the periodogram is computed at a finite number of frequency samples.

Resolution. Resol ution refers to the ability to discriminate spectral features, and is a key concept on the analysis of spectral estimator performance.

In order to resolve two sinusoids that arerelatively close together in frequency, it is necessary for the difference between the two frequencies to be greater than the width of the mainl obe of the leaked spectra for either one of these sinusoids. The mainlobe width is defined to be the width of the mainl obe at the point where the power is half the peak mainlobe power (i.e., 3 dB width). This width is approximately equal to $f_{s} / L$.

In other words, for two sinusoids of frequencies $f_{1}$ and $f_{2}$, the resolvability condition requires that

$$
\Delta f=\left(f_{1}-f_{2}\right)>\frac{f_{s}}{L}
$$

In the example above, where two sinusoids are separated by only 10 Hz , the data record must be greater than 100 samples to allow resolution of two distinct sinusoids by a periodogram.
Consider a case where this criterion is not met, as for the sequence of 67 samples below.

```
randn('state',0)
fs = 1000; % Sampling frequency
t = (0:fs/15)./fs; % 67 samples
A = [1 2]; % Sinusoid amplitudes
f = [150;140]; % Sinusoid frequencies
xn = A*sin(2*pi*f*t) + 0.1*randn(size(t));
periodogram(xn,[],1024,fs);
```



The above discussion about resolution did not consider the effects of noise since the signal-to-noise ratio (SNR) has been relatively high thus far. When the SNR is low, true spectral features are much harder to distinguish, and noise artifacts appear in spectral estimates based on the periodogram. The example below illustrates this.

```
randn('state',0)
fs = 1000; % Sampling frequency
t = (0:fs/10)./fs; % One-tenth of a second worth of samples
A = [1 2]; % Sinusoid amplitudes
f = [150;140]; % Sinusoid frequencies
xn = A*sin(2*pi*f*t) + 2*randn(size(t));
periodogram(xn,[],1024,fs);
```



Bias of the Periodogram. The periodogram is a biased estimator of the PSD. Its expected value can be shown to be

$$
E\left\{\frac{\left|X_{L}(f)\right|^{2}}{f_{s} L}\right\}=\frac{1}{f_{s} L} \int_{-f_{s} / 2}^{f_{s} / 2} P_{x x}(\rho)\left|W_{R}(f-\rho)\right|^{2} d \rho
$$

which is similar to the first expression for $\mathrm{X}_{\mathrm{L}}(\mathrm{f})$ in "Spectral Leakage" on page 3-12, except that the expression here is in terms of average power rather than magnitude. This suggests that the estimates produced by the periodogram correspond to a leaky PSD rather than the true PSD.
Note that $\left|W_{R}(f-\rho)\right|^{2}$ essentially yields a triangular Bartlett window (which is apparent from the fact that the convolution of two rectangular pulses is a triangular pulse). This results in a height for the largest sidel obes of the leaky power spectra that is about 27 dB below themainlobepeak; i.e., about twice the frequency separation relative to the non-squared rectangular window.
The periodogram is asymptotically unbiased, which is evident from the earlier observation that as the data record length tends to infinity, the frequency response of the rectangular window more closely approximates the Dirac delta function (also true for a Bartlett window). However, in some cases the periodogram is a poor estimator of the PSD even when the data record is long. This is due to the variance of the periodogram, as explained below.

Variance of the Periodogram. The variance of the periodogram can be shown to be approximately

$$
\operatorname{var}\left\{\frac{\left|X_{L}(f)\right|^{2}}{f_{s} L}\right\} \approx P_{x x}^{2}(f)\left[1+\left(\frac{\sin \left(2 \pi L f / f_{s}\right)}{L \sin \left(2 \pi f / f_{s}\right)}\right)^{2}\right]
$$

which indicates that the variance does not tend to zero as the data length $L$ tends to infinity. In statistical terms, the periodogram is not a consistent estimator of the PSD. Nevertheless, the periodogram can be a useful tool for spectral estimation in situations where the SNR is high, and especially if the data record is long.

## The Modified Periodogram

The modified periodogram windows thetime-domain signal prior to computing the FFT in order to smooth the edges of the signal. This has the effect of reducing the height of the sidel obes or spectral leakage. This phenomenon gives rise to the interpretation of sidel obes as spurious frequencies introduced into the signal by the abrupt truncation that occurs when a rectangular window is used. For nonrectangular windows, the end points of the truncated signal areattenuated smoothly, and hencethe spurious frequencies introduced are much less severe. On the other hand, nonrectangular windows also broaden the mainlobe, which results in a net reduction of resolution.

The periodogram function allows you to compute a modified periodogram by specifying the window to be used on the data. F or example, compare a rectangular window and a Hamming window.

```
randn('state',0)
fs = 1000; % Sampling frequency
t = (0:fs/10)./fs; % One-tenth of a second worth of samples
A = [1 2]; % Sinusoid amplitudes
f = [150;140]; % Sinusoid frequencies
xn = A*sin(2*pi*f*t) + 0.1*randn(size(t));
periodogram(xn,rectwin(length(xn)),1024,fs);
```


periodogram(xn, hamming(length(xn)), 1024,fs);

Periodogram PSD Estimate


You can verify that although the sidel obes are much less evident in the Hamming-windowed periodogram, the two main peaks are wider. In fact, the 3 dB width of the mainlobe corresponding to a Hamming window is approximately twice that of a rectangular window. Hence, for a fixed data length, the PSD resolution attainable with a Hamming window is
approximately half that attainable with a rectangular window. The competing interests of mainlobe width and sidel obe height can be resolved to some extent by using variable windows such as the Kaiser window.

Nonrectangular windowing affects the average power of a signal because some of the time samples are attenuated when multiplied by the window. To compensate for this, the periodogram function normalizes the window to have an average power of unity. This way the choice of window does not affect the average power of the signal.

The modified periodogram estimate of the PSD is

$$
\hat{P}_{x x}(f)=\frac{\left|X_{L}(f)\right|^{2}}{f_{s} L U}
$$

where U is the window normalization constant

$$
\mathrm{U}=\frac{1}{\mathrm{~L}} \sum_{\mathrm{n}=0}^{\mathrm{L}-1}|\mathrm{w}(\mathrm{n})|^{2}
$$

which is independent of the choice of window. The addition of $U$ as a normalization constant ensures that the modified periodogram is asymptotically unbiased.

## Welch's Method

An improved estimator of the PSD is the one proposed by Welch [8]. The method consists of dividing the time series data into (possibly overlapping) segments, computing a modified periodogram of each segment, and then averaging the PSD estimates. The result is Welch's PSD estimate.

Welch's method is implemented in the Signal Processing Tool box by the pwelch function. By default, the data is divided into eight segments with $50 \%$ overlap between them. A Hamming window is used to compute the modified periodogram of each segment.

The averaging of modified periodograms tends to decrease the variance of the estimate relative to a single periodogram estimate of the entire data record. Although overlap between segmentstends to introduce redundant information, this effect is diminished by the use of a nonrectangular window, which reduces
the importance or weight given to the end samples of segments (the samples that overlap).

However, as mentioned above, the combined use of short data records and nonrectangular windows results in reduced resolution of the estimator. In summary, there is a tradeoff between variance reduction and resolution. One can manipulate the parameters in Welch's method to obtain improved estimates relative to the periodogram, especially when the SNR is low. This is illustrated in the following example.

Consider an original signal consisting of 301 samples.

```
randn('state',1)
fs = 1000; % Sampling frequency
t = (0:0.3*fs)./fs; % 301 samples
A = [2 8]; % Sinusoid amplitudes (row vector)
f = [150;140]; % Sinusoid frequencies (column vector)
xn = A*sin(2*pi*f*t) + 5*randn(size(t));
periodogram(xn,rectwin(length(xn)),1024,fs);
```



We can obtain Welch's spectral estimate for 3 segments with $50 \%$ overlap with pwelch(xn, rectwin(150), 75,512,fs);


In the periodogram above, noise and the leakage make one of the sinusoids essentially indistinguishable from the artificial peaks. In contrast, although the PSD produced by Welch's method has wider peaks, you can still distinguish the two sinusoids, which stand out from the "noise floor."

However, if we try to reduce the variance further, the loss of resolution causes one of the sinusoids to be lost altogether.

```
pwelch(xn, hamming(100),75,512,fs);
```



For a more detailed discussion of Welch's method of PSD estimation, see Kay [2] and Welch [8].

## Bias and Normalization in Welch's Method

Welch's method yields a biased estimator of the PSD. The expected value can be found to be

$$
E\left\{\hat{P}_{\text {welch }}\right\}=\frac{1}{f_{s} L_{s} U} \int_{-f_{s} / 2}^{f_{s} / 2} P_{x x}(\rho)|W(f-\rho)|^{2} d \rho
$$

where $L_{s}$ is the length of the data segments and $U$ is the same normalization constant present in the definition of the modified periodogram. As is the case for all periodograms, Welch's estimator is asymptotically unbiased. For a fixed length data record, the bias of Welch's estimate is larger than that of the periodogram because $L_{s}<L$.

The variance of Welch's estimator is difficult to compute because it depends on both the window used and the amount of overlap between segments. Basically, the variance is inversely proportional to the number of segments whose modified periodograms are being averaged.

## Multitaper Method

The periodogram can be interpreted as filtering a length $L$ signal, $x_{L}[n]$, through a filter bank (a set of filters in parallel) of L FIR bandpass filters. The 3 dB bandwidth of each of these bandpass filters can be shown to be approximately equal to $f_{s} / \mathrm{L}$. The magnitude response of each one of these bandpass filters resembles that of the rectangular window discussed in "Spectral Leakage" on page 3-12. The periodogram can thus be viewed as a computation of the power of each filtered signal (i.e., the output of each bandpass filter) that uses just one sample of each filtered signal and assumes that the PSD of $x_{L}[n]$ is constant over the bandwidth of each bandpass filter.
As the length of the signal increases, the bandwidth of each bandpass filter decreases, making it a more selective filter, and improving the approximation of constant PSD over the bandwidth of the filter. This provides another interpretation of why the PSD estimate of the periodogram improves as the length of the signal increases. However, there are two factors apparent from this standpoint that compromise the accuracy of the periodogram estimate. First, the rectangular window yields a poor bandpass filter. Second, the computation of the power at the output of each bandpass filter relies on a single sample of the output signal, producing a very crude approximation.
Welch's method can be given a similar interpretation in terms of a filter bank. In Welch's implementation, several samples are used to compute the output power, resulting in reduced variance of the estimate. On the other hand, the bandwidth of each bandpass filter is larger than that corresponding to the periodogram method, which results in a loss of resolution. The filter bank model thus provides a new interpretation of the compromise between variance and resolution.

Thompson's multitaper method (MTM) builds on these results to provide an improved PSD estimate. Instead of using bandpass filters that are essentially rectangular windows (as in the periodogram method), the MTM method uses a bank of optimal bandpass filters to compute the estimate. These optimal FIR filters are derived from a set of sequences known as discreteprolatespheroidal sequences (DPSSs, also known as Slepian sequences).

In addition, the MTM method provides a time-bandwidth parameter with which to balance the variance and resolution. This parameter is given by the time-bandwidth product, NW and it is directly related to the number of tapers used to compute the spectrum. There are always $2 *$ NW-1 tapers used to form the estimate. This means that, as NW increases, there are more estimates of
the power spectrum, and the variance of the estimate decreases. However, the bandwidth of each taper is also proportional to NW, so as NW increases, each estimate exhibits more spectral leakage (i.e., wider peaks) and the overall spectral estimate is more biased. For each data set, there is usually a value for NW that allows an optimal trade-off between bias and variance.

The Signal Processing Tool box function that implements the MTM method is called pmtm. Use pmtm to compute the PSD of xn from the previous examples.

```
randn('state',0)
fs = 1000; % Sampling frequency
t = (0:fs)/fs; % One second worth of samples
A = [1 2]; % Sinusoid amplitudes
f = [150;140]; % Sinusoid frequencies
xn = A*sin(2*pi*f*t) + 0.1*randn(size(t));
[P,F] = pmtm(xn,4,1024,fs);
plot(F,10*log10(P)) % Plot in dB/Hz
xlabel('Frequency (Hz)');
ylabel('Power Spectral Density (dB/Hz)');
```



By lowering thetime-bandwidth product, you can increase the resolution at the expense of larger variance.

```
[P1,f] = pmtm(xn,3/2,1024,fs);
plot(f,10*log10(P1)) % Plot in dB/Hz
xlabel('Frequency (Hz)');
ylabel('Power Spectral Density (dB/Hz)');
```



Note that the average power is conserved in both cases.

```
Pow = (fs/1024) * sum(P)
Pow =
    2.4926
Pow1 = (fs/1024) * sum(P1)
Pow1 =
```

2.4927

This method is more computationally expensive than Welch's method due to the cost of computing the discrete prolate spheroidal sequences. For long data series ( 10,000 points or more), it is useful to compute the DPSSs once and save them in a MAT-file. The M-files dpsssave, dpssload, dpssdir, and dpssclear are provided to keep a database of saved DPSSs in the MAT-file dpss.mat.

## Cross-Spectral Density Function

The PSD is a special case of the cross spectral density (CSD) function, defined between two signals $x_{n}$ and $y_{n}$ as

$$
S_{x y}(\omega)=\sum_{m=-\infty} R_{x y}(m) e^{-j \omega m}
$$

As is the case for the correlation and covariance sequences, the tool box estimates the PSD and CSD because signal lengths are finite.
To estimate the cross-spectral density of two equal length signals $x$ and $y$ using Welch's method, the csd function forms the periodogram as the product of the FFT of $x$ and the conjugate of the FFT of $y$. Unlike the real-valued PSD, the CSD is a complex function. csd handles the sectioning and windowing of $x$ and $y$ in the same way as the pwelch function.

```
Sxy = csd(x,y,nfft,fs,window, numoverlap)
```


## Confidence Intervals

You can compute confidence intervals using the csd function by including an additional input argument $p$ that specifies the percentage of the confidence interval, and setting the numoverlap argument to 0 .

$$
[S x y, S x y c, f]=\operatorname{csd}(x, y, n f f t, f s, \text { window, } 0, p)
$$

p must be a scalar between 0 and 1. This function assumes chi-squared distributed periodograms of the nonoverlapping sections of windowed data in computing the confidence intervals. This assumption is valid when the signal is a Gaussian distributed random process. Provided these assumptions are correct, the confidence interval

```
[Sxy-Sxyc(:,1) Sxy+Sxyc(:,2)]
```

covers the true CSD with probability $p$. If you set numoverlap to any value other than 0 , you generate a warning indicating that the sections overlap and the confidence interval is not reliable.

## Transfer Function Estimate

One application of Welch's method is nonparametric system identification. Assume that $H$ is a linear, time invariant system, and $x(n)$ and $y(n)$ are the input to and output of $H$, respectively. Then the power spectrum of $x(n)$ is related to the CSD of $x(n)$ and $y(n)$ by

$$
S_{x y}(\omega)=H(\omega) S_{x x}(\omega)
$$

An estimate of the transfer function between $x(n)$ and $y(n)$ is

$$
\hat{H}(\omega)=\frac{\hat{S}_{x y}(\omega)}{\hat{S}_{x x}(\omega)}
$$

This method estimates both magnitude and phase information. The tfe function uses Welch's method to compute the CSD and power spectrum, and then forms their quotient for the transfer function estimate. Use tfe the same way that you use the csd function.
Filter the signal xn with an FIR filter, then plot the actual magnituderesponse and the estimated response.

```
h = ones(1,10)/10; % Moving average filter
yn = filter(h,1,xn);
[HEST,f] = tfe(xn,yn,256,fs,256,128,'none');
H = freqz(h,1,f,fs);
subplot(2,1,1); plot(f,abs(H));
title('Actual Transfer Function Magnitude');
subplot(2,1,2); plot(f,abs(HEST));
title('Transfer Function Magnitude Estimate');
xlabel('Frequency (Hz)');
```



## Coherence Function

The magnitude-squared coherence between two signals $x(n)$ and $y(n)$ is

$$
C_{x y}(\omega)=\frac{\left|S_{x y}(\omega)\right|^{2}}{S_{x x}(\omega) S_{y y}(\omega)}
$$

This quotient is a real number between 0 and 1 that measures the correlation between $x(n)$ and $y(n)$ at the frequency $\omega$.

The cohere function takes sequences $x$ and $y$, computes their power spectra and CSD, and returns the quotient of the magnitude squared of the CSD and the product of the power spectra. Its options and operation are similar to the csd and tfe functions.

The coherence function of $x n$ and the filter output $y n$ versus frequency is cohere(xn, yn, 256,fs,256,128, ' none')


If the input sequence length nfft, window length window, and the number of overlapping data points in a window numoverlap, are such that cohere operates on only a single record, the function returns all ones. This is because the coherence function for linearly dependent data is one.

## Parametric Methods

Parametric methods can yield higher resolutions than nonparametric methods in cases when the signal length is short. These methods use a different approach to spectral estimation; instead of trying to estimate the PSD directly from the data, they model the data as the output of a linear system driven by white noise, and then attempt to estimate the parameters of that linear system.

The most commonly used linear system model is the all-pol e model, a filter with all of its zeroes at the origin in the z-plane. The output of such a filter for white noise input is an autoregressive (AR) process. For this reason, these methods are sometimes referred to as AR methods of spectral estimation.

The AR methods tend to adequately describe spectra of data that is "peaky," that is, data whose PSD is large at certain frequencies. The data in many practical applications (such as speech) tends to have "peaky spectra" so that AR models are often useful. In addition, the AR models lead to a system of linear equations which is relatively simple to solve.

The Signal Processing Tool box offers the following AR methods for spectral estimation:

- Yule-Walker AR method (autocorrelation method)
- Burg method
- Covariance method
- Modified covariance method

All AR methods yield a PSD estimate given by

$$
\hat{P}_{A R}(f)=\frac{1}{f_{s} \mid} \frac{\varepsilon_{p}}{1+\left.\sum_{L-1} \hat{a}_{p}(k) e^{-2 \pi j k f / f_{s}}\right|^{2}}
$$

The different AR methods estimate the AR parameters $a_{p}(k)$ slightly differently, yielding different PSD estimates. The following table provides a summary of the different AR methods.

|  | Burg | Covariance | Modified Covariance | Yule-Walker |
| :--- | :--- | :--- | :--- | :--- |
| Characteristics | Does not apply <br> window to data | Does not apply <br> window to data | Does not apply <br> window to data | Applies window to <br> data |
|  | Minimizes the <br> forward and <br> backward prediction <br> errors in the least <br> squares sense, with <br> the AR coefficients <br> constrained to satisfy <br> the L-D recursion | Minimizes the <br> forward prediction <br> error in the least <br> squares sense | Minimizes the <br> forward and <br> backward prediction <br> errors in the least <br> squares sense | Minimizes the <br> forward prediction <br> error in the least <br> squares sense <br> (also called <br> "Autocorrelation <br> method") |
|  | High resolution for <br> short data records | Better resolution than <br> Y-W for short data <br> records (more <br> accurate estimates) | High resolution for <br> short data records | Performs as well as <br> other methods for <br> large data records |
| Advantages | Able to extract <br> frequencies from data <br> consisting of p or more <br> pure sinusoids | Able to extract <br> frequencies from data <br> consisting of por more <br> pure sinusoids | Always produces a <br> stable model |  |
|  | Always produces a <br> stable model |  | Does not suffer <br> spectral line-splitting |  |


|  | Burg | Covariance | Modified Covariance | Yule-Walker |
| :--- | :--- | :--- | :--- | :--- |
| Disadvantages | Peak locations highly <br> dependent on initial <br> phase | May produce unstable <br> models | May produce unstable <br> models | Performs relatively <br> poorly for short data <br> records |
|  | May suffer spectral <br> linesplitting for <br> sinusoids in noise, or <br> when order is very <br> large | Frequency bias for <br> estimates of sinusoids <br> in noise | Peak locations <br> slightly dependent on <br> initial phase | Frequency bias for <br> estimates of sinusoids <br> in noise |
|  | Frequency bias for <br> estimates of sinusoids <br> in noise |  | Minor frequency bias <br> for estimates of <br> sinusoids in noise |  |
| Conditions for <br> Nonsingularity |  | Order must be less <br> than or equal to half <br> the input frame size | Order must be less <br> than or equal to $2 / 3$ <br> the input frame size | Because of the biased <br> estimate, the <br> autocorrelation <br> matrix is guaranteed |
| to positive-definite, |  |  |  |  |
| hence nonsingular |  |  |  |  |

## Yule-Walker AR Method

The YuleWalker AR method of spectral estimation computes the AR parameters by forming a biased estimate of the signal's autocorrelation function, and solving the least squares minimization of the forward prediction error. This results in the Yule-Walker equations

$$
\left[\begin{array}{cccc}
r(1) & r(2)^{*} & \cdots & r(p)^{*} \\
r(2) & r(1) & \cdots & r(p-1)^{*} \\
\vdots & \ddots & \ddots & \vdots \\
r(p) & \cdots & r(2) & r(1)
\end{array}\right]\left[\begin{array}{c}
a(2) \\
a(3) \\
\vdots \\
a(p+1)
\end{array}\right]=\left[\begin{array}{c}
-r(2) \\
-r(3) \\
\vdots \\
-r(p+1)
\end{array}\right]
$$

The use of a biased estimate of the autocorrelation function ensures that the autocorrelation matrix above is positive definite. Hence, the matrix is invertible and a solution is guaranteed to exist. M oreover, the AR parameters thus computed always result in a stable all-pole model. The Yule-Walker equations can be solved efficiently via Levinson's algorithm, which takes advantage of the Toeplitz structure of the autocorrelation matrix.

The tool box function pyulear implements the Yule-Walker AR method.

F or example, compare the spectrum of a speech signal using Welch's method and the Yule-Walker AR method.

```
load mtlb
[P1,f] = pwelch(mtlb,hamming(256),128,1024,fs);
[P2,f] = pyulear(mtlb,14,1024,fs);
plot(f,10*log10(P1),':',f,10*log10(P2)); grid
ylabel('PSD Estimates (dB/Hz)');
xlabel('Frequency (Hz)');
legend('Welch','Yule-Walker AR')
```



The solid-line Yule-Walker AR spectrum is smoother than the periodogram because of the simple underlying all-pole model.

## Burg Method

The Burg method for AR spectral estimation is based on minimizing the forward and backward prediction errors while satisfying the Levinson-Durbin recursion (see Marple [3], Chapter 7, and Proakis [6], Section 12.3.3). In contrast to other AR estimation methods, the Burg method avoids calculating the autocorrelation function, and instead estimates the reflection coefficients directly.

The primary advantages of the Burg method are resolving closely spaced sinusoids in signals with low noiselevels, and estimating short data records, in
which case the AR power spectral density estimates are very close to the true values. In addition, the Burg method ensures a stable AR model and is computationally efficient.

The accuracy of the Burg method is lower for high-order models, long data records, and high signal-to-noise ratios (which can cause line splitting, or the generation of extraneous peaks in the spectrum estimate). The spectral density estimate computed by the Burg method is al so susceptible to frequency shifts (relative to the true frequency) resulting from the initial phase of noisy sinusoidal signals. This effect is magnified when analyzing short data sequences.

The tool box function pburg implements the Burg method. Compare the spectrum of the speech signal generated by both the Burg method and the Yule-Walker AR method. They are very similar for large signal lengths.

```
load mtlb
[P1,f] = pburg(mtlb(1:512),14,1024,fs); % 14th order model
[P2,f] = pyulear(mtlb(1:512),14,1024,fs); % 14th order model
plot(f,10*log10(P1),':',f,10*log10(P2)); grid
ylabel('Magnitude (dB)'); xlabel('Frequency (Hz)');
legend('Burg','Yule-Walker AR')
```



Compare the spectrum of a noisy signal computed using the Burg method and the Welch method.

```
randn('state',0)
fs = 1000; % Sampling frequency
t = (0:fs)/fs; % One second worth of samples
A = [1 2]; % Sinusoid amplitudes
f = [150;140]; % Sinusoid frequencies
xn = A*sin(2*pi*f*t) + 0.1*randn(size(t));
[P1,f] = pwelch(xn,hamming(256),128,1024,fs);
[P2,f] = pburg(xn,14,1024,fs);
plot(f,10*log10(P1),':',f,10*log10(P2)); grid
ylabel('PSD Estimates (dB/Hz)');
xlabel('Frequency (Hz)');
legend('Welch','Burg')
```



Note that, as the model order for the Burg method is reduced, a frequency shift due to the initial phase of the sinusoids will become apparent.

## Covariance and Modified Covariance Methods

The covariance method for AR spectral estimation is based on minimizing the forward prediction error. The modified covariance method is based on minimizing the forward and backward prediction errors. The tool box functions pcov and pmcov implement the respective methods.

Compare the spectrum of the speech signal generated by both the covariance method and the modified covariance method. They are nearly identical, even for a short signal length.

```
load mtlb
[P1,f] = pcov(mtlb(1:64),14,1024,fs); % 14th order model
[P2,f] = pmcov(mtlb(1:64),14,1024,fs); % 14th order model
plot(f,10*log10(P1),':',f,10*log10(P2)); grid
ylabel('Magnitude (dB)'); xlabel('Frequency (Hz)');
legend('Covariance','Modified Covariance')
```



## MUSIC and Eigenvector Analysis Methods

The pmusic and peig functions provide two related spectral analysis methods:

- pmusic provides the multiple signal classification (MUSIC) method developed by Schmidt
- peig provides the eigenvector (EV) method developed by J ohnson

See Marple [3] (pgs. 373-378) for a summary of these methods.

Both of these methods are frequency estimator techniques based on eigenanalysis of the autocorrelation matrix. This type of spectral analysis categorizes the information in a correlation or data matrix, assigning information to either a signal subspace or a noise subspace.

## Eigena nalysis 0 verview

Consider a number of complex sinusoids embedded in white noise. Y ou can write the autocorrelation matrix R for this system as the sum of the signal autocorrelation matrix ( S ) and the noise autocorrelation matrix (W).

$$
\mathrm{R}=\mathrm{S}+\mathrm{W}
$$

There is a close relationship between the eigenvectors of the signal autocorrelation matrix and the signal and noise subspaces. The eigenvectors $v$ of S span the same signal subspace as the signal vectors. If the system contains $M$ complex sinusoids and the order of the autocorrelation matrix is $p$, eigenvectors $\mathrm{v}_{\mathrm{M}+1}$ through $\mathrm{v}_{\mathrm{p}+1}$ span the noise subspace of the autocorrelation matrix.

Frequency Estimator Functions. To generate their frequency estimates, eigenanalysis methods calculate functions of the vectors in thesignal and noise subspaces. Both the MUSIC and EV techniques choose a function that goes to infinity (denominator goes to zero) at one of the sinusoidal frequencies in the input signal. Using digital technology, the resulting estimate has sharp peaks at the frequencies of interest; this means that there might not be infinity values in the vectors.
The MUSIC estimate is given by the formula

$$
P_{\text {music }^{(f)}}(f)=\frac{1}{\mathbf{e}^{H}(f)\left(\sum_{k=p+1}^{N} \mathbf{v}_{k} \mathbf{v}_{k}^{H}\right) \mathbf{e}(f)}=\frac{1}{\sum_{k=p+1}^{N}\left|\mathbf{v}_{k}^{H} \mathbf{e}(f)\right|^{2}}
$$

where $N$ is the size of the eigenvectors and $\mathbf{e}(f)$ is a vector of complex sinusoids.

$$
\mathbf{e}(f)=[1 \exp (j 2 \pi f) \exp (j 2 \pi f \cdot 2) \exp (j 2 \pi f \cdot 4) \ldots \exp (j 2 \pi f \cdot(n-1))]^{H}
$$

$\mathbf{v}$ represents the eigenvectors of the input signal's correlation matrix; $\mathbf{v}_{\mathrm{k}}$ is the $\mathrm{k}^{\text {th }}$ eigenvector. H is the conjugate transpose operator. The eigenvectors used
in the sum correspond to the smallest eigenvalues and span the noise subspace ( $p$ is the size of the signal subspace).
The expression $\mathbf{v}_{k}^{H} \mathbf{e}(f)$ is equivalent to a Fourier transform (the vector $\mathbf{e}(f)$ consists of complex exponentials). This form is useful for numeric computation because the FFT can be computed for each $\mathbf{v}_{\mathrm{k}}$ and then the squared magnitudes can be summed.

The EV method weights the summation by the eigenvalues of the correlation matrix.

$$
P_{e v}(f)=\frac{1}{\left(\sum_{k=p+1}^{N}\left|\mathbf{v}_{k}^{H} \mathbf{e}(f)\right|^{2}\right) / \lambda_{k}}
$$

The pmusic and peig functions in this tool box use the svd (singular value decomposition) function in the signal case and the eig function for analyzing the correlation matrix and assigning eigenvectors to the signal or noise subspaces. When svd is used, pmusic and peig never compute the correlation matrix explicitly, but the singular values are the eigenvalues.

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## Special Topics

Overview ..... 4-2
Windows ..... 4-3
Basic Shapes ..... 4-3
Generalized Cosine Windows ..... 4-5
Kaiser Window ..... 4-6
Chebyshev Window ..... 4-10
Parametric Modeling ..... 4-12
Time-Domain Based Modeling ..... 4-14
Frequency-Domain Based Modeling ..... 4-19
Resampling ..... 4-22
Cepstrum Analysis ..... 4-25
I nverse Complex Cepstrum ..... 4-27
FFT-Based Time-Frequency Analysis ..... 4-29
Median Filtering ..... $4-30$
Communications Applications ..... 4-31
Deconvolution ..... 4-35
Specialized Transforms ..... 4-36
Chirp z-Transform ..... 4-36
Discrete Cosine Transform ..... 4-38
Hilbert Transform ..... 4-40
Selected Bibliography ..... 4-42

## Overview

The Signal Processing Tool box provides functions that allow you to apply a variety of signal processing techniques. The following sections describe how to use some of these functions:

- "Windows"
- "Parametric Modeling"
- "Resampling"
- "Cepstrum Analysis"
- "FFT-Based Time-Frequency Analysis"
- "Median Filtering"
- "Communications Applications"
- "Deconvolution"
- "Specialized Transforms"
- "Selected Bibliography"


## Windows

In both digital filter design and power spectrum estimation, the choice of a windowing function can play an important role in determining the quality of overall results. The main role of the window is to damp out the effects of the Gibbs phenomenon that results from truncation of an infinite series.

The tool box window functions are shown in the table below.

| Window | Function |
| :--- | :--- |
| Bartlett-Hann window | barthannwin |
| Bartlett window | bartlett |
| Blackman window | blackman |
| Blackman-harris window | blackmanharris |
| Bohman window | bohmanwin |
| Chebyshev window | chebwin |
| Gaussian window | gausswin |
| Hamming window | hamming |
| Hann window | hann |
| Kaiser window | kaiser |
| Nuttall's Blackman-harris window | nuttallwin |
| Rectangular window | rectwin |
| Tapered cosine window | tukeywin |
| Triangular window | triang |

## Basic Shapes

The basic window is the rectangular window, a vector of ones of the appropriate length. A rectangular window of length 50 is

$$
\mathrm{n}=50 ;
$$

$$
\text { w = rectwin }(n) \text {; }
$$

This tool box stores windows in column vectors by convention, so an equivalent expression is

```
w = ones(50,1);
```

The Bartlett (or triangular) window is the convolution of two rectangular windows. The functions bartlett and triang compute similar triangular windows, with three important differences. The bartlett function always returns a window with two zeros on the ends of the sequence, so that for $n$ odd, the center section of bartlett $(n+2)$ is equivalent to triang $(n)$.

```
bartlett(7)
ans =
    0
    0.3333
    0.6667
    1.0000
    0.6667
    0.3333
        0
triang(5)
ans =
    0.3333
    0.6667
    1.0000
    0.6667
    0.3333
```

For $n$ even, bartlett is still the convolution of two rectangular sequences. There is no standard definition for the triangular window for $n$ even; the slopes of the line segments of the triang result are slightly steeper than those of bartlett in this case.

```
w = bartlett(8);
[w(2:7) triang(6)]
ans =
```

| 0.2857 | 0.1667 |
| :--- | :--- |
| 0.5714 | 0.5000 |
| 0.8571 | 0.8333 |
| 0.8571 | 0.8333 |
| 0.5714 | 0.5000 |
| 0.2857 | 0.1667 |

The final difference between the Bartlett and triangular windows is evident in the F ourier transforms of these functions. The Fourier transform of a Bartlett window is negative for $n$ even. The Fourier transform of a triangular window, however, is always nonnegative.

This difference can be important when choosing a window for some spectral estimation techniques, such as the Blackman-Tukey method. Blackman-Tukey forms the spectral estimate by calculating the Fourier transform of the autocorrelation sequence. The resulting estimate might be negative at some frequencies if the window's F ourier transform is negative (see Kay [1], pg. 80).

## Generalized Cosine Windows

Blackman, Hamming, Hann, and rectangular windows are all special cases of the generalized cosine window. These windows are combinations of sinusoidal sequences with frequencies $0,2 \pi /(N-1)$, and $4 \pi /(N-1)$, where $N$ is the window length. One way to generate them is

```
ind = (0:n-1)'*2*pi/(n-1);
w = A - B* cos(ind) + C*}\operatorname{cos(2*ind);
```

where $\mathrm{A}, \mathrm{B}$, and C are constants you define. The concept behind these windows is that by summing the individual terms toform the window, the low frequency peaks in the frequency domain combine in such a way as to decrease sidel obe height. This has the side effect of increasing the mainl obe width.

The Hamming and Hann windows are two-term generalized cosine windows, given by $\mathrm{A}=0.54, \mathrm{~B}=0.46$ for Hamming and $\mathrm{A}=0.5, \mathrm{~B}=0.5$ for Hann ( $\mathrm{C}=0$ in both cases). The hamming and hann functions, respectively, compute these windows.

Note that the definition of the generalized cosine window shown in the earlier MATLAB code yields zeros at samples 1 and $n$ for $A=0.5$ and $B=0.5$.

The Blackman window is a popular three-term window, given by $\mathrm{A}=0.42$, $B=0.5, C=0.08$. The blackman function computes this window.

## Kaiser Window

The Kaiser window is an approximation to the prolate-spheroidal window, for which the ratio of the mainlobeenergy tothesidel obe energy is maximized. For a Kaiser window of a particular length, the parameter $\beta$ controls the sidel obe height. F or a given $\beta$, the sidel obe height is fixed with respect to window length. The statement kaiser(n, beta) computes a length $n$ Kaiser window with parameter beta.

Examples of Kaiser windows with length 50 and various values for the beta parameter are

```
n = 50;
w1 = kaiser(n,1);
w2 = kaiser(n,4);
w3 = kaiser(n,9);
[W1,f] = freqz(w1/sum(w1),1,512,2);
[W2,f] = freqz(w2/sum(w2),1,512,2);
[W3,f] = freqz(w3/sum(w3),1,512,2);
plot(f,20*log10(abs([W1 W2 W3]))); grid;
legend('beta = 1','beta = 4','beta = 9',3)
title('Three Kaiser Window Responses')
xlabel('Normalized Frequency (Nyquist = 1)')
ylabel('Normalized Magnitude (dB)')
```



As $\beta$ increases, the sidel obe height decreases and the mainl obe width increases. To see how the sidel obe height stays the same for a fixed $\beta$ parameter as the length is varied, try

```
w1 = kaiser (50,4);
w2 = kaiser(20,4);
w3 = kaiser(101,4);
[W1,f] = freqz(w1/sum(w1),1,512,2);
[W2,f] = freqz(w2/sum(w2),1,512,2);
[W3,f] = freqz(w3/sum(w3),1,512,2);
plot(f,20*log10(abs([W1 W2 W3]))); grid;
legend('length = 50','length = 20','length = 101')
title('Three Kaiser Window Responses, Beta Fixed')
xlabel('Normalized Frequency (Nyquist = 1)')
ylabel('Normalized Magnitude (dB)')
```



## Kaiser Windows in FIR Design

There are two design formulas that can help you design FIR filters to meet a set of filter specifications using a Kaiser window. To achieve a sidel obe height of $-\alpha \mathrm{dB}$, the beta parameter is

$$
\beta= \begin{cases}0.1102(\alpha-8.7), & \alpha>50 \\ 0.5842(\alpha-21)^{0.4}+0.07886(\alpha-21), & 50 \geq \alpha \geq 21 \\ 0, & \alpha<21\end{cases}
$$

For a transition width of $\Delta \omega \mathrm{rad} / \mathrm{s}$, use the length

$$
n=\frac{\alpha-8}{2.285 \Delta \omega}+1
$$

Filters designed using these heuristics will meet the specifications approximately, but you should verify this. To design a lowpass filter with cutoff frequency $0.5 \pi \mathrm{rad} / \mathrm{s}$, transition width $0.2 \pi \mathrm{rad} / \mathrm{s}$, and 40 dB of attenuation in the stopband, try

```
[n,wn,beta] = kaiserord([0.4 0.6]*pi,[1 0],[0.01 0.01],2*pi);
h = fir1(n,wn,kaiser(n+1,beta),'noscale');
```

The kaiserord function estimates the filter order, cutoff frequency, and K aiser window beta parameter needed to meet a given set of frequency domain specifications.
The ripple in the passband is roughly the same as the ripple in the stopband. As you can see from the frequency response, this filter nearly meets the specifications.

```
[H,f] = freqz(h,1,512,2);
plot(f,20*log10(abs(H))), grid
```



## Chebyshev Window

The Chebyshev window minimizes the mainlobe width, given a particular sidel obe height. It is characterized by an equiripple behavior, that is, its sidel obes all have the same height. The chebwin function, with length and sidel obe height parameters, computes a Chebyshev window.

```
n = 51;
Rs = 40; % Sidelobe height in decibels
w = chebwin(n,Rs);
stem(w); title('Length 51 Chebyshev Window');
xlabel('Sample Number');
```



As shown in the plot, the Chebyshev window has Iarge spikes at its outer samples. Plot the frequency response to see the equiripples at -40 dB .

```
[W,f] = freqz(w,1,512,2);
plot(f,20*log10(abs(W)/sum(w))), grid
title('Chebyshev Window Magnitude Response');
xlabel('Normalized Frequency (Nyquist = 1)');
ylabel('Normalized Magnitude (dB)');
```



F or a detailed discussion of the characteristics and applications of the various window types, see Oppenheim and Schafer [2], pgs. 444-462, and Parks and Burrus [3], pgs. 71-73.

## Parametric Modeling

Parametric modeling techniques find the parameters for a mathematical model describing a signal, system, or process. These techniques use known information about the system to determine the model. Applications for parametric modeling include speech and music synthesis, data compression, high-resolution spectral estimation, communications, manufacturing, and simulation.

The tool box parametric modeling functions operate with the rational transfer function model. Given appropriate information about an unknown system (impulse or frequency response data, or input and output sequences), these functions find the coefficients of a linear system that models the system.

One important application of the parametric modeling functions is in the design of filters that have a prescribed time or frequency response. These functions provide a data-oriented alternative to the IIR and FIR filter design functions discussed in Chapter 2, "Filter Design."

Here is a summary of the parametric modeling functions in this toolbox. N ote that the System I dentification Tool box provides a more extensive collection of parametric modeling functions.

| Domain | Functions | Description |
| :--- | :--- | :--- |
| Time | arburg | Generate all-pole filter coefficients that model an input data <br> sequence using the Levinson-Durbin algorithm. |
|  | Generate all-pole filter coefficients that model an input data <br> sequence by minimizing the forward prediction error. |  |
|  | Generate all-pole filter coefficients that model an input data <br> sequence by minimizing the forward and backward prediction <br> errors. |  |
|  | lpc, <br> levinson | Linear Predictive Coding. Generate all-pole recursive filter whose <br> impulse response matches a given sequence. |
| prony | Generate all-pole filter coefficients that model an input data <br> sequence using an estimate of the autocorrelation function. <br> sequence. |  |
| stmcb | Find IIR filter whose impulse response matches a given <br> matches a given output sequence. |  |
| Frequency | invfreqz, <br> invfreqs | Generate digital or analog filter coefficients given complex <br> frequency response data. |

Because yulewalk is geared explicitly toward ARMA filter design, it is discussed in Chapter 2, "Filter Design." pburg and pyulear are discussed in Chapter 3, "Statistical Signal Processing," along with the other (nonparametric) spectral estimation methods.

## Time-Domain Based Modeling

The lpc, prony, and stmcb functions find the coefficients of a digital rational transfer function that approximates a given time-domain impulse response. The al gorithms differ in complexity and accuracy of the resulting model.

## Linear Prediction

Linear prediction modeling assumes that each output sample of a signal, $x(k)$, is a linear combination of the past $n$ outputs (that is, it can be "linearly predicted" from these outputs), and that the coefficients are constant from sample to sample.

$$
x(k)=-a(2) x(k-1)-a(3) x(k-2)-\ldots-a(n+1) x(k-n)
$$

An nth-order all-pole model of a signal $x$ is

$$
a=\operatorname{lpc}(x, n)
$$

To illustrate lpc, create a sample signal that is the impulse response of an all-pole filter with additive white noise.

```
randn('state',0);
x = impz(1,[1 0.1 0.1 0.1 0.1],10) + randn(10,1)/10;
```

The coefficients for a fourth-order all-pole filter that models the system are

```
a = lpc(x,4)
a =
    1.0000 0.2574 0.1666 0.1203 0.2598
```

lpc first calls xcorr to find a biased estimate of the correlation function of $x$, and then uses the Levinson-Durbin recursion, implemented in the levinson function, to find the model coefficients a. The Levinson-Durbin recursion is a fast al gorithm for solving a system of symmetric Toeplitz linear equations. lpc's entire algorithm for $n=4$ is

```
r = xcorr(x);
r(1:length(x)-1) = []; % Remove corr. at negative lags
a = levinson(r,4)
a =
    1.0000 0.2574 0.1666 0.1203 0.2598
```

You could form the linear prediction coefficients with other assumptions by passing a different correlation estimate to levinson, such as the biased correlation estimate.

```
r = xcorr(x,'biased');
r(1:length(x)-1) = []; % Remove corr. at negative lags
a = levinson(r,4)
a =
    1.0000 0.2574 0.1666 0.1203 0.2598
```


## Prony's Method (ARMA Modeling)

The prony function models a signal using a specified number of pol es and zeros. Given a sequence $x$ and numerator and denominator orders $n$ and $m$, respectively, the statement

```
[b,a] = prony(x,n,m)
```

finds the numerator and denominator coefficients of an IIR filter whose impulse response approximates the sequence $x$.
The prony function implements the method described in [3] Parks and Burrus (pgs. 226-228). This method uses a variation of the covariance method of AR modeling to find the denominator coefficients a, and then finds the numerator coefficients b for which the resulting filter's impulse response matches exactly the first $n+1$ samples of $x$. The filter is not necessarily stable, but it can potentially recover the coefficients exactly if the data sequence is truly an autoregressive moving average (ARMA) process of the correct order.

[^0]A model for the test sequence x (from the earlier lpc example) using a third-order IIR filter is

```
[b,a] = prony(x,3,3)
b =
    0.9567 -0.3351 0.1866 -0.3782
a =
    1.0000 -0.0716 0.2560 -0.2752
```

The impz command shows how well this filter's impulse response matches the original sequence.

```
format long
[x impz(b,a,10)]
ans =
    0.95674351884718 0.95674351884718
    -0.26655843782381 -0.26655843782381
    -0.07746676935252 -0.07746676935252
    -0.05223235796415 -0.05223235796415
    -0.18754713506815 -0.05726777015121
    0.15348154656430 -0.01204969926150
    0.13986742016521 -0.00057632797226
    0.00609257234067 -0.01271681570687
    0.03349954614087 -0.00407967053863
    0.01086719328209 0.00280486049427
```

Notice that the first four samples match exactly. For an example of exact recovery, recover the coefficients of a Butterworth filter from its impulse response.

```
[b,a] = butter(4,.2);
h = impz(b,a,26);
[bb,aa] = prony(h,4,4);
```

Try this example; you'll see that bb and aa match the original filter coefficients to within a tolerance of $10^{-13}$.

## Steiglitz-McBride Method (ARMA Modeling)

The stmcb function determines the coefficients for the system $b(z) / a(z)$ given an approximate impulse response $x$, as well as the desired number of zeros and poles. This function identifies an unknown system based on both input and output sequences that describe the system's behavior, or just the impulse response of the system. In its default mode, stmcb works like prony.

```
[b,a] = stmcb(x,3,3)
b =
    0.9567 -0.5181 0.5702 -0.5471
a =
    1.0000 -0.2384 0.5234 -0.3065
```

stmcb also finds systems that match given input and output sequences.

```
y = filter(1,[1 1],x); % Create an output signal.
[b,a] = stmcb(y,x,0,1)
b =
    1.0000
a =
    1
```

In this example, stmcb correctly identifies the system used to create y from x .
The Steiglitz-McBride method is a fast iterative algorithm that solves for the numerator and denominator coefficients simultaneously in an attempt to minimize the signal error between the filter output and the given output signal. This algorithm usually converges rapidly, but might not converge if the model order is too large. As for prony, stmcb's resulting filter is not necessarily stable due to its exact modeling approach.
stmcb provides control over several important algorithmic parameters; modify these parameters if you are having trouble modeling the data. To change the number of iterations from the default of five and provide an initial estimate for the denominator coefficients

```
n = 10; % Number of iterations
a = lpc(x,3); % Initial estimates for denominator
[b,a] = stmcb(x,3,3,n,a);
```

The function uses an all-pole model created with prony as an initial estimate when you do not provide one of your own.

To compare the functions lpc, prony, and stmcb, compute the signal error in each case.

```
a1 = lpc(x,3);
[b2,a2] = prony(x,3,3);
[b3,a3] = stmcb(x,3,3);
[x-impz(1,a1,10) x-impz(b2,a2,10) x-impz(b3,a3,10)]
ans =
\begin{tabular}{rrr}
-0.0433 & 0 & -0.0000 \\
-0.0240 & 0 & 0.0234 \\
-0.0040 & 0 & -0.0778 \\
-0.0448 & -0.0000 & 0.0498 \\
-0.2130 & -0.1303 & -0.0742 \\
0.1545 & 0.1655 & 0.1270 \\
0.1426 & 0.1404 & 0.1055 \\
0.0068 & 0.0188 & 0.0465 \\
0.0329 & 0.0376 & 0.0530 \\
0.0108 & 0.0081 & -0.0162
\end{tabular}
sum(ans.^2)
ans =
    0.0953 0.0659 0.0471
```

In comparing modeling capabilities for a given order IIR model, the last result shows that for this example, stmcb performs best, followed by prony, then lpc. This relative performance is typical of the modeling functions.

## Frequency-Domain Based Modeling

The invfreqs and invfreqz functions implement the inverse operations of freqs and freqz; they find an analog or digital transfer function of a specified order that matches a given complex frequency response. Though the following examples demonstrate invfreqz, the discussion also applies to invfreqs.

To recover the original filter coefficients from the frequency response of a simple digital filter

```
[b,a] = butter(4,0.4) % Design Butterworth lowpass
b =
    0.0466 0.1863 0.2795 0.1863 0.0466
a =
    1.0000 -0.7821 0.6800 -0.1827 0.0301
[h,w] = freqz(b,a,64); % Compute frequency response
[bb,aa] = invfreqz(h,w,4,4) % Model: n = 4, m = 4
bb =
    0.0466 0.1863 0.2795 0.1863 0.0466
aa =
    1.0000 -0.7821 0.6800 -0.1827 0.0301
```

The vector of frequencies w has the units in rad/sample, and the frequencies need not be equally spaced. invfreqz finds a filter of any order to fit the frequency data; a third-order example is

```
[bb,aa] = invfreqz(h,w,3,3) % Find third-order IIR
bb =
    0.0464 0.1785 0.2446 0.1276
aa =
    1.0000 -0.9502 0.7382 -0.2006
```

Both invfreqs and invfreqz design filters with real coefficients; for a data point at positive frequency $f$, the functions fit the frequency response at both $f$ and $-f$.

By default invfreqz uses an equation error method to identify the best model from the data. This finds $b$ and $a$ in

$$
\min _{b, a} \sum_{k=1}^{n} w t(k)|h(k) A(w(k))-B(w(k))|^{2}
$$

by creating a system of linear equations and solving them with MATLAB's \} operator. Here $A(w(k))$ and $B(w(k))$ are the Fourier transforms of the polynomials $a$ and $b$ respectively at the frequency $w(k)$, and $n$ is the number of frequency points (the length of $h$ and $w$ ). $w t(k)$ weights the error relative to the error at different frequencies. The syntax

```
invfreqz(h,w,n,m,wt)
```

includes a weighting vector. In this mode, the filter resulting from invfreqz is not guaranteed to be stable.
invfreqz provides a superior ("output-error") al gorithm that solves the direct problem of minimizing the weighted sum of the squared error between the actual frequency response points and the desired response

$$
\min _{b, a} \sum_{k=1}^{n} w t(k)\left|h(k)-\frac{B(w(k))}{A(w(k))}\right|^{2}
$$

To use this algorithm, specify a parameter for the iteration count after the weight vector parameter

```
wt = ones(size(w)); % Create unity weighting vector
[bbb,aaa] = invfreqz(h,w,3,3,wt,30) % 30 iterations
bbb =
    0.0464 0.1829 0.2572 0.1549
aaa =
    1.0000 -0.8664 0.6630
```

The resulting filter is always stable.

Graphically compare the results of the first and second algorithms to the original Butterworth filter.

```
[H1,w] = freqz(b,a);
[H2] = freqz(bb,aa);
[H3] = freqz(bbb,aaa);
s.plot = 'mag';
s.xunits = 'rad/sample';
s.yunits = 'linear';
freqzplot([H1 H2 H3],w);
legend('Original','First Estimate','Second Estimate',3);
grid on
```




To verify the superiority of the fit numerically, type

```
sum(abs(h-freqz(bb,aa,w)).^2) % Total error, algorithm 1
ans =
    0.0200
sum(abs(h-freqz(bbb,aaa,w)).^2) % Total error, algorithm 2
ans =
    0.0096
```


## Resampling

The tool box provides a number of functions that resample a signal at a higher or lower rate.

| Operation | Function |
| :--- | :--- |
| Apply FIR filter with resampling | upfirdn |
| Cubic spline interpolation | spline |
| Decimation | decimate |
| Interpolation | interp |
| Other 1-D interpolation | interp1 |
| Resample at new rate | resample |

The resample function changes the sampling rate for a sequence to any rate that is a ratio of two integers. The basic syntax for resample is

$$
y=\operatorname{resample}(x, p, q)
$$

where the function resamples the sequence x at $\mathrm{p} / \mathrm{q}$ times the original sampling rate. The length of the result y is $\mathrm{p} / \mathrm{q}$ times the length of x .

One resampling application is the conversion of digitized audio signals from one sampling rate to another, such as from 48 kHz (the digital audio tape standard) to 44.1 kHz (the compact disc standard). In the next example, the sampling rates are different but the idea is the same.
The example file contains a length 4001 vector of speech sampled at 7418 Hz .

```
clear
load mtlb
whos
\begin{tabular}{crrl} 
Name & Size & Bytes & \multicolumn{1}{l}{ Class } \\
Fs & \(1 \times 1\) & 8 & double array \\
mtlb & \(4001 \times 1\) & 32008 & double array
\end{tabular}
Grand total is 4002 elements using 32016 bytes
```

```
Fs
Fs =
    7418
```

To play this speech signal on a workstation that can only play sound at 8192 Hz , use the rat function to find integers p and q that yield the correct resampling factor.

```
[p,q] = rat(8192/Fs,0.0001)
p =
    1 2 7
q =
    115
```

Since p/q*Fs = 8192.05 Hz , the tolerance of 0.0001 is acceptable; to resample the signal at very close to 8192 Hz .

```
y = resample(mtlb,p,q);
```

resample applies a lowpass filter to the input sequence to prevent aliasing during resampling. It designs this filter using the firls function with a Kaiser window. The syntax

```
resample(x,p,q,l,beta)
```

controls the filter's length and the beta parameter of the Kaiser window. Alternatively, use the function intfilt to design an interpolation filter b and use it with

```
resample(x,p,q,b)
```

The decimate and interp functions do the same thing as resample with $p=1$ and $q=1$, respectively. These functions provide different anti-alias filtering options, and they incur a slight signal delay due to filtering. The interp function is significantly less efficient than the resample function with $q=1$.

The tool box also contains a function, upfirdn, that applies an FIR filter to an input sequence and outputs the filtered sequence at a different sample rate than its original rate. See "Multirate Filter Bank Implementation" on page 1-20.

The standard MATLAB environment contains a function, spline, that works with irregularly spaced data. The MATLAB function interp1 performs
interpolation, or table lookup, using various methods including linear and cubic interpolation.

## Cepstrum Analysis

Cepstrum analysis is a nonlinear signal processing technique with a variety of applications in areas such as speech and image processing. The Signal Processing Tool box provides three functions for cepstrum analysis.

| Operation | Function |
| :--- | :--- |
| Complex cepstrum | cceps |
| Inverse complex cepstrum | icceps |
| Real cepstrum | rceps |

The complex cepstrum for a sequence $x$ is calculated by finding the complex natural logarithm of the F ourier transform of $x$, then the inverse F ourier transform of the resulting sequence.

$$
\hat{x}=\frac{1}{2 \pi} \int_{-\pi}^{\pi} \log \left[X\left(\mathrm{e}^{\mathrm{j} \omega}\right)\right] \mathrm{e}^{\mathrm{j} \omega \mathrm{n}} \mathrm{~d} \omega
$$

The tool box function cceps performs this operation, estimating the complex cepstrum for an input sequence. It returns a real sequence the same size as the input sequence.

```
xhat = cceps(x)
```

The complex cepstrum transformation is central to the theory and application of homomorphic systems, that is, systems that obey certain general rules of superposition. See Oppenheim and Schafer [2] for a discussion of the complex cepstrum and homomorphictransformations, with details on speech processing applications.

Try using cceps in an echo detection application. First, create a 45 Hz sine wave sampled at 100 Hz .

```
t = 0:0.01:1.27;
s1 = sin(2*pi*45*t);
```

Add an echo of the signal, with half the amplitude, 0.2 seconds after the beginning of the signal.

$$
s 2=s 1+0.5^{*}[\operatorname{zeros}(1,20) s 1(1: 108)]
$$

The complex cepstrum of this new signal is

```
c = cceps(s2);
plot(t,c)
```



Note that the complex cepstrum shows a peak at 0.2 seconds, indicating the echo.

The real cepstrum of a signal $x$, sometimes called simply the cepstrum, is calculated by determining the natural logarithm of magnitude of the F ourier transform of x , then obtaining the inverse F ourier transform of the resulting sequence.

$$
C_{X}=\frac{1}{2 \pi} \int_{-\pi}^{\pi} \log \left|X\left(e^{j \omega}\right)\right| e^{j \omega n} d \omega
$$

The tool box function rceps performs this operation, returning the real cepstrum for a sequence $x$. The returned sequence is a real-valued vector the same size as the input vector.

$$
y=\operatorname{rceps}(x)
$$

By definition, you cannot reconstruct the original sequence from its real cepstrum transformation, as the real cepstrum is based only on the magnitude of theF ourier transform for the sequence (seeOppenheim and Schafer [2]). The rceps function, however, can reconstruct a minimum-phase version of the original sequence by applying a windowing function in the cepstral domain. To obtain both the real cepstrum and the minimum phase reconstruction for a sequence, use

```
[y,ym] = rceps(x)
```

where $y$ is the real cepstrum and $y m$ is the minimum phase reconstruction of $x$.

## Inverse Complex Cepstrum

To invert the complex cepstrum, use the icceps function. Inversion is complicated by the fact that the cceps function performs a data dependent phase modification so that the unwrapped phase of its input is continuous at zero frequency. The phase modification is equivalent to an integer delay. This delay term is returned by cceps if you ask for a second output. For example,

```
x = 1:10;
[xh,nd] = cceps(x)
xh =
    Columns 1 through 7
        2.2428 -0.0420 -0.0210
    Columns 8 through 10
        0.2327 0.4114 0.9249
nd =
    1
```

To invert the complex cepstrum, use icceps with the original delay parameter.

```
icceps(xh,nd)
ans =
    Columns 1 through 7
        1.0000 2.0000 3.0000 4.0000 5.0000 6.0000 7.0000
        Columns 8 through 10
            8.0000 9.0000 10.0000
```

Note With any modification of the complex cepstrum, the original delay term may no longer be valid. Use the icceps function with care.

## FFT-Based Time-Frequency Analysis

The Signal Processing Tool box provides a function, specgram, that returns the time-dependent F ourier transform for a sequence, or displays this information as a spectrogram. The Tool box also inclues a spectrogram demo. The timedependent Fourier transform is the discrete-time Fourier transform for a sequence, computed using a sliding window. This form of the F ourier transform, also known as the short-time Fourier transform (STFT), has numerous applications in speech, sonar, and radar processing. The spectrogram of a sequence is the magnitude of the time-dependent F ourier transform versus time.

To display the spectrogram of a linear FM signal

```
fs = 10000;
t = 0:1/fs:2;
x = vco(sawtooth(2*pi*t,.75),[0.1 0.4]*fs,fs);
specgram(x,512,fs,kaiser(256,5),220)
```



Note that the spectrogram display is an image, not a plot.

## Median Filtering

The function medfilt1 implements one-dimensional median filtering, a nonlinear technique that applies a sliding window to a sequence. The median filter replaces the center value in the window with the median value of all the points within the window [4]. In computing this median, medfilt1 assumes zeros beyond the input points.

When the number of elements $n$ in the window is even, medfilt1 sorts the numbers, then takes the average of the $(n-1) / 2$ and $(n-1) / 2+1$ elements.

Two simple examples with fourth- and third-order median filters are

```
medfilt1([4 3 5 2 8 9 1],4)
ans =
    1.500 3.500 3.500 4.000 6.500 5.000 4.500
medfilt1([4 3 5 2 8 9 1],3)
ans =
    3 
```

See the medfilt2 function in the Image Processing Tool box User's Guidefor information on two-dimensional median filtering.

## Communications Applications

The tool box provides three functions for communications simulation.

| Operation | Function |
| :--- | :--- |
| Modulation | modulate |
| Demodulation | demod |
| Voltage controlled oscillation | vco |

Modulation varies the amplitude, phase, or frequency of a carrier signal with reference to a message signal. The modulate function modulates a message signal with a specified modulation method.
The basic syntax for the modulate function is

```
    y = modulate(x,fc,fs,'method',opt)
```

where:

- x is the message signal.
- fc is the carrier frequency.
- fs is the sampling frequency.
- method is a flag for the desired modulation method.
- opt is any additional argument that the method requires. (Not all modulation methods require an option argument.)

The table bel ow summarizes the modulation methods provided; see the documentation for modulate, demod, and vco for complete details on each.

| Method | Description |
| :--- | :--- |
| amdsb-sc or am | Amplitude modulation, double side-band, suppressed <br> carrier |
| amdsb-tc | Amplitude modulation, double side-band, transmitted <br> carrier |


| Method | Description |
| :--- | :--- |
| amssb | Amplitude modulation, single side-band |
| fm | Frequency modulation |
| pm | Phase modulation |
| ppm | Pulse position modulation |
| pwm | Pulse width modulation |
| qam | Quadrature amplitude modulation |

If the input x is an array rather than a vector, modulate modulates each column of the array.

To obtain the time vector that modulate uses to compute the modulated signal, specify a second output parameter.

```
[y,t] = modulate(x,fc,fs,'method',opt)
```

The demod function performs demodulation, that is, it obtains the original message signal from the modulated signal.

The syntax for demod is

```
x = demod(y,fc,fs,'method',opt)
```

demod uses any of the methods shown for modulate, but the syntax for quadrature amplitude demodulation requires two output parameters.

```
[X1,X2] = demod(y,fc,fs,'qam')
```

If the input $y$ is an array, demod demodulates all columns.
Try modulating and demodulating a signal. A 50 Hz sine wave sampled at 1000 Hz is

```
t = (0:1/1000:2);
x = sin(2*pi*50*t);
```

With a carrier frequency of 200 Hz , the modulated and demodulated versions of this signal are

$$
\begin{aligned}
& y=\operatorname{modulate}(x, 200,1000, ' a m ') ; \\
& z=\operatorname{demod}\left(y, 200,1000, ' a m^{\prime}\right) ;
\end{aligned}
$$

To plot portions of the original, modulated, and demodulated signal

```
figure; plot(t(1:150),x(1:150)); title('Original Signal');
figure; plot(t(1:150),y(1:150)); title('Modulated Signal');
figure; plot(t(1:150),z(1:150)); title('Demodulated Signal');
```




Note The demodulated signal is attenuated because demodulation includes two steps: multiplication and lowpass filtering. The multiplication produces a component with frequency centered at 0 Hz and a component with frequency at twice the carrier frequency. The filtering removes the higher frequency component of the signal, producing the attenuated result.

The voltage controlled oscillator function vco creates a signal that oscillates at a frequency determined by the input vector. The basic syntax for vco is

$$
y=v c o(x, f c, f s)
$$

where fc is the carrier frequency and fs is the sampling frequency.
To scale the frequency modulation range, use

$$
y=\operatorname{vco}(x,[F m i n \text { Fmax }], f s)
$$

In this case, vco scales the frequency modulation range so values of $x$ on the interval [-1 1] map to oscillations of frequency on [Fmin Fmax].

If the input $x$ is an array, vco produces an array whose columns oscillate according to the columns of $x$.
See "FFT-Based Time-Frequency Analysis" on page 4-29 for an example using the vco function.

## Deconvolution

Deconvolution, or polynomial division, is the inverse operation of convolution. Deconvolution is useful in recovering the input to a known filter, given the filtered output. This method is very sensitive to noise in the coefficients, however, so use caution in applying it.

The syntax for deconv is

```
[q,r] = deconv(b,a)
```

where $b$ is the polynomial dividend, $a$ is the divisor, $q$ is the quotient, and $r$ is the remainder.

Totry deconv, first convolve two simple vectors a and b (see Chapter 1, "Signal Processing Basics," for a description of the convolution function).

```
a = [11 2 3];
b = [4 5 6];
c = conv (a,b)
c =
    4 13 28 27 18
```

Now use deconv to deconvolve b from c.

```
[q,r] = deconv(c,a)
```

q =
$4 \quad 5 \quad 6$
$r=$
$\begin{array}{lllll}0 & 0 & 0 & 0 & 0\end{array}$

## Specialized Transforms

In addition to the discrete Fourier transform (DFT) described in Chapter 1, "Signal Processing Basics," the Signal Processing Tool box and the MATLAB environment together provide the following transform functions:

- The chirp z-transform (CZT), useful in evaluating the z-transform along contours other than the unit circle. The chirp z-transform is also more efficient than the DFT algorithm for the computation of prime-length transforms, and it is useful in computing a subset of the DFT for a sequence.
- The discrete cosine transform (DCT), closely related to the DFT. The DCT's energy compaction properties are useful for applications like signal coding.
- The Hilbert transform, which facilitates the formation of the analytic signal. The analytic signal is useful in the area of communications, particularly in bandpass signal processing.


## Chirp z-Transform

The chirp z-transform, or CZT, computes the z-transform al ong spiral contours in the z-plane for an input sequence. Unlike the DFT, the CZT is not constrained to operate along the unit circle, but can evaluate the $z$-transform along contours described by

$$
z_{I}=A W^{-1}, \quad I=0, \ldots, M-1
$$

where A is the complex starting point, W is a complex scalar describing the complex ratio between points on the contour, and M is the length of the transform.

One possible spiral is

```
A = 0.8*exp(j*pi/6);
W = 0.995* exp(-j*pi*.05);
M = 91;
z = A*(W.^(-(0:M-1)));
zplane([],z.')
```


czt ( $x, M, W, A$ ) computes the $z$-transform of $x$ on these points.
An interesting and useful spiral set is $m$ evenly spaced samples around the unit circle, parameterized by $A=1$ and $w=\exp (-j * p i / M)$.Thez-transform on this contour is simply the DFT, obtained by

$$
y=c z t(x)
$$

czt may be faster than the fft function for computing the DFT of sequences with certain odd lengths, particularly long prime-length sequences.

## Discrete Cosine Transform

The tool box function dct computes the unitary discrete cosine transform, or DCT, for an input vector or matrix. Mathematically, the unitary DCT of an input sequence $x$ is

$$
y(k)=w(k) \sum_{n=1}^{i v} x(n) \cos \frac{\pi(2 n-1)(k-1)}{2 N}, \quad k=1, \ldots, N
$$

where

$$
w(k)= \begin{cases}\frac{1}{\sqrt{N}}, & k=1 \\ \sqrt{\frac{2}{N}}, & 2 \leq k \leq N\end{cases}
$$

The DCT is closely related to the discrete Fourier transform; the DFT is actually one step in the computation of the DCT for a sequence. The DCT, however, has better energy compaction properties, with just a few of the transform coefficients representing the majority of the energy in the sequence. The energy compaction properties of the DCT make it useful in applications such as data communications.

The function idct computes the inverse DCT for an input sequence, reconstructing a signal from a complete or partial set of DCT coefficients. The inverse discrete cosine transform is

$$
x(n)=w(n) \sum_{k=1} y(k) \cos \frac{\pi(2 n-1)(k-1)}{2 N}, \quad n=1, \ldots, N
$$

where

$$
w(n)= \begin{cases}\frac{1}{\sqrt{N}}, & n=1 \\ \sqrt{\frac{2}{N}}, & 2 \leq n \leq N\end{cases}
$$

Because of the energy compaction mentioned above, it is possibleto reconstruct a signal from only a fraction of its DCT coefficients. For example, generate a 25 Hz sinusoidal sequence, sampled at 1000 Hz .

```
t = (0:1/999:1);
x = sin(2*pi*25*t);
```

Compute the DCT of this sequence and reconstruct the signal using only those components with value greater than 0.1 ( 64 of the original 1000 DCT coefficients).

```
y = dct(x)
% Compute DCT
y2 = find(abs(y) < 0.9); % Use 17 coefficients
y(y2) = zeros(size(y2)); % Zero out points < 0.9
z = idct(y); % Reconstruct signal using inverse DCT
```

Plot the original and reconstructed sequences.

```
subplot(2,1,1); plot(t,x);
title('Original Signal')
subplot(2,1,2); plot(t,z), axis([[0 1 -1 1])
title('Reconstructed Signal')
```




One measure of the accuracy of the reconstruction is

```
norm(x-z)/norm(x)
```

that is, the norm of the difference between the original and reconstructed signals, divided by the norm of the original signal. In this case, the relative error of reconstruction is 0.1443 . The reconstructed signal retains approximately $85 \%$ of the energy in the original signal.

## Hilbert Transform

The tool box function hilbert computes the Hilbert transform for a real input sequence $x$ and returns a complex result of the same length

$$
y=\text { hilbert(x) }
$$

where the real part of $y$ is the original real data and the imaginary part is the actual Hilbert transform. y is sometimes called the analytic signal, in reference to the continuous-time analytic signal. A key property of the discrete-time analytic signal is that its z-transform is 0 on the lower half of the unit circle. Many applications of the analytic signal are related to this property; for example, the analytic signal is useful in avoiding aliasing effects for bandpass sampling operations. The magnitude of the analytic signal is the complex envel ope of the original signal.

The Hilbert transform is related to the actual data by a $90^{\circ}$ phase shift; sines become cosines and vice versa. To plot a portion of data (solid line) and its Hilbert transform (dotted line)

```
t = (0:1/1023:1);
x = sin(2*pi*60*t);
y = hilbert(x);
plot(t(1:50),real(y(1:50))), hold on
plot(t(1:50),imag(y(1:50)),':'), hold off
```



The analytic signal is useful in calculating instantaneous attributes of a time series, the attributes of the series at any point in time. The instantaneous amplitude of the input sequence is the amplitude of the analytic signal. The instantaneous phase angle of the input sequence is the (unwrapped) angle of the analytic signal; the instantaneous frequency is the time rate of change of the instantaneous phase angle. You can calculate the instantaneous frequency using the MATLAB function, diff.

## Selected Bibliography

[1] Kay, S.M. M odern Spectral Estimation. Englewood Cliffs, NJ : PrenticeH all, 1988.
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[4] Pratt,W.K. Digital Image Processing. New York: J ohn Wiley \& Sons, 1991.

## Filter Design and Analysis Tool

Overview ..... 5-2
Opening the Filter Design and Analysis Tool ..... 5-6
Choosing a Filter Type ..... 5-7
Choosing a Filter Design Method ..... 5-8
Setting the Filter Design Specifications ..... 5-9
Computing the Filter Coefficients ..... 5-12
Analyzing the Filter ..... 5-13
Converting the Filter Structure ..... 5-15
Importing a Filter Design ..... 5-17
Exporting a Filter Design ..... 5-21
Saving and Opening Filter Design Sessions ..... 5-25

## Overview

Note The Filter Design and Analysis Tool (FDATool) requires resolution greater than $640 \times 480$.

The Filter Design and Analysis Tool (FDATool) is a powerful user interface for designing and analyzing filters. FDATool enables you to quickly design digital FIR or IIR filters by setting filter performance specifications, by importing filters from your MATLAB workspace, or by directly specifying filter coefficients. FDATool also provides tools for analyzing filters, such as magnitude and phase response plots and pole-zero plots. You can useFDATool as a convenient alternative to the command line filter design functions. This chapter contains the following sections, which walk you through a typical filter design session using the FDATool:

- "Opening the Filter Design and Analysis Tool"
- "Choosing a Filter Type"
- "Choosing a Filter Type"
- "Choosing a Filter Design Method"
- "Setting the Filter Design Specifications"
- "Computing the Filter Coefficients"
- "Analyzing the Filter"
- "Converting the Filter Structure"
- "Importing a Filter Design"
- "Exporting a Filter Design"
- "Saving and Opening Filter Design Sessions"

Below is a brief introduction to the FDATool that will give you a better understanding of how it can be used.

Note If you have installed external hardware or targets that interact with FDATool, you may see additional options in FDATool. Refer to the specific hardware or target manual for information on these options.

These tool boxes/targets are integrated with F DATool. Filter Design Tool box
Developer's Kit for Texas Instruments ${ }^{\text {TM }}$ DSP

## Filter Design Methods

The tool gives you access to all of the filter design methods in the Signal Processing Tool box:

- Butterworth (butter)
- Chebyshev TypeI (cheby1)
- Chebyshev Type II (cheby2)
- Elliptic (ellip)
- Equiripple (remez)
- Least squares (firls)
- Windows
- Bartlett-Hanning (barthannwin)
- Bartlett (bartlett)
- Blackman (blackman)
- Blackman-Harris (blackmanharris)
- Bohman (bohmanwin)
- Chebyshev (chebwin)
- Gaussian (gausswin)
- Hamming (hamming)
- Hann (hann)
- Kaiser (kaiser)
- Nuttall’s Blackman-Harris (nuttallwin)
- Rectangular (rectwin)
- Tapered cosine (tukeywin)
- Triangular (triang)

You can implement any of these windows manually using fir1 or fir2.
Additional filter design methods are available to users of the Filter Design Tool box.

## Using the Filter Design and Analysis Tool

Thereare different ways that you can design filters using the Filter Design and Analysis Tool. For example:

- You can first choose a filter type, such as bandpass, and then choose from the available FIR or IIR filter design methods.
- You can specify the filter by its type alone, along with certain frequency- or time-domain specifications such as passband frequencies and stopband frequencies. The filter you design is then computed using the default filter design method and filter order.


## Analyzing Filter Responses

Once you have designed your filter, you can analyze different filter responses in FDATool or in a separate Filter Visualization Tool (fvtool):

- Magnitude response (freqz)
- Phase response (freqz)
- Pole-zero plots (zplane)
- Impulse response (impz)
- Group delay (grpdelay)
- Step response

You can also display the filter coefficients, export the coefficients to the MATLAB workspace, and create a C header file containing the coefficients.

## Filter Design and Analysis Tool Modes

The Filter Design and Analysis Tool operates in two modes:

- Design mode In this mode, you can:
- Design filters from scratch.
- Modify existing filters designed by FDATool.
- Analyze filters.
- I mport mode. In this mode, you can:
- Import previously saved filters or filter coefficients that you have stored in the MATLAB workspace.
- Analyze imported filters.

If you also have the Filter Design Tool box installed the additional quantize mode is available. Use this mode to:

- Quantize double-precision filters that you design in FDATool.
- Quantize double-precision filters that you import into FDATool.
- Analyze quantized filters.


## Getting Help

At any time, you can right-click or press the What's this? button, $A$ ?, to get information on the different parts of the GUI.

## Opening the Filter Design and Analysis Tool

To open the Filter Design and Analysis Tool, type
fdatool
The Filter Design and Analysis Tool opens in the default design mode.


## Choosing a Filter Type

You can choose from several filter types:

- Lowpass
- Highpass
- Bandpass
- Bandstop
- Differentiator
- Hilbert transformer
- Multiband
- Arbitrary magnitude
- Arbitrary group delay
- Raised cosine

To design a bandpass filter, select the radio button next to Bandpass in the Filter Type region of the GUI.

```
Filter Type
C Lowpass
CHighpass
c Bandpass
C Bandstop
Differentiator
```

Note Not all filter design methods are available for all filter types. Once you choose your filter type, this may restrict the filter design methods available to you. Filter design methods that are not available for a selected filter type are dimmed in the Method menu, and removed from the Design Method region of the GUI.

You can also use the Type menu to select a filter type.

## Choosing a Filter Design Method

You can use the default filter design method for the filter type that you've selected, or you can select a filter design method from the available FIR and IIR methods listed in the GUI.

To select the Remez al gorithm to computeFIR filter coefficients, select theFIR radio button and choose Equiripple from the list of methods.


You can also use the Method menu to select a filter design method.

## Setting the Filter Design Specifications

Thefilter design specifications that you can set vary according to filter type and design method. For example, to design a bandpass filter, you can enter:

- Bandpass Filter Frequency Specifications
- Bandpass Filter Magnitude Specifications
- Filter Order

The display region illustrates filter specifications when you select Filter Specifications from the Analysis menu.


## Bandpass Filter Frequency Specifications

For a bandpass filter, you can set:

- Units of frequency:
- Hz
- kHz
- MHz
- Normalized (0 to 1)
- Sampling frequency
- Passband frequencies
- Stopband frequencies

You specify the passband with two frequencies. The first frequency determines the lower edge of the passband, and the second frequency determines the upper edge of the passband.
Similarly, you specify the stopband with two frequencies. The first frequency determines the upper edge of the first stopband, and the second frequency determines the lower edge of the second stopband.
For this example:

- Keep the units in $\mathbf{H z}$ (default).
- Set the sampling frequency (Fs) to 2000 Hz .
- Set the end of the first stopband (Fstop1) to 200 Hz .
- Set the beginning of the passband (Fpass1) to 300 Hz .
- Set the end of the passband (Fpass2) to 700 Hz .
- Set the beginning of the second stopband (Fstop2) to 800 Hz .



## Bandpass Filter Magnitude Specifications

For a bandpass filter, you can specify the following magnitude response characteristics:

- Units for the magnitude response (dB or linear)
- Passband ripple
- Stopband attenuation

For this example:

- Keep the units in dB (default).
- Set the passband ripple (Apass) to 0.1 dB .
- Set the stopband attenuation for both stopbands (Astop1, Astop2) to 75 dB .



## Filter Order

You have two mutually exclusive options for determining the filter order when you design an equiripple filter

- Minimum order: The filter design method determines the minimum order filter.
- Specify order: You enter the filter order in a text box.

Select the Minimum order radio button for this example.


Note that filter order specification options depend on the filter design method you choose. Some filter methods may not have both options available.

## Computing the Filter Coefficients

Now that you've specified the filter design, select the Design Filter button to compute the filter coefficients.

Notice that the Design Filter button is dimmed once you've computed the coefficients for your filter design. This button is enabled again once you make any changes to the filter specifications.

## Analyzing the Filter

Once you've designed the filter, you can view the following filter response characteristics in the display region or in a separate window:

- Magnitude response
- Phase response
- Overlaid magnitude and phase responses
- Group delay
- I mpulse response
- Step response
- Pole-zero plot

You can also display the filter coefficients in this region.
You can access the analysis methods as items in the Analysis menu, or by using the toolbar buttons.

## 

F or example, to look at the filter's magnitude response, select the Magnitude Response button $\square$ on the tool bar.


To display the filter response characteristics in a separate window, select Full View Analysis from the Analysis menu. The Filter Visualization Tool (fvtool) opens. Y ou can use this tool to annotate your design, view other filter analyses, and print your filter response.


You can click on the response to add a data marker that displays information about the particular point on the response. Right-clicking displays a menu where you can adjust the appearance of the data markers or delete them.

## Converting the Filter Structure

You can use the Convert structure button to convert the current filter to a new structure. All filters can be converted to the following representations:

- Direct form I
- Direct form II
- Direct form I transposed
- Direct form II transposed
- State-space
- Lattice ARMA

Note If you have installed the Filter Design Toolbox you will see additional structures in the Convert structure dialog box.

In addition, the following conversions are available for particular classes of filters:

- Minimum phase FIR filters can be converted to Lattice MA (min. phase)
- Maximum phase FIR filters can be converted to Lattice MA (max. phase)
- Allpass filters can be converted to Lattice allpass
- IIR filters can be converted to Lattice ARMA

Note Converting from one filter structure to another may produce a result with different characteristics than the original. This is due to the computer's finite-precision arithmetic and the variations in the conversion's round-off computations.

When selected, the Use second-order sections check box instructs the tool to store the converted filter structure as a collection of second-order sections rather than as a monolithic higher-order structure. The subordinate Scale menu lets you select from the following options.

- None (default)
- L-2 (L ${ }^{2}$ norm)
- L-infinity ( ${ }^{\infty}$ norm)

The ordering of the second-order sections is optimized for the selected scaling option. (The tf2sos function that performs the conversion is called with option 'down' for $L^{2}$ norm scaling, and with option 'up' for $L^{\infty}$ norm scaling.)

For example:

- Press the Convert structure button to open the Convert structure dialog box.
- Select Direct form I in the list of filter structures.
- Select the Use second-order sections check box.
- Select L-infinity from the Scale menu for $L^{\infty}$ norm scaling.



## Importing a Filter Design

The Import Filter region allows you to import a filter by specifying the filter coefficients, either by entering them explicitly or by referring to variables in the MATLAB workspace. Y ou can access this region by selecting I mport Filter from the Filter menu, or by pressing Ctrl+H.

The imported filter can be in any of the representations listed in the Filter Structure menu, and described in "Filter Structures".

Select the frequency units from among thefollowing options in the Units menu, and specify the value of the sampling frequency in the Fs field.
To import the filter, press the Import Filter button. The Display Region is automatically updated when the new filter has been imported.

## Filter Structures

- Direct Form filters
- Direct form I
- Direct form II
- Direct form I transposed
- Direct form II transposed
- Direct form II (Second-order sections)
- State-space
- Lattice filters
- Lattica allpass
- Lattice MA min. phase
- Lattice MA max. phase
- Lattice ARMA
- Quantized filter (Qfilt object) - availableonly when Filter Design Tool box is installed

The structure that you choose determines the type of coefficients that you need to specify in the text fields to the right.

## Direct Form

For Direct Form I, Direct Form II, Direct Form I transposed, and Direct Form II transposed, specify the filter by its transfer function representation:

$$
H(z)=\frac{B(z)}{A(z)}=\frac{b(1)+b(2) z^{-1}+\cdots+b(m+1) z^{-m}}{a(1)+a(2) z^{-1}+\cdots+a(n+1) z^{-n}}
$$

- The Numerator field specifies a variable name or value for the numerator coefficient vector $b$, which contains $m+1$ coefficients in descending powers of $z$.
- The Denominator field specifies a variable name or value for the denominator coefficient vector a, which contains $\mathrm{n}+1$ coefficients in descending powers of z. For FIR filters, the Denominator is 1.

Filters in transfer function form can be produced by all of the Signal Processing Toolbox filter design functions (such as fir1, fir2, remez, butter, yulewalk). See "Transfer Function" on page 1-33 for more information.

## Direct Form II (Second-O rder Sections)

For Direct form II (Second-order sections), specify the filter by its second-order section representation:

$$
H(z)=g \prod_{k=1}^{L} H_{k}(z)=g \prod_{k=1}^{L} \frac{b_{0 k}+b_{1 k} z^{-1}+b_{2 k} z^{-2}}{1+a_{1 k^{2}} z^{-1}+a_{2 k} z^{-2}}
$$

The Gain field specifies a variable name or a value for the gain $g$, and the SOS Matrix field specifies a variable name or a value for the L-by-6 SOS matrix

$$
\text { SOS }=\left[\begin{array}{cccccc}
b_{01} & b_{11} & b_{21} & 1 & a_{11} & a_{21} \\
b_{02} & b_{12} & b_{22} & 1 & a_{12} & a_{22} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
b_{0 L} & b_{1 L} & b_{2 L} & 1 & a_{1 L} & a_{2 L}
\end{array}\right]
$$

whose rows contain the numerator and denominator coefficients $\mathrm{b}_{\mathrm{ik}}$ and $\mathrm{a}_{\mathrm{ik}}$ of the second-order sections of $\mathrm{H}(\mathrm{z})$.

Filters in second-order section form can be produced by functions such as tf2sos, zp2sos, ss2sos, and sosfilt. See "Second-Order Sections (SOS)" on page 1-38 for more information.

## State-Space

For State-Space, specify the filter by its state-space representation:

$$
\begin{aligned}
& x=A x+B u \\
& y=C x+D u
\end{aligned}
$$

The $\mathbf{A}, \mathbf{B}, \mathbf{C}$, and $\mathbf{D}$ fields each specify a variable name or a value for the matrices in this system.
Filters in state-space form can be produced by functions such as tf2ss and zp2ss. See "State-Space" on page 1-35 for more information.

## Lattice

For Lattice allpass, Lattice MA, and Lattice ARMA filters, specify the filter by its lattice representation:

- For Lattice allpass, the Lattice coeff field specifies the lattice (reflection) coefficients, $\mathrm{k}(1)$ to $\mathrm{k}(\mathrm{N})$, were N is the filter order.
- For Lattice MA (minimum or maximum phase), the Lattice coeff field specifies the lattice (reflection) coefficients, $\mathrm{k}(1)$ to $\mathrm{k}(\mathrm{N})$, were N is the filter order.
- For Lattice ARMA, the Lattice coeff field specifies the lattice (reflection) coefficients, $\mathrm{k}(1)$ to $\mathrm{k}(\mathrm{N})$, and the Ladder coeff field specifies the ladder coefficients, $\mathrm{v}(1)$ to $\mathrm{v}(\mathrm{N}+1)$, were N is the filter order.

Filters in lattice form can be produced by tf2latc. See "Lattice Structure" on page 1-38 for more information.

## Quantized Filter (Q filt $\mathbf{O}$ bject)

For Quantized filter, specify thefilter as a Qfilt object. Seeqfilt in theFilter Design Tool box for more information.

## Exporting a Filter Design

You can save your filter design by:

- Exporting Filter Coefficients to the Workspace
- Exporting Filter Coefficients to a Text File
- Exporting the filter coefficients to a MAT-file (seeSaving and Opening Filter Design Sessions)
- Creating a C header file containing the coefficients


## Exporting Filter Coefficients to the Workspace

To save filter coefficients as variables in the MATLAB workspace
1 Select Export from the File menu. The Export dialog box appears.
2 Select Workspace from the Export To menu.
3 Assign variable names using the text boxes in the Variable Names region. If you have variables with the same names in your workspace and you want to overwrite them, check the Overwrite existing variables box.

4 Press the $\mathbf{O K}$ button.


## Exporting Filter Coefficients to a Text File

To save filter coefficients to a text file
1 Select Export from the File menu. The Export dialog box appears.
2 Select Text-file from the Export To menu.
3 Press the OK button. The Export Filter Coefficients to a Text-file dialog box appears.

4 Choose a filename and press Save.
The coefficients are saved in the text file that you specified, and the MATLAB Editor opens to display the file.

## Exporting to a C Header File

You may want to includefilter information in an external C program. To create a C header file with variables that contain filter parameter data, follow this procedure:

1 Select Export to C Header File from the File menu. The Export to C Header File dialog box appears.


2 Enter the variablenames to be used in the C header file. The particular filter structure determines the variables that are created in the file.

| Filter Structure | Variable Parameter |
| :--- | :--- |
| Direct Form I | Numerator, Numerator length*, <br> Denominator, Denominator length*, and <br> Number of sections (inactive if filter has only <br> one section) |
| Direct Form I transposed <br> Direct Form II transposed | Lattice coeffs, Lattice coeffs length*, Ladder <br> coeffs, Ladder coeffs length*, Number of <br> sections (inactive if filter has only one <br> section) |
| Lattice ARMA | Lattice coeffs, Lattice coeffs length*, and <br> Number of sections (inactive if filter has only <br> one section) |
| Lattice MA | Numerator, Numerator length*, and N umber <br> of sections (inactive if filter has only one <br> section) |
| Direct Form FIR | Direct Form FIR |
| transposed |  |

*length variables contain the total number of coefficients of that type.

Note Variable names cannot be C language reserved words, such as "for."

3 Select the Export Suggested button to use the suggested data type or select Export As and select the desired data type from the pulldown and select the desired Fractional length.

Note If you do not have the Filter Design Toolbox installed, selecting any data type other than double-precision floating point results in a filter that does not exactly match the one you designed in the FDATool. This is due to rounding and truncating differences.

4 Click OK to save the file and close the dialog box or click Apply to save the file, but leave the dialog box open for additional $C$ header file definitions.

## Saving and Opening Filter Design Sessions

You can save your filter design session as a MAT-file and return to the same session another time.
Select the Save session button to to ave your session as a MAT-file. Thefirst time you save a session, a Save Filter Design File browser opens, prompting you for a session name.


For example, save this design session as TestFilter.fda in your current working directory by typing TestFilter in the File name field.

The .fda extension is added automatically to all filter design sessions you save.

Note You can also use the Save session and Save session as menu items in the File menu to save a session. This dialog opens every time you select the Save As menu item.

You can load existing sessions into the Filter Design and Analysis Tool by selecting the Open session button, A Load Filter Design File browser opens that allows you to select from your previously saved filter design sessions.

## SPTool: A Signal Processing GUI Suite

Overview ..... 6-2
SPTool: An Interactive Signal Processing Environment ..... 6-3
Opening SPTool ..... 6-5
Getting Help ..... 6-7
Overview of the Signal Browser: Signal Analysis ..... 6-8
Overview of the Filter Designer: Filter Design ..... 6-11
Overview of the Filter Viewer: Filter Analysis ..... 6-14
Overview of the Spectrum Viewer: Spectral Analysis ..... 6-17
Using SPTool: Filtering and Analysis of Noise ..... 6-20
Exporting Signals, Filters, and Spectra ..... 6-32
Accessing Filter Parameters ..... 6-34
Importing Filters and Spectra into SPTool ..... 6-39
Loading Variables from the Disk ..... 6-43
Selecting Signals, Filters, and Spectra in SPTool ..... 6-44
Editing Signals, Filters, or Spectra in SPTool ..... 6-45
Designing a Filter with the Pole/Zero Editor ..... 6-46
Redesigning a Filter Using the Magnitude Plot ..... 6-49

## Overview

SPTool is a graphical user interface (GUI) for analyzing and manipulating digital signals, filters, and spectra. The first few sections of this chapter give an overview of SPTool and its associated GUIs

- "SPTool: An Interactive Signal Processing Environment"
- "Opening SPTool"
- "Overview of the Signal Browser: Signal Analysis"
- "Overview of the Filter Designer: Filter Design"
- "Overview of the Filter Viewer: Filter Analysis"
- "Overview of the Spectrum Viewer: Spectral Analysis"
- "Using SPTool: Filtering and Analysis of Noise"

The rest of this chapter illustrates in detail how to use the GUI-based interactive tools by walking through some examples

- "Using SPTool: Filtering and Analysis of Noise"
- "Importing a Signal into SPTool"
- "Designing a Filter"
- "Applying a Filter to a Signal"
- "Analyzing Signals: Opening the Signal Browser"
- "Spectral Analysis in the Spectrum Viewer"
- "Exporting Signals, Filters, and Spectra"
- "Accessing Filter Parameters"
- "Redesigning a Filter Using the Magnitude Plot"
- "Accessing Parameters in a Saved Spectrum"
- "I mporting Filters and Spectra into SPTool"
- "Loading Variables from the Disk"
- "Selecting Signals, Filters, and Spectra in SPTool"
- "Editing Signals, Filters, or Spectra in SPTool"
- "Designing a Filter with the Pole/Zero Editor"
- "Making Signal M easurements: Using Markers"


## SPTool: An Interactive Signal Processing Environment

SPTool is an interactive GUI for digital signal processing that can be used to

- Analyze signals.
- Design filters.
- Analyze (view) filters.
- Filter signals.
- Analyze signal spectra.

You can accomplish these tasks using four GUIs that you access from within SPTool

- The Signal Browser is for analyzing signals. You can also play portions of signals using your computer's audio hardware.
- The Filter Designer is for designing or editing FIR and IIR digital filters. Most of the Signal Processing Tool box filter design methods available at the command line are also available in the Filter Designer. Additionally, you can design a filter by using the Pole/Zero Editor to graphically place poles and zeros on the z-plane.
- The Filter Viewer is for analyzing filter characteristics. See Overview of the Filter Viewer: Filter Analysis.
- The Spectrum Viever is for spectral analysis. You can use the Signal Processing Tool box spectral estimation methods to estimate the power spectral density of a signal. See Overview of the Spectrum Viewer: Spectral Analysis.


## SPTool Data Structures

You can use SPTool to analyze signals, filters, or spectra that you create at the MATLAB command line.

You can bring signals, filters, or spectra from the MATLAB workspace into the SPTool workspace using the Import item under the File menu. Signals, filters, or spectra that you create in (or import into) the SPTool workspace exist as MATLAB structures. Seethe MATLAB documentation for moreinformation on MATLAB structures.

When you use the Export item under the File menu to savesignals, filters, and spectra that you create or modify in SPTool, these are also saved as MATLAB structures.

## Opening SPTool

To open SPTool, type
sptool

4 SPTool: startup.spt - - प区
File Edit Window Help
Signals Filters Spectra


When you first open SPTool, it contains a collection of default signals, filters, and spectra. You can specify your own preferences for what signals, filters, and spectra you want to see when SPTool opens. See "Designing a Filter with the Pole/Zero Editor" on page 6-46 for more details.
You can access these three GUIs from SPTool by selecting a signal, filter, or spectrum and pressing the appropriate View button.

- Signal Browser
- Filter Viewer
- Spectrum Viewer

You can access the Filter Designer GUI by pressing the New button to create a new filter or the E dit button to edit a selected filter. TheApply button applies a selected filter to a selected signal.

The Create button opens the Spectrum Viewer and creates the power spectral density of the selected signal. The Update button opens the Spectrum Viewer for the selected spectrum.

## Getting Help

Use the What's this? button to find out more information about a particular region of the GUI.

## Context-Sensitive Help: The What's This? Button

To find information on a particular region of the Signal Browser, Filter Designer, Filter Viewer, or Spectrum Viewer
1 Press the What's this? button, A?
2 Click on the region of the GUI you want information on.
You can also use the What's this? menu item in the Help menu to launch context-sensitive help.

## Overview of the Signal Browser: Signal Analysis

You can use the Signal Browser to display and analyze signals listed in the Signals list box in SPTool.
Using the Signal Browser you can

- Analyze and compare vector or array (matrix) signals.
- Zoom in on portions of signal data.
- Measure a variety of characteristics of signal data.
- Compare multiple signals.
- Play portions of signal data on audio hardware.
- Print signal plots.


## Opening the Signal Browser

To open the Signal Browser from SPTool
1 Selecting one or more signals in the Signals list in SPTool
2 Pressing the View button under the Signals list


The Signal Browser has the following components

- A tool bar with buttons for convenient access to frequently used functions

| 旨 | Print and print preview |
| :---: | :---: |
| (1) | Play an audio signal |
| ${ }^{\text {[2] }}$ ] $a_{i b}^{a+}$ | Display array and complex signals |
| + X X | Zoom the signal in and out |
| $\stackrel{\text { \% }}{\substack{\text { \% }}}$ | Select one of several loaded signals |
| = | Set the display color and line style of a signal |


| M | Toggle the markers on and off |
| :---: | :---: |
|  | Set marker types |
| A? | Turn on the What's This help |

- A display region for analyzing signals, including markers for measuring, comparing, or playing signals
- A "panner" that displays the entire signal length, highlighting the portion currently active in the display region
- A Marker measurements area


## Overview of the Filter Designer: Filter Design

The Filter Designer provides an interactive graphical environment for the design of digital IIR and FIR filters based on specifications that you enter on a magnitude or pole-zero plot.

Note You can also use the Filter Design and Analysis Tool (FDATool) described in Chapter 5, "Filter Design and Analysis Tool," for filter design and analysis.

## Filter Types

You can design filters of the following types using the Filter Designer

- Bandpass
- Lowpass
- Bandstop
- Highpass


## FIR Filter Methods

You can use the following filter methods to design FIR filters

- Equiripple
- Least squares
- Window


## IIR Filter Methods

You can use the following filter methods to design IIR filters

- Butterworth
- Chebyshev Type I
- Chebyshev Type II
- Elliptic


## Pole/ Zero Editor

You can use the Pole/Zero Editor to design arbitrary FIR and IIR filters by placing and moving poles and zeros on the complex z-plane.

## Spectral Overlay Feature

You can also superimpose spectra on a filter's magnitude response to see if the filtering requirements are met.

## Opening the Filter Designer

Open the Filter Designer from SPTool by either

- Pressing the New button in the Filters list in SPTool
- Selecting a filter you want to edit from the Filters list in SPTool, and then pressing the Edit button


The Filter Designer has the following components

- A toolbar with the following buttons

| 㫛 | Print and print preview |
| :---: | :---: |
| + X X | Zoom in and out |
| $\bar{M}$ | Passband view |
| A | Overlay spectrum |
| A? | Turn on the What's This help |

- A pulldown Filter menu for selecting a filter from the list in SPTool
- A Sampling Frequency text box
- A pulldown Algorithm menu for selecting a filter design method or a pole-zero plot display
- A Specifications area for viewing or modifying a filter's design parameters or pole-zero locations
- A plot display region for graphically adjusting filter magnitude responses or the pole-zero locations
- A Measurements area for viewing the response characteristics and stability of the current filter


## Overview of the Filter Viewer: Filter Analysis

You can use the Filter Viewer to analyze the following response characteristics of selected filters

- Magnitude response
- Phase response
- Impulse response
- Step response
- Group delay
- Pole and zero locations

The Filter Viewer can display up to six different response characteristics plots for a selected filter at any time. The Filter Viewer provides features for

- Zooming
- Measuring filter responses
- Overlaying filter responses
- Modifying display parameters such as frequency ranges or magnitude units


## Opening the Filter Viewer

You can open the Filter Viewer from SPTool by
1 Selecting one or more filters in the Filters list in SPTool
2 Pressing the View button under the Filters list
When you first open theFilter Viewer, it displays the default plot configuration for the selected filter(s).


The filter's magnitude and phase plots are displayed by default. In addition, the frequency is displayed with a linear scale on the interval [0,Fs/2].

The Filter Viewer has the following components

- A tool bar with buttons for convenient access to frequently used functions

| 验 | Print and print preview |
| :---: | :---: |
|  | Zoom the signal in and out |
|  | Select one of several loaded signals |
| = | Set the display color and line style of a signal |


| M | Toggle the markers on and off |
| :---: | :---: |
|  | Set marker types |
| A? | Turn on the What's This help |

- A filter identification region that displays the filter name and sampling frequency for the currently selected filter(s)
- A Plots region for selecting the response plots you want to display in the display area, and for specifying some frequency response display characteristics
- A Frequency Axis region for specifying frequency scaling in the display area
- A display area for analyzing one or more frequency response plots for the selected filter(s)
- A Marker measurements area


## Overview of the Spectrum View er: Spectral Analysis

You can use the Spectrum Viewer for estimating and analyzing a signal's power spectral density (PSD). You can use the PSD estimates to understand a signal's frequency content.

Using the Spectrum Viewer you can

- Analyze and compare spectral density plots.
- Use different spectral estimation methods to create spectra
- Burg (pburg)
- Covariance (pcov)
- FFT (fft)
- Modified covariance (pmcov)
- MTM (multitaper method) (pmtm)
- MUSIC (pmusic)
- Welch (pwelch)
- Yule-Walker AR (pyulear)
- M odify power spectral density parameters such as FFT length, window type, and sample frequency.
- Print spectral plots.


## Opening the Spectrum Viewer

To open the Spectrum Viewer and create a PSD estimate from SPTool
1 Select a signal from the Signal list box in SPTool.
2 Press the Create button in the Spectra list.
3 Press the Apply button in the Spectrum Viewer.

To open the Spectrum Viewer with a PSD estimate already listed in SPTool
1 Select a PSD estimate from the Spectra list box in SPTool.
2 Press the View button in the Spectra list.

## For example

1 Select mtlb in the default Signals list in SPTool.
2 Press the Create button in SPTool to open the Spectrum Viewer.
3 Press the Apply button in the Spectrum Viewer to plot the spectrum.


The Spectrum Viewer has the following components

- A tool bar with buttons for convenient access to frequently used functions

| 晶 | Print and print preview |
| :---: | :---: |
|  | Zoom the signal in and out |
| $\stackrel{x}{\text { ¢ }}$ | Select one of several loaded signals |


| =-: | Set the display color and line style of a signal |
| :---: | :---: |
| M | Toggle the markers on and off |
|  | Set marker types |
| 4? | Turn on the What's This help |

- A signal identification region that provides information about the signal whose power spectral density estimate is displayed
- A Parameters region for modifying the PSD parameters
- A display region for analyzing spectra and an Options menu for modifying display characteristics
- Spectrum management controls
- Inherit from menu to inherit PSD specifications from another PSD object listed in the menu
- Revert button to revert to the named PSD's original specifications
- Apply button for creating or updating PSD estimates


## Using SPTool: Filtering and Analysis of Noise

The following sections provide an example of using the GUI-based interactive tools to

- Design and implement an FIR bandpass digital filter
- Apply the filter to a noisy signal
- Analyze signals and their spectra

The steps include
1 Creating a noisy signal in the MATLAB workspace and importing it into SPTool

2 Designing a bandpass filter using the Filter Designer
3 Applying the filter to the original noise signal to create a bandlimited noise signal

4 Comparing the time domain information of the original and filtered signals using the Signal Browser

5 Comparing the spectra of both signals using the Spectrum Viewer
6 Exporting the filter design to the MATLAB workspace as a structure
7 Accessing the filter coefficients from the exported MATLAB structure

## Importing a Signal into SPTool

To import a signal into SPTool from the workspace or disk, the signal must be either

- A special MATLAB signal structure, such as that saved from a previous SPTool session
- A signal created as a variable (vector or matrix) in the MATLAB workspace For this example, create a new signal at the command line and then import it as a structure into SPTool.

1 Create a random signal in the MATLAB workspace by typing

```
randn('state',0);
x = randn(5000,1);
```

2 If SPTool is not already open, open SPTool by typing sptool

The SPTool window is displayed.
3 Select Import from the File menu in SPTool. The Import to SPTool dialog opens.


Notice that the variable x is displayed in the Workspace Contents list. (If it is not, select the From Workspace radio button to display the contents of the workspace.)

4 Select the signal and import it into the Data field
a Make sure that Signal is selected in the Import As pull-down menu.
b Select the signal variable x in the Workspace Contents list.
c Click on the arrow to the left of the Data field or type x in the Data field.
d Type 5000 in the Sampling Frequency field.
e Name the signal by typing noise in the Name field.
f Press OK.
At this point, the signal noise [vector] is selected in SPTool's Signals list.

Note You can import filters and spectra into SPTool in much the same way as you import signals. See "I mporting Filters and Spectra into SPTool" on page 6-39 for specific details.

You can also import signals from MAT-files on your disk, rather than from the workspace. See "Loading Variables from the Disk" on page 6-43 for more information.

Type help sptool for information about importing from the command line.

## Designing a Filter

You can import an existing filter into SPTool, or you can design and edit a new filter using the Filter Designer.

In this example
1 Open a default filter in the Filter Designer.
2 Specify an equiripple bandpass FIR filter.

## $O$ pening the Filter Designer

To open the Filter Designer, press the New button in SPTool. This opens the Filter Designer with a default filter named filt1.

## Specifying the Bandpass Filter

Design an equiripple bandpass FIR filter with the following characteristics

- Sampling frequency of 5000 Hz
- Stopband frequency ranges of [0 500] Hz and [1500 2500] Hz
- Passband frequency range of [750 1250] Hz
- Ripple in the passband of 0.01 dB
- Stopband attenuation of 75 dB

To modify your filter in the Filter Designer to meet these specifications
1 Change the filter sampling frequency to 5000 by entering this value in the Sampling Frequency text box.

2 Select Equiripple FIR from the Algorithm list.
3 Select bandpass from the Type list.
4 Set the passband edge frequencies by entering 750 for $\mathbf{F p 1}$ and 1250 for $\mathbf{F p 2}$.
5 Set the stopband edge frequencies by entering 500 for $\mathbf{F s 1}$ and 1500 for $\mathbf{F s 2}$.
6 Type 0.01 into the $\mathbf{R p}$ field and 75 into the Rs field.
Rp sets the maximum passband ripple and $\mathbf{R s}$ sets the stopband attenuation for the filter.

7 Press the Apply button to design the new filter. When the new filter is designed, the magnitude response of the filter is displayed with a solid line in the display region.


The resulting filter is an order-78 bandpass equiripple filter.

Note You can use the solid line in the plot to modify your filter design. See "Redesigning a Filter Using the Magnitude Plot" on page 6-49 for more information.

## Applying a Filter to a Signal

When you apply a filter to a signal, you create a new signal in SPTool representing the filtered signal.

To apply the filter filt1 you just created to the signal noise
1 Select SPTool from the Window menu in the Filter Designer.

2 Select the signal noise[vector] from the Signals list and select the filter (named filt1[design]) from the Filters list, as shown below.


3 Press Apply to apply the filter filt1 to the signal noise.
The Apply Filter dialog box is displayed.


4 Keep the default filter structure selected in the Algorithm list.
5 Name the new signal by typing blnoise in the Output Signal field in this dialog box.

6 Press OK to close the Apply Filter dialog box.
The filter is applied to the selected signal and the filtered signal blnoise[vector] is listed in the Signals list in SPTool.

## Analyzing Signals: Opening the Signal Browser

You can analyze and print signals using the Signal Browser. You can also play the signals if your computer has audio output capabilities.

For example, compare the signal noise to the filtered signal blnoise
1 Shift+click on the noise and blnoise signals in the Signals list of SPTool to select both signals.

2 Press the View button under the Signals list.
The Signal Browser is activated and both signals are displayed in the display region. (The names of both signals are shown above the display region.) Initially, the original noise signal covers up the bandlimited blnoise signal.

3 Push the selection button on the tool bar, $\underset{\substack{x \\ \frac{x}{+},-}}{ }$, to select the blnoise signal.
The display area is updated. Now you can see the blnoise signal superimposed on top of the noise signal. The signals are displayed in different col ors in both the display region and the panner. You can change the color of the selected signal using the Line Properties button on the tool bar, $=$.


## Playing a Signal

When you press the Play button in the Signal Browser tool bar, 组, the active signal is played on the computer's audio hardware.

1 To hear a portion of the active (selected) signal
a Usethevertical markers to select a portion of the signal you want to play. Vertical markers are enabled by the 1 and $\phi i$ buttons.
b Press the Play button.
2 To hear the other signal
a Select the signal as in step 3 above. You can also select the signal directly in the display region.
b Press the Play button again.

## Printing a Signal

You can print from the Signal Browser using the Print button,

```
曷
```

You can use the line display buttons to maximize the visual contrast between the signals by setting the line col or for noise to gray and the line col or for blnoise to white. Do this before printing two signals together.

Note You can follow the same rules to print spectra, but you can't print filter responses directly from SPTool.

Use the Signal Browser region in the Preferences dialog box in SPTool to suppress printing of both the panner and the marker settings.

To print both signals, press the Print button in the Signal Browser tool bar.


## Spectral Analysis in the Spectrum View er

You can analyze the frequency content of a signal using the Spectrum Viewer, which estimates and displays a signal's power spectral density.

For example, to analyze and compare the spectra of noise and blnoise
1 Create a power spectral density (PSD) object, spect1, that is associated with the signal noise, and a second PSD object, spect2, that is associated with the signal blnoise.

2 Open the Spectrum Viewer to analyze both of these spectra.
3 Print both spectra.

## Creating a PSD Object From a Signal

1 Click on SPTool, or select SPTool from the Window menu of any active open GUI. SPTool is now the active window.

2 Select the noise[vector] signal in the Signals list of SPTool.
3 Press Create in the Spectra list.
The Spectrum Viewer is activated, and a PSD object (spect1) corresponding to the noise signal is created in the Spectra list. The PSD is not computed or displayed yet.

4 Press Apply in the Spectrum Viewer to compute and display the PSD estimate spect1 using the default parameters.

The PSD of the noise signal is displayed in the display region. The identifying information for the PSD's associated signal (noise) is displayed above the Parameters region.

The PSD estimate spect1 is within 2 or 3 dB of 0 , so the noise has a fairly "flat" power spectral density.

5 Follow steps 1 through 4 for the bandlimited noise signal blnoise to create a second PSD estimate spect2.

The PSD estimate spect2 is flat between 750 and 1250 Hz and has 75 dB less power in the stopband regions of filt1.

## $O$ pening the Spectrum Viewer with Two Spectra

1 Reactivate SPTool again, as in step 1 above.
2 Shift+click on spect1 and spect2 in the Spectra list to select them both.
3 Press View in the Spectra list to reactivate the Spectrum Viewer and display both spectra together.


## Printing the Spectra

Before printing the two spectra together, use the col or and line style selection button, $=:=$, to differentiate the two plots by line style, rather than by color.
To print both spectra
1 Press the Print Preview button, 3 . in the tool bar on the Spectrum Viewer.

2 From the Spectrum Viewer Print Preview window, drag the legend out of the display region so that it doesn't obscure part of the plot.

3 Press the Print button in the Spectrum Viewer Print Preview window.


## Exporting Signals, Filters, and Spectra

You can export SPTool signals, filters, and spectra as structures to the MATLAB workspace or to your disk.

In each case you
1 Select the items in SPTool you want to export.
2 Select Export from the File menu.

## Opening the Export Dialog Box

To save the filter filt1 you just created in this example, open the Export dialog box with filt1 preselected

1 Select filt1 in the SPTool Filters list.
2 Select Export from the File menu.
The Export dialog box opens with filt1 preselected.


## Exporting a Filter to the MATLAB Workspace

To export the filter filt1 to the MATLAB workspace
1 Select filt1 from the Export List and deselect all other items using Ctrl+click.

2 Press the Export to Workspace button.

## Accessing Filter Parameters

## Accessing Filter Parameters in a Saved Filter

The MATLAB structures created by SPTool have several associated fields, many of which are also MATLAB structures. Seethe MATLAB documentation for general information about MATLAB structures.

For example, after exporting a filter filt1 to the MATLAB workspace, type filt1
to display the fields of the MATLAB filter structure. The tf, Fs, and specs fields of the structure contain the information that describes the filter.

## The tf Field: Accessing Filter Coefficients

The tf field is a structure containing the transfer function representation of the filter. Use this field to obtain the filter coefficients

- filt1.tf.num contains the numerator coefficients.
- filt1.tf. den contains the denominator coefficients.

The vectors contained in these structures represent polynomials in descending powers of $z$. The numerator and denominator polynomials are used to specify the transfer function

$$
H(z)=\frac{B(z)}{A(z)}=\frac{b(1)+b(2) z^{-1}+\cdots+b(n b+1) z^{-m}}{a(1)+a(2) z^{-1}+\cdots+a(n a+1) z^{-n}}
$$

where

- b is a vector containing the coefficients from the tf. num field.
- a is a vector containing the coefficients from the tf. den field.
- $m$ is the numerator order.
- n is the denominator order.

You can change the filter representation from the default transfer function to another form by using the tf2ss or tf2zp functions.

## The Fs Field: Accessing Filter Sample Frequency

The Fs field contains the sampling frequency of the filter in hertz.

## The specs Field: Accessing other Filter Parameters

The specs field is a structure containing parameters that you specified for the filter design. The first field, specs.currentModule, contains a string representing the most recent design method selected from the Filter Designer's Algorithm list before you exported the filter. The possible contents of the currentModule field and the corresponding design methods are shown below.

Table 6-1: Filter Specifications currentModule Field Values

| Contents of the currentModule field | Design Method |
| :--- | :--- |
| fdbutter | Butterworth IIR |
| fdcheby1 | Chebyshev Type I IIR |
| fdcheby2 | Chebyshev Type II IIR |
| fdellip | Elliptic IIR |
| fdfirls | Least Squares FIR |
| fdkaiser | Kaiser Window FIR |
| fdremez | Equiripple FIR |

F ollowing the specs. currentModule field, there may be up to seven additional fields, with labels such as specs.fdremez, specs.fdfirls, etc. The design specifications for the most recently exported filter are contained in the field whose label matches the currentModule string. For example, if the specs structure is

```
filt1.specs
ans
    currentModule: 'fdremez'
    fdremez: [1x1 struct]
```

thefilter specifications are contained in the fdremez field, which is itself a data structure.

The specifications include the parameter values from the Specifications region of the Filter Designer, such as band edges and filter order. For example,
the filter above has the following specifications stored in filt1.specs.fdremez.
filt1.specs.fdremez
ans =
setOrderFlag: 0
type: 3
f: [0 0.20000 .30000 .50000 .6000 1]
m: [6x1 double]
Rp: 0.0100
Rs: 75
wt: [3.2371 1 3.2371]
order: 78
Because certain filter parameters are unique to a particular design, this structure has a different set of fields for each filter design.

The table below describes the possible fields associated with the filter design specification field (the specs field) that can appear in the exported structure.

Table 6-2: SPTool Structure Specifications for Filters

| Parameter | Description |
| :--- | :--- |
| Beta | Kaiser window $\beta$ parameter. |
| $f$ | Contains a vector of band-edge frequencies, normalized so <br> that 1 Hz corresponds to half the sample frequency. |
| Fpass | Passband cutoff frequencies. Scalar for lowpass and <br> highpass designs, two-element vector for bandpass and <br> bandstop designs. |
| Fstop | Stopband cutoff frequencies. Scalar for lowpass and <br> highpass designs, two-element vector for bandpass and <br> bandstop designs. |
| m | The response magnitudes corresponding to the band-edge <br> frequencies in $f$. |
| order | Filter order. |

Table 6-2: SPTool Structure Specifications for Filters (Continued)

| Parameter | Description |
| :--- | :--- |
| Rp | Passband ripple (dB) |
| Rs | Stopband attenuation (dB) |
| setOrderFlag | Contains 1 if the filter order was specified manually (i.e., <br> the Minimum Order box in the Specifications region <br> was not checked). Contains 0 if the filter order was <br> computed automatically. |
| type | Contains 1 for lowpass, 2 for highpass, 3 for bandpass, or <br> 4 for bandstop. |
| w3db | -3 dB frequency for Butterworth IIR designs. <br> windVector of Kaiser window coefficients. <br> WnCutoff frequency for the Kaiser window FIR filter when <br> setOrderFlag = 1. |
| wt | Vector of weights, one weight per frequency band. |

## Accessing Parameters in a Saved Spectrum

The following structure fields describe the spectra saved by SPTool.

| Field | Description |
| :--- | :--- |
| P | The spectral power vector. |
| f | The spectral frequency vector. |

\(\left.$$
\begin{array}{l|l}\hline \text { Field } & \text { Description } \\
\hline \text { confid } & \begin{array}{l}\text { A structure containing the confidence intervals data } \\
\text { - The confid. level field contains the chosen } \\
\text { confidence level. }\end{array}
$$ <br>
- The confid.Pc field contains the spectral power <br>
data for the confidence intervals. <br>
- The confid.enable field contains a 1 if confidence <br>

levels are enabled for the power spectral density.\end{array}\right]\)| The name of the signal from which the power spectral |
| :--- |
| density was generated. |

[^1]
## Importing Filters and Spectra into SPTool

In addition to importing signals into SPTool, you can import filters or spectra into SPTool from either the workspace or from a file.
The procedures are very similar to those explained in

- "Importing a Signal into SPTool" on page 6-20 for loading variables from the workspace
- "Loading Variables from the Disk" on page 6-43 for loading variables from your disk


## Importing Filters

When you import filters, first select the appropriate filter form from the Form list.


For every filter you specify a variable name or a value for the filter's sampling frequency in the Sampling F requency field. E ach filter form requires different variables.

Transfer Function. For Transfer Function, you specify thefilter by its transfer function representation

$$
H(z)=\frac{B(z)}{A(z)}=\frac{b(1)+b(2) z^{-1}+\cdots+b(m+1) z^{-m}}{a(1)+a(2) z^{-1}+\cdots+a(n+1) z^{-n}}
$$

- The Numerator field specifies a variable name or value for the numerator coefficient vector $b$, which contains $m+1$ coefficients in descending powers of z.
- The Denominator field specifies a variable name or value for the denominator coefficient vector $a$, which contains $n+1$ coefficients in descending powers of $z$.

State Space. For State Space, you specify the filter by its state-space representation

$$
\begin{aligned}
& x=A x+B u \\
& y=C x+D u
\end{aligned}
$$

The A-Matrix, B-Matrix, C-Matrix, and D-Matrix fields specify a variable name or a value for each matrix in this system.

Zeros, Poles, Gain. For Zeros, Poles, Gain, you specify the filter by its zero-pole-gain representation

$$
H(z)=\frac{Z(z)}{P(z)}=k \frac{(z-z(1))(z-z(2)) \cdots(z-z(m))}{(z-p(1))(z-p(2)) \cdots(z-p(n))}
$$

- The Zeros field specifies a variable name or value for the zeros vector $z$, which contains the locations of $m$ zeros.
- The Poles field specifies a variable name or value for the zeros vector $p$, which contains the locations of $n$ poles.
- The Gain field specifies a variable name or value for the gain $k$.

Second Order Sections. F or 2nd Order Sections you specify the filter by its second-order section representation

$$
H(z)=\prod_{k=1}^{L} H_{k}(z)=\prod_{k=1}^{L} \frac{b_{0 k}+b_{1 k} z^{-1}+b_{2 k} z^{-2}}{1+a_{1 k^{2}} z^{-1}+a_{2 k^{2}} z^{-2}}
$$

The SOS Matrix field specifies a variable name or a value for the L-by-6 SOS matrix

$$
\text { sOS }=\left[\begin{array}{cccccc}
b_{01} & b_{11} & b_{21} & 1 & a_{11} & a_{21} \\
b_{02} & b_{12} & b_{22} & 1 & a_{12} & a_{22} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
b_{0 L} & b_{1 L} & b_{2 L} & 1 & a_{1 L} & a_{2 L}
\end{array}\right]
$$

whose rows contain the numerator and denominator coefficients $\mathrm{b}_{\mathrm{ik}}$ and $\mathrm{a}_{\mathrm{ik}}$ of the second-order sections of $\mathrm{H}(\mathrm{z})$.

Note If you import a filter that was not created in SPTool, you can only edit that filter using the Pole/Zero Editor.

## Importing Spectra

When you import a power spectral density (PSD), you specify

- A variable name or a value for the PSD vector in the PSD field
- A variable name or a value for the frequency vector in the Freq. Vector field

The PSD values in the PSD vector correspond to the frequencies contained in the Freq. Vector vector; the two vectors must have the same length.


## Loading Variables from the Disk

To import variables representing signals, filters, or spectra from a MAT-file on your disk

1 Select the From Disk radio button and do either of the following

- Type the name of the file you want to import into the MAT-file Name field and press either the Tab or the Enter key on your keyboard.
- Select Browse, and then find and select the file you want to import using the Select File to Open dialog. Press OK to close that dialog.

In either case, all variables in the MAT-file you selected are displayed in the File Contents list.

2 Select the variables to be imported into SPTool.
You can now import one or more variables from the File Contents list into SPTool, as long as these variables are scalars, vectors, or matrices.

## Selecting Signals, Filters, and Spectra in SPTool

All signals, filters, or spectra listed in SPTool exist as special MATLAB structures. Y ou can bring data representing signals, filters, or spectra into SPTool from the MATLAB workspace. In general, you can select one or several items in a given list box. An item is selected when it is highlighted.

The Signals list shows all vector and array signals in the current SPTool session.

The Filters list shows all designed and imported filters in the current SPTool session.

The Spectra list shows all spectra in the current SPTool session.
Y ou can select a single data object in a list, a range of data objects in a list, or multiple separate data objects in a list. You can also have data objects simultaneously selected in different lists

- To select a single item, click on it. All other items in that list box become deselected.
- To add or remove a range of items, Shift+click on the items at the top and bottom of the section of the list that you want to add. Y ou can also drag your mouse pointer to select these items.
- To add a single data object to a selection or remove a single data object from a multiple selection, CtrI+click on the object.


## Editing Signals, Filters, or Spectra in SPTool

You can edit selected items in SPTool by
1 Selecting the names of the signals, filters, or spectra you want to edit.
2 Selecting the appropriate Edit menu item

- Duplicate to copy an item in an SPTool list
- Clear to delete an item in an SPTool list
- Name to rename an item in an SPTool list
- Sampling Frequency to modify the sampling frequency associated with either a signal (and its associated spectra) or filter in an SPTool list

The pull-down menu next to each menu item shows the names of all selected items.

You can also edit the following signal characteristics by right-clicking in the display region of theSignal Browser, theFilter Viewer, or theSpectrum Viewer

- The signal name
- The sampling frequency
- The line style properties

Note If you modify the sampling frequency associated with a signal's spectrum using the right-click menu on the Spectrum Viewer display region, the sampling frequency of the associated signal is automatically updated.

## Designing a Filter with the Pole/ Zero Editor

To design a filter transfer function using the Filter Designer Pole/Zero Editor
1 Select the Pole/Zero Editor option from the Algorithm list to open the Pole/Zero Editor in the Filter Designer display.

Equiripple FIR
Least Squares FIR
Kaiser Window FIR
Butterworth IIR
Chebyshev Type 1 IIR
Chebyshev Type 2 IIR
Elliptic IIR
PolerZero Editor

2 E nter the desired filter gain in the Gain edit box.
3 Select a pole or zero (or conjugate pair) by selecting one of the $\times$ (pole) or O (zero) symbols on the plot.

4 Choose the coordinates to work in by specifying Polar or Rectangular from the Coordinates list.

5 Specify the new location(s) of the selected pole, zero, or conjugate pair by typing values into the Mag and Angle fields (for angular coordinates) or $\mathbf{X}$ and $\mathbf{Y}$ (for rectangular coordinates) fields. Alternatively, position the poles and zeros by dragging the $x$ and $O$ symbols.

6 Usethe Conjugate pair check box to create a conjugate pair from a lone pole or zero, or to break a conjugate pair into two individual poles or zeros.

Design a new filter or edit an existing filter in the same way.

[^2]
## Positioning Poles and Zeros

You can use your mouse to move poles and zeros around the pole/zero plot and modify your filter design

- Add poles or zeros using the tool bar buttons for pole placement, ", and zero placement, ${ }^{\circ} \mathrm{s}$.
- Erase poles and zeros using the eraser button,
- M ove both members of a conjugate pair simultaneously by manipulating just one of the poles or zeros.

To ungroup conjugates, select the desired pair and uncheck Conjugate pair in the Specifications region on the Filter Designer.


When you place two or more poles (or two or more zeros) directly on top of each other, a number is displayed next to the symbols (on the left for poles, and on theright for zeros) indicating the number of poles or zeros at that location (e.g., 03 for three zeros). This number makes it easy to keep track of all the poles and zeros in the plot area, even when several are superimposed on each other and are not visually differentiable. Note, however, that this number does not indicate the multiplicity of the poles or zeros to which it is attached.

To detect whether or not a set of poles or zeros aretruly multiples, use the zoom tools to magnify the region around the poles or zeros in question. Because numerical limitations usually prevent any set of poles or zeros from sharing exactly the same value, at a high enough zoom level even truly multiple poles or zeros appear distinct from each other.
A common way to assess whether a particular group of poles or zeros contains multiples is by comparing the mutual proximity of the group members against a selected threshold value. As an example, the residuez function defines a pole or zero as being a multiple of another pole or zero if the absolute distance separating them is less than $0.1 \%$ of the larger pole or zero's magnitude.

## Redesigning a Filter Using the Magnitude Plot

After designing a filter in the Filter Designer, you can redesign it by dragging the specification lines on the magnitude plot. Use the specification lines to change passband ripple, stopband attenuation, and edge frequencies.

In the following example, create a Chebyshev filter and modify it by dragging the specification lines

1 Select Chebyshev Type I I IR from the Algorithm menu.
2 Select highpass from the Type menu.
3 Type 2000 in the Sampling Frequency field.
4 Set the following parameters
a $\mathbf{F p}=800$
b $\mathbf{F s}=700$
c $\mathbf{R} \mathbf{p}=2.5$
d $\mathbf{R s}=35$
5 Check Minimum Order sotheFilter Designer can calculatethe lowest filter order that produces the desired characteristics.

6 Press Apply to compute the filter and update the response plot.
7 Position the cursor over the horizontal filter specification line for the stopband. This is the first (leftmost) horizontal specification line you see.

The cursor changes to the up/down drag indicator.
8 Drag the line until the Rs (stopband attenuation) field reads 100.

Note The Order value in the Measurements region changes because a higher filter order is needed to meet the new specifications.

## Setting Preferences

Use Preferences from the SPTool File menu to customize displays and certain parameters for SPTool and its four component GUIs. The new settings are saved on disk and are used when you restart SPTool from MATLAB.

In the Preferences regions, you can

- Select colors and markers for all displays.
- Select colors and line styles for displayed signals.
- Configure labels, and enable/disable markers, panner, and zoom in the Signal Browser.
- Configure display parameters, and enable/disable markers and zoom in the Spectrum Viewer.
- Configure filter and display parameters, and enable/disable zoom in the Filter Viewer.
- Configure tiling preferences in the Filter Viewer.
- Specify FFT Iength, and enable/disable mouse zoom and grid in the Filter Designer.
- Enable/disable use of a default session file.
- Export filters for use with the Control System Toolbox.
- Enable/disable search for plug-ins at start-up.

When you first select Preferences, the Preferences dialog box opens with Markers selected by default.


## You can

- Change the settings for markers from this panel of the Preferences dialog.
- Choose any of the other categories listed to customize its settings.

Click once on any listed category in the left pane of the Preferences dialog to select it.

## Making Signal Measurements: Using Markers

You can use the markers on the Signal Browser, the Filter Viewer, or the Spectrum Viewer to make measurements on any of the following

- A signal in the Signal Browser
- A filter response in the Filter Viewer
- A power spectral density plotted in the Spectrum Viewer

The marker buttons from left to right are

## 

- toggle markers on/off
- vertical markers
- horizontal markers
- vertical markers with tracking
- vertical markers with tracking and slope
- display peaks (local maxima)
- display valleys (local minima)

To make a measurement
1 Select a line to measure (or play, if you are in the Signal Browser).
2 Select one of the marker buttons to apply a marker to the displayed signal.
3 Position a marker in the main display area by grabbing it with your mouse and dragging
a Select a marker setting. If you choose the Vertical, Track, or Slope buttons, you can drag a marker to the right or left. If you choose the Horizontal button, you can drag a marker up or down.
b Move the mouse over the marker (1 or 2 ) that you want to drag.
The hand cursor with the marker number inside it $\$_{17}^{7}$ is displayed when your mouse passes over a marker.
c Drag the marker to where you want it on the signal.
As you drag a marker, the bottom of the Signal Browser shows the current position of both markers. Depending on which marker setting you select, some or all of the following fields are displayed - $\mathbf{x 1}, \mathbf{y 1}, \mathbf{x 2}, \mathbf{y 2}, \mathbf{d x}, \mathbf{d y}, \mathbf{m}$. These fields are also displayed when you print from the Signal Browser, unless you suppress them.
You can also position a marker by typing its $\mathbf{x 1}$ and $\mathbf{x 2}$ or $\mathbf{y 1}$ and $\mathbf{y 2}$ values in the region at the bottom.

## Function Reference

Function Category List ..... 7-3
Alphabetical List of Functions ..... 7-20

Detailed descriptions of all Signal Processing Tool box functions are in these two sections:

- "Function Category List" - a list of functions, grouped by subject area
- "Alphabetical List of Functions" - reference pages in alphabetical order


## Function Category List

The Signal Processing Tool box functions are divided into the following categories

- "Filter Analysis"
- "Filter Implementation"
- "FIR Digital Filter Design"
- "IIR Digital Filter Design—Classical and Direct"
- "IIR Filter Order Estimation"
- "Analog Lowpass Filter Prototypes"
- "Analog Filter Design"
- "Analog Filter Transformation"
- "Filter Discretization"
- "Linear System Transformations"
- "Windows"
- "Transforms"
- "Cepstral Analysis"
- "Statistical Signal Processing and Spectral Analysis"
- "Parametric Modeling"
- "Linear Prediction"
- "Multirate Signal Processing"
- "Waveform Generation"
- "Specialized Operations"
- "Graphical User Interfaces".

Filter Analysis

| abs | Absolute value (magnitude). |
| :--- | :--- |
| angle | Phase angle. |
| freqs | Frequency response of analog filters. |
| freqspace | Frequency spacing for frequency response. |


| Filter Analysis (Continued) |  |
| :--- | :--- |
| freqz | Compute the frequency response of digital filters. |
| freqzplot | Plot frequency response data. |
| grpdelay | Compute the average filter delay (group delay). |
| impz | Compute the impulse response of digital filters. |
| unwrap | Unwrap phase angles. |
| zplane | Zero-pole plot. |

## Filter Implementation

| conv | Convolution and polynomial multiplication. |
| :--- | :--- |
| conv2 | Two-dimensional convolution. |
| deconv | Deconvolution and polynomial division. |
| fftfilt | FFT-based FIR filtering using the overlap-add method. |
| filter | Filter data with a recursive (IIR) or nonrecursive (FIR) <br> filter. |
| filter2 | Two-dimensional digital filtering. |
| filtfilt | Zero-phase digital filtering. |
| filtic | Find initial conditions for a transposed direct form II filter <br> implementation. |
| latcfilt | Lattice and lattice-ladder filter implementation. |
| medfilt1 | One-dimensional median filtering. |
| sgolayfilt | Savitzky-Golay filtering. |
| sosfilt | Second-order (biquadratic) IIR digital filtering. |

## Filter Implementation (Continued)

upfirdn Upsample, apply an FIR filter, and downsample.

| FIR Digital Filter Design |  |
| :--- | :--- |
| convmtx | Convolution matrix. |
| cremez | Complex and nonlinear-phase equiripple FIR filter design. |
| fir1 | Design a window-based finite impulse response filter. |
| fir2 | Design a frequency sampling-based finite impulse response <br> filter. |
| fircls | Constrained least square FIR filter design for multiband <br> filters. |
| fircls1 | Constrained least square filter design for lowpass and <br> highpass linear phase FIR filters. |
| firls | Least squarelinear-phase FIR filter design. |
| firrcos | Raised cosine FIR filter design. |
| intfilt | Interpolation FIR filter design. |
| kaiserord | Estimate parameters for an FIR filter design with Kaiser <br> window. |
| remez | Compute the Parks-McClellan optimal FIR filter design. |
| remezord | Parks-McClellan optimal FIR filter order estimation. |
| sgolay | Savitzky-Golay filter design. |


| IIR Digital Filter Design-Classical and Direct |  |
| :--- | :--- |
| butter | Butterworth analog and digital filter design. |
| cheby1 | Chebyshev Type I filter design (passband ripple). |
| cheby2 | Chebyshev Type Il filter design (stopband ripple). |
| ellip | Elliptic (Cauer) filter design. |
| maxflat | Generalized digital Butterworth filter design. |
| prony | Prony's method for time-domain IIR filter design. |
| stmcb | Compute a linear model using Steiglitz-McBride iteration. |
| yulewalk | Recursive digital filter design. |

## IIR Filter Order Estimation

| buttord | Calculate the order and cutoff frequency for a Butterworth <br> filter. |
| :--- | :--- |
| cheb1ord | Calculate the order for a Chebyshev Type I filter. |
| cheb2ord | Calculate the order for a Chebyshev Type II filter. |
| ellipord | Calculate the minimum order for elliptic filters. |

## Analog Low pass Filter Prototypes

| besselap | Bessel analog lowpass filter prototype. |
| :--- | :--- |
| buttap | Butterworth analog lowpass filter prototype. |
| cheb1ap | Chebyshev Type I analog lowpass filter prototype. |
| cheb2ap | Chebyshev Type II analog lowpass filter prototype. |
| ellipap | Elliptic analog lowpass filter prototype. |

## Analog Filter Design

| besself | Bessel analog filter design. |
| :--- | :--- |
| butter | Butterworth analog and digital filter design. |
| cheby1 | Chebyshev Type I filter design (passband ripple). |
| cheby2 | Chebyshev Type Il filter design (stopband ripple). |
| ellip | Elliptic (Cauer) filter design. |

## Analog Filter Transformation

| lp2bp | Transform lowpass analog filters to bandpass. |
| :--- | :--- |
| lp2bs | Transform lowpass analog filters to bandstop. |
| lp2hp | Transform lowpass analog filters to highpass. |
| lp2lp | Change the cut-off frequency for a lowpass analog filter. |


| Filter Discretization |  |
| :--- | :--- |
| bilinear | Bilinear transformation method for analog-to-digital filter <br> conversion. |
| impinvar | Impulse invariance method for analog-to-digital filter <br> conversion. |
| Linear System Transformations |  |
| latc2tf | Convert lattice filter parameters to transfer function form. |
| polystab | Stabilize a polynomial. |
| polyscale | Scale the roots of a polynomial. |
| residuez | z-transform partial-fraction expansion. |
| sos2ss | Convert digital filter second-order section parameters to <br> state-space form. |
| sos2tf | Convert digital filter second-order section data to transfer <br> function form. |
| sos2zp | Convert digital filter second-order sections parameters to <br> zero-pole-gain form. |
| ss2sos | Convert digital filter state-space parameters to <br> second-order sections form. |
| ss2tf | Convert state-space filter parameters to transfer function <br> form. |
| ss2zp | Convert state-space filter parameters to zero-pole-gain <br> form. |
| Convert transfer function filter parameters to lattice filter |  |
| form. |  |


| Linear System Transformations (Continued) |  |
| :--- | :--- |
| tf2sos | Convert digital filter transfer function data to second-order <br> sections form. |
| tf2ss | Convert transfer function filter parameters to state-space <br> form. |
| tf2zp | Convert transfer function filter parameters to <br> zero-pole-gain form. |
| zp2sos | Convert digital filter zero-pole-gain parameters to <br> second-order sections form. |
| zp2ss | Convert zero-pole-gain filter parameters to state-space <br> form. |
| zp2tf | Convert zero-pole-gain filter parameters to transfer <br> function form. |


| Windows |  |
| :--- | :--- |
| barthannwin | Compute a modified Bartlett-Hann window. |
| bartlett | Compute a Bartlett window. |
| blackman | Compute a Blackman window. |
| blackmanharris | Compute a minimum 4-term Blackman-Harris window. |
| bohmanwin | Compute a Bohman window. |
| chebwin | Compute a Chebyshev window. |
| gausswin | Compute a Gaussian window. |
| hamming | Compute a Hamming window. |
| hann | Compute the Hann (Hanning) window. |
| kaiser | Compute a Kaiser window. |


| Windows (Continued) |  |
| :--- | :--- |
| nuttallwin | Compute a Nuttall-defined minimum 4-term <br> Blackman-Harris window. |
| rectwin | Compute a rectangular window. |
| triang | Compute a triangular window. |
| tukeywin | Compute a Tukey (tapered cosine) window. |
| window | Window function gateway. |


| Transforms |  |
| :--- | :--- |
| bitrevorder | Permute input into bit-reversed order. |
| czt | Chirp z-transform. |
| dct | Discrete cosine transform (DCT). |
| dftmtx | Discrete Fourier transform matrix. |
| fft | Compute the one-dimensional fast Fourier transform. |
| fft2 | Compute the two-dimensional fast Fourier transform. |
| fftshift | Rearrange the outputs of the FFT functions. |
| goertzel | Compute the discrete Fourier transform using the second <br> order Goertzel algorithm. |
| hilbert | Compute the discrete-time analytic signal using the Hilbert <br> transform. |
| idct | Inverse discrete cosine transform. |
| ifft | One-dimensional inverse fast Fourier transform. |
| ifft2 | Two-dimensional inverse fast Fourier transform. |
|  |  |

## Cepstral Analysis

| cceps | Complex cepstral analysis. |
| :--- | :--- |
| icceps | Inverse complex cepstrum. |
| rceps | Real cepstrum and minimum phase reconstruction. |


| Statistical Signal Processing and Spectral Analysis |  |
| :--- | :--- |
| cohere | Estimate magnitude squared coherence function between <br> two signals. |
| corrcoef | Compute the correlation coefficient matrix. |
| corrmtx | Compute a data matrix for autocorrelation matrix <br> estimation. |
| cov | Compute the covariance matrix. |
| csd | Estimate the cross spectral density (CSD) of two signals. |
| pburg | Estimate the power spectral density using the Burg <br> method. |
| pcov | Estimate the power spectral density using the covariance <br> method. |
| peig | Estimate the pseudospectrum using the eigenvector <br> method. |
| periodogram | Estimate the power spectral density (PSD) of a signal using <br> a periodogram. <br> pmcov |
| Estimate the power spectral density using the modified <br> covariance method. |  |
| pmtm | Estimate the power spectral density using the multitaper <br> method (MTM). |
| pmusic | Estimate the power spectral density using MUSIC <br> algorithm. |
| psdplot | Plot power spectral density (PSD) data. |
| pwelch | Estimate the power spectral density (PSD) of a signal using <br> Welch's method. |


| Statistical Signal Processing and Spectral Analysis (Continued) |  |
| :--- | :--- |
| pyulear | Estimate the power spectral density using the Yule-Walker <br> AR method. |
| rooteig | Estimate frequency and power content using the <br> eigenvector method. |
| rootmusic | Estimate frequency and power content using the root <br> MUSIC algorithm. |
| tfe | Estimate the transfer function from input and output. |
| xcorr | Estimate the cross-correlation function. |
| xcorr2 | Estimate the two-dimensional cross-correlation. |
| xcov | Estimate the cross-covariance function (equal to <br> mean-removed cross-correlation). |

## Parametric Modeling

| arburg | Compute an estimate of AR model parameters using the <br> Burg method. |
| :--- | :--- |
| arcov | Compute an estimate of AR model parameters using the <br> covariance method. |
| armcov | Compute an estimate of AR model parameters using the <br> modified covariance method. |
| aryule | Compute an estimate of AR model parameters using the <br> Yule-Walker method. |
| ident | See the System Identification Tool box documentation. <br> invfreqsIdentify continuous-time filter parameters from frequency <br> response data. |


| Parametric Modeling (Continued) |  |
| :--- | :--- |
| invfreqz | Identify discrete-time filter parameters from frequency <br> response data. |
| prony | Prony's method for time domain IIR filter design. |
| stmcb | Compute a linear model using Steiglitz-McBride iteration. |


| Linear Prediction |  |
| :--- | :--- |
| ac2poly | Convert an autocorrelation sequence to prediction <br> polynomial. |
| ac2rc | Convert an autocorrelation sequence to reflection <br> coefficients. |
| is2rc | Convert inverse sine parameters to reflection coefficients. |
| lar2rc | Convert log area ratio parameters to reflection coefficients. |
| levinson | Compute the Levinson-Durbin recursion. |
| lpc | Compute linear prediction filter coefficients. |
| lsf2poly | Convert line spectral frequencies to a prediction filter <br> coefficients. |
| poly2ac | Convert a prediction filter polynomial to an autocorrelation <br> sequence. |
| poly2lsf | Convert prediction filter coefficients to line spectral <br> frequencies. |
| poly2rc | Convert a prediction filter polynomial to reflection <br> coefficients. |
| rc2ac | Convert reflection coefficients to an autocorrelation <br> sequence. |
| rc2is | Convert reflection coefficients to inverse sine parameters. <br> rc2larConvert reflection coefficients to log area ratio parameters. <br> rc2polyConvert reflection coefficients to a prediction filter <br> polynomial. |
| rlevinson | Compute the reverse Levinson-Durbin recursion. |
| schurrc | Compute reflection coefficients from an autocorrelation <br> sequence. |


| Multirate Signal Processing |  |
| :--- | :--- |
| decimate | Decrease the sampling rate for a sequence (decimation). |
| downsample | Reduce the sampling rate by an integer factor. |
| interp | Increase sampling rate by an integer factor (interpolation). |
| interp1 | One-dimensional data interpolation (table lookup). |
| resample | Change sampling rate by any rational factor. |
| spline | Cubic spline interpolation. |
| upfirdn | Upsample, apply an FIR filter, and downsample. |
| upsample | Increase the sampling rate by an integer factor |


| Waveform Generation |  |
| :--- | :--- |
| chirp | Generate a swept-frequency cosine. |
| diric | Compute the Dirichlet or periodic sinc function. |
| gauspuls | Generate a Gaussian-modulated sinusoidal pulse. |
| gmonopuls | Generate a Gaussian monopulse. |
| pulstran | Generate a pulse train. |
| rectpuls | Generate a sampled aperiodic rectangle. |
| sawtooth | Generate a sawtooth or triangle wave. |
| sinc | Sinc function. |
| square | Generate a square wave. |
| tripuls | Generate a sampled aperiodic triangle. |
| vco | Voltage controlled oscillator. |


| Specialized Operations |  |
| :--- | :--- |
| buffer | Buffer a signal vector into a matrix of data frames. |
| cell2sos | Convert a cell array for second-order sections to a <br> second-order section matrix. |
| cplxpair | Group complex numbers into complex conjugate pairs. |
| demod | Demodulation for communications simulation. |
| dpss | Discrete prolate spheroidal sequences (Slepian sequences). |
| dpssclear | Remove discrete prolate spheroidal sequences from <br> database. |
| dpssdir | Discrete prolate spheroidal sequences database directory. |
| dpssload | Load discrete prolate spheroidal sequences from database. |
| dpsssave | Save discrete prolate spheroidal sequences in database. |
| eqtflength | Make the lengths of a transfer function's numerator and <br> denominator equal. |
| modulate | Modulation for communications simulation. |
| seqperiod | Compute the period of a sequence. <br> sos2cell |
| Convert a second-order section matrix to cell arrays. |  |
| specgram | Time-dependent frequency analysis (spectrogram). |
| stem | Plot discrete sequence data. |
| strips | Strip plot. <br> udecode |
| Decode ${ }^{\text {n }}$-level quantized integer inputs to floating-point |  |
| outputs. |  |
| uencode | Quantize and encode floating-point inputs to integer <br> outputs. |


| Graphical User Interfaces |  |
| :--- | :--- |
| fdatool | Open the Filter Design and Analysis Tool. |
| fvtool | Open the Filter Visualization Tool. |
| sptool | Interactive digital signal processing tool (SPTool). |

## Alphabetical List of Functions

abs ..... 7-26
ac2poly ..... 7-27
ac2rc ..... 7-28
angle ..... 7-29
arburg ..... 7-30
arcov ..... 7-31
armcov ..... 7-32
aryule ..... 7-33
barthannwin ..... 7-34
bartlett ..... 7-36
besselap ..... 7-38
besself ..... 7-39
bilinear ..... 7-42
bitrevorder ..... 7-47
blackman ..... 7-49
blackmanharris ..... 7-51
bohmanwin ..... 7-53
buffer ..... 7-55
buttap ..... 7-64
butter ..... 7-65
buttord ..... 7-70
cceps ..... 7-75
cell2sos ..... 7-77
cheblap ..... 7-78
cheblord ..... 7-79
cheb2ap ..... 7-83
cheb2ord ..... 7-84
chebwin ..... 7-89
cheby1 ..... 7-90
cheby2 ..... 7-95
chirp ..... 7-100
cohere ..... 7-106
conv ..... 7-110
conv2 ..... 7-111
convmtx ..... 7-113
corrcoef ..... 7-115
corrmtx ..... 7-116
cov ..... 7-119
cplxpair ..... 7-120
cremez ..... 7-121
csd ..... 7-129
czt ..... 7-133
dct ..... 7-136
decimate ..... 7-138
deconv ..... 7-141
demod ..... 7-142
dftmtx ..... 7-144
diric ..... 7-145
downsample ..... 7-146
dpss ..... 7-148
dpssclear ..... 7-151
dpssdir ..... 7-152
dpssload ..... 7-153
dpsssave ..... 7-154
ellip ..... 7-155
ellipap ..... 7-161
ellipord ..... 7-162
eqtflength ..... 7-167
fdatool ..... 7-168
fft ..... 7-170
fft2 ..... 7-173
fftfilt ..... 7-174
fftshift ..... 7-176
filter ..... 7-177
filter2 ..... 7-180
filternorm ..... 7-181
filtfilt ..... 7-183
filtic ..... 7-184
fir1 ..... 7-186
fir2 ..... 7-190
fircls ..... 7-193
fircls1 ..... 7-196
firls ..... 7-199
firrcos ..... 7-204
freqs ..... 7-206
freqspace ..... 7-208
freqz ..... 7-209
freqzplot ..... 7-213
fvtool ..... 7-216
gauspuls ..... 7-220
gausswin ..... 7-222
gmonopuls ..... 7-224
goertzel ..... 7-226
grpdelay ..... 7-231
hamming ..... 7-234
hann ..... 7-236
hilbert ..... 7-238
icceps ..... 7-242
idct ..... 7-243
ifft ..... 7-244
ifft2 ..... 7-245
impinvar ..... 7-246
impz ..... 7-248
interp ..... 7-251
intfilt ..... 7-253
invfreqs ..... 7-255
invfreqz ..... 7-259
is2rc ..... 7-262
kaiser ..... 7-263
kaiserord ..... 7-265
lar2rc ..... 7-270
latc2tf ..... 7-271
latcfilt ..... 7-272
levinson ..... 7-274
Ip2bp ..... 7-276
Ip2bs ..... 7-279
Ip2hp ..... 7-281
Ip2lp ..... 7-283
Ipc ..... 7-285
Isf2poly ..... 7-289
maxflat ..... 7-290
medfilt1 ..... 7-292
modulate ..... 7-293
nuttallwin ..... 7-296
pburg ..... 7-299
pcov ..... 7-304
peig ..... 7-309
periodogram ..... 7-316
pmcov ..... 7-321
pmtm ..... 7-326
pmusic ..... 7-331
poly2ac ..... 7-339
poly2lsf ..... 7-340
poly2rc ..... 7-341
polyscale ..... 7-343
polystab ..... 7-344
prony ..... 7-345
psdplot ..... 7-347
pulstran ..... 7-349
pwelch ..... 7-353
pyulear ..... 7-359
rc2ac ..... 7-364
rc2is ..... 7-365
rc2lar ..... 7-366
rc2poly ..... 7-367
rceps ..... 7-368
rectpuls ..... 7-369
rectwin ..... 7-370
remez ..... 7-371
remezord ..... 7-378
resample ..... 7-381
residuez ..... 7-384
rlevinson ..... 7-387
rooteig ..... 7-390
rootmusic ..... 7-393
sawtooth ..... 7-396
schurrc ..... 7-397
seqperiod ..... 7-398
sgolay ..... 7-400
sgolayfilt ..... 7-404
sinc ..... 7-406
sos2cell ..... 7-408
sos2ss ..... 7-409
sos2tf ..... 7-411
sos2zp ..... 7-413
sosfilt ..... 7-415
specgram ..... 7-416
sptool ..... 7-420
square ..... 7-425
ss2sos ..... 7-426
ss2tf ..... 7-430
ss2zp ..... 7-431
stmcb ..... 7-433
strips ..... 7-436
tf2latc ..... 7-438
tf2sos ..... 7-439
tf2ss ..... 7-442
tf2zp ..... 7-444
tfe ..... 7-447
triang ..... 7-451
tripuls ..... 7-453
tukeywin ..... 7-454
udecode ..... 7-456
uencode ..... 7-459
unwrap ..... 7-462
upfirdn ..... 7-463
upsample ..... 7-467
vco ..... 7-469
window ..... 7-471
xcorr ..... 7-473
xcorr2 ..... 7-477
xcov ..... 7-478
yulewalk ..... 7-481
zp2sos ..... 7-483
zp2ss ..... 7-487
zp2tf ..... 7-488
zplane ..... 7-489

## Purpose Absolute value (magnitude)

## Syntax <br> $y=a b s(x)$

Description

## Example

See Also angle

| Purpose | Convert an autocorrelation sequence to a linear prediction filter polynomial |
| :---: | :---: |
| Syntax | $\begin{aligned} & a=\text { ac2poly }(r) \\ & {[a, e f i n a l]=\operatorname{ac2poly}(r)} \end{aligned}$ |
| Description | $a=\operatorname{ac} 2 p o l y(r)$ finds the linear prediction, FIR filter polynomial a corresponding to the autocorrelation sequence $r$. a is the same length as $r$, and $\mathrm{a}(1)=1$. The prediction filter polynomial represents the coefficients of the prediction filter whose output produces a signal whose autocorrelation sequence is approximately the same as the given autocorrelation sequence $r$. <br> [a,efinal] =ac2poly (r) returns the final prediction error efinal, determined by running the filter for length ( $r$ ) steps. |
| Remarks | You can apply this function to real or complex data. |
| Example | Consider the autocorrelation sequence $r=\left[\begin{array}{llllll} 5.0000 & -1.5450 & -3.9547 & 3.9331 & 1.4681 & -4.7500 \end{array}\right] ;$ |
|  | The corresponding prediction filter polynomial is ```[a,efinal] = ac2poly(r) a= 1.0000 0.6147 0.9898 0.0004 0.0034 -0.0077``` |
|  | efinal = |
|  | 0.1791 |
| See Also | ac2rc, poly2ac, rc2poly |
| References | [1] Kay, S.M. Modern Spectral Estimation. Englewood Cliffs, NJ : Prentice-Hall, 1988. |


| Purpose | Convert an autocorrelation sequence to reflection coefficients |
| :--- | :--- |
| Syntax | $[k, r 0]=\operatorname{ac2rc}(r)$ |
| Description | $[k, r 0]=\operatorname{ac2rc}(r)$ finds the reflection coefficients k corresponding to the <br> autocorrelation sequence $r$. ro contains the initial zero-lag autocorrelation. <br> These reflection coefficients can be used to specify the lattice prediction filter <br> that produces a sequence with approximately the same autocorrelation <br> sequence as the given sequence $r$. |
| Remarks | You can apply this function to real or complex data. |
| See Also | ac2poly, poly2rc, rc2ac |
| References | [1] Kay, S.M. Modern Spectral Estimation. Englewood Cliffs, NJ : <br> Prentice-Hall, 1988. |

Purpose Phase angle
Syntax p = angle(h)
Description
Example
Algorithmangle can be expressed as

    \(\operatorname{angle}(x)=\operatorname{imag}(\log (x))=\operatorname{atan} 2(i m a g(x), \operatorname{real}(x))\)
    See Also ..... abs

## Purpose Compute an estimate of AR model parameters using the Burg method

## Syntax

```
a = arburg(x,p)
[a,e] = arburg(x,p)
[a,e,k] = arburg(x,p)
```

Description

See Also arcov, armcov, aryule, lpc, pburg, prony

## Purpose <br> Compute an estimate of AR model parameters using the covariance method

## Syntax <br> Description

$a=\operatorname{arcov}(x, p)$
$[\mathrm{a}, \mathrm{e}]=\operatorname{arcov}(\mathrm{x}, \mathrm{p})$

See Also
arburg, armcov, aryule, lpc, pcov, prony

| Purpose | Compute an estimate of AR model parameters using the modified covariance method |
| :---: | :---: |
| Syntax | $\begin{aligned} & a=\operatorname{armcov}(x, p) \\ & {[a, e]=\operatorname{armcov}(x, p)} \end{aligned}$ |
| Description | $a=\operatorname{armcov}(x, p)$ uses the modified covariance method to fit a pth order autoregressive (AR) model to the input signal, $x$, which is assumed to be the output of an AR system driven by white noise. This method minimizes the forward and backward prediction errors in the least-squares sense. Vector a contains the normalized estimate of the AR system parameters, $A(z)$, in descending powers of $z$. |
|  | $H(z)=\frac{\sqrt{e}}{A(z)}=\frac{\sqrt{e}}{1+a_{2} z^{-1}+\ldots+a_{(p+1)} z^{-p}}$ |
|  | Because the method characterizes the input data using an all-pole model, the correct choice of the model order p is important. |
|  | $[a, e]=\operatorname{armcov}(x, p)$ returns the variance estimate, $e$, of the white noise input to the AR model. |
| See Also | arburg, arcov, aryule, lpc, pmcov, prony |

## Purpose

Syntax

```
a = aryule(x,p)
[a,e] = aryule(x,p)
[a,e,k] = aryule(x,p)
```

See Also arburg, arcov, armcov, lpc, prony, pyulear

## barthannw in

## Purpose

## Syntax

Description

Compute a modified Bartlett-Hann window
w = barthannwin(n)
$\mathrm{w}=$ barthannwin( n ) returns an n-point modified Bartlett-Hann window in the column vector w. Like Bartlett, Hann, and Hamming windows, this window has a mainlobe at the origin and asymptotically decaying sidel obes on both sides. It is a linear combination of weighted Bartlett and Hann windows with near sidel obes lower than both Bartlett and Hann and with far sidel obes lower than both Bartlett and Hamming windows. Themainlobe width of the modified Bartlett-Hann window is not increased relative to either Bartlett or Hann window mainlobes.

Note The Hann window is also called the Hanning window.

```
N=64;
w = barthannwin(N);
plot(w); axis([1 N O 1]);
title('64-point Modified Bartlett-Hann window');
```



Algorithm

See Also

References

The equation for computing the coefficients of a Modified Bartlett-Hanning window is

$$
w[k+1]=0.62-0.48\left|\left(\frac{k}{n-1}-0.5\right)\right|+0.38 \cos \left(2 \pi\left(\frac{k}{n-1}-0.5\right)\right)
$$

where $0 \leq k \leq(n-1)$.
bartlett, hann, blackman, blackmanharris, bohmanwin, chebwin, gausswin, hamming, kaiser, nuttallwin, rectwin, triang, tukeywin, window
[1] Ha, Y.H., and J.A. Pearce. "A New Window and Comparison to Standard Windows." IEEE Transactions on Acoustics, Speech, and Signal Processing. Vol. 37, No. 2, (February 1999). pp. 298-301.
[2] Oppenheim, A.V., and R.W. Schafer. DiscreteTimeSignal Processing. Upper Saddle River, NJ : Prentice-H all, 1999, p. 468.

## Purpose Compute a Bartlett window

## Syntax <br> w = bartlett(n)

Description
$w=$ bartlett ( $n$ ) returns an $n$-point Bartlett window in the column vector $w$, where $n$ must be a positive integer. The coefficients of a Bartlett window are computed as follows:

- For n odd

$$
w[k+1]= \begin{cases}\frac{2 k}{n-1}, & 0 \leq k \leq \frac{n-1}{2} \\ 2-\frac{2(k)}{n-1}, & \frac{n-1}{2} \leq k \leq n-1\end{cases}
$$

- For $n$ even

$$
w[k+1]= \begin{cases}\frac{2(k)}{n-1}, & 0 \leq k \leq \frac{n}{2}-1 \\ \frac{2(n-k-1)}{n-1}, & \frac{n}{2} \leq k \leq n-1\end{cases}
$$

The Bartlett window is very similar to a triangular window as returned by the triang function. The Bartlett window always ends with zeros at samples 1 and n , however, while the triangular window is nonzero at those points. For $n$ odd, the center $n-2$ points of bartlett ( $n$ ) are equivalent to triang ( $n-2$ ).

Note If you specify a one-point window (set $\mathrm{n}=1$ ), the value 1 is returned.

## Example

$\mathrm{N}=64$;
w = bartlett(N);
plot(w); axis([1 N 0 1]);
title('Bartlett Window')


[^3]References
[1] Oppenheim, A.V., and R.W. Schafer. Discrete-TimeSignal Processing. Upper Saddle River, NJ : Prentice-H all, 1999, pp. 468-471.

| Purpose | Bessel analog lowpass filter prototype |
| :---: | :---: |
| Syntax | [z, p, k] = besselap(n) |
| Description | [ $\mathrm{z}, \mathrm{p}, \mathrm{k}]=$ besselap( n ) returns the poles and gain of an order n Bessel analog lowpass filter prototype. $n$ must be less than or equal to 25 . The function returns the poles in the length $n$ column vector $p$ and the gain in scalar $k . z$ is an empty matrix because there are no zeros. The transfer function is |
|  | $H(s)=\frac{k}{(s-p(1))(s-p(2)) \cdots(s-p(n))}$ |
|  | besselap normalizes the poles and gain so that at low frequency and high frequency the Bessel prototype is asymptotically equivalent to the Butterworth prototype of the same order [1]. The magnitude of the filter is less than $\sqrt{1 / 2}$ at the unity cutoff frequency $\Omega_{\mathrm{C}}=1$. |
|  | Analog Bessel filters are characterized by a group delay that is maximally flat at zero frequency and almost constant throughout the passband. The group delay at zero frequency is |
|  | $\left(\frac{(2 n)!}{2^{n} n!}\right)^{1 / n}$ |
| Algorithm | besselap finds the filter roots from a look-up table constructed using the Symbolic Math Tool box. |
| See Also | besself, buttap, cheb1ap, cheb2ap, ellipap |
|  | Also see the Symbolic M ath Tool box documentation. |
| References | [1] Rabiner, L.R., and B. Gold. Theory and Application of Digital Signal Processing. Englewood Cliffs, NJ : Prentice-Hall, 1975. Pgs. 228-230. |


| Purpose | Bessel analog filter design |
| :--- | :--- |
| Syntax | $[b, a]=\operatorname{besself}(n, W n)$ |
|  | $[b, a]=\operatorname{bessel} f(n, W n, ' f t y p e$ |
|  | $[z, p, k]=\operatorname{bessel}(\ldots)$ |
|  | $[A, B, C, D]=\operatorname{bessel}(\ldots)$ |

besself designs lowpass, bandpass, highpass, and bandstop analog Bessel filters. Analog Bessel filters are characterized by almost constant group delay across the entire passband, thus preserving the wave shape of filtered signals in the passband. Digital Bessel filters do not retain this quality, and besself therefore does not support the design of digital Bessel filters.
[b,a] = besself( $\mathrm{n}, \mathrm{Wn}$ ) designs an order n lowpass analog filter with cutoff frequency $W n$. It returns the filter coefficients in the length $n+1$ row vectors $b$ and $a$, with coefficients in descending powers of $s$, derived from the transfer function

$$
H(s)=\frac{B(s)}{A(s)}=\frac{b(1) s^{n}+b(2) s^{n-1}+\cdots+b(n+1)}{s^{n}+a(2) s^{n-1}+\cdots+a(n+1)}
$$

Cutoff frequency is the frequency at which the magnitude response of the filter begins to decrease significantly. For besself, the cutoff frequency wn must be greater than 0 . The magnitude response of a Bessel filter designed by besself is always less than $\sqrt{1 / 2}$ at the cutoff frequency, and it decreases as the order n increases.

If $W n$ is a two-element vector, $W n=[w 1 w 2]$ with $w 1<w 2$, then besself $(n, W n)$ returns an order $2 * \mathrm{n}$ bandpass analog filter with passband $w 1<\omega<w 2$.
[b,a] = besself( $\mathrm{n}, \mathrm{Wn}$, 'ftype') designs a highpass or bandstop filter, where the string 'ftype' is:

- 'high' for a highpass analog filter with cutoff frequency Wn
- 'stop' for an order $2 * n$ bandstop analog filter if Wn is a two-element vector, Wn = [w1 w2]

The stopband is w1 $<\omega<w 2$.

With different numbers of output arguments, besself directly obtains other realizations of the anal og filter. To obtain zero-pole-gain form, use three output arguments as shown below.
$[z, p, k]=\operatorname{besself}(n, W n)$ or
[ $\left.\mathrm{z}, \mathrm{p}, \mathrm{k}]=\operatorname{besself(\mathrm {n},\mathrm {Wn},'ftype}{ }^{\prime}\right)$ returns the zeros and poles in length n or $2^{*} n$ column vectors $z$ and $p$ and the gain in the scalar $k$.

To obtain state-space form, use four output arguments as shown below.

$$
\begin{aligned}
& {[A, B, C, D]=\operatorname{besself}(n, W n) \text { or }} \\
& {[A, B, C, D]=\operatorname{besself}\left(n, W n, '^{\prime} \text { ftype' }\right) \text { where } A, B, C, \text { and } D \text { are }} \\
& x=A x+B u \\
& y=C x+D u
\end{aligned}
$$

and u is the input, x is the state vector, and y is the output.

## Example

Design a fifth-order analog lowpass Bessel filter that suppresses frequencies greater than $10,000 \mathrm{rad} / \mathrm{s}$ and plot the frequency response of the filter using freqs.

```
[b,a] = besself(5,10000);
freqs(b,a) % Plot frequency response
```



## Limitations

## Algorithm

See Also besselap, butter, cheby1, cheby2, ellip

Purpose Bilinear transformation method for analog-to-digital filter conversion

```
Syntax [zd,pd,kd] = bilinear(z,p,k,fs)
[zd,pd,kd] = bilinear(z,p,k,fs,Fp)
[numd,dend] = bilinear(num,den,fs)
[numd,dend] = bilinear(num,den,fs,Fp)
[Ad,Bd,Cd,Dd] = bilinear(A,B,C,D,fs)
[Ad,Bd,Cd,Dd] = bilinear(A,B,C,D,fs,Fp)
```

Description The bilinear transformation is a mathematical mapping of variables. In digital filtering, it is a standard method of mapping the s or analog plane into the z or digital plane. It transforms analog filters, designed using classical filter design techniques, into their discrete equivalents.

The bilinear transformation maps the s-plane into the z-plane by

$$
H(z)=\left.H(s)\right|_{S=2 f_{s} \frac{z-1}{z+1}}
$$

This transformation maps the $\mathrm{j} \Omega$ axis (from $\Omega=-\infty$ to $+\infty$ ) repeatedly around the unit circle ( $\mathrm{e}^{\mathrm{j} \omega}$, from $\omega=-\pi$ to $\pi$ ) by

$$
\omega=2 \tan ^{-1}\left(\frac{\Omega}{2 \mathrm{f}_{\mathrm{s}}}\right)
$$

bilinear can accept an optional parameter Fp that specifies prewarping. Fp, in hertz, indicates a "match" frequency, that is, a frequency for which the frequency responses before and after mapping match exactly. In prewarped mode, the bilinear transformation maps the s-plane into the z-plane with

$$
H(z)=\left.H(s)\right|_{s=\frac{2 \pi f_{p}}{}} ^{\tan \left(\pi \frac{f_{\mathrm{p}}}{f_{\mathrm{s}}}\right)} \frac{(z-1)}{(z+1)}
$$

With the prewarping option, bilinear maps the $j \Omega$ axis (from $\Omega=-\infty$ to $+\infty$ ) repeatedly around the unit circle ( $\mathrm{e}^{\mathrm{j} \omega}$, from $\omega=-\pi$ to $\pi$ ) by

$$
\omega=2 \tan ^{-1}\left(\frac{\Omega \tan \left(\pi \frac{f_{p}}{f_{s}}\right)}{2 \pi f_{p}}\right)
$$

In prewarped mode, bilinear matches the frequency $2 \pi \mathrm{f}_{p}$ (in radians per second) in the s-plane to the normalized frequency $2 \pi \mathrm{f}_{p} / \mathrm{f}_{s}$ (in radians per second) in the z-plane.

The bilinear function works with three different linear system representations: zero-pole-gain, transfer function, and state-space form.

## Zero-Pole-G ain

[zd,pd,kd] = bilinear(z, p,k,fs) and
[zd, pd,kd] = bilinear (z, p, k,fs, Fp) convert the s-domain transfer function specified by $z, p$, and $k$ to a discrete equivalent. Inputs $z$ and $p$ are column vectors containing the zeros and poles, k is a scalar gain, and fs is the sampling frequency in hertz. bilinear returns the discrete equivalent in column vectors zd and pd and scalar kd. Fp is the optional match frequency, in hertz, for prewarping.

## Transfer Function

[numd, dend] = bilinear (num, den,fs) and
[numd, dend] = bilinear(num, den,fs,Fp) convert an s-domain transfer function given by num and den to a discreteequivalent. Row vectors num and den specify the coefficients of the numerator and denominator, respectively, in descending powers of $s$.

$$
\frac{\text { num }(s)}{\operatorname{den}(s)}=\frac{\operatorname{num}(1) s^{n}+\cdots+\operatorname{num}(n) s+\operatorname{num}(n+1)}{\operatorname{den}(1) s^{m}+\cdots+\operatorname{den}(m) s+\operatorname{den}(m+1)}
$$

fs is the sampling frequency in hertz. bilinear returns the discrete equivalent in row vectors numd and dend in descending powers of $z$ (ascending powers of $z^{-1}$ ). Fp is the optional match frequency, in hertz, for prewarping.

## State-Space

$[A d, B d, C d, D d]=$ bilinear (A, B, C, D,fs) and
[Ad, Bd, Cd, Dd] = bilinear (A, B , C, D, fs , Fp) convert the continuous-time state-space system in matrices $A, B, C, D$,

$$
\begin{aligned}
& x=A x+B u \\
& y=C x+D u
\end{aligned}
$$

to the discrete-time system

$$
\begin{aligned}
x[n+1] & =A_{d} x[n]+B_{d} u[n] \\
y[n] & =C_{d} x[n]+D_{d} u[n]
\end{aligned}
$$

fs is the sampling frequency in hertz. bilinear returns the discrete equivalent in matrices Ad, Bd, Cd, Dd. Fp is the optional match frequency, in hertz, for prewarping.

Algorithm bilinear uses one of two algorithms depending on the format of the input linear system you supply. One algorithm works on the zero-pole-gain format and the other on the state-space format. For transfer function representations, bilinear converts to state-space form, performs the transformation, and converts the resulting state-space system back to transfer function form.

## Zero-Pole-G ain Algorithm

For a system in zero-pole-gain form, bilinear performs four steps:
1 If Fp is present, $\mathrm{k}=2 * \mathrm{pi} \mathrm{FFp}^{2} / \tan (\mathrm{pi} * \mathrm{Fp} / \mathrm{fs})$; otherwise $\mathrm{k}=2 * \mathrm{fs}$.
2 It strips any zeros at $\pm \infty$ using
z = z(find(finite(z)));

3 It transforms the zeros, poles, and gain using

```
pd = (1+p/k)./(1-p/k);
zd = (1+z/k)./(1-z/k);
kd = real(k*prod(fs-z)./prod(fs-p));
```

4 It adds extra zeros at -1 so the resulting system has equivalent numerator and denominator order.

## State-Space Algorithm

For a system in state-space form, bilinear performs two steps:
1 If Fp is present, $\mathrm{k}=2^{*} \mathrm{pi}^{*} \mathrm{Fp} / \tan \left(\mathrm{pi} \mathrm{F}_{\mathrm{Fp}} / \mathrm{fs}\right)$; else $\mathrm{k}=2 * \mathrm{fs}$.
2 It computes Ad, Bd, Cd, and Dd in terms of A, B, C, and D using

$$
\begin{aligned}
& A_{d}=\left(I+\left(\frac{1}{k}\right) A\right)\left(I-\left(\frac{1}{k}\right) A\right)^{-1} \\
& B_{d}=\frac{2 k}{r}\left(I-\left(\frac{1}{k}\right) A\right)^{-1} B \\
& C_{d}=r C\left(I-\left(\frac{1}{k}\right) A\right)^{-1} \\
& D_{d}=\left(\frac{1}{k}\right) C\left(I-\left(\frac{1}{k}\right) A\right)^{-1} B+D
\end{aligned}
$$

bilinear implements these relations using conventional MATLAB statements. The scalar $r$ is arbitrary; bilinear uses $r=\sqrt{2 / k}$ to ensure good quantization noise properties in the resulting system.

## Diagnostics

See Also
bilinear requires that the numerator order be no greater than the denominator order. If this is not the case, bilinear displays

Numerator cannot be higher order than denominator.
For bilinear to distinguish between the zero-pole-gain and transfer function linear system formats, the first two input parameters must be vectors with the same orientation in these cases. If this is not the case, bilinear displays

First two arguments must have the same orientation.
impinvar, lp2bp, lp2bs, lp2hp, lp2lp

## bilinear

References [1] Parks, T.W., and C.S. Burrus. Digital Filter Design. New York: J ohn Wiley \& Sons, 1987. Pgs. 209-213.
[2] Oppenheim, A.V., and R.W. Schafer. Discrete-TimeSignal Processing. Upper Saddle River, NJ : Prentice-H all, 1999, pp. 450-454.

## Purpose Permute data into bit-reversed order

| Syntax | $y=$ bitrevorder $(x)$ |
| :--- | :--- |
| $[y, i]=\operatorname{bitrevorder}(x)$ |  |

Description bitrevorder is useful for pre-arranging filter coefficients so that bit-reversed ordering does not have to be performed as part of an FFT or inverse FFT computation. This can improve run-time efficiency for external applications or for Simulink Blockset models. Note that MATLAB fft and ifft process linear input and output.
$y=$ bitrevorder(x) returns the input data in bit-reversed order in vector or matrix $y$. The length of $x$ must be an integer power of 2. If $x$ is a matrix, the bit-reversal occurs on the first dimension of $x$ with size greater than $1 . y$ is the same size as $x$.
[y,i] = bitrevorder(x) returns the bit-reversed vector or matrix y and the bit-reversed indices $i$, such that $y=x(i)$. Recall that MATLAB uses 1-based indexing, so the first index of $y$ will be 1 , not 0 .

The following table shows the numbers 0 through 7, the corresponding bits and the bit-reversed numbers.

| Linear <br> Index | Bits | Bit- <br> Reversed | Bit-Reversed <br> Index |
| :---: | :---: | :---: | :---: |
| 0 | 000 | 000 | 0 |
| 1 | 001 | 100 | 4 |
| 2 | 010 | 010 | 2 |
| 3 | 011 | 110 | 6 |
| 4 | 100 | 001 | 1 |
| 5 | 101 | 101 | 5 |
| 6 | 110 | 011 | 3 |
| 7 | 111 | 111 | 7 |

## bitrevorder



See Also fft, ifft

## Purpose Compute a Blackman window

Syntax $\quad$| $\mathrm{w}=\operatorname{blackman}(\mathrm{n})$ |
| :--- |
| w |$=\operatorname{blackman}\left(\mathrm{n}, \mathrm{sflag} \mathrm{I}^{\prime}\right)$

## Description

$w=$ blackman ( $n$ ) returns the n-point symmetric Blackman window in the column vector $w$, where $n$ is a positive integer.
$\mathrm{w}=\mathrm{blackman}(\mathrm{n}$, 'sflag') returns an n-point Blackman window using the window sampling specified by 'sflag', which can be either 'periodic' or 'symmetric' (the default). When 'periodic' is specified, blackman computes a length $n+1$ window and returns the first $n$ points.

Note If you specify a one-point window (set $\mathrm{n}=1$ ), the value 1 is returned.

## Algorithm

The equation for computing the coefficients of a Blackman window is

$$
\mathrm{w}[\mathrm{k}+1]=0.42-0.5 \cos \left(2 \pi \frac{\mathrm{k}}{\mathrm{n}-1}\right)+0.08 \cos \left(4 \pi \frac{\mathrm{k}}{\mathrm{n}-1}\right), \quad \mathrm{k}=0, \ldots, \mathrm{n}-1
$$

Blackman windows have slightly wider central lobes and less sideband leakage than equivalent length Hamming and Hann windows.

## Examples

```
N=64;
w = blackman(N);
plot(w); axis([1 N O 1]);
title('Blackman Window')
```



## Algorithm

References

## See Also

The equation for computing the coefficients of a Blackman window is

$$
w[k+1]=0.42-0.5 \cos \left(2 \pi \frac{k}{n-1}\right)+0.08 \cos \left(4 \pi \frac{k}{n-1}\right), \quad k=0, \ldots, n-1
$$

Blackman windows haveslightly wider central lobes and less sideband leakage than equivalent length Hamming and Hann windows.
barthannwin, bartlett, blackmanharris, bohmanwin, chebwin, gausswin, hamming, hann, kaiser, nuttallwin, rectwin, triang, tukeywin, window
[1] Oppenheim, A.V., and R.W. Schafer. Discrete-TimeSignal Processing. U pper Saddle River, NJ : Prentice-H all, 1999, pp. 468-471.

## blackmanharris

## Purpose Compute a minimum 4-term Blackman-harris window

## Syntax <br> w = blackmanharris(n)

Description

## Example

$\mathrm{w}=$ blackmanharris( n ) returns an n-point, minimum, 4-term
Blackman-harris window in the column vector w . The window is minimum in the sense that its maximum sidel obes are minimized.

```
N=32;
w = blackmanharris(N);
plot(w); axis([1 N 0 1]);
title('32-point Blackman-harris window');
```

32-point Blackman-harris window


## Algorithm

The equation for computing the coefficients of a minimum 4-term Blackman-harris window is

$$
w[k+1]=a_{0}-a_{1} \cos \left(2 \pi \frac{k}{n-1}\right)+a_{2} \cos \left(4 \pi \frac{k}{n-1}\right)-a_{3} \cos \left(6 \pi \frac{k}{n-1}\right)
$$

where $0 \leq k \leq(n-1)$.

The coefficients for this window are

$$
\begin{aligned}
& a_{0}=0.35875 \\
& a_{1}=0.48829 \\
& a_{2}=0.14128 \\
& a_{3}=0.01168
\end{aligned}
$$

# See Also barthannwin, bartlett, blackman, bohmanwin, chebwin, gausswin, hann, hamming, kaiser, nuttallwin, rectwin, triang, tukeywin, window 

References
[1] harris, f. j. "On the Use of Windows for Harmonic Analysis with theDiscrete Fourier Transform." Proceedings of theIEEE. Vol. 66 (J anuary 1978). pp. 51-84.

## Purpose Compute a Bohman window

## Syntax <br> w = bohmanwin(n)

Description

## Example

Compute a 64-point Bohman window.

```
```

N=64;

```
```

N=64;
w = bohmanwin(N);
w = bohmanwin(N);
plot(w); axis([1 N 0 1]);
plot(w); axis([1 N 0 1]);
title('64-point Bohman window');

```
```

title('64-point Bohman window');

```
```



Algorithm time domain, it is the product of a triangular window and a single cycle of a cosine with a term added to set the first derivative to zero at the boundary. Bohman windows fall off as $1 / w^{4}$.

The equation for computing the coefficients of a Bohman window is
$\mathrm{w}=$ bohmanwin( n ) returns an n-point Bohman window in column vector w . A Bohman window is the convolution of two half-duration cosine lobes. In the

## bohmanw in

$$
w[k+1]=\left[1.0-\frac{\left(\mathrm{k}-\frac{\mathrm{N}}{2}\right)}{\frac{\mathrm{N}}{2}}\right] \cos \left[\pi \frac{\left(\mathrm{k}-\frac{\mathrm{N}}{2}\right)}{\frac{\mathrm{N}}{2}}\right]+\frac{1}{\pi} \sin \left[\pi \frac{\left(\mathrm{k}-\frac{\mathrm{N}}{2}\right)}{\frac{\mathrm{N}}{2}}\right]
$$

where $0 \leq|k| \leq N$.
See Also barthannwin, bartlett, blackman, blackmanharris, chebwin, gausswin, hann, hamming, kaiser, nuttallwin, rectwin, triang, tukeywin, window

References [1] harris, f. j. "On the Use of Windows for Harmonic Analysis with the Discrete Fourier Transform." Proceedings of theIEEE. Vol. 66 (J anuary 1978). p. 67.

## Purpose

Syntax

Description

```
y = buffer(x,n)
```

y = buffer(x,n)
y = buffer(x,n,p)
y = buffer(x,n,p)
y = buffer(x,n,p,opt)
y = buffer(x,n,p,opt)
[y,z] = buffer(...)
[y,z] = buffer(...)
[y,z,opt] = buffer(...)

```
[y,z,opt] = buffer(...)
```

Buffer a signal vector into a matrix of data frames
$y=\operatorname{buffer}(x, n)$ partitions a length-L signal vector $x$ into nonoverlapping data segments (frames) of length n. Each data frame occupies one column of matrix output $y$, which has $n$ rows and ceil ( $\mathrm{L} / \mathrm{n}$ ) columns. If L is not evenly divisible by $n$, the last column is zero-padded to length $n$.
$y=\operatorname{buffer}(x, n, p)$ overlaps or underlaps successive frames in the output matrix by $p$ samples:

- F or $0<p<n$ (overlap), buffer repeats the final $p$ samples of each frame at the beginning of the following frame. For example, if $x=1: 30$ and $n=7$, an overlap of $p=3$ looks like this.


The first frame starts with p zeros (the default initial condition), and the number of columns in $y$ is ceil( $L /(n-p)$ ).

- For $p<0$ (underlap), buffer skips p samples between consecutive frames. For example, if $x=1: 30$ and $n=7$, a buffer with underlap of $p=-3$ looks like this.

| $y=$ |  |  |
| ---: | :--- | :--- |
| 1 | 11 | 21 |
| 2 | 12 | 22 |
| 3 | 13 | 23 |
| 4 | 14 | 24 |
| 5 | 15 | 25 |
| 6 | 16 | 26 |
| 7 | 17 | 27 |$\quad$ skipped \(\left\{\begin{array}{rrr}8 \& 18 \& 28 <br>

9 \& 19 \& 29 <br>
10 \& 20 \& 30\end{array}\right\}\)

The number of columns in $y$ is ceil( $L /(n-p)$ ).
$y=$ buffer ( $x, n, p, o p t$ ) specifies a vector of samples to precede $x(1)$ in an overlapping buffer, or the number of initial samples to skip in an underlapping buffer:

- For $0<p<n$ (overlap), opt specifies a length-p vector to insert beforex(1) in the buffer. This vector can be considered an initial condition, which is needed when the current buffering operation is one in a sequence of consecutive buffering operations. To maintain the desired frame overlap from one buffer to the next, opt should contain the final $p$ samples of the previous buffer in the sequence. See "Continuous Buffering" below.
By default, opt is zeros ( $\mathrm{p}, 1$ ) for an overlapping buffer. Set opt to ' nodelay ' to skip the initial condition and begin filling the buffer immediately with $x(1)$. In this case, $L$ must be length ( $p$ ) or longer. For example, if $x=1: 30$ and $n=7$, a buffer with overlap of $p=3$ looks like this.

- For $p<0$ (underlap), opt is an integer value in the range [ $0,-\mathrm{p}$ ] specifying the number of initial input samples, $x$ (1:opt), toskip before adding samples
to the buffer. The first value in the buffer is therefore $\times(o p t+1)$. By default, opt is zero for an underlapping buffer.
This option is especially useful when the current buffering operation is one in a sequence of consecutive buffering operations. To maintain the desired frame underlap from one buffer to the next, opt should equal the difference between the total number of points to skip between frames ( $p$ ) and the number of points that were available to be skipped in the previous input to buffer. If the previous input had fewer than $p$ points that could be skipped after filling the final frame of that buffer, the remaining opt points need to be removed from the first frame of the current buffer. See "Continuous Buffering" below for an example of how this works in practice.
$[y, z]=\operatorname{buffer}(\ldots)$ partitions the length-L signal vector $x$ into frames of length $n$, and outputs only the full frames in $y$. If $y$ is an overlapping buffer, it has n rows and m columns, where

```
m = floor(L/(n-p)) % When length(opt) =p
```

or

```
    m = floor((L-n)/(n-p))+1 % When opt = 'nodelay'
```

If y is an underlapping buffer, it has n rows and m columns, where

```
m = floor((L-opt)/(n-p)) + (rem((L-opt),(n-p)) >= n)
```

If the number of samples in the input vector (after the appropriate overlapping or underlapping operations) exceeds the number of places available in the n-by-m buffer, the remaining samples in $x$ are output in vector $z$, which for an overlapping buffer has length

```
length(z) = L - m*(n-p) % When length(opt) = p
```

or

```
length(z) = L - ((m-1)*(n-p)+n)% When opt ='nodelay'
```

and for an underlapping buffer has length

```
length(z) = (L-opt) - m*(n-p)
```

Output $z$ shares the same orientation (row or column) as $x$. If there are no remaining samples in the input after the buffer with the specified overlap or underlap is filled, z is an empty vector.
[ $y, z$, opt $]=\operatorname{buffer}(\ldots)$ returns the last $p$ samples of a overlapping buffer in output opt. In an underlapping buffer, opt is the difference between the total number of points to skip between frames ( -p ) and the number of points in x that were available to be skipped after filling the last frame:

- For $0<p<n$ (overlap), opt (as an output) contains the final p samples in the last frame of the buffer. This vector can be used as the initial condition for a subsequent buffering operation in a sequence of consecutive buffering operations. This allows the desired frame overlap to be maintained from one buffer to the next. See "Continuous Buffering" below.
- For $p<0$ (underlap), opt (as an output) is the difference between the total number of points to skip between frames $(-\mathrm{p})$ and the number of points in x that were available to be skipped after filling the last frame.

```
opt = m*(n-p) + opt - L % z is the empty vector.
```

where opt on the right-hand side is the input argument to buffer, and opt on the left-hand side is the output argument. Here $m$ is the number of columns in the buffer, which is

```
m = floor((L-opt)/(n-p)) + (rem((L-opt),(n-p))>=n)
```

Note that for an underlapping buffer output opt is always zero when output z contains data.
The opt output for an underlapping buffer is especially useful when the current buffering operation is one in a sequence of consecutive buffering operations. The opt output from each buffering operation specifies the number of samples that need to be skipped at the start of the next buffering operation to maintain the desired frame underlap from one buffer to the next. If fewer than $p$ points were available to be skipped after filling the final frame of the current buffer, the remaining opt points need to be removed from the first frame of the next buffer.
In a sequence of buffering operations, the opt output from each operation should be used as the opt input to the subsequent buffering operation. This ensures that the desired frame overlap or underlap is maintained from buffer
to buffer, as well as from frame to frame within the same buffer. See
"Continuous Buffering" below for an example of how this works in practice.

## Continuous Buffering

In a continuous buffering operation, the vector input to the buffer function represents one frame in a sequence of frames that make up a discrete signal. Thesesignal frames can originate in a frame-based data acquisition process, or within a frame-based algorithm like the FFT.

As an example, you might acquire data from an A/D card in frames of 64 samples. In the simplest case, you could rebuffer the data into frames of 16 samples; buffer with $n=16$ creates a buffer of four frames from each 64 -element input frame. The result is that the signal of frame size 64 has been converted to a signal of frame size 16; no samples were added or removed.

In the general case where the original signal frame size, $L$, is not equally divisible by the new frame size, $n$, the overflow from the last frame needs to be captured and recycled into the following buffer. Y ou can do this by iteratively calling buffer on input $x$ with the two-output-argument syntax.

```
\([y, z]=\operatorname{buffer}([z ; x], n) \quad \% x\) is a column vector.
\([y, z]=\operatorname{buffer}([z, x], n) \quad \% x\) is a row vector.
```

This simply captures any buffer overflow in $z$, and prepends the data to the subsequent input in the next call to buffer. Again, the input signal, $x$, of frame size L , has been converted to a signal of frame size n without any insertion or deletion of samples.

Note that continuous buffering cannot be done with the single-output syntax $y=$ buffer (...), because thelast frame of $y$ in this case is zero padded, which adds new samples to the signal.

Continuous buffering in the presence of overlap and underlap is handled with the opt parameter, which is used as both an input and output to buffer. The following two examples demonstrate how the opt parameter should be used.

## Examples Example 1: Continuous 0 verlapping Buffers

First create a buffer containing 100 frames, each with 11 samples.

```
data = buffer(1:1100,11); % 11 samples per frame
```

Imagine that the frames (columns) in the matrix called data are the sequential outputs of a data acquisition board sampling a physical signal: data ( $:, 1$ ) is the first D/A output, containing the first 11 signal samples; data $(:, 2)$ is the second output, containing the next 11 signal samples, and so on.

You want to rebuffer this signal from the acquired frame size of 11 to a frame size of 4 with an overlap of 1 . To do this, you will repeatedly call buffer to operate on each successive input frame, using the opt parameter to maintain consistency in the overlap from one buffer to the next.

Set the buffer parameters.

```
n = 4; % New frame size
p = 1; % Overlap
opt = -5; % Value of y(1)
z = []; % Initialize the carry-over vector.
```

Now repeatedly call buffer, each time passing in a new signal frame from data. Note that overflow samples (returned in z) are carried over and prepended to the input in the subsequent call to buffer.

```
for i=1:size(data,2), % Loop over each source frame (column).
    x = data(:,i); % A single frame of the D/A output
    [y,z,opt] = buffer([z;x],n,p,opt);
    disp(y); % Display the buffer of data.
    pause
end
```


## buffer

Here's what happens during the first four iterations.

| Iteration | Input frame [z; $\mathrm{l}^{\prime}$ ' | opt (input) | opt (output) | Output buffer (y) | Overflow (z) |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $\mathrm{i}=1$ | [1:11] | $-5$ | (9) | $\left[\begin{array}{ccc}-5 & 3 & 6 \\ 1 & 4 & 7 \\ 2 & 5 & 8 \\ 3 & 6 & 9\end{array}\right]$ | [10 11] |
| i=2 | [10 11 12:22] |  | (21) | $\left[\begin{array}{llll}9 & 12 & 15 & 18 \\ 10 & 13 & 16 & 19 \\ 11 & 14 & 17 & 20 \\ 12 & 15 & 18 & 21\end{array}\right]$ | [22] |
| $i=3$ | [22 23:33] | (21) | (33) | $\left[\begin{array}{llll}21 & 24 & 27 & 30 \\ 22 & 25 & 28 & 31 \\ 23 & 26 & 29 & 32 \\ 24 & 27 & 30 & 33\end{array}\right]$ | [] |
| $i=4$ | [34:44] |  | 42 |  | [43 44] |

Note that the size of the output matrix, $y$, can vary by a single column from one iteration to the next. This is typical for buffering operations with overlap or underlap.

## Example 2: Continuous Underlapping Buffers

Again create a buffer containing 100 frames, each with 11 samples.

```
data = buffer(1:1100,11); % 11 samples per frame
```

Again, imagine that data (:, 1 ) is the first D/A output, containing the first 11 signal samples; data ( $:, 2$ ) is the second output, containing the next 11 signal samples, and so on.
You want to rebuffer this signal from the acquired frame size of 11 to a frame size of 4 with an underlap of 2. To do this, you will repeatedly call buffer to operate on each successive input frame, using the opt parameter to maintain consistency in the underlap from one buffer to the next.

Set the buffer parameters.

```
n = 4; % New frame size
p = -2; % Underlap
opt = 1; % Skip the first input element, x(1).
z = []; % Initialize the carry-over vector.
```

Now repeatedly call buffer, each time passing in a new signal frame from data. Note that overflow samples (returned in z) are carried over and prepended to the input in the subsequent call to buffer.

```
for i=1:size(data,2), % Loop over each source frame (column).
    x = data(:,i); % A single frame of the D/A output
    [y,z,opt] = buffer([z;x],n,p,opt);
    disp(y); % Display the buffer of data.
    pause
end
```


## buffer

Here's what happens during the first three iterations.

| Iteration | Input frame [ $z ; x]^{\prime}$ | opt (input) | opt (output) | Output buffer (y) | Overflow (z) |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $\mathrm{i}=1$ | [1:11] | (1) | (2) |  | [] |
| i=2 | [12:22] | (2) | $0$ | $\begin{aligned} \longrightarrow & {\left.\left[\begin{array}{l} 12 \\ 13 \end{array}\right]\right\} \text { skip } } \\ & {\left[\begin{array}{l} 14 \\ 15 \\ 16 \\ 17 \end{array}\right] } \\ & {\left.\left[\begin{array}{l} 18 \\ 19 \end{array}\right]\right\} \text { skip } } \end{aligned}$ | [20 2122 22] |
| $i=3$ | [20 2122 23:33] |  | 0 | $\begin{aligned} - & {\left.\left[\begin{array}{ll} - & - \end{array}\right]\right\} \text { skip } } \\ & {\left[\begin{array}{ll} 20 & 26 \\ 21 & 27 \\ 22 & 28 \\ 23 & 29 \end{array}\right] } \\ & {\left.\left[\begin{array}{ll} 24 & 30 \\ 25 & 31 \end{array}\right]\right\} \text { skip } } \end{aligned}$ | [32 33] |

Diagnostics

See Also

Error messages are displayed when $p \geq n$ or length (opt) $\neq$ length $(p)$ in an overlapping buffer case.

Frame overlap P must be less than the buffer size $N$.
Initial conditions must be specified as a length-P vector.
reshape

## Purpose Butterworth analog lowpass filter prototype

## Syntax $\quad[z, p, k]=\operatorname{buttap}(n)$

Description

## Algorithm

See Also besselap, butter, cheb1ap, cheb2ap, ellipap
References are no zeros. The transfer function is

$$
H(s)=\frac{z(s)}{p(s)}=\frac{k}{(s-p(1))(s-p(2)) \cdots(s-p(n))}
$$

Butterworth filters are characterized by a magnitude response that is squared magnitude response function is

$$
|H(\omega)|^{2}=\frac{1}{1+\left(\omega / \omega_{0}\right)^{2 n}}
$$ result.

```
z = [];
p = exp(sqrt(-1)*(pi*(1:2:2*n-1)/(2*n)+pi/2)).';
k = real(prod(-p));
```

[ $\mathrm{z}, \mathrm{p}, \mathrm{k}]=$ buttap( n ) returns the poles and gain of an order n Butterworth analog lowpass filter prototype. The function returns the poles in the length $n$ column vector $p$ and the gain in scalar $k$. $z$ is an empty matrix because there maximally flat in the passband and monotonic overall. In the lowpass case, the first $2 n-1$ derivatives of the squared magnitude response are zero at $\omega=0$. The
corresponding to a transfer function with poles equally spaced around a circle in the left half plane. The magnitude response at the cutoff frequency $\omega_{0}$ is always $1 / \sqrt{2}$ regardless of the filter order. buttap sets $\omega_{0}$ to 1 for a normalized
[1] Parks, T.W., and C.S. Burrus. Digital Filter Design. New York: J ohn Wiley \& Sons, 1987. Chapter 7.

## Purpose Butterworth analog and digital filter design

```
Syntax [b,a] = butter(n,Wn)
[b,a] = butter(n,Wn,'ftype')
[b,a] = butter(n,Wn,'s')
[b,a] = butter(n,Wn,'ftype','s')
[z,p,k] = butter(...)
[A,B,C,D] = butter(...)
```

Description butter designs lowpass, bandpass, highpass, and bandstop digital and analog Butterworth filters. Butterworth filters are characterized by a magnitude response that is maximally flat in the passband and monotonic overall.

Butterworth filters sacrifice roll off steepness for monotonicity in the pass- and stopbands. Unless the smoothness of the Butterworth filter is needed, an elliptic or Chebyshev filter can generally provide steeper rolloff characteristics with a lower filter order.

## Digital Domain

[ $b, a]=$ butter ( $n, W n$ ) designs an order $n$ lowpass digital Butterworth filter with cutoff frequency $W$. It returns the filter coefficients in length $n+1$ row vectors $b$ and $a$, with coefficients in descending powers of $z$.

$$
H(z)=\frac{B(z)}{A(z)}=\frac{b(1)+b(2) z^{-1}+\cdots+b(n+1) z^{-n}}{1+a(2) z^{-1}+\cdots+a(n+1) z^{-n}}
$$

Cutoff frequency is that frequency where the magnitude response of the filter is $\sqrt{1 / 2}$. For butter, the normalized cutoff frequency $W n$ must be a number between 0 and 1 , where 1 corresponds to the $N$ yquist frequency, $\pi$ radians per sample.
If $W n$ is a two-element vector, $\mathrm{Wn}=\left[\begin{array}{ll}w 1 & w 2\end{array}\right]$, butter returns an order $2 *$ digital bandpass filter with passband w1 < $\omega<\mathrm{w} 2$.
$[\mathrm{b}, \mathrm{a}]=\operatorname{butter}(\mathrm{n}, \mathrm{Wn}$, 'ftype') designs a highpass or bandstop filter, where the string 'ftype' is either:

- 'high' for a highpass digital filter with cutoff frequency Wn
- 'stop' for an order $2 * \mathrm{n}$ bandstop digital filter if Wn is a two-element vector, $W n=[w 1 \quad w 2]$. The stopband is $w 1<\omega<w 2$.

With different numbers of output arguments, butter directly obtains other realizations of the filter. To obtain zero-pole-gain form, use three output arguments as shown below.
$[z, p, k]=\operatorname{butter}(n, W n)$ or
[z,p,k] = butter(n,Wn,'ftype') returns the zeros and poles in length n column vectors $z$ and $p$, and the gain in the scalar $k$.

To obtain state-space form, use four output arguments as shown below.

$$
\begin{aligned}
{[A, B, C, D] } & =\operatorname{butter}(n, W n) \text { or } \\
{[A, B, C, D] } & =\operatorname{butter}\left(n, W n, \text { ' ftype' }^{\prime}\right) \text { where } A, B, C, \text { and } D \text { are } \\
x[n+1] & =A x[n]+B u[n] \\
y[n] & =C x[n]+\operatorname{Du}[n]
\end{aligned}
$$

and u is the input, x is the state vector, and y is the output.

## Analog Domain

[b,a] = butter ( $\mathrm{n}, \mathrm{Wn}, \mathrm{'s}^{\prime}$ ') designs an order n lowpass analog Butterworth filter with cutoff frequency Wn rad/s. It returns the filter coefficients in the length $n+1$ row vectors $b$ and $a$, in descending powers of $s$, derived from the transfer function

$$
H(s)=\frac{B(s)}{A(s)}=\frac{b(1) s^{n}+b(2) s^{n-1}+\cdots+b(n+1)}{s^{n}+a(2) s^{n-1}+\cdots+a(n+1)}
$$

butter's cutoff frequency Wn must be greater than 0 rad/s.
If Wn is a two-element vector with $w 1<w 2$, butter ( $\mathrm{n}, \mathrm{Wn}, \mathrm{s}$ ' ) returns an order $2 * n$ bandpass analog filter with passband $w 1<\omega<w 2$.
$[\mathrm{b}, \mathrm{a}]=\operatorname{butter}(\mathrm{n}, \mathrm{Wn}$, 'ftype ', 's') designs a highpass or bandstop filter. With different numbers of output arguments, butter directly obtains other realizations of theanalog filter. To obtain zero-pole-gain form, usethree output arguments as shown below.

[ $\mathrm{z}, \mathrm{p}, \mathrm{k}]=$ butter( $\mathrm{n}, \mathrm{Wn}$, 'ftype','s') returns the zeros and poles in length $n$ or $2 * n$ column vectors $z$ and $p$ and the gain in the scalar $k$.
To obtain state-space form, use four output arguments as shown below.
[A, B , C , D] $=$ butter $\left(\mathrm{n}, \mathrm{Wn}, \mathrm{s}^{\prime} \mathrm{s}\right)$ or
$[A, B, C, D]=\operatorname{butter}\left(\mathrm{n}, \mathrm{Wn}\right.$, 'ftype' ${ }^{\prime} \mathrm{s}$ ') where $\mathrm{A}, \mathrm{B}, \mathrm{C}$, and D are
$x=A x+B u$
$y=C x+D u$
and u is the input, x is the state vector, and y is the output.

## Examples Example 1

For data sampled at 1000 Hz , design a 9th-order highpass Butterworth filter with cutoff frequency of 300 Hz .

```
[b,a] = butter(9,300/500,'high');
```

The filter's frequency response is

```
freqz(b,a,128,1000)
```



## Example 2

Design a 10th-order bandpass Butterworth filter with a passband from 100 to 200 Hz and plot its impulse response, or unit sample response

```
n = 5; Wn = [100 200]/500;
```

$[b, a]=\operatorname{butter}(n, W n)$;
[y,t] = impz(b,a,101);
stem(t,y)


| Limitations | F or high order filters, the state-space form is the most numerically accurate, followed by the zero-pole-gain form. The transfer function coefficient form is the least accurate; numerical problems can arise for filter orders as low as 15. |
| :---: | :---: |
| Algorithm | butter uses a five-step algorithm: |
|  | 1 It finds the lowpass analog prototype poles, zeros, and gain using the buttap function. |
|  | 2 It converts the poles, zeros, and gain into state-space form. |
|  | 3 It transforms the lowpass filter into a bandpass, highpass, or bandstop filter with desired cutoff frequencies, using a state-space transformation. |
|  | 4 For digital filter design, butter uses bilinear to convert the analog filter into a digital filter through a bilinear transformation with frequency prewarping. Careful frequency adjustment guarantees that the analog filters and the digital filters will have the same frequency response magnitude at Wn or w1 and w2. |
|  | 5 It converts the state-space filter back to transfer function or zero-pole-gain form, as required. |
| See Also | besself, buttap, buttord, cheby1, cheby2, ellip, maxflat |

Purpose Calculate the order and cutoff frequency for a Butterworth filter
Syntax $\quad \begin{aligned} {[n, W n] } & =\text { buttord }(W p, W s, R p, R s) \\ {[n, W n] } & =\text { buttord }\left(W p, W s, R p, R s, s^{\prime}\right)\end{aligned}$

## Description

buttord calculates the minimum order of a digital or analog Butterworth filter required to meet a set of filter design specifications.

## Digital Domain

[ $n, W n$ ] = buttord (Wp,Ws, Rp, Rs) returns the lowest order, $n$, of the digital Butterworth filter that loses no more than Rp dB in the passband and has at least Rs dB of attenuation in the stopband. The scalar (or vector) of corresponding cutoff frequencies, Wn, is also returned. Use the output arguments n and Wn in butter.

Choose the input arguments to specify the stopband and passband according to the following table.

Table 7-1: Description of Stopband and Passband Filter Parameters

| Wp | Passband corner frequency wp, the cutoff frequency, is a scalar <br> or a two-element vector with values between 0 and 1, with 1 <br> corresponding to the normalized $N$ yquist frequency, $\pi$ radians <br> per sample. |
| :--- | :--- |
| Ws | Stopband corner frequency Ws, is a scalar or a two-element <br> vector with values between 0 and 1, with 1 corresponding to <br> the normalized Nyquist frequency. |
| Rp | Passband ripple, in decibels. This value is the maximum <br> permissible passband loss in decibels. |
| Rs | Stopband attenuation, in decibels. This value is the number of <br> decibels the stopband is down from the passband. |

Use the following guide to specify filters of different types.
Table 7-2: Filter Type Stopband and Passband Specifications

| Filter Type | Stopband and Passband Conditions | Stopband | Passband |
| :---: | :---: | :---: | :---: |
| Lowpass | Wp <Ws, both scalars | (Ws, 1) | (0,Wp) |
| Highpass | Wp > Ws, both scalars | (0,Ws) | (Wp, 1) |
| Bandpass | The interval specified by ws contains the one specified by wp <br> (Ws(1) < Wp(1) < Wp(2) < Ws(2)). | $\begin{aligned} & (0, \mathrm{Ws}(1)) \\ & \text { and } \\ & (\text { Ws }(2), 1) \end{aligned}$ | (Wp(1), Wp (2)) |
| Bandstop | The interval specified by wp contains the one specified by ws $(W p(1)<W s(1)<W s(2)<W p(2))$. | $\begin{aligned} & (0, W p(1)) \\ & \text { and } \\ & (W p(2), 1) \end{aligned}$ | (Ws(1), Ws (2)) |

If your filter specifications call for a bandpass or bandstop filter with unequal ripple in each of the passbands or stopbands, design separate lowpass and highpass filters according to the specifications in this table, and cascade the two filters together.

## Analog Domain

[ $\mathrm{n}, \mathrm{Wn}$ ] = buttord (Wp,Ws,Rp,Rs, 's') finds the minimum order n and cutoff frequencies Wn for an analog Butterworth filter. You specify the frequencies Wp and Ws similar to Table 7-1, only in this case you specify the frequency in radians per second, and the passband or the stopband can be infinite.

Use buttord for lowpass, highpass, bandpass, and bandstop filters as described in Table 7-2.

## Examples

## Example 1

For data sampled at 1000 Hz , design a lowpass filter with less than 3 dB of ripple in the passband, defined from 0 to 40 Hz , and at least 60 dB of attenuation in the stopband, defined from 150 Hz to the Nyquist frequency ( 500 Hz ). Plot the filter's frequency response.

```
Wp = 40/500; Ws = 150/500;
[n,Wn] = buttord(Wp,Ws,3,60)
n =
        5
Wn =
        0.0810
[b,a] = butter(n,Wn);
freqz(b,a,512,1000); title('n=5 Butterworth Lowpass Filter')
```




## Example 2

Next design a bandpass filter with passband of 60 Hz to 200 Hz , with less than 3 dB of ripple in the passband, and 40 dB attenuation in the stopbands that are 50 Hz wide on both sides of the passband.

```
Wp = [60 200]/500; Ws = [50 250]/500;
Rp = 3; Rs = 40;
[n,Wn] = buttord(Wp,Ws,Rp,Rs)
n =
    1 6
Wn =
    0.1198 0.4005
[b,a] = butter(n,Wn);
freqz(b,a,128,1000)
title('n=16 Butterworth Bandpass Filter')
```



Algorithm

| buttord's order prediction formula is described in [1]. It operates in the analog |
| :--- |
| domain for both analog and digital cases. For the digital case, it converts the |
| frequency parameters to the s-domain before estimating the order and natural |
| frequency, and then converts back to the z-domain. |
| buttord initially devel ops a lowpass filter prototype by transforming the |
| passband frequencies of the desired filter to 1 rad/s (for lowpass and highpass |
| filters) and to -1 and 1 rad/s (for bandpass and bandstop filters). It then |
| computes the minimum order required for a lowpass filter to meet thestopband |
| specification. |

See Also
References

butter, cheb1ord, cheb2ord, ellipord, kaiserord | [1] Rabiner, L.R., and B. Gold. Theory and Application of Digital Signal |
| :--- |

| Purpose | Complex cepstral analysis |
| :---: | :---: |
| Syntax | ```xhat = cceps(x) [xhat,nd] = cceps(x) [xhat,nd,xhat1] = cceps(x) [...] = cceps(x,n)``` |
| Description | Cepstral analysis is a nonlinear signal processing technique that is applied most commonly in speech processing and homomorphic filtering [1]. <br> xhat $=$ cceps $(x)$ returns the complex cepstrum of the (assumed real) sequence $x$. The input is altered, by the application of a linear phase term, to have no phase discontinuity at $\pm \pi$ radians. That is, it is circularly shifted (after zero padding) by some samples, if necessary, to have zero phase at $\pi$ radians. <br> [ xhat, nd ] = cceps (x) returns the number of samples nd of (circular) delay added to x prior to finding the complex cepstrum. <br> [xhat, nd, xhat1] $=$ cceps ( $x$ ) returns a second complex cepstrum, computed using an alternate rooting algorithm, in xhat1. The alternate method ([1] p.795) is useful for short sequences that can be rooted and do not have zeros on the unit circle. For these signals, xhat1 can provide a verification of xhat. <br> [...] = cceps ( $\mathrm{x}, \mathrm{n}$ ) zero pads x to length n and returns the length n complex cepstrum of $x$. |
| Algorithm | cceps, in its basic form, is an M-file implementation of algorithm 7.1 in [2]. A lengthy Fortran program reduces to three lines of MATLAB code: ```h = fft(x); logh = log(abs(h)) + sqrt(-1)*rcunwrap(angle(h)); y = real(ifft(logh));``` <br> rcunwrap is a special version of unwrap that subtracts a straight line from the phase. |
| See Also | icceps, hilbert, rceps, unwrap |
| References | [1] Oppenheim, A.V., and R.W. Schafer. DiscreteTime Signal Processing. Upper Saddle River, NJ : Prentice-H all, 1999, pp. 788-789. |

[2]IEEE. Programs for Digital Signal Processing. IEEE Press. New York:J ohn Wiley \& Sons, 1979.
Purpose Convert a cell array for second-order sections to a second-order section matrix
Syntax m = cell2sos(c)
Description $m=$ cell2sos (c) changes a 1-by-L cell array c consisting of 1-by-2 cell arraysinto an L-by- 6 second-order section matrix $m$. Matrix $m$ takes the same form asthe matrix generated by tf2sos. You can use $m=$ cell2sos( $c$ ) to invert theresults of $c=\operatorname{sos} 2 c e l l(m)$.
c must be a cell array of the form

$$
c=\{\text { \{b1 a1\} \{b2 a2\} } \ldots \text { \{bL aL\} \} }
$$

where both bi and ai are row vectors of at most length 3 , and $\mathrm{i}=1,2, \ldots, \mathrm{~L}$. The resulting matrix $m$ is given by

$$
m=[b 1 a 1 ; b 2 a 2 ; \ldots ; b L a L]
$$

See Also sos2cell, tf2sos

| Purpose | Chebyshev Type I analog lowpass filter prototype |
| :---: | :---: |
| Syntax | [ $\mathrm{z}, \mathrm{p}, \mathrm{k}]=\operatorname{cheb1ap}(\mathrm{n}, \mathrm{Rp})$ |
| Description | $[z, p, k]=c h e b 1 a p(n, R p)$ returns the poles and gain of an order $n$ Chebyshev Typel analog lowpass filter prototype with Rp dB of ripplein the passband. The function returns the poles in the length $n$ column vector $p$ and the gain in scalar k. z is an empty matrix, because there are no zeros. The transfer function is |
|  | $H(s)=\frac{z(s)}{p(s)}=\frac{k}{(s-p(1))(s-p(2)) \cdots(s-p(n))}$ |
|  | Chebyshev Type I filters are equiripple in the passband and monotonic in the stopband. The poles are evenly spaced about an ellipse in the left half plane. The Chebyshev Type I cutoff frequency $\omega_{0}$ is set to 1.0 for a normalized result. This is the frequency at which the passband ends and the filter has magnitude response of $10^{-\mathrm{Rp} / 20}$. |
| See Also | besselap, buttap, cheby1, cheb2ap, ellipap |
| References | [1] Parks, T.W., and C.S. Burrus. Digital Filter Design. New York: J ohn Wiley \& Sons, 1987. Chapter 7. |


| Purpose | Calculate the order for a Chebyshev Typel filter |
| :--- | :--- |
| Syntax | $[n, W n]=$ cheb1ord $(W p, W s, R p, R s)$ <br> $[n, W n]=$ cheb1ord $(W p, W s, R p, R s, ~ ' s ')$ |
| Description | cheb1ord calculates the minimum order of a digital or analog Chebyshev <br> Typel filter required to meet a set of filter design specifications. |

## Digital Domain

[ $\mathrm{n}, \mathrm{Wn}$ ] = cheb1ord (Wp,Ws,Rp,Rs) returns the lowest order $n$ of theChebyshev Type I filter that loses no more than Rp dB in the passband and has at least Rs dB of attenuation in the stopband. The scalar (or vector) of corresponding cutoff frequencies Wn , is al so returned. Use the output arguments n and Wn with the cheby 1 function.

Choose the input arguments to specify the stopband and passband according to the following table.

Table 7-3: Description of Stopband and Passband Filter Parameters

| Wp | Passband corner frequency wp, the cutoff frequency, is a scalar <br> or a two-element vector with values between 0 and 1 , with 1 <br> corresponding to the normalized Nyquist frequency, $\pi$ radians <br> per sample. |
| :--- | :--- |
| Ws | Stopband corner frequency Ws, is a scalar or a two-element <br> vector with values between 0 and 1 , with 1 corresponding to <br> the normalized Nyquist frequency. |
| Rp | Passband ripple, in decibels. This value is the maximum <br> permissible passband loss in decibels. |
| Rs | Stopband attenuation, in decibels. This value is the number of <br> decibels the stopband is down from the passband. |

Use the following guide to specify filters of different types
Table 7-4: Filter Type Stopband and Passband Specifications

| Filter Type | Stopband and Passband Conditions | Stopband | Passband |
| :---: | :---: | :---: | :---: |
| Lowpass | Wp <Ws, both scalars | (Ws, 1) | (0,Wp) |
| Highpass | Wp > Ws, both scalars | (0,Ws) | (Wp, 1) |
| Bandpass | The interval specified by ws contains the one specified by wp $(W s(1)<W p(1)<W p(2)<W s(2)) .$ | $\begin{aligned} & (0, \operatorname{Ws}(1)) \\ & \text { and } \\ & (\operatorname{Ws}(2), 1) \end{aligned}$ | (Wp (1) , Wp (2)) |
| Bandstop | The interval specified by Wp contains the one specified by Ws $(W p(1)<W s(1)<W s(2)<W p(2))$ | $\begin{aligned} & (0, W p(1)) \\ & \text { and } \\ & (W p(2), 1) \end{aligned}$ | (Ws (1) , Ws (2)) |

If your filter specifications call for a bandpass or bandstop filter with unequal ripple in each of the passbands or stopbands, design separate lowpass and highpass filters according to the specifications in this table, and cascade the two filters together.

## Analog Domain

[ $\mathrm{n}, \mathrm{Wn}$ ] = cheb1ord (Wp,Ws,Rp,Rs, 's') finds the minimum order $n$ and cutoff frequencies Wn for an analog Chebyshev Typel filter. You specify the frequencies Wp and Ws similar to Table 7-3, only in this case you specify the frequency in radians per second, and the passband or the stopband can be infinite.

Use cheb1ord for lowpass, highpass, bandpass, and bandstop filters as described in Table 7-4.

Examples For data sampled at 1000 Hz , design a lowpass filter with less than 3 dB of ripple in the passband defined from 0 to 40 Hz and at least 60 dB of ripple in the stopband defined from 150 Hz to the Nyquist frequency $(500 \mathrm{~Hz})$.

```
Wp = 40/500; Ws = 150/500;
Rp = 3; Rs = 60;
[n,Wn] = cheb1ord(Wp,Ws,Rp,Rs)
```

```
n =
    4
Wn =
    0.0800
[b,a] = cheby1(n,Rp,Wn);
freqz(b,a,512,1000);
title('n=4 Chebyshev Type I Lowpass Filter')
```




Next design a bandpass filter with a passband of 60 Hz to 200 Hz , with less than 3 dB of ripple in the passband, and 40 dB attenuation in the stopbands that are 50 Hz wide on both sides of the passband.

```
Wp = [60 200]/500; Ws = [50 250]/500;
Rp = 3; Rs = 40;
[n,Wn] = cheb1ord(Wp,Ws,Rp,Rs)
n =
    7
Wn =
    0.1200
                                0.4000
[b,a] = cheby1(n,Rp,Wn);
freqz(b,a,512, 1000);
title('n=7 Chebyshev Type I Bandpass Filter')
```



## Algorithm

See Also
References
cheb1ord uses theChebyshev lowpass filter order prediction formula described in [1]. The function performs its calculations in the analog domain for both analog and digital cases. F or the digital case, it converts the frequency parameters to thes-domain before the order and natural frequency estimation process, and then converts them back to the z-domain.
cheb1ord initially develops a lowpass filter prototype by transforming the passband frequencies of the desired filter to 1 rad/s (for low- or highpass filters) or to -1 and $1 \mathrm{rad} / \mathrm{s}$ (for bandpass or bandstop filters). It then computes the minimum order required for a lowpass filter to meet the stopband specification.
buttord, cheby1, cheb2ord, ellipord, kaiserord
[1] Rabiner, L.R., and B. Gold. Theory and Application of Digital Signal Processing. Englewood Cliffs, NJ : Prentice-Hall, 1975. Pg. 241.

| Purpose | Chebyshev Type II analog lowpass filter prototype |
| :---: | :---: |
| Syntax | [ $\mathrm{z}, \mathrm{p}, \mathrm{k}$ ] $=\operatorname{cheb} 2 \mathrm{ap}(\mathrm{n}, \mathrm{Rs}$ ) |
| Description | [ $z, p, k]=$ cheb2ap( $n, R s$ ) finds the zeros, poles, and gain of an order $n$ Chebyshev Type II analog lowpass filter prototype with stopband ripple Rs dB down from the passband peak value. cheb2ap returns the zeros and poles in length $n$ column vectors $z$ and $p$ and the gain in scalar $k$. If $n$ is odd, $z$ is length $n-1$. The transfer function is |
|  | $H(s)=\frac{z(s)}{p(s)}=k \frac{(s-z(1))(s-z(2)) \cdots(s-z(n))}{(s-p(1))(s-p(2)) \cdots(s-p(n))}$ |
|  | Chebyshev Type II filters are monotonic in the passband and equiripple in the stopband. The pole locations are the inverse of the pole locations of cheb1ap, whose poles are evenly spaced about an ellipse in the left half plane. The Chebyshev Type II cutoff frequency $\omega_{0}$ is set to 1 for a normalized result. This is the frequency at which the stopband begins and the filter has magnitude response of $10^{-\mathrm{Rs} / 20}$. |
| Algorithm | Chebyshev Type II filters are sometimes called inverse Chebyshev filters because of their relationship to Chebyshev Type I filters. The cheb2ap function is a modification of the Chebyshev Type I prototype algorithm: |
|  | 1 cheb2ap replaces the frequency variable $\omega$ with $1 / \omega$, turning the lowpass filter into a highpass filter while preserving the performance at $\omega=1$. <br> 2 cheb2ap subtracts the filter transfer function from unity. |
| See Also | besselap, buttap, cheb1ap, cheby2, ellipap |
| References | [1] Parks, T.W., and C.S. Burrus. Digital Filter Design. New Y ork: J ohn Wiley \& Sons, 1987. Chapter 7. |

Purpose Calculate the order for a Chebyshev Type II filter
Syntax $\quad \begin{aligned} {[n, W n] } & =\operatorname{cheb2ord}(W p, W s, R p, R s) \\ {[n, W n] } & =\text { cheb2ord }(W p, W s, R p, R s, ' s ')\end{aligned}$
Description
cheb2ord calculates the minimum order of a digital or analog Chebyshev Type II filter required to meet a set of filter design specifications.

## Digital Domain

[ $n, W n$ ] $=$ cheb2ord (Wp,Ws, Rp,Rs) returns thelowest order $n$ of the Chebyshev Type II filter that loses no more than Rp dB in the passband and has at least Rs dB of attenuation in the stopband. The scalar (or vector) of corresponding cutoff frequencies Wn, is also returned. Use the output arguments $n$ and Wn in cheby2.

Choose the input arguments to specify the stopband and passband according to the following table.

Table 7-5: Description of Stopband and Passband Filter Parameters

| Wp | Passband corner frequency wp, the cutoff frequency, is a scalar <br> or a two-element vector with values between 0 and 1, with 1 <br> corresponding to the normalized Nyquist frequency, $\pi$ radians <br> per sample. |
| :--- | :--- |
| Ws | Stopband corner frequency ws, is a scalar or a two-element <br> vector with values between 0 and 1, with 1 corresponding to <br> the normalized Nyquist frequency. |
| Rp | Passband ripple, in decibels. This value is the maximum <br> permissible passband loss in decibels. |
| Rs | Stopband attenuation, in decibels. This value is the number of <br> decibels the stopband is down from the passband. |

Use the following guide to specify filters of different types.
Table 7-6: Filter Type Stopband and Passband Specifications

| Filter Type | Stopband and Passband Conditions | Stopband | Passband |
| :---: | :---: | :---: | :---: |
| Lowpass | Wp <Ws, both scalars | (Ws, 1) | (0,Wp) |
| Highpass | Wp > Ws, both scalars | (0,Ws) | (Wp, 1) |
| Bandpass | The interval specified by ws contains the one specified by wp <br> (Ws(1) < Wp(1) < Wp(2) < Ws(2)). | $\begin{aligned} & (0, \mathrm{Ws}(1)) \\ & \text { and } \\ & (\operatorname{Ws}(2), 1) \end{aligned}$ | (Wp(1), Wp (2) ) |
| Bandstop | The interval specified by Wp contains the one specified by Ws $(W p(1)<W s(1)<W s(2)<W p(2)) .$ | $\begin{aligned} & (0, W p(1)) \\ & \text { and } \\ & (W p(2), 1) \end{aligned}$ | (Ws(1),Ws(2)) |

If your filter specifications call for a bandpass or bandstop filter with unequal ripple in each of the passbands or stopbands, design separate lowpass and highpass filters according to the specifications in this table, and cascade the two filters together.

## Analog Domain

[ $\mathrm{n}, \mathrm{Wn}$ ] = cheb2ord (Wp,Ws,Rp,Rs, 's') finds the minimum order $n$ and cutoff frequencies Wn for an analog Chebyshev Type II filter. You specify the frequencies Wp and Ws similar to Table 7-5, only in this case you specify the frequency in radians per second, and the passband or the stopband can be infinite.

Use cheb2ord for lowpass, highpass, bandpass, and bandstop filters as described in Table 7-6.

## Examples

## Example 1

For data sampled at 1000 Hz , design a lowpass filter with less than 3 dB of ripple in the passband defined from 0 to 40 Hz , and at least 60 dB of attenuation in the stopband defined from 150 Hz to the Nyquist frequency ( 500 Hz ).

```
Wp = 40/500; Ws = 150/500;
Rp = 3; Rs = 60;
[n,Wn] = cheb2ord(Wp,Ws,Rp,Rs)
n =
    4
Wn =
    0.2597
[b,a] = cheby2(n,Rs,Wn);
freqz(b,a,512,1000);
title('n=4 Chebyshev Type II Lowpass Filter')
```




## Example 2

Next design a bandpass filter with a passband of 60 Hz to 200 Hz , with less than 3 dB of ripple in the passband, and 40 dB attenuation in the stopbands that are 50 Hz wide on both sides of the passband.

```
Wp = [60 200]/500; Ws = [50 250]/500;
Rp = 3; Rs = 40;
[n,Wn] = cheb2ord(Wp,Ws,Rp,Rs)
n =
    7
Wn =
    0.1019 0.4516
[b,a] = cheby2(n,Rs,Wn);
freqz(b,a,512,1000)
title('n=7 Chebyshev Type II Bandpass Filter')
```




| Algorithm | cheb2ord uses theChebyshev lowpass filter order prediction formula described <br> in [1]. The function performs its calculations in the anal og domain for both <br> analog and digital cases. For the digital case, it converts the frequency <br> parameters to the s-domain before the order and natural frequency estimation <br> process, and then converts them back to the z-domain. <br> cheb2ord initially develops a lowpass filter prototype by transforming the <br> stopband frequencies of the desired filter to 1 rad/s (for low- and highpass <br> filters) and to -1 and 1 rad/s (for bandpass and bandstop filters). It then <br> computes the minimum order required for a lowpass filter to meet the <br> passband specification. |
| :--- | :--- |
| See Also | buttord, cheb1ord, cheby2, ellipord, kaiserord |
| References | [1] Rabiner, L.R., and B. Gold. Theory and Application of Digital Signal <br> Processing. Englewood Cliffs, NJ : Prentice-Hall, 1975. Pg. 241. |

## Purpose Compute a Chebyshev window

Syntax
Description
$w=\operatorname{chebwin}(n, r)$
$w=c h e b w i n(n, r)$ returns the column vector $w$ containing the length $n$ Chebyshev window whose F ourier transform sidelobe magnitude is $r \mathrm{~dB}$ below the mainlobe magnitude.

Note If you specify a one-point window (set $n=1$ ), the value 1 is returned.

## Examples

## See Also

References
barthannwin, bartlett, blackman, blackmanharris, bohmanwin, gausswin, hamming, hann, kaiser, nuttallwin, rectwin, triang, tukeywin, window
[1]IEEE. Programs for Digital Signal Processing. IEEE Press. New York:J ohn Wiley \& Sons, 1979. Program 5.2.

Purpose
Syntax

## Description

Chebyshev Type I filter design (passband ripple)

```
[b,a] = cheby1(n,Rp,Wn)
[b,a] = cheby1(n,Rp,Wn,'ftype')
[b,a] = cheby1(n,Rp,Wn,'s')
[b,a] = cheby1(n,Rp,Wn,'ftype','s')
[z,p,k] = cheby1(...)
[A,B,C,D] = cheby1(...)
```

cheby1 designs lowpass, bandpass, highpass, and bandstop digital and analog Chebyshev Type I filters. Chebyshev Type I filters are equiripple in the passband and monotonic in the stopband. Type I filters roll off faster than type II filters, but at the expense of greater deviation from unity in the passband.

## Digital Domain

[b,a] =cheby1 ( $\mathrm{n}, \mathrm{Rp}, \mathrm{Wn}$ ) designs an order n Chebyshev lowpass digital Chebyshev filter with cutoff frequency Wn and Rp dB of peak-to-peak ripple in the passband. It returns the filter coefficients in the length $n+1$ row vectors $b$ and $a$, with coefficients in descending powers of $z$.

$$
H(z)=\frac{B(z)}{A(z)}=\frac{b(1)+b(2) z^{-1}+\cdots+b(n+1) z^{-n}}{1+a(2) z^{-1}+\cdots+a(n+1) z^{-n}}
$$

Cutoff frequency is the frequency at which the magnitude response of the filter is equal to -Rp dB . For cheby 1 , the cutoff frequency W is a number between 0 and 1 , where 1 corresponds to the Nyquist frequency, $\pi$ radians per sample. Smaller values of passband ripple Rp lead to wider transition widths (shallower rolloff characteristics).

If Wn is a two-element vector, $\mathrm{Wn}=[\mathrm{w} 1 \mathrm{w} 2$ ], cheby1 returns an order $2 * \mathrm{n}$ bandpass filter with passband $\mathrm{w} 1<\omega<\mathrm{w} 2$.
$[b, a]=$ cheby1 ( $n, R p, W n$, 'ftype') designs a highpass or bandstop filter, where the string 'ftype' is either:

- 'high' for a highpass digital filter with cutoff frequency Wn
- 'stop' for an order $2 * \mathrm{n}$ bandstop digital filter if Wn is a two-element vector, Wn $=\left[\begin{array}{ll}w 1 & w 2\end{array}\right]$

The stopband is w1 $<\omega<w 2$.
With different numbers of output arguments, cheby1 directly obtains other realizations of the filter. To obtain zero-pole-gain form, use three output arguments as shown below.
$[z, p, k]=\operatorname{cheby} 1(n, R p, W n)$ or
$[z, p, k]=$ cheby 1 ( $n, R p, W n$, 'ftype') returns the zeros and poles in length $n$ column vectors $z$ and $p$ and the gain in the scalar $k$.

To obtain state-space form, use four output arguments as shown below.

$$
\begin{aligned}
{[A, B, C, D] } & =\text { cheby } 1(n, R p, W n) \text { or } \\
{[A, B, C, D] } & =\text { cheby } 1(n, R p, \text { Wn, 'ftype' }) \text { where } A, B, C, \text { and } D \text { are } \\
x[n+1] & =A x[n]+B u[n] \\
y[n] & =C x[n]+D u[n]
\end{aligned}
$$

and u is the input, x is the state vector, and y is the output.

## Analog Domain

$[b, a]=\operatorname{cheby} 1(n, R p, W n, ' s ')$ designs an order $n$ lowpass analog Chebyshev Typel filter with cutoff frequency $\mathrm{Wn} \mathrm{rad} / \mathrm{s}$. It returns the filter coefficients in length $n+1$ row vectors $b$ and $a$, in descending powers of $s$, derived from the transfer function

$$
H(s)=\frac{B(s)}{A(s)}=\frac{b(1) s^{n}+b(2) s^{n-1}+\cdots+b(n+1)}{s^{n}+a(2) s^{n-1}+\cdots+a(n+1)}
$$

Cutoff frequency is the frequency at which the magnitude response of the filter is -Rp dB . For cheby 1 , the cutoff frequency wn must be greater than $0 \mathrm{rad} / \mathrm{s}$.

If $W n$ is a two-element vector $W n=\left[\begin{array}{ll}w 1 & w 2\end{array}\right]$ with $w 1<w 2$, then cheby1 ( $\mathrm{n}, \mathrm{Rp}, \mathrm{Wn}, \mathrm{s} \mathrm{s}$ ') returns an order $2 * \mathrm{n}$ bandpass analog filter with passband w1 < $\omega<\mathrm{w} 2$.
[b,a] =cheby1 ( $\mathrm{n}, \mathrm{Rp}, \mathrm{Wn}$, 'ftype', 's') designs a highpass or bandstop filter.
You can supply different numbers of output arguments for cheby1 to directly obtain other realizations of the anal og filter. To obtain zero-pole-gain form, use three output arguments as shown below.
$[z, p, k]=$ cheby1 ( $n, R p, W n, ' s ')$ or
$[z, p, k]=$ cheby1 ( $n, R p, W n$, 'ftype', 's') returns the zeros and poles in length $n$ or $2 * n$ column vectors $z$ and $p$ and the gain in the scalar $k$.

To obtain state-space form, use four output arguments as shown below.
$[A, B, C, D]=$ cheby $1(n, R p, W n, ' s ')$ or
[A,B,C,D] =cheby1(n,Rp,Wn, 'ftype','s') where A, B, C, and D are defined as

$$
\begin{aligned}
& x=A x+B u \\
& y=C x+D u
\end{aligned}
$$

and u is the input, x is the state vector, and y is the output.

## Examples

## Example 1: Low pass Filter

For data sampled at 1000 Hz , design a 9th-order lowpass Chebyshev Type I
filter with 0.5 dB of ripple in the passband and a cutoff frequency of 300 Hz .

```
[b,a] = cheby1(9,0.5,300/500);
```

The frequency response of the filter is
freqz(b, a, 512, 1000)



## Example 2: Bandpass Filter

Design a 10th-order bandpass Chebyshev Type I filter with a passband from 100 to 200 Hz and plot its impulse response.

```
n = 10; Rp = 0.5;
Wn = [100 200]/500;
[b,a] = cheby1(n,Rp,Wn);
[y,t] = impz(b,a,101); stem(t,y)
```



## Limitations

## Algorithm

[^4]For high order filters, the state-space form is the most numerically accurate, followed by the zero-pole-gain form. The transfer function form is the least accurate; numerical problems can arise for filter orders as low as 15.
cheby 1 uses a five-step algorithm:
1 It finds the lowpass analog prototype poles, zeros, and gain using the cheb1ap function.
2 It converts the poles, zeros, and gain into state-space form.
3 It transforms the lowpass filter into a bandpass, highpass, or bandstop filter with desired cutoff frequencies, using a state-space transformation.
4 For digital filter design, cheby1 uses bilinear to convert the analog filter into a digital filter through a bilinear transformation with frequency prewarping. Careful frequency adjustment guarantees that the analog filters and the digital filters will have the same frequency response magnitude at Wn or w1 and w2.
5 It converts the state-space filter back to transfer function or zero-pole-gain form, as required.

## Purpose

## Syntax

## Description

Chebyshev Type II filter design (stopband ripple)

```
[b,a] = cheby2(n,Rs,Wn)
[b,a] = cheby2(n,Rs,Wn,'ftype')
[b,a] = cheby2(n,Rs,Wn,'s')
[b,a] = cheby2(n,Rs,Wn,'ftype','s')
[z,p,k] = cheby2(...)
[A,B,C,D] = cheby2(...)
```

cheby2 designs lowpass, highpass, bandpass, and bandstop digital and analog Chebyshev Type II filters. Chebyshev Type II filters are monotonic in the passband and equiripple in the stopband. Type II filters do not roll off as fast as typel filters, but are free of passband ripple.

## Digital Domain

[ $b, a]=c h e b y 2(n, R s, W n)$ designs an order $n$ lowpass digital Chebyshev Type II filter with cutoff frequency Wn and stopband ripple Rs dB down from the peak passband value. It returns the filter coefficients in the length $n+1$ row vectors $b$ and $a$, with coefficients in descending powers of $z$.

$$
H(z)=\frac{B(z)}{A(z)}=\frac{b(1)+b(2) z^{-1}+\cdots+b(n+1) z^{-n}}{1+a(2) z^{-1}+\cdots+a(n+1) z^{-n}}
$$

Cutoff frequency is the beginning of the stopband, where the magnitude response of the filter is equal to -Rs dB . For cheby2, the normalized cutoff frequency Wn is a number between 0 and 1 , where 1 corresponds to the $N$ yquist frequency. Larger values of stopband attenuation Rs lead to wider transition widths (shallower rolloff characteristics).

If Wn is a two-element vector, $\mathrm{Wn}=[\mathrm{w} 1 \mathrm{w} 2$ ], cheby2 returns an order $2 * \mathrm{n}$ bandpass filter with passband $w 1<\omega<w 2$.
[b, a] = cheby2( $\mathrm{n}, \mathrm{Rs}, \mathrm{Wn}$, ' ftype ') designs a highpass or bandstop filter, where the string 'ftype' is either:

- 'high' for a highpass digital filter with cutoff frequency Wn
- 'stop' for an order $2 * \mathrm{n}$ bandstop digital filter if Wn is a two-element vector, $W n=[w 1 \quad w 2]$. The stopband is $w 1<\omega<w 2$.

With different numbers of output arguments, cheby2 directly obtains other realizations of the filter. To obtain zero-polegain form, use three output arguments as shown below.

$$
[z, p, k]=\operatorname{cheby} 2(n, R s, W n) \text { or }
$$

[ $\mathrm{z}, \mathrm{p}, \mathrm{k}]=$ cheby2( $\mathrm{n}, \mathrm{Rs}, \mathrm{Wn}$, 'ftype') returns the zeros and poles in length n column vectors $z$ and $p$ and the gain in the scalar $k$.

To obtain state-space form, use four output arguments as shown below.

$$
\begin{aligned}
{[A, B, C, D] } & =\operatorname{cheby} 2(n, R s, W n) \text { or } \\
{[A, B, C, D] } & =\operatorname{cheby} 2\left(n, R s, W n, \text { ' ftype' }^{\prime}\right) \text { where } A, B, C, \text { and } D \text { are } \\
x[n+1] & =A x[n]+B u[n] \\
y[n] & =C x[n]+D u[n]
\end{aligned}
$$

and u is the input, x is the state vector, and y is the output.

## Analog Domain

[b, a] = cheby2 ( $\mathrm{n}, \mathrm{Rs}, \mathrm{Wn}, \mathrm{s}$ ' ) designs an order n lowpass analog Chebyshev Type II filter with cutoff frequency Wn. It returns the filter coefficients in the length $n+1$ row vectors $b$ and $a$, with coefficients in descending powers of $s$, derived from the transfer function.

$$
H(s)=\frac{B(s)}{A(s)}=\frac{b(1) s^{n}+b(2) s^{n-1}+\cdots+b(n+1)}{s^{n}+a(2) s^{n-1}+\cdots+a(n+1)}
$$

Cutoff frequency is the frequency at which the magnitude response of the filter is equal to -Rs dB. F or cheby2, the cutoff frequency Wn must be greater than 0 rad/s.

If Wn is a two-element vector $\mathrm{Wn}=[\mathrm{w} 1 \mathrm{w} 2$ ] with $\mathrm{w} 1<\mathrm{w} 2$, then cheby2( $\mathrm{n}, \mathrm{Rs}, \mathrm{Wn}, \mathrm{s} \mathrm{s}$ ') returns an order 2*n bandpass analog filter with passband w1 < $\omega<$ w2.
$[\mathrm{b}, \mathrm{a}]=\operatorname{cheby2}(\mathrm{n}, \mathrm{Rs}, \mathrm{Wn}$, ' ftype ', 's') designs a highpass or bandstop filter.

With different numbers of output arguments, cheby2 directly obtains other realizations of the analog filter. To obtain zero-pole-gain form, use three output arguments as shown below.

$$
[z, p, k]=\operatorname{cheby} 2(n, R s, W n, ' s ') \text { or }
$$

[ $\mathrm{z}, \mathrm{p}, \mathrm{k}]=$ cheby2( $\mathrm{n}, \mathrm{Rs}, \mathrm{Wn}$, 'ftype', 's') returns the zeros and poles in length $n$ or $2 * n$ column vectors $z$ and $p$ and the gain in the scalar $k$.

To obtain state-space form, use four output arguments as shown below.

$$
\begin{aligned}
& {[A, B, C, D]=\operatorname{cheby} 2\left(n, R s, W n, '^{\prime}\right) \text { or }} \\
& {[A, B, C, D]=\operatorname{cheby} 2\left(n, R s, W n, ' f t y p e^{\prime}, '^{\prime} s^{\prime}\right) \text { where } A, B, C, \text { and } D \text { are }} \\
& x=A x+B u \\
& y=C x+D u
\end{aligned}
$$

and u is the input, x is the state vector, and y is the output.

## Examples

## Example 1: Low pass Filter

For data sampled at 1000 Hz , design a ninth-order lowpass Chebyshev Type II filter with stopband attenuation 20 dB down from the passband and a cutoff frequency of 300 Hz .

$$
[b, a]=\text { cheby2 }(9,20,300 / 500) ;
$$

The frequency response of the filter is

```
freqz(b,a,512,1000)
```



## Example 2: Bandpass Filter

Design a fifth-order bandpass Chebyshev Typell filter with passband from 100 to 200 Hz and plot the impulse response of the filter.

```
n = 5; r = 20;
Wn = [100 200]/500;
[b,a] = cheby2(n,r,Wn);
[y,t] = impz(b,a,101); stem(t,y)
```



| Limitations | F or high order filters, the state-space form is the most numerically accurate, followed by the zero-pole-gain form. The transfer function coefficient form is the least accurate; numerical problems can arise for filter orders as low as 15. |
| :---: | :---: |
| Algorithm | cheby2 uses a five-step algorithm: |
|  | 1 It finds the lowpass analog prototype poles, zeros, and gain using the cheb2ap function. |
|  | 2 It converts poles, zeros, and gain into state-space form. |
|  | 3 It transforms the lowpass filter into a bandpass, highpass, or bandstop filter with desired cutoff frequencies, using a state-space transformation. |
|  | 4 For digital filter design, cheby2 uses bilinear to convert the analog filter into a digital filter through a bilinear transformation with frequency prewarping. Careful frequency adjustment guarantees that the analog filters and the digital filters will have the same frequency response magnitude at Wn or w1 and w2. |
|  | 5 It converts the state-space filter back to transfer function or zero-pole-gain form, as required. |
| See Also | besself, butter, cheb2ap, cheb1ord, cheby1, ellip |

## Purpose <br> Generate a swept-frequency cosine

## Syntax

```
y = chirp(t,f0,t1,f1)
y = chirp(t,f0,t1,f1,'method')
y = chirp(t,f0,t1,f1,'method',phi)
y = chirp(t,f0,t1,f1,'quadratic',phi,'shape')
```


## Description

$y=\operatorname{chirp}(t, f 0, t 1, f 1)$ generates samples of a linear swept-frequency cosine signal at the time instances defined in array $t$, where fo is the instantaneous frequency at time 0 , and $f 1$ is the instantaneous frequency at time t 1 . f 0 and f 1 are both in hertz. If unspecified, f 0 is $0, \mathrm{t} 1$ is 1 , and f 1 is 100 .
$y=\operatorname{chirp}(t, f 0, t 1, f 1$, 'method') specifies alternative sweep method options, where method can be:

- linear, which specifies an instantaneous frequency sweep $f_{i}(t)$ given by $\mathrm{f}_{\mathrm{i}}(\mathrm{t})=\mathrm{f}_{0}+\beta \mathrm{t}$
where

$$
\beta=\left(f_{1}-f_{0}\right) / t_{1}
$$

$\beta$ ensures that the desired frequency breakpoint $f_{1}$ at time $t_{1}$ is maintained.

- quadratic, which specifies an instantaneous frequency sweep $f_{i}(t)$ given by
$f_{i}(t)=f_{0}+\beta t^{2}$
where
$\beta=\left(f_{1}-f_{0}\right) / t_{1}{ }^{2}$
If $f_{0}>f_{1}$ (downsweep), the default shape is convex. If $f_{0}<f_{1}$ (upsweep), the default shape is concave.
- logarithmic specifies an instantaneous frequency sweep $f_{i}(t)$ given by

$$
\mathrm{f}_{\mathrm{i}}(\mathrm{t})=\mathrm{f}_{0}+10^{\beta t}
$$

where

$$
\beta=\left[\log _{10}\left(f_{1}-f_{0}\right)\right] / t_{1}
$$

F or a log-sweep, f1 must be greater than f0.
Each of the above methods can be entered as ' $1 \mathrm{i}^{\prime}$, ' q ', and ' 10 ', respectively.
$y=\operatorname{chirp}(t, f 0, t 1, f 1$, 'method', phi) allows an initial phase phi to be specified in degrees. If unspecified, phi is 0 . Default values are substituted for empty or omitted trailing input arguments.
$y=\operatorname{chirp}(t, f 0, t 1, f 1$, 'quadratic ', phi, 'shape') specifies the shape of the quadratic swept-frequency signal's spectrogram. shape is either concave or convex, which describes the shape of the parabola in the positive frequency axis. If shape is omitted, the default is convex for downsweep ( $f_{0}>f_{1}$ ) and is concave for upsweep ( $\mathrm{f}_{0}<\mathrm{f}_{1}$ ).


## Examples <br> Example 1

Compute the spectrogram of a chirp with linear instantaneous frequency deviation.

```
t = 0:0.001:2; % 2 secs @ 1kHz sample rate
y = chirp(t,0,1,150); % Start @ DC, cross 150Hz at t=1 sec
specgram(y,256,1e3,256,250) % Display the spectrogram
```



## Example 2

Compute the spectrogram of a chirp with quadratic instantaneous frequency deviation.

```
t = -2:0.001:2; % 土2 secs @ 1kHz sample rate
y = chirp(t,100,1,200,'quadratic'); % Start @ 100Hz, cross 200Hz
% at t=1 sec
specgram(y,128,1e3,128,120) % Display the spectrogram
```



## Example 3

Compute the spectrogram of a convex quadratic chirp.

```
t= -1:0.001:1;
    % +/-1 second @ 1kHz sample rate
fo=100; f1=400; % Start at 100Hz, go up to 400Hz
y=chirp(t,fo,1,f1,'q',[],'convex');
specgram(y,256,1000) % Display the spectrogram.
```



## Example 4

Compute the spectrogram of a concave quadratic chirp.

```
t= 0:0.001:1; %1 second @ 1kHz sample rate
fo=100; f1=25; % Start at 100Hz, go down to 25Hz
y=chirp(t,fo,1,f1,'q',[],'concave');
specgram(y,256,1000) % Display the spectrogram.
```

Concave chirp


See Also
cos, diric, gauspuls, pulstran, rectpuls, sawtooth, sin, sinc, square, tripuls

## Purpose

Estimate magnitude squared coherence function between two signals
Syntax

Description

```
Cxy = cohere(x,y)
Cxy = cohere(x,y,nfft)
[Cxy,f] = cohere(x,y,nfft,fs)
Cxy = cohere(x,y,nfft,fs,window)
Cxy = cohere(x,y,nfft,fs,window, numoverlap)
Cxy = cohere(x,y,\ldots.,'dflag')
cohere(x,y)
```

Cxy $=$ cohere $(x, y)$ finds the magnitude squared coherence between length $n$ signal vectors $x$ and $y$. The coherence is a function of the power spectra of $x$ and $y$ and the cross spectrum of $x$ and $y$.

$$
C_{x y}(f)=\frac{\left|P_{x y}(f)\right|^{2}}{P_{x x}(f) P_{y y}(f)}
$$

$x$ and $y$ must be the same length.
nfft specifies the FFT length that cohere uses. This value determines the frequencies at which the coherence is estimated. fs is a scalar that specifies the sampling frequency. window specifies a windowing function and the number of samples cohere uses in its sectioning of the $x$ and $y$ vectors. numoverlap is the number of samples by which the window sections overlap for both $x$ and $y$. Any arguments that you omit from the end of the parameter list use the default values shown below.

Cxy $=$ cohere $(x, y)$ uses the following default values:

- nfft $=$ min(256,length(x))
- $f s=2$
- window is a periodic Hann window of length nfft.
- numoverlap $=0$

If $x$ is real, cohere estimates the coherence function at positive frequencies only; in this case, the output Cxy is a column vector of length nfft/2 +1 for $n f f t$ even and ( $n f f t+1$ )/2 for $n$ odd. If $x$ or $y$ is complex, cohere estimates the coherence function at both positive and negative frequencies, and Cxy has length nfft.

Cxy = cohere ( $x, y, n f f t$ ) uses the FFT length nfft in estimating the power spectrum for $x$. Specify nfft as a power of 2 for fastest execution.

Cxy = cohere ( $x, y, n f f t, f s$ ) returns a vector $f$ of frequencies at which the function evaluates the coherence. $f s$ is the sampling frequency. $f$ is the same sizeas Cxy, so plot ( $\mathrm{f}, \mathrm{Cxy}$ ) plots the coherencefunction versus properly scaled frequency. fs has no effect on the output Cxy; it is a frequency scaling multiplier.
cohere ( $x, y, n f f t, f s$, window) specifies a windowing function and the number of samples per section of the vectors $x$ and $y$. If you supply a scalar for window, cohere uses a Hann window of that length. The length of the window must be less than or equal to $n f f t$; cohere zero pads the sections if the window length exceeds nfft.
cohere ( $x, y, n f f t, f s$, window, numoverlap) overlaps the sections of $x$ by numoverlap samples.

Note If you use cohere on two linearly related signals [1] with a single, non-overlapping window, the output for all frequencies is $\mathrm{Cxy}=1$.

You can use the empty matrix [ ] to specify the default value for any input argument except $x$ or $y$. For example,
cohere (x,y,[],[],kaiser(128,5));
uses 256 as the value for $n f f t$ and 2 as the value for fs .
cohere ( $\mathrm{x}, \mathrm{y}, \ldots, \mathrm{I}^{\prime}$ 'dflag') specifies a detrend option, where 'dflag' is:

- 'linear', to remove the best straight-linefit from the prewindowed sections of $x$ and $y$
- 'mean ', to remove the mean from the prewindowed sections of $x$ and $y$
- 'none ', for no detrending (default)

The 'dflag' parameter must appear last in the list of input arguments. cohere recognizes a 'dflag' string no matter how many intermediate arguments are omitted.
cohere with no output arguments plots the coherence estimate versus frequency in the current figure window.

## Example

Compute and plot the coherence estimate between two col ored noise sequences $x$ and $y$.

```
randn('state',0);
h = fir1(30,0.2,rectwin(31));
h1 = ones(1,10)/sqrt(10);
r = randn(16384,1);
x = filter(h1,1,r);
y = filter(h,1,x);
cohere(x,y,1024,[],[],512)
```



## Diagnostics

An appropriate diagnostic message is displayed when incorrect arguments are used.

Requires window's length to be no greater than the FFT length. Requires NOVERLAP to be strictly less than the window length. Requires positive integer values for NFFT and NOVERLAP. Requires vector (either row or column) input. Requires inputs $X$ and $Y$ to have the same length.
Algorithm
cohere estimates the magnitude squared coherence function [2] using Welch's method of power spectrum estimation (see references [3] and [4]), as follows:
1 It divides the signals x and y into separate overlapping sections, detrends each section, and multiplies each section by window.
2 It calculates the length nfft fast Fourier transform of each section.
3 It averages the squares of the spectra of the x sections to form Pxx, averages the squares of the spectra of the $y$ sections to form Pyy, and averages the products of the spectra of the $x$ and $y$ sections to form Pxy. It calculates Cxy by the following formula.

```
Cxy = abs(Pxy).^2/(Pxx.*Pyy)
```


## See Also

References
[1] Stoica, P., and R. Moses. Introduction to Spectral Analysis. Upper Saddle River, NJ : Prentice-Hall, 1997. Pgs. 61-64.
[2] Kay, S.M. Modern Spectral Estimation. Englewood Cliffs, NJ : Prentice-Hall, 1988. Pg. 454.
[3] Rabiner, L.R., and B. Gold. Theory and Application of Digital Signal Processing. Englewood Cliffs, NJ : Prentice-Hall, 1975.
[4] Welch, P.D. ‘The Use of Fast Fourier Transform for the Estimation of Power Spectra: A Method Based on Time Averaging Over Short, Modified Periodograms." IEEE Trans. Audio Electroacoust. Vol. AU-15 (J une 1967). Pgs. 70-73.

| Purpose | Convolution and polynomial multiplication |
| :---: | :---: |
| Syntax | $c=\operatorname{conv}(\mathrm{a}, \mathrm{b})$ |
| Description | $c=\operatorname{conv}(\mathrm{a}, \mathrm{b})$ convolves vectors a and b . The convolution sum is |
|  | N-1 |
|  | $c(n+1)=\sum_{k=0} a(k+1) b(n-k)$ |
|  | where $N$ is the maximum sequence length. The series is indexed from $n+1$ and $k+1$ instead of the usual $n$ and $k$ because MATLAB vectors run from 1 to $n$ instead of from 0 to $n-1$. |
|  | The conv function is part of the standard MATLAB language. |
| Example | The convolution of $a=\left[\begin{array}{ll}1 & 2\end{array}\right]$ and $b=\left[\begin{array}{ll}4 & 5\end{array}\right]$ is $c=\operatorname{conv}(a, b)$ |
|  | c $=$ |
|  | $\begin{array}{lllll}4 & 13 & 28 & 27 & 18\end{array}$ |
| Algorithm | The conv function is an M-file that uses the filter primitive. conv computes the convolution operation as FIR filtering with an appropriate number of zeros appended to the input. |
| See Also | conv2, convmtx, convn, deconv, filter, residuez, xcorr |

## Purpose

Syntax
$C=\operatorname{conv2}(A, B)$
$\mathrm{C}=\operatorname{conv2(\mathrm {A},\mathrm {B},\mathrm {shape}{}^{\prime })}$

## Description

## Examples

In image processing, the Sobel edge-finding operation is a two-dimensional convolution of an input array with the special matrix

```
s = [1 2 1; 0 0 0; -1 -2 -1];
```

Given any image, the following code extracts the horizontal edges.

$$
h=\operatorname{conv2}(I, s) ;
$$

The following code extracts the vertical edges first, and then extracts both horizontal and vertical edges combined.

```
v = conv2(I, s');
v2 = (sqrt(h.^2 + v.^2))
```

See Also conv, convn, deconv, filter2, xcorr, xcorr2

## Purpose <br> Convolution matrix

## Syntax <br> $A=$ convmtx (c,n) <br> $A=\operatorname{convmtx}(r, n)$

## Description

A convolution matrix is a matrix, formed from a vector, whose inner product with another vector is the convolution of the two vectors.
A $=$ convmtx ( $c, n$ ) where $c$ is a length $m$ column vector returns a matrix $A$ of size $(m+n-1)$-by- $n$. The product of $A$ and another column vector $x$ of length $n$ is the convolution of $c$ with $x$.
$A=$ convmtx $(r, n)$ where $r$ is a length $m$ row vector returns a matrix $A$ of size $n$-by- $(m+n-1)$. The product of $A$ and another row vector $x$ of length $n$ is the convolution of $r$ with $x$.
Example
Generate a simple convolution matrix.
h = [1 2 3 2 1];
h = [1 2 3 2 1];
convmtx(h,7)
convmtx(h,7)
ans =
ans =

| 1 | 2 | 3 | 2 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 0 | 1 | 2 | 3 | 2 | 1 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 1 | 2 | 3 | 2 | 1 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 1 | 2 | 3 | 2 | 1 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 1 | 2 | 3 | 2 | 1 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 1 | 2 | 3 | 2 | 1 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 1 | 2 | 3 | 2 | 1 |

Note that convmtx handles edge conditions by zero padding.
In practice, it is more efficient to compute convolution using

```
y = conv(c,x)
```

than by using a convolution matrix.

```
n = length(x);
y = convmtx(c,n)*x
```

Algorithm convmtx uses the function toeplitz to generate the convolution matrix.

## convmtx

See Also<br>conv, convn, conv2, dftmtx

## Purpose Compute the correlation coefficient matrix

Syntax $\quad$| $C$ | $=\operatorname{corrcoef}(X)$ |
| ---: | :--- |
| $C$ | $=\operatorname{corrcoef}(X, Y)$ |

## Description

See Also
cov, mean, median, std, xcorr, xcov

## Purpose

Syntax

Description

## Examples

randn('state', 1); n=0:99;
$\mathrm{s}=\exp \left(\mathrm{i}^{*} \mathrm{pi} / 2^{*} \mathrm{n}\right)+2 * \exp \left(\mathrm{i}^{*} \mathrm{pi} / 4 * \mathrm{n}\right)+\exp \left(\mathrm{i}^{*} \mathrm{pi} / 3^{*} \mathrm{n}\right)+\operatorname{randn}(1,100)$;
X=corrmtx (s,12, 'mod');

## Algorithm

The Toeplitz data matrix computed by corrmtx depends on the method you select. The matrix determined by the autocorrelation (default) method is given by the following matrix.


In this matrix, $m$ is the same as the input argument $m$ to corrmtx, and $n$ is length ( $x$ ). Variations of this matrix are used to return the output $x$ of corrmtx for each method:

- 'autocorrelation': (default) X =X, above.
- 'prewindowed' $: X$ is the $n$-by- $(m+1)$ submatrix of $X$ that is given by the portion of $X$ above the lower gray line.
- 'postwindowed ': $X$ is the $n$-by- $(m+1)$ submatrix of $X$ that is given by the portion of $X$ below the upper gray line.
- 'covariance ': $X$ is the $(n-m)$-by- $(m+1)$ submatrix of $X$ that is given by the portion of $X$ between the two gray lines.
- 'modified ' $: X$ is the $2(n-m)$-by- $(m+1)$ matrix $X_{\text {mod }}$ shown below.

$$
x_{\text {mod }}=\left[\begin{array}{ccc}
x(m+1) & \cdots & x 1) \\
\vdots & \ddots & \vdots \\
x(n-m) & \cdots & x(m+1) \\
\vdots & \ddots & \vdots \\
x(n) & \cdots & x(n-m) \\
x^{*}(1) & \cdots & x^{*}(m+1) \\
\vdots & \therefore & \vdots \\
x^{*}(m+1) & \cdots & x^{*}(n-m) \\
\vdots & \therefore & \vdots \\
x^{*}(n-m) & \cdots & x^{*}(n)
\end{array}\right]
$$

## See Also

References
peig, pmusic, rooteig, rootmusic, xcorr
[1] Marple, S.L. Digital Spectral Analysis, Englewood Cliffs, NJ , Prentice-Hall, 1987, pp. 216-223.

## Purpose Compute the covariance matrix

Syntax $\quad$| $c$ | $=\operatorname{cov}(x)$ |
| ---: | :--- |
| $c$ | $=\operatorname{cov}(x, y)$ |

Description
cov computes the covariance matrix. If $x$ is a vector, c is a scalar containing the variance. For an array where each row is an observation and each column a variable, $\operatorname{cov}(X)$ is the covariance matrix. diag $(\operatorname{cov}(X))$ is a vector of variances for each column, and sqrt $(\operatorname{diag}(\operatorname{cov}(X)))$ is a vector of standard deviations.
$\operatorname{cov}(x)$ is the zeroth lag of the covariance function, that is, the zeroth lag of $x \operatorname{cov}(x) /(n-1)$ packed into a square array.
$\operatorname{cov}(x, y)$ where $x$ and $y$ are column vectors of equal length is equivalent to $\operatorname{cov}([x y])$, that is, it concatenates $x$ and $y$ in the row direction before its computation.
cov removes the mean from each column before calculating the results.
The cov function is part of the standard MATLAB Ianguage.

## Algorithm

See Also

```
[n,p] = size(x);
x = x-ones(n,1)*(sum(x)/n);
y = x'*x/(n-1);
```

corrcoef, mean, median, std, xcorr, xcov

## cplxpair

## Purpose Group complex numbers into complex conjugate pairs

Syntax $\quad$| $y$ | $=\operatorname{cplxpair}(x)$ |
| ---: | :--- |
| $y$ | $=\operatorname{cplxpair}(x, t o l)$ |

Description

## Example

Diagnostics

Order five poles evenly spaced around the unit circle into complex pairs.

```
cplxpair(exp(2*pi*sqrt(-1)*(0:4)/5)')
ans =
    -0.8090 - 0.5878i
    -0.8090 + 0.5878i
    0.3090 - 0.9511i
    0.3090 + 0.9511i
    1.0000
```

If there is an odd number of complex numbers, or if the complex numbers cannot be grouped into complex conjugate pairs within the tolerance, cplxpair generates the error message.

## Purpose Complex and nonlinear-phase equiripple FIR filter design

Syntax<br>\section*{Description}

b = cremez(n,f,'fresp')
b = cremez(n,f,'fresp',w)
b = cremez(n,f,\{'fresp',p1,p2,...\},w)
b = cremez(n,f,a,w)
b = cremez(...,'sym')
b = cremez(...,'skip_stage2')
b = cremez(...,'debug')
b = cremez(...,\{lgrid\})
[b,delta,opt] = cremez(...)
cremez allows arbitrary frequency-domain constraints to be specified for the design of a possibly complex FIR filter. TheChebyshev (or minimax) filter error is optimized, producing equiripple FIR filter designs.
b = cremez(n,f,'fresp') returns a length n+1 FIR filter with the best approximation to the desired frequency response as returned by function fresp. $f$ is a vector of frequency band edge pairs, specified in the range - 1 and 1 , where 1 corresponds to the normalized $N$ yquist frequency. The frequencies must be in increasing order, and f must have even length. The frequency bands span $f(k)$ to $f(k+1)$ for $k$ odd; the intervals $f(k+1)$ to $f(k+2)$ for $k$ odd are "transition bands" or "don't care" regions during optimization.
$\mathrm{b}=\mathrm{cremez}(\mathrm{n}, \mathrm{f}$, 'fresp', w) uses thereal, non-negative weights in vector $w$ to weight the fit in each frequency band. The length of $w$ is half the length of $f, s o$ there is exactly one weight per band.
b = cremez( $\mathrm{n}, \mathrm{f},\left\{{ }^{\prime}\right.$ fresp', p1, p2, ...\},...) supplies optional parameters p1, p2, ..., to the frequency response function fresp. Predefined ' fresp ' frequency response functions are included for a number of common filter designs, as described below. For all of the predefined frequency response functions, the symmetry option 'sym' defaults to 'even' if no negative frequencies are contained in $f$ and $d=0$; otherwise 'sym' defaults to ' none '. (See the 'sym' option below for details.) F or all of the predefined frequency response functions, d specifies a group-delay offset such that thefilter response
has a group delay of $n / 2+d$ in units of the sample interval. Negative values create less delay; positive values create more delay. By default $d=0$ :

- lowpass, highpass, bandpass, bandstop

These functions share a common syntax, exemplified below by the string 'lowpass'.
b = cremez(n,f,'lowpass',...) and
b = cremez( $\mathrm{n}, \mathrm{f},\left\{\right.$ 'lowpass $\left.^{\prime}, \mathrm{d}\right\}, \ldots$ ) design a linear-phase ( $\mathrm{n} / 2+\mathrm{d}$ delay) filter.

- multiband designs a linear-phase frequency response filter with arbitrary band amplitudes.
b = cremez( $\mathrm{n}, \mathrm{f},\left\{\right.$ 'multiband' $\left.^{\prime}, \mathrm{a}\right\}, \ldots$ ) and
b = cremez( $\mathrm{n}, \mathrm{f},\left\{\right.$ 'multiband $\left.^{\prime}, \mathrm{a}, \mathrm{d}\right\}, \ldots$ ) specify vector a containing the desired amplitudes at the band edges in $f$. The desired amplitude at frequencies between pairs of points $f(k)$ and $f(k+1)$ for $k$ odd is the line segment connecting the points $(f(k), a(k))$ and ( $f(k+1), a(k+1))$.
- differentiator designs a linear-phase differentiator. For these designs, zero-frequency must be in a transition band, and band weighting is set to be inversely proportional to frequency.
$b=\operatorname{cremez}\left(n, f,\left\{\right.\right.$ 'differentiator $\left.^{\prime}, f s\right\}, \ldots$ ) and
b = cremez( $\mathrm{n}, \mathrm{f},\left\{\right.$ 'differentiator $\left.^{\prime}, \mathrm{fs}, \mathrm{d}\right\}, \ldots$ ) specifythesamplerate fs used to determine the slope of the differentiator response. If omitted, fs defaults to 1.
- hilbfilt designs a linear-phase Hilbert transform filter response. F or Hilbert designs, zero-frequency must be in a transition band.
b = cremez( $n, f$, 'hilbfilt',...) and
b = cremez(N,F,\{'hilbfilt',d\},...) design a linear-phase ( $\mathrm{n} / 2+\mathrm{d}$ delay) Hilbert transform filter.
$b=\operatorname{cremez}(n, f, a, w)$ is a synonym for
b = cremez(n,f,\{'multiband',a\},w).
b = cremez(..., 'sym') imposes a symmetry constraint on the impulse response of the design, where 'sym' may be one of the following:
- ' none ' indicates no symmetry constraint. This is the default if any negative band edge frequencies are passed, or if fresp does not supply a default.
- 'even' indicates a real and even impulse response. This is the default for highpass, lowpass, bandpass, bandstop, and multiband designs.
- ' odd ' indicates a real and odd impulse response. This is the default for Hilbert and differentiator designs.
- 'real ' indicates conjugate symmetry for the frequency response

If any 'sym' option other than 'none' is specified, the band edges should only be specified over positive frequencies; the negative frequency region is filled in from symmetry. If a 'sym' option is not specified, the fresp function is queried for a default setting.
b = cremez(...,'skip_stage2') disables the second-stage optimization algorithm, which executes only when cremez determines that an optimal solution has not been reached by the standard Remez error-exchange. Disabling this algorithm may increase the speed of computation, but may incur a reduction in accuracy. By default, the second-stage optimization is enabled.
b = cremez(...,'debug') enables the display of intermediateresults during the filter design, where 'debug' may be one of 'trace', 'plots', 'both', or 'off'. By default it is set to 'off'.
$b=\operatorname{cremez}(. . .,\{l g r i d\})$ uses the integer lgrid to control the density of the frequency grid, which has roughly $2^{\wedge}$ nextpow $2\left(\operatorname{lgrid}{ }^{*} n\right.$ ) frequency points. The default value for lgrid is 25 . Note that the $\{1$ grid $\}$ argument must be a 1-by-1 cell array.

Any combination of the 'sym', 'skip_stage2', 'debug', and \{lgrid\} options may be specified.
[b,delta] = cremez(...) returns the maximum ripple height delta.
[b,delta,opt] = cremez(...) returns a structure opt of optional results computed by cremez and contains the following fields.

| opt.fgrid | Frequency grid vector used for the filter design optimization |
| :--- | :--- |
| opt.des | Desired frequency response for each point in opt.fgrid |
| opt.wt | Weighting for each point in opt.fgrid |
| opt.H | Actual frequency response for each point in opt.fgrid |
| opt.error | Error at each point in opt.fgrid |
| opt.iextr | Vector of indices into opt.fgrid for extremal frequencies |
| opt.fextr | Vector of extremal frequencies |

User-definable functions may be used, instead of the predefined frequency response functions for fresp. The function is called from within cremez using the following syntax

```
[dh,dw] = fresp(n,f,gf,w,p1,p2,...)
```

where:

- n is the filter order.
- f is the vector of frequency band edges that appear monotonically between -1 and 1 , where 1 corresponds to the Nyquist frequency.
- gf is a vector of grid points that have been linearly interpolated over each specified frequency band by cremez. gf determines the frequency grid at which the response function must be evaluated. This is the same data returned by cremez in the fgrid field of the opt structure.
- wis a vector of real, positive weights, one per band, used during optimization. $w$ is optional in the call to cremez; if not specified, it is set to unity weighting before being passed to fresp.
- dh and dw are the desired complex frequency response and band weight vectors, respectively, evaluated at each frequency in grid gf.
- p1, p2, . . . are optional parameters that may be passed to fresp.

Additionally, a preliminary call is made to fresp to determine the default symmetry property 'sym'. This call is made using the syntax.

```
sym = fresp('defaults',{n,f,[],w,p1,p2,...})
```

The arguments may be used in determining an appropriate symmetry default as necessary. Thefunction private/lowpass.m may be useful as a templatefor generating new frequency response functions.

## Examples Example 1

Design a 31-tap, linear-phase, lowpass filter.

```
b = cremez(30,[-1 -0.5 -0.4 0.7 0.8 1],'lowpass');
freqz(b,1,512,'whole');
```




## Example 2

Design a nonlinear-phase allpass FIR filter.
First select (or create) the function fresp that returns the desired frequency response. For this example, fresp is the allpass.m function in the signal/signal/private directory which returns the frequency response of a nonlinear-phase allpass filter. Copy allpass.m to another location on the MATLAB path before trying the example.

Before using cremez with allpass.m to generate the filter coefficients, call allpass alone to create the desired response.

```
n = 22;
f = [-1 1];
w = [1 1]; % Weights for optimization
    % Filter order
    % Frequency band edges
gf = linspace(-1,1,256); % Grid of frequency points
d = allpass(n,f,gf,w); % Desired frequency response
```

Vector d now contains the complex frequency response that we desire for the FIR filter computed by cremez.

Now compute the FIR filter that best approximates this response.
b = cremez(n,f,'allpass', w,'real'); \% Approximation
freqz(b,1,256,'whole');



The freqz plot shows the frequency response of the filter computed by cremez to approximate the desired response. Check the accuracy of the approximation by overlaying the desired frequency response on the plot.

```
subplot(2,1,1); hold on
plot(pi*(gf+1), 20*log10(abs(fftshift(d))),'r--')
subplot(2,1,2); hold on
plot(pi*(gf+1),unwrap(angle(fftshift(d)))*180/pi,'r--')
legend('Approximation','Desired')
```




## Algorithm

See Also
References

An extended version of the Remez exchange method is implemented for the complex case. This exchange method obtains the optimal filter when the equiripple nature of the filter is restricted to have $\mathrm{n}+2$ extremals. When it does not converge, the al gorithm switches to an ascent-descent al gorithm that takes over to finish the convergence to the optimal solution. See the references for further details.
fir1, fir2, firls, remez
[1] Karam, L.J ., and J .H. McClellan. "Complex Chebyshev Approximation for FIR Filter Design." IEEE Trans. on Circuits and Systems II. March 1995.
Pgs. 207-216.
[2] Karam, L.J. Design of Complex Digital FIR Filters in the Chebyshev Sense Ph.D. Thesis, Georgia Institute of Technol ogy, March 1995.
[3] Demjanjov, V.F ., and V.N. M al ozemov. Introduction to Minimax. New York: J ohn Wiley \& Sons, 1974.

## Purpose <br> Estimate the cross spectral density (CSD) of two signals

## Syntax <br> Description

```
Pxy = csd(x,y)
Pxy = csd(x,y,nfft)
[Pxy,f] = csd(x,y,nfft,fs)
Pxy = csd(x,y,nfft,fs,window)
Pxy = csd(x,y,nfft,fs,window, numoverlap)
Pxy = csd(x,y,...,'dflag')
[Pxy,Pxyc,f] = csd(x,y,nfft,fs,window,numoverlap,p)
csd(x,y,...)
```

Pxy $=\operatorname{csd}(x, y)$ estimates the cross spectral density of the length $n$ sequences $x$ and $y$ using the Welch method of spectral estimation. Pxy $=\operatorname{csd}(x, y)$ uses the following default values:

- nfft $=$ min(256,length(x))
- $\mathrm{fs}=2$
- window is a periodic Hann window of length nfft.
- numoverlap $=0$
nfft specifies the FFT length that csd uses. This value determines the frequencies at which the cross spectrum is estimated. fs is a scal ar that specifies the sampling frequency. window specifies a windowing function and the number of samples csd uses in its sectioning of the $x$ and $y$ vectors. numoverlap is the number of samples by which the sections overlap. Any arguments omitted from the end of the parameter list use the default values shown above.

If $x$ and $y$ are real, csd estimates the cross spectral density at positive frequencies only; in this case, the output Pxy is a column vector of length $n f f t / 2+1$ for $n f f t$ even and ( $n f f t+1$ )/2 for nfft odd. If $x$ or $y$ is complex, csd estimates the cross spectral density at both positive and negative frequencies and Pxy has length nfft.

Pxy $=\operatorname{csd}(x, y, n f f t)$ uses the FFT length nfft in estimating the cross spectral density of $x$ and $y$. Specify nfft as a power of 2 for fastest execution.
$[P x y, f]=\operatorname{csd}(x, y, n f f t, f s)$ returns a vector $f$ of frequencies at which the function evaluates the CSD. f is the samesize as Pxy, so plot ( $\mathrm{f}, \mathrm{Pxy}$ ) plots the
spectrum versus properly scaled frequency. fs has no effect on the output Pxy; it is a frequency scaling multiplier.

Pxy $=\operatorname{csd}(x, y, n f f t, f s$, window $)$ specifies a windowing function and the number of samples per section of the $x$ vector. If you supply a scalar for window, csd uses a Hann window of that length. The length of the window must be less than or equal to $n f f t$; csd zero pads the sections if the length of the window is less than nfft. csd returns an error if the length of the window is greater than nfft.

Pxy $=\operatorname{csd}(x, y, n f f t, f s$, window, numoverlap) overlaps thesections of $x$ and $y$ by numoverlap samples.

You can use the empty matrix [ ] to specify the default value for any input argument except $x$ or $y$. For example,

```
    csd(x,y,[],10000)
```

is equivalent to

```
csd(x)
```

but with a sampling frequency of $10,000 \mathrm{~Hz}$ instead of the default of 2 Hz .
Pxy $=\operatorname{csd}(x, y, \ldots, ' d f l a g ')$ specifies a detrend option, where the string ' $d f l a g$ ' is one of the following:

- 'linear ', to remove the best straight-linefit from the prewindowed sections of $x$ and $y$
- 'mean ', to remove the mean from the prewindowed sections of $x$ and $y$
- ' none' , for no detrending (default)

The dflag parameter must appear last in the list of input arguments. csd recognizes a dflag string no matter how many intermediate arguments are omitted.
[Pxy, Pxyc,f] = csd (x,y,nfft,fs, window, numoverlap, $p$ ) where pis a positive scal ar between 0 and 1 returns a vector Pxyc that contains an estimate of the $p * 100$ percent confidence interval for Pxy. Pxyc is a two-column matrix the same length as Pxy. The interval $[\operatorname{Pxyc}(:, 1), \operatorname{Pxyc}(:, 2)]$ covers the true

CSD with probability p. plot (f, [Pxy Pxyc]) plots the cross spectrum inside the $p * 100$ percent confidence interval. If unspecified, $p$ defaults to 0.95 .
$\operatorname{csd}(x, y, \ldots)$ plots the CSD versus frequency in the current figure window. If the p parameter is specified, the plot includes the confidence interval.

Example

Algorithm

Generate two colored noise signals and plot their CSD with a confidence interval of $95 \%$. Specify a length 1024 FFT, a 500 point triangular window with no overlap, and a sampling frequency of 10 Hz .

```
randn('state',0);
h = fir1(30,0.2,rectwin(31));
h1 = ones(1,10)/sqrt(10);
r = randn(16384,1);
x = filter(h1,1,r);
y = filter(h,1,x);
csd(x,y,1024,10000,triang(500),0,[])
```


csd implements the Welch method of spectral density estimation (see references [1] and [2]):

1 It applies the window specified by the window vector to each successive detrended section.
2 It transforms each section with an nfft-point FFT.

3 It forms the periodogram of each section by scaling the product of the transform of the $y$ section and the conjugate of the transformed $x$ section.
4 It averages the periodograms of the successive overlapping sections to form Pxy, the cross spectral density of $x$ and $y$.
The number of sections that csd averages is $k$, where $k$ is

```
fix((length(x)-numoverlap)/(length(window)-numoverlap))
```


## Diagnostics

See Also
References

An appropriate diagnostic message is displayed when incorrect arguments to csd are used.

```
Requires window's length to be no greater than the FFT length.
Requires NOVERLAP to be strictly less than the window length.
Requires positive integer values for NFFT and NOVERLAP.
Requires vector (either row or column) input.
Requires inputs }X\mathrm{ and }Y\mathrm{ to have the same length.
Requires confidence parameter to be a scalar between 0 and 1.
```

cohere, pburg, pmtm, pmusic, pwelch, pyulear, tfe
[1] Rabiner, L.R., and B. Gold. Theory and Application of Digital Signal Processing. Englewood Cliffs, NJ : Prentice-Hall, 1975. Pgs. 414-419.
[2] Welch, P.D. "TheU se of F ast Fourier Transform for theEstimation of Power Spectra: A Method Based on Time Averaging Over Short, Modified Periodograms." IEEE Trans. Audio Electroacoust. Vol. AU-15 (J une 1967). Pgs. 70-73.
[3] Oppenheim, A.V., and R.W. Schafer. Discrete-TimeSignal Processing. Upper Saddle River, NJ : Prentice-Hall, 1999, pp. 737.

## Purpose Chirp z-transform

## Syntax <br> $y=c z t(x, m, w, a)$ <br> $y=\operatorname{czt}(x)$

## Description

$y=\operatorname{czt}(x, m, w, a)$ returns the chirp z-transform of signal $x$. The chirp z-transform is the z-transform of $x$ along a spiral contour defined by wand a. m is a scalar that specifies the length of the transform, $w$ is the ratio between points along the z-plane spiral contour of interest, and scalar a is the complex starting point on that contour. The contour, a spiral or "chirp" in thez-plane, is given by

$$
z=a^{*}(w . \wedge-(0: m-1))
$$

$y=\operatorname{czt}(x)$ uses the following default values:

- $m=$ length $(x)$
- $w=\exp (j * 2 * p i / m)$
- $a=1$

With these defaults, czt returns the z-transform of $x$ at m equally spaced points around the unit circle. This is equivalent to the discreteF ourier transform of $x$, or fft (x). The empty matrix [ ] specifies the default value for a parameter.

If $x$ is a matrix, $c z t(x, m, w, a)$ transforms the columns of $x$.

## Examples

Create a random vector x of length 1013 and compute its DFT using czt.

```
randn('state',0);
x = randn(1013,1);
y = czt(x);
```

Use czt to zoom in on a narrow-band section (100 to 150 Hz ) of a filter's frequency response. First design the filter.

```
h = fir1(30,125/500,rectwin(31)); % filter
```

Establish frequency and CZT parameters.

```
fs = 1000; f1 = 100; f2 = 150; % in hertz
m = 1024;
w = exp(-j*2*pi*(f2-f1)/(m*fs));
a = exp(j*2*pi*f1/fs);
```

Compute both the DFT and CZT of the filter.

```
y = fft(h,1000);
z = czt(h,m,w,a);
```

Create frequency vectors and compare the results.

```
fy = (0:length(y)-1)'*1000/length(y);
fz = ((0:length(z)-1)'*(f2-f1)/length(z)) + f1;
plot(fy(1:500),abs(y(1:500))); axis([1 500 0 1.2])
title('FFT')
figure
plot(fz,abs(z)); axis([f1 f2 0 1.2])
title('CZT')
```



## Algorithm

Diagnostics

See Also
czt uses the next power-of-2 length FFT to perform a fast convolution when computing the $z$-transform on a specified chirp contour [1].

If $m, w$, or a is not a scalar, czt gives the following error message.
Inputs $\mathrm{M}, \mathrm{W}$, and A must be scalars.
fft, freqz

References [1] Rabiner, L.R., and B. Gold. Theory and Application of Digital Signal Processing. Englewood Cliffs, NJ : Prentice-Hall, 1975. Pgs. 393-399.

## Purpose Discrete cosine transform (DCT)

## Syntax

$$
\begin{aligned}
& y=\operatorname{dct}(x) \\
& y=\operatorname{dct}(x, n)
\end{aligned}
$$

## Description

$y=\operatorname{dct}(x)$ returns the unitary discrete cosine transform of $x$

$$
y(k)=w(k) \sum_{n=1}^{1 v} x(n) \cos \frac{\pi(2 n-1)(k-1)}{2 N}, \quad k=1, \ldots, N
$$

where

$$
w(k)= \begin{cases}\frac{1}{\sqrt{N}}, & k=1 \\ \sqrt{\frac{2}{N}}, & 2 \leq \mathrm{k} \leq \mathrm{N}\end{cases}
$$

$N$ is the length of $x$, and $x$ and $y$ are the same size. If $x$ is a matri $x$, dct transforms its columns. The series is indexed from $n=1$ and $k=1$ instead of the usual $\mathrm{n}=0$ and $\mathrm{k}=0$ because MATLAB vectors run from 1 to N instead of from 0 to $\mathrm{N}-1$.
$y=\operatorname{dct}(x, n)$ pads or truncates $x$ to length $n$ before transforming.
The DCT is closely related to the discrete Fourier transform. You can often reconstruct a sequence very accurately from only a few DCT coefficients, a useful property for applications requiring data reduction.

## Example

## See Also

References

Find how many DCT coefficients represent $99 \%$ of the energy in a sequence.

```
x = (1:100) + 50*cos((1:100)*2*pi/40);
X = dct(x);
[XX,ind] = sort(abs(X)); ind = fliplr(ind);
i = 1;
while (norm([X(ind(1:i)) zeros(1,100-i)])/norm(X)<.99)
    i = i + 1;
end
i =
            3
```

fft, idct, dct2, idct2
[1]J ain, A.K. F undamental s of Digital ImageProcessing. Englewood Cliffs, NJ : Prentice-Hall, 1989.
[2] Pennebaker, W.B., and J.L. Mitchell. J PEG Still ImageData Compression Standard. New York, NY: Van Nostrand Reinhold, 1993. Chapter 4.

## Purpose Decrease the sampling rate for a sequence (decimation)

Syntax

```
y = decimate(x,r)
y = decimate(x,r,n)
y = decimate(x,r,'fir')
y = decimate(x,r,n,'fir')
```

Description
Decimation reduces the original sampling rate for a sequence to a lower rate, theopposite of interpolation. The decimation process filters the input data with a lowpass filter and then resamples the resulting smoothed signal at a lower rate.
$y=$ decimate $(x, r)$ reduces the sample rate of $x$ by a factor $r$. The decimated vector $y$ is $r$ times shorter in length than the input vector $x$. By default, decimate employs an eighth-order lowpass Chebyshev Typel filter. It filters the input sequence in both the forward and reverse directions to remove all phase distortion, effectively doubling the filter order.
$y=\operatorname{dec}$ imate $(x, r, n)$ uses an order $n$ Chebyshev filter. Orders above 13 arenot recommended because of numerical instability. MATLAB displays a warning in this case.
$y=$ decimate ( $x, r$, 'fir') uses a 30-point FIR filter, instead of the Chebyshev IIR filter. Here decimate filters the input sequence in only one direction. This technique conserves memory and is useful for working with long sequences.
$y=\operatorname{dec}$ imate ( $x, r, n$, 'fir') uses a length $n$ FIR filter.

## Example Decimate a signal by a factor of four.

```
t = 0:.00025:1; % Time vector
x = sin(2*pi*30*t) + sin(2*pi*60*t);
y = decimate(x,4);
```

View the original and decimated signals.

```
stem(x(1:120)), axis([0 120 -2 2]) % Original signal
title('Original Signal')
figure
stem(y(1:30)) % Decimated signal
title('Decimated Signal')
\% Decimated signal
```




## Algorithm

Diagnostics

See Also downsample, interp, resample, spline, upfirdn, upsample

References [1]IEEE. Programs for Digital Signal Processing. IEEE Press. New York:J ohn Wiley \& Sons, 1979. Chapter 8.
Purpose Deconvolution and polynomial division
Syntax $[q, r]=\operatorname{deconv}(b, a)$
DescriptionExample
AlgorithmThis function calls filter to compute the deconvolution as the impulseresponse of an IIR filter.
See Also ..... conv, filter, residuez

Purpose Demodulation for communications simulation
Syntax

```
x = demod(y,fc,fs,'method')
x = demod(y,fc,fs,'method',opt)
x = demod(y,fc,fs,'pwm','centered')
[x1,x2] = demod(y,fc,fs,'qam')
```


## Description

demod performs demodulation, that is, it obtains the original signal from a modulated version of the signal. demod undoes the operation performed by modulate.
x = demod (y,fc,fs,'method') and
$x=\operatorname{demod}(y, f c, f s$, 'method', opt $)$ demodulatethereal carrier signal $y$ with a carrier frequency fc and sampling frequency fs, using one of the options listed below for method. (N ote that some methods accept an option, opt.)
amdsb-sc Amplitude demodulation, double sideband, suppressed or carrier. Multiplies y by a sinusoid of frequency fc and applies a am fifth-order Butterworth lowpass filter using filtfilt.

```
x = y.* cos(2*pi*fc*t);
[b,a] =butter(5,fc*2/fs);
x =filtfilt(b,a,x);
```

amdsb-tc Amplitude demodulation, double sideband, transmitted carrier. Multiplies y by a sinusoid of frequency fc, and applies a fifth-order Butterworth lowpass filter using filtfilt.

```
x = y.* cos(2*pi*fc*t);
[b,a] =butter(5,fc*2/fs);
x =filtfilt(b,a,x);
```

If you specify opt, demod subtracts scalar opt from $x$. The default value for opt is 0 .
amssb Amplitude demodulation, single sideband. Multiplies y by a sinusoid of frequency fc and applies a fifth-order Butterworth lowpass filter using filtfilt.

```
x = y.* cos(2*pi*fc*t);
[b,a] =butter(5,fc*2/fs);
x =filtfilt(b,a,x);
```

| fm | Frequency demodulation. Demodulates the FM waveform by modulating the Hilbert transform of y by a complex exponential of frequency -fc Hz and obtains the instantaneous frequency of the result. |
| :---: | :---: |
| pm | Phase demodulation. Demodulates the PM waveform by modulating the Hilbert transform of y by a complex exponential of frequency -fc Hz and obtains the instantaneous phase of the result. |
| ppm | Pulse-position demodulation. Finds the pulse positions of a pulse-position modulated signal y. For correct demodulation, the pulses cannot overlap. x is length length ( t ) $\mathrm{*fc}_{\mathrm{f}} / \mathrm{fs}$. |
| pwm | Pulse-width demodulation. Finds the pulse widths of a pulse-width modulated signal y. demod returns in x a vector whose elements specify the width of each pulse in fractions of a period. The pulses in y should start at the beginning of each carrier period, that is, they should be left justified. |
| qam | Quadrature amplitude demodulation. <br> [ $\mathrm{x} 1, \mathrm{x} 2$ ] $=\operatorname{demod}(\mathrm{y}, \mathrm{fc}, \mathrm{fs}$, 'qam') multiplies y by a cosine and a sine of frequency fc and applies a fifth-order Butterworth lowpass filter using filtfilt. |
|  | ```x1 =y.* cos(2*pi*fc*t); x2 =y.*sin(2*pi*fc*t); [b,a] = butter(5,fc*2/fs); x1 =filtfilt(b,a,x1); x2 =filtfilt (b,a,x2);``` |

The default method is 'am'. In all cases except 'ppm' and 'pwm', $x$ is the same size as $y$.

If $y$ is a matrix, demod demodulates its columns.
$x=\operatorname{demod}(y, f c, f s$, 'pwm', 'centered') finds the pulse widths assuming they are centered at the beginning of each period. $x$ is length length $(y) * f c / f s$.

See Also modulate, vco

## dftmtx

Purpose Discrete Fourier transform matrix
Syntax $A=\operatorname{dftmtx}(n)$
Description
Example
Algorithmdftmtx takes the FFT of the identity matrix to generate the transform matrix.
See Also ..... convmtx, fft

## Purpose <br> Compute the Dirichlet or periodic sinc function

## Syntax

$y=\operatorname{diric}(x, n)$

Description

## Diagnostics

See Also
$y=\operatorname{diric}(x, n)$ returns a vector or array $y$ the same size as $x$. The elements of $y$ are the Dirichlet function of the elements of $x . n$ must be a positive integer.

The Dirichlet function, or periodic sinc function, is

$$
\operatorname{diric}(x, n)= \begin{cases}-1^{\frac{x}{2 \pi}(n-1)} & x=0, \pm 2 \pi, \pm 4 \pi, \ldots \\ \frac{\sin (n x / 2)}{n \sin (x / 2)} & \text { else }\end{cases}
$$

for any nonzero integer $n$. This function has period $2 \pi$ for $n$ odd and period $4 \pi$ for $n$ even. Its peak value is 1 , and its minimum value is -1 for $n$ even. The magnitude of this function is $(1 / n)$ times the magnitude of the discrete-time Fourier transform of the n-point rectangular window.

If n is not a positive integer, diric gives the following error message.

```
Requires n to be a positive integer.
```

cos, gauspuls, pulstran, rectpuls, sawtooth, sin, sinc, square, tripuls

Purpose Decrease the sampling rate of the input signal

Syntax $\quad$| $y$ | $=\operatorname{downsample}(x, n)$ |
| ---: | :--- |
| $y$ | $=\operatorname{downsample}(x, n$, phase $)$ |

Description

Examples
Decrease the sampling rate of a sequence by 3.

```
x = [1 2 3 4 5 6 7 8 9 10];
y = downsample(x,3)
y =
    1 4 7 7 10
```

Decrease the sampling rate of the sequence by 3 and add a phase offset of 2 .

```
y = downsample(x,3,2)
y =
    3 6 9
```

Decrease the sampling rate of a matrix by 3.

```
x = [1 2 3; 4 5 6; 7 8 9; 10 11 12];
y = downsample(x,3);
x,y
x =
            1 2
            4 5
            7 8 9
            10 11 12
y =
    1 2 3
    10 11 12
```

Purpose Discrete prolate spheroidal sequences (Slepian sequences)

## Syntax

```
[e,v] = dpss(n,nw)
[e,v] = dpss(n,nw,k)
[e,v] = dpss(n,nw,[k1 k2])
[e,v] = dpss(n,nw,'int')
[e,v] = dpss(n,nw,'int',Ni)
[e,v] = dpss(...,'trace')
```

Description $[e, v]=\operatorname{dpss}(n, n w)$ generates the first $2 * n w$ discrete prolate spheroidal sequences (DPSS) of length $n$ in the columns of e, and their corresponding concentrations in vector $v$. They are also generated in the DPSS MAT-file database dpss.mat. nw must be less than n/2.
$[e, v]=\operatorname{dpss}(n, n w, k)$ returns the $k$ most band-limited discrete prolate spheroidal sequences. $k$ must be an integer such that $1 \leq k \leq n$.
$[e, v]=d p s s(n, n w,[k 1 k 2])$ returns the k1st through the k2nd discrete prolate spheroidal sequences, where $1 \leq \mathrm{k} 1 \leq \mathrm{k} 2 \leq \mathrm{n}$.

For all of the above forms:

- The Slepian sequences are calculated directly.
- The sequences are generated in the frequency band $|\omega| \leq(2 \pi \mathrm{~W})$, where $\mathrm{w}=\mathrm{nw} / \mathrm{n}$ is the half-bandwidth and $\omega$ is in rad/sample.
- $e(:, 1)$ is the length $n$ signal most concentrated in the frequency band $|\omega| \leq(2 \pi W)$ radians, $e(:, 2)$ is the signal orthogonal to $e(:, 1)$ that is most concentrated in this band, $\mathrm{e}(:, 3)$ is the signal orthogonal to both $\mathrm{e}(:, 1)$ and $e(:, 2)$ that is most concentrated in this band, etc.
- For multitaper spectral analysis, typical choices for nw are $2,5 / 2,3,7 / 2$, or 4.
[ $e, v$ ] $=$ dpss( $n, n w$, 'int') uses the interpolation method specified by the string 'int' to compute e and v from the sequences in dpss. mat with length closest to $n$. The string 'int' can be either:
- 'spline': Use spline interpolation.
- 'linear': Use linear interpolation. This is much faster but less accurate than spline interpolation.
[ $\mathrm{e}, \mathrm{v}]=\mathrm{dpss}(\mathrm{n}, \mathrm{nw}$, 'int' Ni$)$ interpolates from existing length Ni sequences. The interpolation method 'linear' requires $\mathrm{Ni}>\mathrm{n}$.
$[e, v]=d p s s(\ldots$, 'trace') uses the trailing string 'trace' to display which interpolation method DPSS uses. If you don't specify the interpolation method, the display indicates that you are using the direct method.


## Examples

## Example 1: Using dpss, dpssave, and dpssdir

Create a catalogue of 16 DPSS functions with $n w=4$, and use spline interpolation on 10 of these functions while displaying the interpolation method you use. Y ou can do this using dpss, dpsssave, and dpssdir.

```
% Create the catalogue of functions.
[e,v] = dpss(16,4);
% Save e and v in a MAT-file.
dpsssave(4,e,v);
% Find nw = 4. First create a structure called index.
index = dpssdir;
index.wlists
ans =
    NW: 4
    key: 1
% Use spline interpolation on 10 of the DPSS functions.
[e1,v1] = dpss(10,4,'spline',size(e,1),'trace');
```


## Example 2: Using dpss and dpssload

Create a set of DPSS functions using dpss, and use the spline method on a subset of these functions. Use dpssload to load the MAT-file created by dpss.

```
% Create the catalogue of functions.
[e,v] = dpss(16,4);
% Load dpss.mat, where e and v are saved.
[e1,v1] = dpssload(16,4);
% Use spline interpolation on 10 of the DPSS functions.
[e1,v1] = dpss(10,4,'spline');
```

See Also dpssclear, dpssdir, dpssload, dpsssave, pmtm

References [1] Percival, D.B., and A.T. Walden. Spectral Analysis for Physical Applications: Multitaper and Conventional UnivariateTechniques. Cambridge: Cambridge University Press, 1993.

Purpose Remove discrete prolate spheroidal sequences from database
Syntax ..... dpssclear(n,nw)
Description dpssclear( $\mathrm{n}, \mathrm{nw}$ ) removes sequences with length n and time-bandwidthproduct nw from the DPSS MAT-file database dpss.mat.
See Also dpss, dpssdir, dpssload, dpsssave

| Purpose | Discrete prolate spheroidal sequences database directory |
| :---: | :---: |
| Syntax | dpssdir |
|  | dpssdir(n) |
|  | dpssdir(nw, 'nw') |
|  | dpssdir ( $\mathrm{n}, \mathrm{nw}$ ) |
|  | index = dpssdir |
| Description | dpssdir manages the database directory that contains the generated DPSS |
|  | samples in the DPSS MAT-file database dpss.mat. |
|  | dpssdir lists the directory of saved sequences in dpss.mat. |
|  | dpssdir ( n ) lists the sequences saved with length n . |
|  | dpssdir(nw, 'nw' ) lists the sequences saved with time-bandwidth product nw. |
|  | dpssdir( $n, n w$ ) lists the sequences saved with length $n$ and time-bandwidth product nw. |
|  | index = dpssdir is a structure array describing the DPSS database. Pass n and nw options as for the no output case to get a filtered index. |
| Examples | See "Example 1: Using dpss, dpssave, and dpssdir" on page 7-149. |
| See Also | dpss, dpssclear, dpssload, dpsssave |

Purpose Load discrete prolate spheroidal sequences from database
Syntax [e,v] = dpssload(n,nw)
Description [ $\mathrm{e}, \mathrm{v}]=\mathrm{dpssload}(\mathrm{n}, \mathrm{nw})$ loads all sequences with length n and time-bandwidth product nw in the columns of e and their corresponding concentrations in vector v from the DPSS MAT-file database dpss.mat.
Examples See "Example 2: Using dpss and dpssload" on page 7-149.
See Also ..... dpss, dpssclear, dpssdir, dpsssave

| Purpose | Save discrete prolate spheroidal sequences in database |
| :--- | :--- |
| Syntax | dpsssave $(n w, e, v)$ <br> status $=d p s s s a v e(n w, e, v)$ |
| Description | dpsssave $(n w, e, v)$ saves the sequences in the columns of e and their <br> corresponding concentrations in vector $v$ in the DPSS MAT-file database <br> dpss.mat. |
| - It is not necessary to specify sequence length, because the length of the |  |
| sequence is determined by the number of rows of e. |  |
| - nw is the timebandwidth product that was specified when the sequence was |  |
| created using dpss. |  |

## Purpose <br> Elliptic (Cauer) filter design

```
Syntax
[b,a] = ellip(n,Rp,Rs,Wn)
[b,a] = ellip(n,Rp,Rs,Wn,'ftype')
\([b, a]=\operatorname{ellip}(n, R p, R s, W n, ' s ')\)
[b,a] = ellip(n,Rp,Rs,Wn,'ftype','s')
[z, p,k] = ellip(...)
[A,B,C,D] = ellip(...)
```

Description ellip designs lowpass, bandpass, highpass, and bandstop digital and analog elliptic filters. Elliptic filters offer steeper rolloff characteristics than Butterworth or Chebyshev filters, but are equiripple in both the pass- and stopbands. In general, elliptic filters meet given performance specifications with the lowest order of any filter type.

## Digital Domain

[b,a] =ellip( $\mathrm{n}, \mathrm{Rp}, \mathrm{Rs}, \mathrm{Wn}$ ) designs an order n lowpass digital elliptic filter with cutoff frequency $\mathrm{Wn}, \mathrm{Rp} \mathrm{dB}$ of ripple in the passband, and a stopband Rs dB down from the peak value in the passband. It returns the filter coefficients in the length $n+1$ row vectors $b$ and $a$, with coefficients in descending powers of $z$.

$$
H(z)=\frac{B(z)}{A(z)}=\frac{b(1)+b(2) z^{-1}+\cdots+b(n+1) z^{-n}}{1+a(2) z^{-1}+\cdots+a(n+1) z^{-n}}
$$

The cutoff frequency is the edge of the passband, at which the magnitude response of the filter is - Rp dB. For ellip, the cutoff frequency Wn is a number between 0 and 1 , where 1 corresponds to half the sampling frequency (Nyquist frequency). Smaller values of passband ripple Rp and larger values of stopband attenuation Rs both lead to wider transition widths (shallower rolloff characteristics).

If Wn is a two-element vector, $\mathrm{Wn}=[\mathrm{w} 1 \mathrm{w} 2$ ], ellip returns an order $2 * \mathrm{n}$ bandpass filter with passband $w 1<\omega<w 2$.
[b, a] =ellip(n, Rp,Rs,Wn, 'ftype') designs a highpass or bandstop filter, where the string 'ftype' is either:

- 'high' for a highpass digital filter with cutoff frequency Wn
- 'stop' for an order $2 * n$ bandstop digital filter if Wn is a two-element vector, $W n=[w 1 \mathrm{w} 2]$. The stopband is $\mathrm{w} 1<\omega<w 2$.

With different numbers of output arguments, ellip directly obtains other realizations of the filter. To obtain zero-pole-gain form, use three output arguments as shown below.
$[z, p, k]=\operatorname{ellip}(n, R p, R s, W n)$ or
[ $\mathrm{z}, \mathrm{p}, \mathrm{k}]=\mathrm{ellip}(\mathrm{n}, \mathrm{Rp}, \mathrm{Rs}, \mathrm{Wn}$, 'ftype') returns the zeros and poles in length $n$ column vectors $z$ and $p$ and the gain in the scalar $k$.

To obtain state-space form, use four output arguments as shown below.

$$
\begin{aligned}
{[A, B, C, D] } & =\operatorname{ellip}(n, R p, R s, W n) \text { or } \\
{[A, B, C, D] } & =\operatorname{ellip}(n, R p, R s, W n, ' f t y p e ') \text { where } A, B, C, \text { and } D \text { are } \\
x[n+1] & =A x[n]+B u[n] \\
y[n] & =C x[n]+D u[n]
\end{aligned}
$$

and u is the input, x is the state vector, and y is the output.

## Analog Domain

[b,a] =ellip( $n, R p, R s, W n$, 's') designs an order n lowpass analog elliptic filter with cutoff frequency Wn and returns the filter coefficients in the length $\mathrm{n}+1$ row vectors b and a , in descending powers of s , derived from the transfer function

$$
H(s)=\frac{B(s)}{A(s)}=\frac{b(1) s^{n}+b(2) s^{n-1}+\cdots+b(n+1)}{s^{n}+a(2) s^{n-1}+\cdots+a(n+1)}
$$

The cutoff frequency is the edge of the passband, at which the magnitude response of the filter is -Rp dB . For ellip, the cutoff frequency Wn must be greater than 0 rad/s.

If Wn is a two-element vector with $w 1<w 2$, then ellip( $\mathrm{n}, \mathrm{Rp}, \mathrm{Rs}, \mathrm{Wn}, \mathrm{s}$ ' ') returns an order $2 * n$ bandpass analog filter with passband $w 1<\omega<w 2$.
$[\mathrm{b}, \mathrm{a}]=\operatorname{ellip}(\mathrm{n}, \mathrm{Rp}, \mathrm{Rs}, \mathrm{Wn}$, 'ftype ' , 's') designs a highpass or bandstop filter.

With different numbers of output arguments, ellip directly obtains other realizations of the anal og filter. To obtain zero-pole-gain form, use three output arguments as shown below.
$[z, p, k]=\operatorname{llip}(n, R p, R s, W n, ' s ')$ or
[z,p,k] =ellip(n,Rp,Rs,Wn, 'ftype', 's') returns the zeros and poles in length $n$ or $2 * n$ column vectors $z$ and $p$ and the gain in the scalar $k$.

To obtain state-space form, use four output arguments as shown below.

$$
\begin{aligned}
& {[A, B, C, D]=\operatorname{ellip}\left(n, R p, R s, W n, '^{\prime} '^{\prime}\right) \text { or }} \\
& {[A, B, C, D]=\operatorname{ellip}\left(n, R p, R s, W n, ' f t y p e ', '^{\prime}\right) \text { where } A, B, C, \text { and } D \text { are }} \\
& \dot{x}=A x+B u \\
& y=C x+D u
\end{aligned}
$$

and u is the input, x is the state vector, and y is the output.

## Examples Example 1

For data sampled at 1000 Hz , design a sixth-order lowpass elliptic filter with a cutoff frequency of $300 \mathrm{~Hz}, 3 \mathrm{~dB}$ of ripple in the passband, and 50 dB of attenuation in the stopband.

```
[b,a] = ellip(6,3,50,300/500);
```

The filter's frequency response is

```
freqz(b,a,512,1000)
title('n=6 Lowpass Elliptic Filter')
```



## Example 2

Design a 20th-order bandpass elliptic filter with a passband from 100 to 200 Hz and plot its impulse response.

```
n = 10; Rp = 0.5; Rs = 20;
Wn = [100 200]/500;
[b,a] = ellip(n,Rp,Rs,Wn);
[y,t] = impz(b,a,101); stem(t,y)
title('Impulse Response of n=10 Elliptic Filter')
```



## Limitations

Algorithm

For high order filters, the state-space form is the most numerically accurate, followed by the zero-pole-gain form. The transfer function form is the least accurate; numerical problems can arise for filter orders as low as 15.

The design of elliptic filters is the most difficult and computationally intensive of the Butterworth, Chebyshev Type I and II, and elliptic designs. ellip uses a five-step algorithm:

1 It finds the lowpass analog prototype poles, zeros, and gain using the ellipap function.
2 It converts the poles, zeros, and gain into state-space form.
3 It transforms the lowpass filter to a bandpass, highpass, or bandstop filter with the desired cutoff frequencies using a state-space transformation.
4 For digital filter design, ellip uses bilinear to convert the analog filter into a digital filter through a bilinear transformation with frequency prewarping. Careful frequency adjustment guarantees that the analog filters and the digital filters will have the same frequency response magnitude at Wn or w1 and w2.
5 It converts the state-space filter back to transfer function or zero-pole-gain form, as required.

## See Also

besself, butter, cheby1, cheby2, ellipap, ellipord
Purpose Elliptic analog lowpass filter prototype
Syntax

    [z,p,k] = ellipap(n,Rp,Rs)References
    [ $\mathrm{z}, \mathrm{p}, \mathrm{k}]=$ ellipap( $\mathrm{n}, \mathrm{Rp}, \mathrm{Rs}$ ) returns the zeros, poles, and gain of an order n elliptic analog lowpass filter prototype, with Rp dB of ripple in the passband, and a stopband Rs dB down from the peak value in the passband. Thezeros and poles are returned in length $n$ column vectors $z$ and $p$ and the gain in scalar $k$. If $n$ is odd, $z$ is length $n-1$. The transfer function is

$$
H(s)=\frac{z(s)}{p(s)}=k \frac{(s-z(1))(s-z(2)) \cdots(s-z(n))}{(s-p(1))(s-p(2)) \cdots(s-p(n))}
$$

Elliptic filters offer steeper rolloff characteristics than Butterworth and Chebyshev filters, but they are equiripple in both the passband and the stopband. Of the four classical filter types, elliptic filters usually meet a given set of filter performance specifications with the lowest filter order.
ellip sets the cutoff frequency $\omega_{0}$ of the elliptic filter to 1 for a normalized result. The cutoff frequency is the frequency at which the passband ends and the filter has a magnitude response of $10^{-\mathrm{Rp} / 20}$.
ellipap uses the algorithm outlined in [1]. It employs the M-file ellipk to calculate the complete elliptic integral of the first kind and the M-file ellipj to calculateJ acobi elliptic functions.
besselap, buttap, cheb1ap, cheb2ap, ellip
[1] Parks, T.W., and C.S. Burrus. Digital Filter Design. New Y ork: J ohn Wiley \& Sons, 1987. Chapter 7.

## ellipord

## Purpose Calculate the minimum order for elliptic filters

## Syntax [n,Wn] = ellipord(Wp,Ws,Rp,Rs) <br> [ $\mathrm{n}, \mathrm{Wn}$ ] = ellipord(Wp,Ws,Rp,Rs,'s') <br> Description ellipord calculates the minimum order of a digital or analog elliptic filter required to meet a set of filter design specifications.

## Digital Domain

[ $\mathrm{n}, \mathrm{Wn}$ ] =ellipord(Wp,Ws,Rp,Rs) returns the lowest order $n$ of the elliptic filter that loses no more than Rp dB in the passband and has at least Rs dB of attenuation in the stopband. The scalar (or vector) of corresponding cutoff frequencies Wn, is also returned. Use the output arguments $n$ and $W n$ in ellip.

Choose the input arguments to specify the stopband and passband according to the following table.

Table 7-7: Description of Stopband and Passband Filter Parameters

| Wp | Passband corner frequency Wp, the cutoff frequency, is a scalar <br> or a two-element vector with values between 0 and 1 , with 1 <br> corresponding to the normalized Nyquist frequency, $\pi$ radians <br> per sample. |
| :--- | :--- |
| Ws | Stopband corner frequency Ws, is a scalar or a two-element <br> vector with values between 0 and 1, with 1 corresponding to <br> the normalized Nyquist frequency. |
| Rp | Passband ripple, in decibels. Twice this value specifies the <br> maximum permissible passband width in decibels. |
| Rs | Stopband attenuation, in decibels. This value is the number of <br> decibels the stopband is attenuated with respect to the <br> passband response. |

Use the following guide to specify filters of different types.
Table 7-8: Filter Type Stopband and Passband Specifications

| Filter Type | Stopband and Passband Conditions | Stopband | Passband |
| :---: | :---: | :---: | :---: |
| Lowpass | Wp <Ws, both scalars | (Ws, 1) | (0,Wp) |
| Highpass | Wp > Ws, both scalars | $(0, \mathrm{Ws})$ | (Wp, 1) |
| Bandpass | The interval specified by ws contains the one specified by wp <br> (Ws(1) < Wp(1) < Wp(2) < Ws(2)). | $\begin{aligned} & (0, \mathrm{Ws}(1)) \\ & \text { and } \\ & (\operatorname{Ws}(2), 1) \end{aligned}$ | (Wp (1) , Wp (2)) |
| Bandstop | The interval specified by Wp contains the one specified by ws $(W p(1)<W s(1)<W s(2)<W p(2)) .$ | $\begin{aligned} & (0, W p(1)) \\ & \text { and } \\ & (W p(2), 1) \end{aligned}$ | (Ws(1), Ws (2)) |

If your filter specifications call for a bandpass or bandstop filter with unequal ripple in each of the passbands or stopbands, design separate lowpass and highpass filters according to the specifications in this table, and cascade the two filters together.

## Analog Domain

[ $n, W n$ ] =ellipord (Wp,Ws, Rp, Rs, 's') finds the minimum order $n$ and cutoff frequencies Wn for an analog filter. Y ou specify the frequencies Wp and Ws similar to Table 7-7, only in this case you specify the frequency in radians per second, and the passband or the stopband can be infinite.

Use ellipord for lowpass, highpass, bandpass, and bandstop filters as described in Table 7-8.

## ellipord

## Examples

## Example 1

For 1000 Hz data, design a lowpass filter with less than 3 dB of ripple in the passband defined from 0 to 40 Hz and at least 60 dB of ripple in the stopband defined from 150 Hz to the Nyquist frequency ( 500 Hz ).

```
\(W p=40 / 500 ; W s=150 / 500 ;\)
Rp = 3; Rs = 60;
[n,Wn] = ellipord(Wp,Ws,Rp,Rs)
n =
        4
Wn =
    0.0800
\([b, a]=\operatorname{lllip}(n, R p, R s, W n) ;\)
freqz(b,a,512,1000);
title('n=4 Elliptic Lowpass Filter')
```




## Example 2

Now design a bandpass filter with a passband from 60 Hz to 200 Hz , with less than 3 dB of ripple in the passband, and 40 dB attenuation in the stopbands that are 50 Hz wide on both sides of the passband.

```
Wp = [60 200]/500; Ws = [50 250]/500;
Rp = 3; Rs = 40;
[n,Wn] = ellipord(Wp,Ws,Rp,Rs)
n =
    5
Wn =
    0.1200 0.4000
[b,a] = ellip(n,Rp,Rs,Wn);
freqz(b,a,512,1000);
title('n=5 Elliptic Bandpass Filter')
```




## ellipord

| Algorithm | ellipord uses the elliptic lowpass filter order prediction formula described <br> in [1]. Thefunction performs its cal culations in the analog domain for both the <br> analog and digital cases. For the digital case, it converts the frequency <br> parameters to the s-domain before estimating the order and natural <br> frequencies, and then converts them back to the z-domain. |
| :--- | :--- |
| ellipord initially develops a lowpass filter prototype by transforming the |  |
| passband frequencies of the desired filter to 1 rad/s (for low- and highpass |  |
| filters) and to - 1 and 1 rad/s (for bandpass and bandstop filters). It then |  |
| computes the minimum order required for a lowpass filter to meet thestopband |  |
| specification. |  |

## Purpose Make the lengths of a transfer function's numerator and denominator equal

| Syntax | $[b, a]=$ eqtflength(num, den) |
| :--- | :--- |
|  | $[b, a, n, m]=$ eqtflength (num, den) |

Description
Examples
num = [1 0.5];
num = [1 0.5];
den = [1 0.75 0.6 0];
den = [1 0.75 0.6 0];
[b,a,n,m] = eqtflength(num,den)
[b,a,n,m] = eqtflength(num,den)
b =
b =
1.0000 0.5000 0
1.0000 0.5000 0
a =
a =
1.0000 0.7500 0.6000
1.0000 0.7500 0.6000
n =
n =
1
1
m =
m =
2
2
Algorithm $\quad$ eqtflength (num, den) appends zeros to either num or den as necessary. If both
num and den have trailing zeros in common, these are removed.
See Also tf2ss, tf2zp

Purpose

## Syntax

Description

Remarks

Open the Filter Design and Analysis Tool

## fdatool

fdatool opens the Filter Design and Analysis Tool (FDATool). Use this tool to:

- Design filters
- Analyze filters
- Modify existing filter designs

See Chapter 5, "Filter Design and Analysis Tool," for more information.


The Filter Design and Analysis Tool provides more design methods than the SPTool Filter Designer.

Note The Filter Design and Analysis Tool requires a screen resolution greater than $640 \times 480$.

See Also sptool, fvtool

## Purpose Compute the one-dimensional fast Fourier transform

## Syntax

$$
\begin{aligned}
& y=f f t(x) \\
& y=f f t(x, n)
\end{aligned}
$$

## Description

## Examples

A common use of the F ourier transform is to find the frequency components of a time-domain signal buried in noise. Consider data sampled at 1000 Hz . Form a signal consisting of 50 Hz and 120 Hz sinusoids and corrupt the signal with zero-mean random noise.

```
randn('state',0)
t = 0:0.001:0.6;
x = sin(2*pi*50*t) + sin(2*pi*120*t);
y = x + 2*randn(1,length(t));
plot(y(1:50))
```



It is difficult to identify the frequency components by studying the original signal. Convert to the frequency domain by taking the discrete Fourier transform of the noisy signal y using a 512-point fast Fourier transform (FFT).

$$
Y=f f t(y, 512) ;
$$

The power spectral density, a measurement of the energy at various frequencies, is

```
Pyy = Y.*conj(Y) / 512;
```

Graph the first 256 points (the other 256 points are symmetric) on a meaningful frequency axis.

```
f = 1000*(0:255)/512;
plot(f,Pyy(1:256))
```



See the pwelch function for details on estimating the spectral density.
Sometimes it is useful to normalize the output of fft so that a unit sinusoid in the time domain corresponds to unit amplitude in the frequency domain. To produce a normalized discrete-time Fourier transform in this manner, use

$$
\operatorname{Pn}=\operatorname{abs}(f f t(x)) * 2 / \text { length }(x)
$$

## Algorithm

See Also
fft is a built-in MATLAB function. See the fft reference page in the MATLAB documentation for details about the algorithm.
dct, dftmtx, fft2, fftshift, filter, freqz, ifft, pwelch

## Purpose Compute the two-dimensional fast Fourier transform

Syntax $\quad$| $Y$ | $=f f t 2(X)$ |
| ---: | :--- |
| $Y$ | $=f f t 2(X, m, n)$ |

Description

## Algorithm

See Also fft, fftshift, ifft, ifft2

Purpose
FFT-based FIR filtering using the overlap-add method

Syntax $\quad$| $y$ | $=\operatorname{fftfilt}(b, x)$ |
| ---: | :--- |
| $y$ | $=\operatorname{fftfilt}(b, x, n)$ |

Examples

Algorithm

Show that the results from fftfilt and filter are identical.

```
b = [1 2 3 4];
x = [1 zeros(1,99)]';
norm(fftfilt(b,x) - filter(b,1,x))
    ans =
        9.5914e-15
```

fftfilt uses fft to implement the overlap-add method [1], a technique that combines successive frequency domain filtered blocks of an input sequence. fftfilt breaks an input sequence $x$ into length $L$ data blocks
x

and convolves each block with the filter b by

```
y = ifft(fft(x(i:i+L-1),nfft).*fft(b,nfft));
```

wherenfft is the FFT length. fftfilt overlaps successive output sections by $\mathrm{n}-1$ points, where n is the length of the filter, and sums them.

fftfilt chooses the key parameters L and nfft in different ways, depending on whether you supply an FFT length n and on the lengths of the filter and signal. If you do not specify a value for $n$ (which determines FFT length), fftfilt chooses these key parameters automatically:

- If length $(x)$ is greater than length(b), fftfilt chooses values that minimize the number of blocks times the number of flops per FFT.
- If length (b) is greater than or equal to length ( $x$ ), fftfilt uses a single FFT of length

```
2^nextpow2(length(b) + length(x) - 1)
```

This essentially computes

```
y = ifft(fft(B,nfft).*fft(X,nfft))
```

If you supply a value for $n$, fftfilt chooses an FFT length, nfft, of 2^nextpow2 ( $n$ ) and a data block length of $n f f t-$ length ( $b$ ) +1 . If $n$ is less than length (b), fftfilt sets $n$ to length (b).

See Also conv, filter, filtfilt
References
[1] Oppenheim, A.V., and R.W. Schafer, DiscreteTimeSignal Processing, Prentice-Hall, 1989.

## fftshift

## Purpose <br> Rearrange the outputs of the FFT functions

## Syntax <br> $y=f f t s h i f t(x)$

Description

Examples
For any array $X$

$$
Y=f f t 2(x)
$$

has $Y(1,1)=\operatorname{sum}(\operatorname{sum}(X))$; the DC component of thesignal is in the upper-left corner of the two-dimensional FFT. For

$$
z=f f t s h i f t(Y)
$$

the DC component is near the center of the matrix.

## See Also

## Purpose

Syntax
$y=f i l t e r(b, a, x)$
[y,zf] = filter(b,a,x)
[...] = filter(b,a,x,zi)
[...] = filter(b,a,x,zi,dim)
[...] =filter(b,a,x,zi,dim)

Filter data with a recursive (IIR) or nonrecursive (FIR) filter
$y=$ filter $(b, a, x)$ filters the data in vector $x$ with the filter described by coefficient vectors $a$ and $b$ to create the filtered data vector $y$. When $x$ is a matrix, filter operates on the columns of $x$. When $x$ is an $N$-dimensional array, filter operates on the first nonsingleton dimension. a(1) cannot be 0 , and if $\mathrm{a}(1) \neq 1$, filter normalizes the filter coefficients by a(1).
$[y, z f]=$ filter $(b, a, x)$ returns thefinal values $z f$ of the state vector. When $x$ is a vector, the size of the final condition vector $z f$ is max (length (b), length (a) ) -1 , the number of delays in the filter. When $x$ is a multidimensional array, $z f$ is an s-by-c matrix, where:

- $s$ is the number of delays in the filter.
- cisprod(size (x))/size (x, dim), where dim is the dimension into which you are filtering (the first nonsingleton dimension by default).
[...] = filter(b,a, x, zi) specifies initial state conditions in the vector zi. The size of the initial condition vector zi must be the same as max (length (b), length (a) )-1, the number of delays in the filter.
[...] = filter(b,a,x,zi, dim) filters the input data located along the dimension dim of $x$. Set zi to the empty vector [ ] to use zero initial conditions.

The filter function is part of the standard MATLAB Ianguage.

Examples
Find and graph the 101-point unit impulse response of a digital filter.

```
x = [1 zeros(1,100)];
[b,a] = butter(12,400/1000);
y = filter(b,a,x);
stem(y)
```



## Algorithm

filter is implemented as a transposed direct form II structure [1], as shown below

where $\mathrm{n}-1$ is the filter order. The state vector z is a vector whose components are derived from the values of the inputs to each delay in the filter.

The operation of filter at sample $m$ is implemented using the transposed direct form II structure. This is calculated by the time domain difference equations for y and the states $\mathrm{z}_{i}$.

$$
\begin{aligned}
y(m) & =\frac{\left(b(1) x(m)+z_{1}(m-1)\right)}{a(1)} \\
z_{1}(m) & =b(2) x(m)+z_{2}(m-1)-a(2) y(m) \\
\vdots & =\vdots \\
z_{n-2}(m) & =b(n-1) x(m)+z_{n-1}(m-1)-a(n-1) y(m) \\
z_{n-1}(m) & =b(n) x(m)-a(n) y(m)
\end{aligned}
$$

Note the division by a(1). F or efficient computation, select this coefficient to be a power of 2.

You can use filtic to generate the state vector $z_{i}(0)$ from past inputs and outputs.

The input-output description of this filtering operation in the z-transform domain is a rational transfer function.

$$
Y(z)=\frac{b(1)+b(2) z^{-1}+\cdots+b(n b+1) z^{-n b}}{a(1)+a(2) z^{-1}+\cdots+a(n a+1) z^{-n a}} X(z)
$$

## See Also fftfilt, filter2,filtfilt,filtic

## References

[1] Oppenheim, A.V., and R.W. Schafer, DiscreteTimeSignal Processing, Prentice-H all, 1989, pp. 311-312.
Purpose Two-dimensional digital filtering
Syntax

$Y=$ filter2(B,X)

$Y=$ filter2( $B, X$, 'shape' $)$
Description
Algorithm
See Also ..... conv2, filter

| Purpose | Compute the 2-norm or infinity-norm of a digital filter |
| :---: | :---: |
| Syntax | $\begin{aligned} & \text { filternorm(b,a) } \\ & \text { filternorm(b,a,pnorm) } \\ & \text { filternorm(b,a,2,tol) } \end{aligned}$ |
| Description | A typical use for filter norms is in digital filter scaling to reduce quantization effects. Scaling often improves the signal-to-noise ratio of the filter without resulting in data overflow. Y ou, also, can use the 2-norm to compute the energy of the impulse response of a filter. <br> filternorm(b, a) computes the 2-norm of the digital filter defined by the numerator coefficients in b and denominator coefficients in a . <br> filternorm(b, a, pnorm) computes the 2- or infinity-norm (inf-norm) of the digital filter, where pnorm is either 2 or inf. <br> filternorm(b, a, 2, tol) computes the 2-norm of an IIR filter with the specified tolerance, tol. The tolerance can be specified only for IIR 2-norm computations. pnorm in this case must be 2. If tol is not specified, it defaults to 1e-8. |
| Examples | Compute the 2-norm with a tolerance of 1e-10 of an IIR filter. ```[b,a]=butter(5,.5); L2=filternorm(b,a,2,1e-10) L2 = 0.7071``` |
|  | Compute the inf-norm of an FIR filter. ```b=remez(30,[.1 .9],[1 1],'Hilbert'); Linf=filternorm(b,1,inf) Linf =``` |

## Algorithm

## See Also

Reference

Given a filter $\mathrm{H}(\mathrm{z})$ with frequency reponse $\mathrm{H}\left(\mathrm{e}^{\mathrm{j} \omega}\right)$, the $\mathrm{L}_{\mathrm{p}}$-norm is given by

$$
\|H\|_{p} \equiv\left[\frac{1}{2 \pi} \int_{-\pi}^{\pi}\left|H\left(e^{j \omega}\right)\right|^{p} d \omega\right]^{\frac{1}{p}}
$$

For the case $p=\infty$, the $L_{\infty}$ norm simplifies to

$$
\|H\|_{\infty}=\max _{-\pi \leq \omega \leq \pi}\left|H\left(\mathrm{e}^{\mathrm{j} \omega}\right)\right|
$$

For the case $p=2$, Parseval's theorem states that

$$
\|H\|_{2}=\left[\frac{1}{2 \pi} \int_{-\pi}^{\pi}\left|H\left(e^{j \omega}\right)\right|^{2} d \omega\right]^{\frac{1}{2}}=\left[\sum_{n=-\infty}^{\infty}|h(n)|^{2}\right]^{\frac{1}{2}}
$$

where $h(n)$ is the impulse response of the filter. The energy of the impulse response, then, is $\|\mathrm{H}\|_{2}^{2}$.
zp2sos, norm
J ackson, L.B., Digital Filters and Signal Processing, Third Edition, Kluwer Academic Publishers, 1996, Chapter 11.

| Purpose | Zero-phase digital filtering |
| :---: | :---: |
| Syntax | $y=$ filtfilt (b, $\mathrm{a}, \mathrm{x}$ ) |
| Description | $y=$ filtfilt (b,a,x) performs zero-phase digital filtering by processing the input data in both the forward and reverse directions (see problem 5.39 in [1]). After filtering in the forward direction, it reverses the filtered sequence and runs it back through the filter. The resulting sequence has precisely zero-phase distortion and doublethefilter order. filtfilt minimizes start-up and ending transients by matching initial conditions, and works for both real and complex inputs. |
|  | Note that filtfilt should not be used with differentiator and Hilbert FIR filters, since the operation of these filters depends heavily on their phase response. |
| Algorithm | filtfilt is an M-file that uses the filter function. In addition to the forward-reverse filtering, it attempts to minimize startup transients by adjusting initial conditions to match the DC component of the signal and by prepending several filter lengths of a flipped, reflected copy of the input signal. |
| See Also | fftfilt, filter, filter2 |
| References | [1] Oppenheim, A.V., and R.W. Schafer, DiscreteTimeSignal Processing, Prentice-Hall, 1989, pp. 311-312. |
|  | [2] Mitra, S.K., Digital Signal Processing, 2nd ed., McGraw-Hill, 2001, Sections 4.4.2 and 8.2.5. |
|  | [3] Gustafsson, F., "Determining the initial states in forward-backward filtering," IEEE Transactions on Signal Processing, April 1996, Volume 44, Issue 4, pp. 988--992, |

Purpose Find initial conditions for a transposed direct form II filter implementation

## Syntax $\quad z=$ filtic $(b, a, y, x)$ <br> $z=$ filtic $(b, a, y)$

## Description $\quad z=$ filtic $(b, a, y, x)$ finds the initial conditions, $z$, for the delays in the

 transposed direct form II filter implementation given past outputs y and inputs $x$. The vectors $b$ and a represent the numerator and denominator coefficients, respectively, of the filter's transfer function.The vectors $x$ and $y$ contain the most recent input or output first, and oldest input or output last.

$$
\begin{aligned}
& x=\{x(-1), x(-2), x(-3), \ldots, x(-n), \ldots\} \\
& y=\{y(-1), y(-2), y(-3), \ldots, y(-m), \ldots\}
\end{aligned}
$$

where n is length ( b ) - -1 (the numerator order) and $m$ is length ( a ) -1 (the denominator order). If length ( x ) is less than n , filtic pads it with zeros to length $n$; if length ( y ) is less than m , filtic pads it with zeros to length m . Elements of $x$ beyond $x(n-1)$ and elements of $y$ beyond $y(m-1)$ are unnecessary so filtic ignores them.
Output $z$ is a column vector of length equal to thelarger of $n$ and $m . z$ describes the state of the delays given past inputs $x$ and past outputs $y$.
$z=$ filtic $(b, a, y)$ assumes that the input $x$ is 0 in the past.
The transposed direct form II structure is

where $n-1$ is the filter order.
filtic works for both real and complex inputs.
Algorithm filtic performs a reverse difference equation to obtain the delay states z.
Diagnostics If any of the input arguments $y, x, b$, or a is not a vector (that is, if anyargument is a scalar or array), filtic gives the following error message.
Requires vector inputs.
See Also ..... filter, filtfilt
References [1] Oppenheim, A.V., and R.W. Schafer, DiscreteTimeSignal Processing,Prentice-Hall, 1989, pp. 296, 301-302.

Purpose Design a window-based finite impulse response filter

Syntax $\quad$| $b$ | $=\operatorname{fir} 1(n, W n)$ |
| ---: | :--- |
| $b$ | $=\operatorname{fir} 1(n, W n, ' f t y p e ')$ |
| $b$ | $=\operatorname{fir} 1(n, W n$, window $)$ |
| $b$ | $=\operatorname{fir} 1(n, W n, ' f t y p e '$, window $)$ |
| $b$ | $=\operatorname{fir} 1(\ldots$, 'normalization' $)$ |

## Description

fir1 implements the classical method of windowed linear-phase FIR digital
filter design [1]. It designs filters in standard lowpass, highpass, bandpass, and bandstop configurations. By default the filter is normalized so that the magnitude response of the filter at the center frequency of the passband is 0 dB .

Note Use fir2 for windowed filters with arbitrary frequency response.
$b=f i r 1(n, W n)$ returns row vector $b$ containing the $n+1$ coefficients of an order $n$ lowpass FIR filter. This is a Hamming-window based, linear-phase filter with normalized cutoff frequency Wn. The output filter coefficients, b, are ordered in descending powers of $z$.

$$
B(z)=b(1)+b(2) z^{-1}+\cdots+b(n+1) z^{-n}
$$

Wn is a number between 0 and 1 , where 1 corresponds to the Nyquist frequency.
If Wn is a two-element vector, $\mathrm{Wn}=[\mathrm{w} 1 \mathrm{w} 2$ ], fir1 returns a bandpass filter with passband w1 < $\omega<\mathrm{w} 2$.

If Wn is a multi-element vector, $\mathrm{Wn}=\left[\begin{array}{lll}w 1 & w 2 & w 3 \\ w\end{array}\right)$ w5 ... wn], fir1 returns an order $n$ multiband filter with bands $0<\omega<w 1$, w1 $<\omega<w 2$, ... wn $<\omega<1$.

By default, the filter is scaled so that the center of the first passband has a magnitude of exactly 1 after windowing.
b = fir1( $\mathrm{n}, \mathrm{Wn}$, 'ftype') specifies a filter type, where 'ftype' is:

- 'high' for a highpass filter with cutoff frequency Wn.
- 'stop' for a bandstop filter, if $\mathrm{Wn}=[\mathrm{w} 1 \mathrm{w} 2]$. The stopband frequency range is specified by this interval.
- 'DC-1' to make the first band of a multiband filter a passband.
- 'DC-0' to make the first band of a multiband filter a stopband.
fir1 always uses an even filter order for the highpass and bandstop configurations. This is because for odd orders, the frequency response at the Nyquist frequency is 0 , which is inappropriate for highpass and bandstop filters. If you specify an odd-valued $n$, fir1 increments it by 1 .
$b=$ fir1 ( $n, W n$, window) uses the window specified in column vector window for the design. The vector window must be $n+1$ elements long. If no window is specified, fir1 uses a Hamming window (see hamming) of length $n+1$.
b = fir1(n,Wn,'ftype', window) accepts both 'ftype' and window parameters.
b = fir1(...,'normalization') specifies whether or not the filter magnitude is normalized. The string 'normalization' can be:
- 'scale ' (default): Normalize the filter so that the magnituderesponse of the filter at the center frequency of the passband is 0 dB .
- 'noscale': Do not normalize the filter.

The group delay of the FIR filter designed by fir1 is n/2.

## Algorithm

fir1 uses the window method of FIR filter design [1]. If $w(n)$ denotes a window, where $1 \leq \mathrm{n} \leq \mathrm{N}$, and the impulse response of the ideal filter is $\mathrm{h}(\mathrm{n})$, where $h(n)$ is the inverse F ourier transform of the ideal frequency response, then the windowed digital filter coefficients are given by

$$
b(n)=w(n) h(n), \quad 1 \leq n \leq N
$$

## Examples Example 1

Design a 48th-order FIR bandpass filter with passband $0.35 \leq \omega \leq 0.65$.

$$
\begin{aligned}
& b=\operatorname{fir} 1(48,[0.350 .65]) ; \\
& \text { freqz(b,1,512) }
\end{aligned}
$$




## Example 2

The chirp. mat file contains a signal, $y$, that has most of its power above fs/4, or half the Nyquist frequency. Design a 34th-order FIR highpass filter to attenuate the components of the signal below fs/4. Use a cutoff frequency of 0.48 and a Chebyshev window with 30 dB of ripple.

```
load chirp % Load y and fs.
b = fir1(34,0.48,'high',chebwin(35,30));
freqz(b,1,512)
```




## See Also <br> cremez, filter, fir2, fircls, fircls1, firls, freqz, kaiserord, remez, window

## References

[1] Programs for Digital Signal Processing, IEEE Press, New York, 1979. Algorithm 5.2.
Purpose Design a frequency sampling-based finite impulse response filter

```
Syntax \(\quad b=\operatorname{fir} 2(n, f, m)\)
b \(=\) fir2(n,f,m,window)
b = fir2(n,f,m,npt)
b = fir2(n,f,m,npt,window)
b \(=\) fir2(n,f,m,npt,lap)
b = fir2(n,f,m,npt,lap,window)
```


## Description

```
fir2 designs frequency sampling-based digital FIR filters with arbitrarily shaped frequency response.
```

Note Use fir1 for windows-based standard lowpass, bandpass, highpass, and bandstop configurations.
$b=f i r 2(n, f, m)$ returns row vector $b$ containing the $n+1$ coefficients of an order $n$ FIR filter. The frequency-magnitude characteristics of this filter match those given by vectors $f$ and $m$ :

- fis a vector of frequency points in the range from 0 to 1 , where 1 corresponds to the Nyquist frequency. The first point of f must be 0 and the last point 1. The frequency points must be in increasing order.
- $m$ is a vector containing the desired magnitude response at the points specified in f.
- $f$ and $m$ must be the same length.
- Duplicate frequency points are allowed, corresponding to steps in the frequency response.

Use plot( $f, m$ ) to view the filter shape.
The output filter coefficients, b, are ordered in descending powers of $z$.

$$
b(z)=b(1)+b(2) z^{-1}+\cdots+b(n+1) z^{-n}
$$

fir2 always uses an even filter order for configurations with a passband at the Nyquist frequency. This is because for odd orders, the frequency response at
the Nyquist frequency is necessarily 0 . If you specify an odd-valued $n$, fir2 increments it by 1 .
$b=f i r 2(n, f, m$, window) uses the window specified in the column vector window. The vector window must be $n+1$ elements long. If no window is specified, fir2 uses a Hamming window (see hamming) of length $n+1$.
$b=f i r 2(n, f, m, n p t)$ or
b = fir2(n,f,m,npt,window) specifies the number of points, npt, for the grid onto which fir2 interpolates the frequency response, without or with a window specification.
b $=\mathrm{fir} 2(\mathrm{n}, \mathrm{f}, \mathrm{m}, \mathrm{npt}, \mathrm{lap})$ and
$b=f i r 2(n, f, m, n p t, l a p, w i n d o w)$ specify the size of the region, lap, that fir2 inserts around duplicate frequency points, with or without a window specification.

See the "Algorithm" section for more on npt and lap.

## Examples

Design a 30th-order lowpass filter and overplot the desired frequency response with the actual frequency response.

```
f = [0 0.6 0.6 1]; m = [1 1 1 0 0];
b = fir2(30,f,m);
[h,w] = freqz(b,1,128);
plot(f,m,w/pi,abs(h))
legend('Ideal','fir2 Designed')
title('Comparison of Frequency Response Magnitudes')
```



## Algorithm

See Also

The desired frequency response is interpol ated onto a dense, evenly spaced grid of length npt. npt is 512 by default. If two successive values of $f$ are the same, a region of lap points is set up around this frequency to provide a smooth but steep transition in the requested frequency response. By default, lap is 25 . The filter coefficients are obtained by applying an inverse fast F ourier transform to the grid and multiplying by a window; by default, this is a Hamming window.
butter, cheby1, cheby2, ellip, fir1, maxflat, remez, yulewalk

## Purpose Constrained least square FIR filter design for multiband filters

| Syntax | $b=\operatorname{fircls}(n, f, a m p, u p, l o)$ |
| :--- | :--- |
|  | $f i r c l s\left(n, f, a m p, u p, l o, ' d e s i g n \_f l a g '\right)$ |

## Description

$b=$ fircls ( $n, f, a m p, u p, l o$ ) generates a length $n+1$ linear phase FIR filter $b$. The frequency-magnitude characteristics of this filter match those given by vectors fand amp:

- f is a vector of transition frequencies in the range from 0 to 1 , where 1 corresponds to the Nyquist frequency. The first point of f must be 0 and the last point 1. The frequency points must be in increasing order.
- amp is a vector describing the piecewise constant desired amplitude of the frequency response. The length of amp is equal to the number of bands in the response and should be equal to length(f)-1.
- up and lo are vectors with the same length as amp. They definethe upper and lower bounds for the frequency response in each band.
fircls always uses an even filter order for configurations with a passband at the Nyquist frequency. This is because for odd orders, the frequency response at the Nyquist frequency is necessarily 0 . If you specify an odd-valued $n$, fircls increments it by 1.
fircls( $\left.n, f, a m p, u p, 10, ' d e s i g n \_f l a g '\right)$ enables you to monitor the filter design, where 'design_flag' can be:
- 'trace', for a textual display of the design error at each iteration step.
- 'plots', for a collection of plots showing the filter's full-band magnitude response and a zoomed view of the magnitude response in each sub-band. All plots are updated at each iteration step.
- 'both', for both the textual display and plots.

Examples

```
n = 50;
f = [0 0.4 0.8 1];
amp = [0 1 0];
up = [0.02 1.02 0.01];
lo = [-0.02 0.98-0.01];
b = fircls(n,f,amp,up,lo,'plots'); % Plot magnitude response
```






Note Normally, the lower value in the stopband will be specified as negative. By setting lo equal to 0 in the stopbands, a nonnegative frequency response amplitude can be obtained. Such filters can be spectrally factored to obtain minimum phase filters.

## Algorithm

See Also fircls1,firls, remez

References [1] Selesnick, I.W., M. Lang, and C.S. Burrus, "Constrained Least Square Design of FIR Filters without Specified Transition Bands," Proceedings of the IEEE Int. Conf. Acoust., Speech, Signal Processing, Vol. 2 (May 1995), pp. 1260-1263.
[2] Selesnick, I.W., M. Lang, and C.S. Burrus. "Constrained Least Square Design of FIR Filters without Specified Transition Bands." IEEE Transactions on Signal Processing, Vol. 44, No. 8 (August 1996).

| Purpose | Constrained least square filter design for lowpass and highpass linear phase |
| :--- | :--- |
| FIR filters |  |

Syntax

```
b = fircls1(n,wo,dp,ds)
b = fircls1(n,wo,dp,ds,'high')
b = fircls1(n,wo,dp,ds,wt)
b = fircls1(n,wo,dp,ds,wt,'high')
b = fircls1(n,wo,dp,ds,wp,ws,k)
b = fircls1(n,wo,dp,ds,wp,ws,k,'high')
b = fircls1(n,wo,dp,ds,...,'design_flag')
```

Description
$b=$ fircls1( $n$, wo, dp, ds) generates a lowpass FIR filter $b$, where $n+1$ is the filter length, wo is the normalized cutoff frequency in the range between 0 and 1 (where 1 corresponds to the $N$ yquist frequency), dp is the maximum passband deviation from 1 (passband ripple), and ds is the maximum stopband deviation from 0 (stopband ripple).
b = fircls1(n,wo,dp,ds, 'high') generates a highpassFIR filter b.fircls1 always uses an even filter order for the highpass configuration. This is because for odd orders, the frequency response at the Nyquist frequency is necessarily 0 . If you specify an odd-valued $n$, fircls1 increments it by 1 .
b = fircls1( $n$, wo, dp, ds, wt) and
b = fircls1(n,wo, dp, ds, wt, 'high') specifies a frequency wt above which (for wt >wo) or below which (for wt <wo) the filter is guaranteed to meet the given band criterion. This will help you design a filter that meets a passband or stopband edge requirement. There are four cases:

## - Lowpass:

- $0<w t$ <wo <1: the amplitude of the filter is within dp of 1 over the frequency range $0<\omega<\omega t$.
- $0<w o<w t<1$ : the amplitude of the filter is within ds of 0 over the frequency range $w t<\omega<1$.
- Highpass:
- $0<w t<w o<1$ : the amplitude of the filter is within ds of 0 over the frequency range $0<\omega<w t$.
- $0<w o<w t<1$ : the amplitude of the filter is within dp of 1 over the frequency range wt $<\omega<1$.
$b=f i r c l s 1(n, w o, d p, d s, w p, w s, k)$ generates $a$ lowpass FIR filter $b$ with $a$ weighted function, where $n+1$ is the filter length, wo is the normalized cutoff frequency, $d p$ is the maximum passband deviation from 1 (passband ripple), and ds is the maximum stopband deviation from 0 (stopband ripple). wp is the passband edge of the L2 weight function and ws is the stopband edge of the L2 weight function, where wp <wo <ws. k is theratio(passband L2 error)/(stopband L2 error)

$$
k=\frac{\int_{0}^{w_{p}}|A(\omega)-D(\omega)|^{2} d \omega}{\int_{w_{c}}^{\pi}|A(\omega)-D(\omega)|^{2} d \omega}
$$

b = fircls1(n,wo, dp, ds, wp,ws, $k$, 'high') generates a highpass FIR filter b with a weighted function, where ws <wo <wp.
b = fircls1(n,wo,dp,ds,...,'design_flag') enables you to monitor the filter design, where 'design_flag' can be:

- 'trace', for a textual display of the design table used in the design
- 'plots', for plots of the filter's magnitude, group delay, and zeros and poles
- 'both', for both the textual display and plots

Note In the design of very narrow band filters with small $d p$ and $d s$, there may not exist a filter of the given length that meets the specifications.

Examples

## Algorithm

See Also
References




Design an order 55 lowpass filter with a cutoff frequency at 0.3.

```
n = 55; wo = 0.3;
```

n = 55; wo = 0.3;
dp = 0.02; ds = 0.008;
dp = 0.02; ds = 0.008;
b = fircls1(n,wo,dp,ds,'plots'); % Plot magnitude response

```

The algorithm is a multiple exchange algorithm that uses Lagrange multipliers and Kuhn-Tucker conditions on each iteration.
```

fircls,firls,remez

```
[1] Selesnick, I.W., M. Lang, and C.S. Burrus, "Constrained Least Square Design of FIR Filters without Specified Transition Bands," Proceedings of the IEEE Int. Conf. Acoust., Speech, Signal Processing, Vol. 2 (May 1995), pp. 1260-1263.
[2] Selesnick, I.W., M. Lang, and C.S. Burrus, "Constrained Least Square Design of FIR Filters without Specified Transition Bands," IEEE Transactions on Signal Processing, Vol. 44, No. 8 (August 1996).

\section*{Purpose \\ Least square linear-phase FIR filter design}
\begin{tabular}{|c|c|}
\hline Syntax & \(\mathrm{b}=\mathrm{firls}(\mathrm{n}, \mathrm{f}, \mathrm{a})\) \\
\hline & \(b=f i r l s(n, f, a, w)\) \\
\hline & b \(=\) firls( \(\mathrm{n}, \mathrm{f}, \mathrm{a}, \mathrm{ftype}{ }^{\text {( }}\) ) \\
\hline & \(\mathrm{b}=\mathrm{firls}(\mathrm{n}, \mathrm{f}, \mathrm{a}, \mathrm{w}, \mathrm{ftype}\) \\
\hline
\end{tabular}

Description
firls designs a linear-phase FIR filter that minimizes the weighted, integrated squared error between an ideal piecewise linear function and the magnitude response of the filter over a set of desired frequency bands.
\(b=\) firls \((n, f, a)\) returns row vector \(b\) containing the \(n+1\) coefficients of the order \(n\) FIR filter whose frequency-amplitude characteristics approximately match those given by vectors f and a. The output filter coefficients, or "taps," in \(b\) obey the symmetry relation.
\[
b(k)=b(n+2-k), \quad k=1, \ldots, n+1
\]

Thesearetypel ( \(n\) odd) and typell ( \(n\) even) linear-phasefilters. Vectors \(f\) and a specify the frequency-amplitude characteristics of the filter:
- f is a vector of pairs of frequency points, specified in the range between 0 and 1 , where 1 corresponds to the Nyquist frequency. The frequencies must be in increasing order. Duplicate frequency points are allowed and, in fact, can be used to design a filter exactly the same as those returned by the fir1 and fir2 functions with a rectangular (rectwin) window.
- a is a vector containing the desired amplitude at the points specified in f.

The desired amplitude function at frequencies between pairs of points \((f(k), f(k+1))\) for \(k\) odd is the line segment connecting the points ( \(f(k), a(k))\) and ( \(f(k+1), a(k+1)\) ).
The desired amplitude function at frequencies between pairs of points \((f(k), f(k+1))\) for \(k\) even is unspecified. These are transition or "don't care" regions.
- \(f\) and a are the same length. This length must be an even number.
firls always uses an even filter order for configurations with a passband at the \(N\) yquist frequency. This is because for odd orders, the frequency response
at the \(N\) yquist frequency is necessarily 0 . If you specify an odd-valued \(n\), firls increments it by 1 .

The figure below illustrates the relationship between the fand a vectors in defining a desired amplitude response.
\[
\begin{aligned}
& f=\left[\begin{array}{llllll}
0 & .3 & .4 & .6 & .7 & .9
\end{array}\right] \\
& a=\left[\begin{array}{lllll}
0 & 1 & 0 & 0 & .5 \\
.5
\end{array}\right]
\end{aligned}
\]

Desired amplitude response (a)

"Don't care"/transition regions
\(b=f i r l s(n, f, a, w)\) uses the weights in vector \(w\) to weight the fit in each frequency band. The length of \(w\) is half the length of \(f\) and \(a\), so there is exactly one weight per band.
b = firls(n,f,a,'ftype') and
b = firls(n,f,a,w, 'ftype') specify a filter type, where 'ftype' is:
- ' hilbert' for linear-phase filters with odd symmetry (type III and typeIV). The output coefficients in \(b\) obey the relation \(b(k)=-b(n+2-k)\), \(\mathrm{k}=1, \ldots, \mathrm{n}+1\). This class of filters includes the Hilbert transformer, which has a desired amplitude of 1 across the entire band.
- 'differentiator' for typelll and typeIV filters, using a special weighting technique. F or nonzero amplitude bands, the integrated squared error has a weight of \((1 / f)^{2}\) so that the error at low frequencies is much smaller than at high frequencies. For FIR differentiators, which have an amplitude characteristic proportional to frequency, the filters minimize the relative integrated squared error (the integral of the square of the ratio of the error to the desired amplitude).

\section*{Examples Example 1}

Design an order 255 lowpass filter with transition band.
\[
\text { b = firls(255,[0 } \left.0.250 .31],\left[\begin{array}{lll}
1 & 1 & 0
\end{array} 0\right]\right) ;
\]

\section*{Example 2}

Design a 31 coefficient differentiator.
```

b = firls(30,[0 0.9],[0 0.9],'differentiator');

```

\section*{Example 3}

Design a 24th-order anti-symmetric filter with piecewise linear passbands and plot the desired and actual frequency response.
```

F = [lllllll
A = [0 1 0 0 0 0.5 0.5];
b = firls(24,F,A,'hilbert');
for i=1:2:6,
plot([F(i) F(i+1)],[A(i) A(i+1)],'--'), hold on
end
[H,f] = freqz(b,1,512,2);
plot(f,abs(H)), grid on, hold off
legend('Ideal','firls Design')

```

\begin{tabular}{|c|c|c|c|c|}
\hline Algorithm & \multicolumn{4}{|r|}{This function designs type I, II, III, and IV linear-phase filters. Type I and II are the defaults for \(n\) even and odd respectively, while the 'hilbert ' and 'differentiator' flags produce type III (n even) and IV (n odd) filters. The various filter types have different symmetries and constraints on their frequency responses (see [2] for details).} \\
\hline Linear Phase Filter Type & Filter Order & Symmetry of Coefficients & \[
\begin{aligned}
& \text { Response } H(f), \\
& \mathbf{f}=\mathbf{0}
\end{aligned}
\] & Response H(f), f = 1 (Nyquist) \\
\hline Typel & Even & even: & No restriction & No restriction \\
\hline Type II & Odd & & No restriction & \(\mathrm{H}(1)=0\) \\
\hline Type III & Even & odd: & \(\mathrm{H}(0)=0\) & \(\mathrm{H}(1)=0\) \\
\hline Type IV & Odd & \(b(k)=-b(n+2-k), k=1, \ldots, n+1\) & \(\mathrm{H}(0)=0\) & No restriction \\
\hline
\end{tabular}

\section*{Diagnostics}

An appropriate diagnostic message is displayed when incorrect arguments are used.
```

F must be even length.
F and A must be equal lengths.
Requires symmetry to be 'hilbert' or 'differentiator'.
Requires one weight per band.
Frequencies in F must be nondecreasing.
Frequencies in F must be in range [0,1].

```

A more serious warning message is
Warning: Matrix is close to singular or badly scaled.
This tends to happen when the product of thefilter length and transition width grows large. In this case, the filter coefficients b might not represent the desired filter. You can check the filter by looking at its frequency response.

\footnotetext{
See Also
fir1, fir2, firrcos, remez
}

References [1] Parks, T.W., and C.S. Burrus, Digital Filter Design, J ohn Wiley \& Sons, 1987, pp. 54-83.
[2] Oppenheim, A.V., and R.W. Schafer, Discrete-TimeSignal Processing, Prentice-H all, 1989, pp. 256-266.

\section*{Purpose Raised cosine FIR filter design}
```

Syntax b = firrcos(n,F0,df,fs)
b = firrcos(n, FO,df,fs,'bandwidth')
b = firrcos(n,FO,df)
b = firrcos(n,FO,r,fs,'rolloff')
b = firrcos(...,'type')
b = firrcos(...,'type',delay)
b = firrcos(...,'type',delay,window)
[b,a] = firrcos(...)

```

\section*{Description}
\(b=f i r r \cos (n, F 0, d f, f s)\) or, equivalently,
b = firrcos(n,F0,df,fs,'bandwidth') returns an order n lowpass linear-phase FIR filter with a raised cosine transition band. The filter has cutoff frequency FO , transition bandwidth df , and sampling frequency fs, all in hertz. df must be small enough so that F0 \(\pm \mathrm{df} / 2\) is between 0 and fs/2. The coefficients in b are normalized so that the nominal passband gain is always equal to 1 . Specify fs as the empty vector [ ] to use the default value \(\mathrm{fs}=2\).
\(b=f i r r \cos (n, F 0, d f)\) uses a default sampling frequency of \(f s=2\).
b = firrcos(n,FO,r,fs, 'rolloff') interprets the third argument, r, as the rolloff factor instead of the transition bandwidth, df. r must be in the range [0,1].
b = firrcos(...,'type') designs either a normal raised cosine filter or a square root raised cosine filter according to how you specify of the string 'type'. Specify 'type' as:
- 'normal', for a regular raised cosine filter. This is the default, and is also in effect when the 'type' argument is left empty, [ ].
- 'sqrt', for a square root raised cosine filter.
b = firrcos(...,'type', delay) specifies an integer delay in the range \([0, n+1]\). The default is \(n / 2\) for even \(n\) and \((n+1) / 2\) for odd \(n\).
b = firrcos(...,'type', delay, window) applies a length \(n+1\) window to the designed filter to reduce the ripple in the frequency response. window must be
a length \(n+1\) column vector. If no window is specified, a rectangular (rectwin) window is used. Care must be exercised when using a window with a delay other than the default.
\([b, a]=\operatorname{firrcos}(\ldots)\) always returns a = 1 .

\section*{Examples}

Design an order 20 raised cosine FIR filter with cutoff frequency 0.25 of the Nyquist frequency and a transition bandwidth of 0.25 .
```

h = firrcos(20,0.25,0.25);
freqz(h,1)

```



\footnotetext{
See Also
}

Purpose Frequency response of analog filters

\section*{Syntax}
\[
\begin{aligned}
& h=\operatorname{freqs}(b, a, w) \\
& {[h, w]=\operatorname{freqs}(b, a)} \\
& {[h, w]=\operatorname{freqs}(b, a, l)} \\
& \text { freqs }(b, a)
\end{aligned}
\]

Description freqs returns the complex frequency response \(\mathrm{H}(\mathrm{j} \omega\) ) (Laplace transform) of an analog filter
\[
H(s)=\frac{B(s)}{A(s)}=\frac{b(1) s^{n}+b(2) s^{n-1}+\cdots+b(n+1)}{a(1) s^{m}+a(2) s^{m-1}+\cdots+a(m+1)}
\]
given the numerator and denominator coefficients in vectors \(b\) and \(a\).
\(h=f r e q s(b, a, w)\) returns the complex frequency response of the analog filter specified by coefficient vectors \(b\) and \(a\). freqs evaluates the frequency response along the imaginary axis in the complex plane at the frequencies specified in real vector \(w\).
[h,w] = freqs(b,a) automatically picks a set of 200 frequency points \(w\) on which to compute the frequency response \(h\).
\([h, w]=\) freqs \((b, a, l)\) picks 1 frequencies on which to computethefrequency response \(h\).
freqs with no output arguments plots the magnitude and phase response versus frequency in the current figure window.
freqs works only for real input systems and positive frequencies.
Find and graph the frequency response of the transfer function given by
\[
\begin{aligned}
& \mathrm{H}(\mathrm{~s})=\frac{0.2 \mathrm{~s}^{2}+0.3 \mathrm{~s}+1}{\mathrm{~s}^{2}+0.4 \mathrm{~s}+1} \\
& \mathrm{a}=\left[\begin{array}{lll}
1 & 0.4 & 1
\end{array}\right] ; \\
& \mathrm{b}=\left[\begin{array}{lll}
0.2 & 0.3 & 1
\end{array}\right] ; \\
& \mathrm{w}=\log \operatorname{space}(-1,1) ; \\
& \text { freqs }(\mathrm{b}, \mathrm{a}, \mathrm{w})
\end{aligned}
\]


You can also create the plot with
```

h = freqs(b,a,w);
mag = abs(h);
phase = angle(h);
subplot(2,1,1), loglog(w,mag)
subplot(2,1,2), semilogx(w, phase)

```

To convert to hertz, degrees, and decibels, use
```

f = w/(2*pi);
mag = 20*log10(mag);
phase = phase*180/pi;

```

\section*{Algorithm}
freqs evaluates the polynomials at each frequency point, then divides the numerator response by the denominator response.
```

s = i*W;
h = polyval(b,s)./polyval(a,s);

```

\author{
See Also
}
abs, angle, freqz, invfreqs, logspace, polyval
\begin{tabular}{|c|c|}
\hline Purpose & Frequency spacing for frequency response \\
\hline \multirow[t]{6}{*}{Syntax} & \(f=\) freqspace ( n ) \\
\hline & \(\mathrm{f}=\) freqspace( \(\mathrm{n}, \mathrm{\prime}\) whole') \\
\hline & [f1,f2] = freqspace(n) \\
\hline & [f1,f2] = freqspace([m n]) \\
\hline & [ \(\mathrm{x} 1, \mathrm{y} 1\) ] = freqspace( \(\mathrm{n}, \mathrm{\prime}\) meshgrid') \\
\hline & [ \(\mathrm{x} 1, \mathrm{y} 1]\) = freqspace([m n\(], \mathrm{\prime m}\) ( \({ }^{\text {cheshgrid') }}\) \\
\hline \multirow[t]{10}{*}{Description} & freqspace returns the implied frequency range for equally spaced frequency responses. This is useful when creating frequency vectors for use with freqz. \\
\hline & \(f=\) freqspace \((n)\) returns the frequency vector \(f\) assuming \(n\) evenly spaced points around the unit circle. For \(n\) even or odd, \(f\) is \((0: 2 / n: 1)\). For \(n\) even, freqspace returns \((n+2) / 2\) points. For \(N\) odd, it returns \((n+1) / 2\) points. \\
\hline & \(\mathrm{f}=\mathrm{freqspace}(\mathrm{n}\), 'whole') returns n evenly spaced points around the whole unit circle. In this case, f is \(0: 2 / \mathrm{n}: 2^{*}(\mathrm{n}-1) / \mathrm{n}\). \\
\hline & [f1,f2] = freqspace(n) returns the two-dimensional frequency vectors f1 and f2 for an n-by-n matrix. For \(n\) odd, both f1 and f2 are \\
\hline & \([-1+1 / n: 2 / n: 1-1 / n]\). For \(n\) even, both f1 and f2 are \([-1: 2 / n: 1-2 / n]\). \\
\hline & [f1,f2] = freqspace([mn]) returns thetwo-dimensional frequency vectors f1 and f2 for an m-by-n matrix. \\
\hline & [ \(\mathrm{x} 1, \mathrm{y} 1]\) = freqspace( \(\mathrm{n}, \mathrm{\prime}\) meshgrid') and \\
\hline & [ \(\mathrm{x} 1, \mathrm{y} 1]\) = freqspace([m n\(]\), 'meshgrid') are equivalent to \\
\hline & [f1,f2] = freqspace(...); \\
\hline & [ \(\mathrm{x} 1, \mathrm{y} 1]\) = meshgrid(f1,f2) ; \\
\hline
\end{tabular}

See the MATLAB documentation for details on the meshgrid function.
See Also freqz, invfreqz

\section*{Purpose \\ Compute the frequency response of digital filters}

\section*{Syntax}
```

[h,w]= freqz(b,a,l)
h = freqz(b,a,w)
[h,w] = freqz(b,a,l,'whole')
[h,w,s] = freqz(...)
[h,f] = freqz(b,a,l,fs)
h = freqz(b,a,f,fs)
[h,f] = freqz(b,a,l,'whole',fs)
[h,f,s] = freqz(...)
freqz(b,a,...)

```

\section*{Description}
[ \(\mathrm{h}, \mathrm{w}\) ] = freqz \((\mathrm{b}, \mathrm{a}, \mathrm{l})\) returns the frequency response vector h and the corresponding frequency vector w for the digital filter whose transfer function is determined by the (real or complex) numerator and denominator polynomials represented in the vectors \(b\) and \(a\), respectively. The vectors \(h\) and \(w\) are both of length 1 . The frequency vector \(w\) has values ranging from 0 to \(\pi\) radians per sample. When you don't specify the integer 1 , or you specify it as the empty vector [ ], the frequency response is calculated using the default value of 512 samples.
h = freqz(b,a,w) returns the frequency response vector \(h\) calculated at the frequencies (in radians per sample) supplied by the vector \(w\). The vector \(w\) can have any length.
\([h, w]=\) freqz(b, a, l, 'whole') uses \(n\) sample points around the entire unit circle to calculate the frequency response. The frequency vector \(w\) has length 1 and has values ranging from 0 to \(2 \pi\) radians per sample.
[h,w,s] = freqz (...) returns a structure of plotting information to be used with freqzplot.
[h,f] = freqz(b,a,l,fs) returns the frequency response vector \(h\) and the corresponding frequency vector f for the digital filter whose transfer function is determined by the (real or complex) numerator and denominator polynomials represented in the vectors \(b\) and \(a\), respectively. The vectors \(h\) and fare both of length 1 . F or this syntax, the frequency response is cal culated using the sampling frequency specified by the scalar fs (in hertz). The
frequency vector \(f\) is calculated in units of hertz \((\mathrm{Hz})\). The frequency vector \(f\) has values ranging from 0 to \(f s / 2 \mathrm{~Hz}\).
\(h=f r e q z(b, a, f, f s)\) returns the frequency response vector \(h\) calculated at the frequencies (in Hz ) supplied in the vector f . The vector f can be any length.
[h,f] = freqz(b,a,l,'whole',fs) uses n points around theentireunit circle to calculate the frequency response. The frequency vector f has length land has values ranging from 0 to fs Hz .
[h,f,units] = freqz(b,a, l, 'whole', fs) returns the optional string argument units, specifying the units for the frequency vector \(f\). The string returned in units is ' Hz ', denoting hertz.
freqz ( \(\mathrm{b}, \mathrm{a}, \ldots\) ) plots the magnitude and unwrapped phase of the frequency response of the filter. The plot is displayed in the current figure window.

Remarks

Examples

It is best to choosea power of two for the third input argument \(n\), because freqz uses an FFT al gorithm to calculate the frequency response. See the reference description of fft for more information.

Plot the magnitude and phase response of an FIR filter.
```

b = fir1(80,0.5,kaiser(81,8));
freqz(b,1);

```


\section*{Algorithm}

See Also

The frequency response [1] of a digital filter can be interpreted as the transfer function evaluated at \(z=\mathrm{e}^{\mathrm{j} \omega}\). Y ou can always write a rational transfer function in the following form.
\[
H(z)=\frac{B(z)}{A(z)}=\frac{b(1)+b(2) z^{-1}+\cdots+b(n+1) z^{-n}}{a(1)+a(2) z^{-1}+\cdots+a(m+1) z^{-m}}
\]
freqz determines the transfer function from the (real or complex) numerator and denominator polynomials you specify, and returns the complex frequency response \(\mathrm{H}\left(\mathrm{e}^{\mathrm{j} \omega}\right)\) of a digital filter. The frequency response is evaluated at sample points determined by the syntax that you use.
freqz generally uses an FFT algorithm to compute the frequency response whenever you don't supply a vector of frequencies as an input argument. It computes the frequency response as the ratio of the transformed numerator and denominator coefficients, padded with zeros to the desired length.

When you do supply a vector of frequencies as an input argument, then freqz evaluates the polynomials at each frequency point using Horner's method of nested polynomial evaluation [1], dividing the numerator response by the denominator response.
abs, angle, fft, filter, freqs, freqzplot, impz, invfreqs, logspace

References [1] Oppenheim, A.V., and R.W. Schafer, Discrete-Time Signal Processing, Prentice-Hall, 1989, pp. 203-205.
\begin{tabular}{|c|c|}
\hline Purpose & Plot frequency response data \\
\hline Syntax & \[
\begin{aligned}
& \text { freqzplot }(h, w) \\
& \text { freqzplot }(h, w, s) \\
& \text { freqzplot }(h, w, s t r)
\end{aligned}
\] \\
\hline Description & \begin{tabular}{l}
freqzplot ( \(\mathrm{h}, \mathrm{w}\) ) plots the frequency response data contained in h at the frequencies specified in the vector \(w\), where \(h\) can be either a vector or a matrix. \(w\) must be a vector whose length is the number of rows in h . The data in h is plotted versus frequency w on two plots: \\
- The magnitude of \(h\) is plotted in dB. \\
- The phase of \(h\) is plotted in degrees. \\
The units for frequency on the plots are in radians per sample. If h is a matrix, the frequency responses of each column of \(h\) is plotted. \\
freqzplot ( \(h, w, s\) ) specifies a structure of plotting options, \(s\), with the following fields: \\
- s. xunits-a string specifying the frequency axis units. The contents of s. xunits can be one of the following: \\
- 'rad/sample' (default) \\
- 'Hz' \\
- 'kHz' \\
- 'MHz' \\
- 'GHz' \\
- A user-specified string \\
- s.yunits-a string specifying the vertical axis units. The contents of s. yunits can be one of the following: \\
- 'dB' (default) \\
- 'linear' \\
- 'squared'
\end{tabular} \\
\hline
\end{tabular}
- s.plot-a string specifying the type of plot to produce. The contents of s. plot can be one of the following:
- 'both' (default)
- 'mag'
- 'phase'

Note that the structure can be obtained as an output of freqz.
freqzplot ( \(\mathrm{h}, \mathrm{w}, \mathrm{str}\) ) specifies a particular string option from the structure. This is a quick way to select a single plotting option.

\section*{Examples}
```

nfft = 512; Fs = 44.1; % Fs is in kHz.
[b1,a1] = cheby1(5,0.4,0.5);
[b2,a2] = cheby1(5,0.5,0.5);
[h1,f,s] = freqz(b1,a1,nfft,Fs);
h2 = freqz(b2,a2,nfft,Fs);% Use the same nfft and Fs.
h = [h1 h2];

```

Use the quick method to specify only the s.yunits. The s.plot and s.xunits use the default values of 'both' and 'rad/sample', respectively.
```

freqzplot(h,f,'squared')

```



Define each of the s structure units to customize the plot.
```

s.plot = 'mag'; % Plot the magnitude only.
s.xunits = 'khz'; % Label the frequency units correctly.
s.yunits = 'squared'; % Plot the magnitude squared.
freqzplot(h,f,s); % Compare the two Chebyshev filters.

```


\footnotetext{
See Also
freqz, grpdelay, psdplot
}

\section*{Purpose Open the Filter Visualization Tool}

\section*{Syntax}
fvtool(b, a)
fvtool ( \(\left.b_{1}, a_{1}, b_{2}, a_{2}, \ldots b_{n}, a_{n}\right)\)

\section*{Description}
fvtool(b, a) opens the Filter Visualization Tool (FVTool) and computes the magnitude response of the filter defined with numerator, \(b\) and denominator, a. Using FVTool you can display the phase response, group delay, impulse response, step response, pole-zero plot, and coefficients of the filter.
fvtool ( \(b_{1}, a_{1}, b_{2}, a_{2}, \ldots b_{n}, a_{n}\) ) opens FVTool and computes the magnitude responses of multiple filters defined with numerators, \(b_{1} \ldots b_{n}\) and denominators, \(a_{1} \ldots a_{n}\).

Note In fdatool, selecting Full View Analysis from the Analysis menu launches FVTool.


Note If you have the Filter Design Tool box installed, you can use fvtool on quantized filter objects by using fvtool(Hq, Hq1).

\section*{Examples}

\section*{Example 1}

Display the magnitude response of an elliptic filter.
```

[b,a]=ellip(6,3,50,300/500);
fvtool(b,a);

```



\section*{Example 2}

Display and analyze multiple FIR filters.
```

n = 20;
% Filter order
f = [0 0.4 0.5 1];
% Frequency band edges
a = [1 1 0 0];
% Desired amplitudes
b = remez(n,f,a);
b2 = remez(n*2,f,a); % Double the filter order
fvtool(b,1,b2,1);

```


\section*{See Also}
fdatool, sptool
\begin{tabular}{|c|c|}
\hline Purpose & Generate a Gaussian-modulated sinusoidal pulse \\
\hline Syntax & ```
yi = gauspuls(t,fc,bw)
yi = gauspuls(t,fc,bw,bwr)
[yi,yq] = gauspuls(...)
[yi,yq,ye] = gauspuls(...)
tc = gauspuls('cutoff',fc,bw,bwr,tpe)
``` \\
\hline \multirow[t]{5}{*}{Description} & gauspuls generates Gaussian-modulated sinusoidal pulses. \\
\hline & yi = gauspuls(t,fc,bw) returnsa unity-amplitudeGaussian RF pulse at the times indicated in array \(t\), with a center frequency fc in hertz and a fractional bandwidth bw, which must be greater than 0 . The default value for fc is 1000 Hz and for bw is 0.5 . \\
\hline & yi = gauspuls(t,fc,bw,bwr) returns a unity-amplitude Gaussian RF pulse with a fractional bandwidth of bw as measured at a level of bwr dB with respect to the normalized signal peak. The fractional bandwidth reference level bwr must be less than 0 , because it indicates a reference level less than the peak (unity) envel ope amplitude. The default value for bwr is -6 dB . \\
\hline & \begin{tabular}{l}
[yi,yq] = gauspuls(...) returns both the in-phase and quadrature pulses. \\
[yi,yq,ye] = gauspuls(...) returns the RF signal envelope.
\end{tabular} \\
\hline & tc = gauspuls('cutoff',fc, bw, bwr, tpe) returns thecutoff timetc (greater than or equal to 0 ) at which the trailing pulseenvel ope falls below tpe dB with respect to the peak envel ope amplitude. The trailing pulse envel ope level tpe must be less than 0 , because it indicates a reference level less than the peak (unity) envelope amplitude. The default value for tpe is -60 dB. \\
\hline Remarks & Default values are substituted for empty or omitted trailing input arguments. \\
\hline
\end{tabular}

\section*{Examples}

Plot a 50 kHz Gaussian RF pulse with \(60 \%\) bandwidth, sampled at a rate of 1 MHz . Truncate the pulse where the envel ope falls 40 dB below the peak.
```

tc = gauspuls('cutoff',50e3,0.6,[], -40);
t = -tc : 1e-6 : tc;
yi = gauspuls(t,50e3,0.6);
plot(t,yi)

```

chirp, cos, diric, pulstran, rectpuls, sawtooth, sin, sinc, square, tripuls

\section*{Purpose Compute a Gaussian window}

\section*{Syntax \\ w = gausswin(n) \\ \(w=\operatorname{gausswin}(\mathrm{n}, \alpha)\)}

\section*{Description}
\(w=\) gausswin( \(n\) ) returns an n-point Gaussian window in the column vector w. \(n\) is a positive integer. The coefficients of a Gaussian window are computed from the following equation.
\[
w\lceil k+1\rceil=e^{-\frac{1}{2}\left(\alpha \frac{k-\frac{N}{2}}{N / 2}\right)^{2}}
\]
where \(0 \leq \mathrm{k} \leq \mathrm{N}\) and \(\alpha \geq 2\).
\(\mathrm{w}=\) gausswin \((\mathrm{n}, \alpha)\) returns an n-point Gaussian window where \(\alpha\) is the reciprocal of the standard deviation. The width of the window is inversely related to the value of \(\alpha\); a larger value of \(\alpha\) produces a narrower window. If \(\alpha\) is omitted, it defaults to 2.5 .

Note If the window appears to be clipped, increase the number of points ( n ) used for gausswin(n) .

\section*{Example}
```

N=64;
w = gausswin(N);
plot(w); axis([1 N 0 1]);
title('64-point Gaussian window');

```


Note The shape of this window is similar in the frequency domain because the Fourier transform of a Gaussian is also a Gaussian.

\section*{See Also}

References
barthannwin, bartlett, blackman, blackmanharris, bohmanwin, chebwin, hann, hamming, kaiser, nuttallwin, rectwin, triang, tukeywin, window
[1] harris, f.j. "On the Use of Windows for Harmonic Analysis with the Discrete Fourier Transform." Proceedings of the IEEE. Vol. 66, No. 1 (J anuary 1978).
[2] Roberts, Richard A., and C.T. Mullis. Digital Signal Processing. Reading, MA: Addison-Wesley, 1987, pp. 135-136.

\section*{Purpose \\ Generate a Gaussian monopulse}

\section*{Syntax}
\(y=\) gmonopuls( \((t, f c)\)
\(t c=\) gmonopuls('cutoff \(\left.{ }^{\prime}, f c\right)\)
Description

Remarks
Default values are substituted for empty or omitted trailing input arguments.

\section*{Examples}

\section*{Example 1}

Plot a 2 GHz Gaussian monopulse sampled at a rate of 100 GHz .
```

    fc = 2E9; fs=100E9;
    tc = gmonopuls('cutoff',fc);
    t = -2*tc : 1/fs : 2*tc;
    y = gmonopuls(t,fc); plot(t,y)
    ```


\section*{gmonopuls}

\section*{Example 2}

Construct a pulse train from the monopulse of Example 1 using a spacing of 7.5 ns.
```

fc = 2E9; fs=100E9; % center freq, sample freq
D = [2.5 10 17.5]' * 1e-9; % pulse delay times
tc = gmonopuls('cutoff',fc); % width of each pulse
t = 0 : 1/fs : 150*tc; % signal evaluation time
yp = pulstran(t,D,@gmonopuls,fc);
plot(t,yp)

```

Purpose Compute the DFT using the second-order Goertzel algorithm
Syntax \(\quad\)\begin{tabular}{rl}
\(y\) & \(=\operatorname{goertzel}(x, i)\) \\
\(y\) & \(=\operatorname{goertzel}(x, i, \operatorname{dim})\)
\end{tabular}

Description

Example
goertzel computes the discrete Fourier transform (DFT) of specific indices in a vector or matrix.
\(y=\) goertzel(x,i) returns the DFT of vector \(x\) at the indices in vector \(i\), computed using the second-order Goertzel algorithm. If \(x\) is a matrix, goertzel computes each column separately. The indices in vector i must be integer values from 1 to \(N\), where \(N\) is the length of the first matrix dimension of \(x\) that is greater than 1 . The resulting y has the same dimensions as \(x\). If i is omitted, it is assumed to be [1:N ], which results in a full DFT computation.
\(y=\) goertzel(x,i,dim) returns the discrete F ourier transform (DFT) of matrix \(x\) at the indices in vector \(i\), computed along the dimension dim of \(x\).

Note fft computes all DFT values at all indices, while goertzel computes DFT values at a specified subset of indices (i.e., a portion of the signal's frequency range). If less than \(\log _{2}(\mathrm{~N})\) points are required, goertzel is more efficient than the Fast Fourier Transform (fft).

Two examples where goertzel can be useful are spectral analysis of very large signals and dual-tone multifrequency (DTMF) signal detection.

Generate an \(8-\mathrm{Hz}\) sinusoid and use the Goertzel al gorithm to detect it using the first 20 indices.
```

Fs = 1024;
Ts = 1/Fs;
f = 8;
N = 1024;
t = Ts*(0:N-1)';
x = sin(2*pi*f*t); %Generate 8 Hz sinusoid
figure(1);
plot(t,x);

```

figure(2);
periodogram(x,[],[],Fs); \% Use periodogram to obtain the PSD \% (computed with all N points of signal)

```

figure(3); % only in the region of interest
plot(vec-1,20*log10(abs(X)));

```

Using Goertzel to Detect the 8 Hz Signal


Algorithm goertzel implements this transfer function
\[
H_{k}(z)=\frac{1-W_{N}^{k} z^{-1}}{1-2 \cos \left(\frac{2 \pi}{N} k\right) z^{-1}+z^{-2}}
\]
where N is the length of the signal and k is the index of the computed DFT. k is related to the indices in vector i above as \(\mathrm{k}=\mathrm{i}-1\).

The signal flow graph for this transfer function is

and it is implemented as
\[
v_{k}[n]=x[n]+2 \cos \left(\frac{2 \pi k}{N}\right) v_{k}[n-1]-v_{k}[n-2]
\]
where \(0 \leq \mathrm{n} \leq \mathrm{N}\) and
\[
X[k]=y_{k}[N]=v_{k}[N]-W_{N}^{k} v_{k}[N-1]
\]

To compute \(\mathrm{X}[\mathrm{k}]\) for a particular k , the Goertzel al gorithm requires 4 N real multiplications and 4 N real additions. Although this is less efficient than computing the DFT by the direct method, Goertzel uses recursion to compute
\[
\mathrm{W}_{\mathrm{N}}^{\mathrm{k}} \text { and } \cos \left(\frac{2 \pi \mathrm{k}}{\mathrm{~N}}\right)
\]
which are evaluated only at \(\mathrm{n}=\mathrm{N}\). The direct DFT does not use recursion and must compute each complex term separately.

\section*{See Also}

References [1]Burrus, C.S. and T.W. Parks. DFT/ FFT and Convolution Algorithms. J ohn Wiley \& Sons, 1985, pp. 32-26.
[2] Mitra, Sanjit K. Digital Signal Processing: A Computer-Based Approach. New York, NY: McGraw-Hill, 1998, pp. 520-523.

\section*{Purpose Compute the average filter delay (group delay)}

\section*{Syntax}
```

[gd,w] = grpdelay(b,a,l)
[gd,f] = grpdelay(b,a,l,fs)
[gd,w] = grpdelay(b,a,l,'whole')
[gd,f] = grpdelay(b,a,l,'whole',fs)
gd = grpdelay(b,a,w)
gd = grpdelay(b,a,f,fs)
grpdelay(b,a)

```

The group delay of a filter is a measure of the average delay of the filter as a function of frequency. It is the negative first derivative of the phase response of the filter. If the complex frequency response of a filter is \(\mathrm{H}\left(\mathrm{e}^{j \omega}\right)\), then the group delay is
\[
\tau_{g}(\omega)=-\frac{d \theta(\omega)}{d \omega}
\]
where \(\omega\) is frequency and \(\theta\) is the phase angle of \(\mathrm{H}\left(\mathrm{e}^{\mathrm{j} \omega}\right)\).
\([g d, w]=\) grpdelay \((b, a, l)\) returns the i-point group delay, \(\tau_{g}(\omega)\), of the digital filter
\[
H(z)=\frac{B(z)}{A(z)}=\frac{b(1)+b(2) z^{-1}+\cdots+b(n+1) z^{-n}}{a(1)+a(2) z^{-1}+\cdots+a(m+1) z^{-m}}
\]
given the numerator and denominator coefficients in vectors b and a. grpdelay returns both gd, the group delay, and \(w\), a vector containing the 1 frequency points in radians. grpdelay evaluates the group delay at 1 points equally spaced around the upper half of the unit circle, so w contains l points between 0 and \(\pi\).
[gd,f] = grpdelay(b,a,l,fs) specifies a positive sampling frequency fs in hertz. It returns a length l vector f containing the actual frequency points at which the group delay is calculated, also in hertz. f contains 1 points between 0 and fs/2.
[gd,w] = grpdelay(b,a,l,'whole') and
[gd,f] = grpdelay(b, a, l, 'whole', fs) use n points around the whole unit circle (from 0 to \(2 \pi\), or from 0 to fs).
gd = grpdelay (b, a,w) and
gd = grpdelay (b, a,f,fs) return the group delay evaluated at the points in w (in radians) or \(f\) (in hertz), respectively, where \(f s\) is the sampling frequency in hertz.
grpdelay with no output arguments plots the group delay versus frequency in the current figure window.
grpdelay works for both real and complex input systems.

\section*{Examples}

Plot the group delay of Butterworth filter \(b(z) / a(z)\).
\[
\begin{aligned}
& {[b, a]=\operatorname{butter}(6,0.2) ;} \\
& \text { grpdelay }(b, a, 128)
\end{aligned}
\]


\section*{grpdelay}

Plot both the group and phase delays of a system on the same graph.
```

gd = grpdelay(b,a,512);
gd(1) = []; % Avoid NaNs
[h,w] = freqz(b,a,512); h(1) = []; w(1) = [];
pd = -unwrap(angle(h))./w;
plot(w,gd,w,pd,':')
xlabel('Frequency (rad/sec)'); grid;
legend('Group Delay','Phase Delay');

```


Algorithm

See Also cceps, fft, freqz, hilbert, icceps, rceps

\section*{Purpose Compute a Hamming window}

\section*{Syntax}
\(\mathrm{w}=\) hamming( n )
\(\mathrm{w}=\) hamming( \(\left.\mathrm{n}, \mathrm{sflag}{ }^{\prime}\right)\)

\section*{Description}
\(w=\) hamming ( \(n\) ) returns an n-point symmetric Hamming window in the column vector \(w\). \(n\) should be a positive integer. The coefficients of a Hamming window are computed from the following equation.
\[
w[k+1]=0.54-0.46 \cos \left(2 \pi \frac{k}{n-1}\right), \quad k=0, \ldots, n-1
\]
w = hamming( n, 'sflag') returns an n-point Hamming window using the window sampling specified by 'sflag', which can be either 'periodic' or 'symmetric' (the default). When 'periodic' is specified, hamming computes a length \(n+1\) window and returns the first \(n\) points.

Note If you specify a one-point window ( \(n=1\) ), the value 1 is returned.
```

Examples
$\mathrm{N}=64$;
w = hamming (N);
plot(w); axis([1 N 0 1]);
title('Hamming Window')

```


See Also

References
barthannwin, bartlett, blackman, blackmanharris, bohmanwin, chebwin, gausswin, hann, kaiser, nuttallwin, rectwin, triang, tukeywin, window
[1] Oppenheim, A.V., and R.W. Schafer, DiscreteTimeSignal Processing, Prentice-Hall, 1989, pp. 447-448.

\section*{Purpose \\ Compute a Hann (Hanning) window}

\section*{Syntax}
w = hann ( n )
w = hann(n, 'sflag')

\section*{Description}
\(\mathrm{w}=\) hann ( n ) returns an n-point symmetric Hann window in the column vector \(w\). \(n\) must be a positive integer. The coefficients of a Hann window are computed from the following equation.
\[
w[k+1]=0.5\left(1-\cos \left(2 \pi \frac{k}{n-1}\right)\right), \quad k=0, \ldots, n-1
\]
w = hann(n, 'sflag') returns an n-point Hann window using the window sampling specified by 'sflag', which can be either 'periodic' or 'symmetric' (the default). When 'periodic' is specified, hann computes a length \(n+1\) window and returns the first \(n\) points.

Note If you specify a one-point window ( \(n=1\) ), the value 1 is returned.
```

Examples
$\mathrm{N}=64$;
w = hann(N);
plot(w); axis([1 N 0 1]);
title('Hann Window')

```


See Also

References
barthannwin, bartlett, blackman, blackmanharris, bohmanwin, chebwin, gausswin, hamming, kaiser, nuttallwin, rectwin, triang, tukeywin, window
[1] Oppenheim, A.V., and R.W. Schafer, DiscreteTimeSignal Processing, Prentice-H all, 1989, pp. 447-448.

\section*{Purpose}

Syntax

Description

Example

Compute the discrete-time analytic signal using the Hilbert transform
\(x=h i l b e r t(x r)\)
\(x=\) hilbert( \(x r, n\) )
\(x=\) hilbert ( \(x r\) ) returns a complex helical sequence, sometimes called the analytic signal, from a real data sequence. The analytic signal \(x=x r+i * x i\) has a real part, xr , which is the original data, and an imaginary part, xi , which contains the Hilbert transform. The imaginary part is a version of the original real sequence with a \(90^{\circ}\) phase shift. Sines are thereforetransformed to cosines and vice versa. The Hilbert transformed series has the same amplitude and frequency content as the original real data and includes phase information that depends on the phase of the original data.

If xr is a matrix, \(\mathrm{x}=\) hilbert \((\mathrm{xr})\) operates columnwise on the matrix, finding the Hilbert transform of each column.
\(\mathrm{x}=\) hilbert ( \(\mathrm{xr}, \mathrm{n}\) ) uses an n point FFT to compute the Hilbert transform. The input data xr is zero-padded or truncated to length n , as appropriate.

The Hilbert transform is useful in calculating instantaneous attributes of a time series, especially the amplitude and frequency. The instantaneous amplitude is the amplitude of the complex Hilbert transform; the instantaneous frequency is the time rate of change of the instantaneous phase angle. For a pure sinusoid, the instantaneous amplitude and frequency are constant. The instantaneous phase, however, is a sawtooth, reflecting the way in which the local phase angle varies linearly over a single cycle. F or mixtures of sinusoids, the attributes are short term, or local, averages spanning no more than two or three points.

Reference [1] describes the K olmogorov method for minimum phase reconstruction, which involves taking the Hilbert transform of the logarithm of the spectral density of a time series. The tool box function rceps performs this reconstruction.

For a discrete-time analytic signal \(x\), the last half of \(f f t(x)\) is zero, and the first (DC) and center (Nyquist) elements of \(\mathrm{fft}(\mathrm{x})\) are purely real.
```

xr = [lllll
x = hilbert(xr)

```
\(x=\)
1.0000+1.0000i 2.0000-1.0000i 3.0000-1.0000i 4.0000+1.0000i

You can see that the imaginary part, imag \((x)=\left[\begin{array}{llll}1 & -1 & -1 & 1\end{array}\right]\), is the Hilbert transform of \(x r\), and the real part, real \((x)=\left[\begin{array}{lll}1 & 2 & 3\end{array}\right]\), is simply \(x r\) itself. Note that the last half of \(\mathrm{fft}(\mathrm{x})=\left[\begin{array}{llll}10 & -4+4 i & -2 & 0\end{array}\right]\) is zero (in this example, the last half is just the last element), and that the DC and Nyquist elements of \(\mathrm{fft}(x), 10\) and -2 respectively, are purely real.
Algorithm The analytic signal for a sequence \(x\) has a onesided Fourier transform, that is, negative frequencies are 0 . To approximate the analytic signal, hilbert calculates the FFT of the input sequence, replaces those FFT coefficients that correspond to negative frequencies with zeros, and calculates the inverse FFT of the result.
In detail, hilbert uses a four-step algorithm:
1 It calculates the FFT of the input sequence, storing the result in a vector x .
2 It creates a vector h whose elements \(\mathrm{h}(\mathrm{i})\) have the values:
- 1 for \(i=1,(n / 2)+1\)
- 2 for \(i=2,3, \ldots,(n / 2)\)
- 0 for \(i=(n / 2)+2, \ldots, n\)
3 It calculates the element-wise product of \(x\) and \(h\).
4 It calculates the inverse FFT of the sequence obtained in step 3 and returns the first \(n\) elements of the result.
If the input data \(x r\) is a matrix, hilbert operates in a similar manner, extending each step above to handle the matrix case.
See Also fft, ifft, rceps

References [1] Claerbout, J.F., Fundamentals of Geophysical Data Processing, McGraw-Hill, 1976, pp. 59-62.
[2] Marple, S.L., "Computing the discrete-time analytic signal via FFT,"IEEE Transactions on Signal Processing, Vol. 47, No. 9 (September 1999), pp. 2600-2603.
[3] Oppenheim, A.V., and R.W. Schafer, DiscreteTimeSignal Processing, 2nd ed., Prentice-Hall, 1998.
\begin{tabular}{|c|c|}
\hline Purpose & Inverse complex cepstrum \\
\hline Syntax & x = icceps(xhat, nd ) \\
\hline Description & \(x\) = icceps (xhat, nd) returns the inverse complex cepstrum of the (assumed real) sequence xhat, removing nd samples of delay. If xhat was obtained with cceps ( \(x\) ), then the amount of delay that was added to \(x\) was the element of round (unwrap (angle(fft(x)))/pi) corresponding to \(\pi\) radians. \\
\hline See Also & cceps, hilbert, rceps, unwrap \\
\hline References & [1] Oppenheim, A.V., and R.W. Schafer, DiscreteTimeSignal Processing, Prentice-Hall, 1989. \\
\hline
\end{tabular}

\section*{Purpose Inverse discrete cosine transform}

\section*{Syntax \\ \(x=\operatorname{idct}(y)\) \\ \(x=\operatorname{idct}(y, n)\)}

\section*{Description}

The inverse discrete cosine transform reconstructs a sequence from its discrete cosine transform (DCT) coefficients. The idct function is the inverse of the dct function.
\(x=\operatorname{idct}(y)\) returns the inverse discrete cosine transform of \(y\)
\[
x(n)=\sum_{k=1}^{\mathrm{N}} w(k) y(k) \cos \frac{\pi(2 n-1)(k-1)}{2 N}, \quad n=1, \ldots, N
\]
where
\[
w(k)= \begin{cases}\frac{1}{\sqrt{N}}, & k=1 \\ \sqrt{\frac{2}{N}}, & 2 \leq k \leq N\end{cases}
\]
and \(N=\) length ( \(x\) ), which is the same as length ( \(y\) ). The series is indexed from \(\mathrm{n}=1\) and \(\mathrm{k}=1\) instead of the usual \(\mathrm{n}=0\) and \(\mathrm{k}=0\) because MATLAB vectors run from 1 to N instead of from 0 to \(\mathrm{N}-1\).
\(x=\operatorname{idct}(y, n)\) appends zeros or truncates the vector \(y\) to length \(n\) before transforming.

If \(y\) is a matrix, idct transforms its columns.
See Also dct, dct2, idct2, ifft
References [1]J ain, A.K., Fundamentals of Digital ImageProcessing, Prentice-Hall, 1989.
[2] Pennebaker, W.B., and J.L. Mitchell, J PEG Still ImageData Compression Standard, Van Nostrand Reinhold, 1993, Chapter 4.

\section*{Purpose One-dimensional inverse fast Fourier transform}

\section*{Syntax \\ \(y=i f f t(x)\) \\ \(y=i f f t(x, n)\)}

\section*{Description}

Algorithm

See Also fft, fft2,fftshift, ifft2

\section*{Purpose \\ Two-dimensional inverse fast Fourier transform}
Syntax \(\quad\)\begin{tabular}{rl}
\(Y\) & \(=\operatorname{ifft} 2(X)\) \\
\(Y\) & \(=\operatorname{ifft} 2(X, m, n)\)
\end{tabular}

Description

Algorithm

See Also
fft, fft2, fftn, fftshift, ifft, ifftn

\section*{impinvar}

Purpose Impulse invariance method for analog-to-digital filter conversion
Syntax \begin{tabular}{rl}
{\([b z, a z]\)} & \(=\) impinvar \((b, a, f s)\) \\
{\([b z, a z]\)} & \(=\) impinvar \((b, a)\) \\
{\([b z, a z]\)} & \(=\) impinvar \((b, a, f s, t o l)\)
\end{tabular}

Description

Examples
Convert an analog lowpass filter to a digital filter using impinvar with a sampling frequency of 10 Hz .
```

[b,a] = butter(4,0.3,'s');
[bz,az] = impinvar(b,a,10)
bz =
1.0e-006 *
-0.0000 0.1324 0.5192 0.1273 0
az =

| 1.0000 | -3.9216 | 5.7679 | -3.7709 | 0.9246 |
| :--- | :--- | :--- | :--- | :--- |

```

\section*{impinvar}
\begin{tabular}{|c|c|}
\hline Algorithm & impinvar performs the impulse-invariant method of analog-to-digital transfer function conversion discussed in reference [1]: \\
\hline & \begin{tabular}{l}
1 It finds the partial fraction expansion of the system represented by \(b\) and \(a\). \\
2 It replaces the poles \(p\) by the poles \(\exp (p / f s)\).
\end{tabular} \\
\hline & 3 It finds the transfer function coefficients of the system from the residues from step 1 and the poles from step 2. \\
\hline See Also & bilinear, lp2bp, lp2bs, lp2hp, 1p2lp \\
\hline References & [1] Parks, T.W., and C.S. Burrus, Digital Filter Design, J ohn Wiley \& Sons, 1987, pp. 206-209. \\
\hline
\end{tabular}

\section*{Purpose Compute the impulse response of digital filters}
```

Syntax [h,t] = impz(b,a)
[h,t] = impz(b,a,n)
[h,t] = impz(b,a,n,fs)
impz(b,a)
impz(...)

```

\section*{Description}

\section*{Examples}
[h,t] = impz (b,a) computes the impulse response of the filter with numerator coefficients \(b\) and denominator coefficients \(a\). impz chooses the number of samples and returns the responsein the column vector \(h\) and sample times in the column vector \(t\) (where \(t=[0: n-1]\) ', and \(n=\) length ( \(t\) ) is computed automatically).
\([h, t]=i m p z(b, a, n)\) computes \(n\) samples of the impulse response when \(n\) is an integer ( \(t=[0: n-1]^{\prime}\) ). If \(n\) is a vector of integers, impz computes the impulse response at those integer locations, starting the response computation from 0 (and \(t=n\) or \(t=[0 \mathrm{n}]\) ). If, instead of \(n\), you include the empty vector [ ] for the second argument, the number of samples is computed automatically by default.
\([h, t]=i m p z(b, a, n, f s)\) computes \(n\) samples and produces a vector \(t\) of length \(n\) so that the samples are spaced \(1 / f s\) units apart.
impz with no output arguments plots the impulse response in the current figure window using stem( \(\mathrm{t}, \mathrm{h}\) ).
impz works for both real and complex input systems.
Plot the first 50 samples of the impulse response of a fourth-order lowpass elliptic filter with cutoff frequency of 0.4 times the N yquist frequency.
```

[b,a] = ellip(4,0.5,20,0.4);
impz(b,a,50)

```


\section*{Algorithm}
impz filters a length \(n\) impulse sequence using
\[
\text { filter }(b, a,[1 \operatorname{zeros}(1, n-1)])
\]
and plots the results using stem.
To compute \(n\) in the auto-length case, impz either uses \(n=\) length(b) for the FIR case or first finds the poles using \(p=\) roots (a), if length (a) is greater than 1.

If the filter is unstable, \(n\) is chosen to be the point at which the term from the largest pole reaches 10^6 times its original value.

If the filter is stable, \(n\) is chosen to be the point at which the term due to the largest amplitude pole is \(5^{*} 10^{\wedge}-5\) of its original amplitude.

If the filter is oscillatory (poles on the unit circle only), impz computes five periods of the slowest oscillation.
If the filter has both oscillatory and damped terms, \(n\) is chosen to equal five periods of the slowest oscillation or the point at which the term due to the largest (nonunity) amplitude pole is \(5^{*} 10^{\wedge}-5\) of its original amplitude, whichever is greater.
impz also allows for delays in the numerator polynomial. The number of delays is incorporated into the computation for the number of samples.

See Also impulse, stem

Purpose Increase sampling rate by an integer factor (interpolation)

\section*{Syntax}
\(y=\operatorname{interp}(x, r)\)
\(y=\operatorname{interp}(x, r, l\), alpha \()\)
\([y, b]=\operatorname{interp}(x, r, l\), alpha \()\)
Description

\section*{Examples}

Interpolation increases the original sampling rate for a sequence to a higher rate. interp performs lowpass interpolation by inserting zeros into the original sequence and then applying a special lowpass filter.
\(y=\operatorname{interp}(x, r)\) increases the sampling rate of \(x\) by a factor of \(r\). The interpolated vector \(y\) is \(r\) times longer than the original input \(x\).
\(y=\) interp ( \(x, r, l\), alpha) specifies \(l\) (filter length) and alpha (cut-off frequency). The default value for 1 is 4 and the default value for alpha is 0.5 .
[ \(y, b]=\) interp( \(x, r, l, a l p h a)\) returns vector b containing the filter coefficients used for the interpolation.

Interpolate a signal by a factor of four.
```

t = 0:0.001:1; % Time vector
x = sin(2*pi*30*t) + sin(2*pi*60*t);
y = interp(x,4);
stem(x(1:30));
title('Original Signal');
figure
stem(y(1:120));
title('Interpolated Signal');

```


\section*{Algorithm}
interp uses the lowpass interpolation Algorithm 8.1 described in [1]:
1 It expands the input vector to the correct length by inserting zeros between the original data values.
2 It designs a special symmetric FIR filter that allows the original data to pass through unchanged and interpolates between so that the mean-square errors between the interpolated points and their ideal values are minimized.
3 It applies the filter to the input vector to produce the interpolated output vector.

The length of the FIR lowpass interpolating filter is \(2 * 1 * r+1\). The number of original sample values used for interpolation is \(2 * 1\). Ordinarily, 1 should be less than or equal to 10 . The original signal is assumed to be band limited with normalized cutoff frequency \(0 \leq\) alpha \(\leq 1\), where 1 is half the original sampling frequency (the Nyquist frequency). The default value for 1 is 4 and the default value for alpha is 0.5.

Diagnostics

References

See Also decimate, downsample, interp1, resample, spline, upfirdn, upsample
If \(r\) is not an integer, interp gives the following error message.
Resampling rate R must be an integer.
[1] Programs for Digital Signal Processing, IEEE Press, New York, 1979, Algorithm 8.1.

\section*{Purpose Interpolation FIR filter design}
Syntax \(\quad\)\begin{tabular}{rl}
\(b\) & \(=\operatorname{intfilt}(r, l\), alpha \()\) \\
\(b\) & \(=\operatorname{intfilt}\left(r, n\right.\), Lagrange \(\left.^{\prime}\right)\)
\end{tabular}

Description

Examples
Design a digital interpolation filter to upsample a signal by four, using the bandlimited method.
```

alpha = 0.5; % "Bandlimitedness" factor
h1 = intfilt(4,2,alpha); % Bandlimited interpolation

```

The filter h1 works best when the original signal is bandlimited to alpha times the Nyquist frequency. Create a bandlimited noise signal.
```

randn('state',0)
x = filter(fir1(40,0.5),1,randn(200,1)); % Bandlimit

```

Now zero pad the signal with three zeros between every sample. The resulting sequence is four times the length of \(x\).
```

xr = reshape([x zeros(length(x),3)]',4*length(x),1);

```

Interpolate using the filter command.
```

y = filter(h1,1,xr);

```
\(y\) is an interpolated version of \(x\), delayed by seven samples (the group-delay of the filter). Zoom in on a section to see this.
```

plot(100:200,y(100:200),7+(101:4:196),x(26:49),'o')

```

intfilt also performs Lagrange polynomial interpolation of the original signal. F or example, first-order polynomial interpolation is just linear interpolation, which is accomplished with a triangular filter.
```

h2 = intfilt(4,1,'l') % Lagrange interpolation
h2 =

| 0.2500 | 0.5000 | 0.7500 | 1.0000 | 0.7500 | 0.5000 | 0.2500 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |

```

\section*{Algorithm}

See Also
References

The bandlimited method uses firls to design an interpolation FIR equivalent to that presented in [1]. The polynomial method uses Lagrange's polynomial interpolation formula on equally spaced samples to construct the appropriate filter.
decimate, downsample, interp, resample, upsample
[1] Oetken, Parks, and Schüßler, "New Results in the Design of Digital Interpolators," IEEE Trans. Acoust., Speech, Signal Processing, Vol. ASSP-23 (J une 1975), pp. 301-309.

\section*{Purpose}

Identify continuous-time filter parameters from frequency response data

\section*{Syntax}

\section*{Description}
```

[b,a] = invfreqs(h,w,n,m)
[b,a] = invfreqs(h,w,n,m,wt)
[b,a] = invfreqs(h,w,n,m,wt,iter)
[b,a] = invfreqs(h,w,n,m,wt,iter,tol)
[b,a] = invfreqs(h,w,n,m,wt,iter,tol,'trace')
[b,a] = invfreqs(h,w,'complex',n,m,···)

```
invfreqs is the inverse operation of freqs. It finds a continuous-time transfer function that corresponds to a given complex frequency response. From a laboratory analysis standpoint, invfreqs is useful in converting magnitude and phase data into transfer functions.
\([b, a]=\) invfreqs \((h, w, n, m)\) returns the real numerator and denominator coefficient vectors \(b\) and \(a\) of the transfer function
\[
H(s)=\frac{B(s)}{A(s)}=\frac{b(1) s^{n}+b(2) s^{n-1}+\cdots+b(n+1)}{a(1) s^{m}+a(2) s^{m-1}+\cdots+a(m+1)}
\]
whose complex frequency response is given in vector \(h\) at the frequency points specified in vector \(w\). Scalars \(n\) and \(m\) specify the desired orders of the numerator and denominator polynomials.

Frequency is specified in radians between 0 and \(\pi\), and the length of \(h\) must be the same as the length of \(w\). invfreqs uses conj ( \(h\) ) at -w to ensure the proper frequency domain symmetry for a real filter.
[b,a] = invfreqs(h,w,n,m,wt) weights the fit-errors versus frequency, where wt is a vector of weighting factors the same length as \(w\).
\([b, a]=i n v f r e q s(h, w, n, m, w t, i t e r)\) and
\([b, a]=i n v f r e q s(h, w, n, m, w t, i t e r, t o l)\) providea superior algorithm that guarantees stability of the resulting linear system and searches for the best fit using a numerical, iterative scheme. The iter parameter tells invfreqs to end the iteration when the solution has converged, or after iter iterations, whichever comes first. invfreqs defines convergence as occurring when the norm of the (modified) gradient vector is less than tol, where tol is an optional parameter that defaults to 0.01 . To obtain a weight vector of all ones, use

\section*{invfreqs}
```

invfreqs(h,w, n, m, [],iter, tol)

```
[b,a] = invfreqs(h,w, n,m,wt,iter,tol,'trace') displays a textual progress report of the iteration.
[b, a] = invfreqs(h,w, complex', n,m,...) creates a complex filter. In this case no symmetry is enforced, and the frequency is specified in radians between \(-\pi\) and \(\pi\).

\section*{Remarks}

\section*{Examples}

When building higher order models using high frequencies, it is important to scale the frequencies, dividing by a factor such as half the highest frequency present in w, so as to obtain well conditioned values of a and b. This corresponds to a rescaling of time.

\section*{Example 1}

Convert a simple transfer function to frequency response data and then back to the original filter coefficients.
```

a = [1 2 3 2 1 4]; b = [1 2 3 2 3];
[h,w] = freqs(b,a,64);
[bb,aa] = invfreqs(h,w,4,5)
bb =
1.0000 2.0000 3.0000 2.0000 3.0000
aa =
1.0000 2.0000 3.0000 2.0000 1.0000 4.0000

```

Notice that bb and aa are equivalent to b and a , respectively. However, aa has poles in the left half-plane and thus the system is unstable. Use invfreqs's iterative al gorithm to find a stable approximation to the system.
```

[bbb,aaa] = invfreqs(h,w,4,5,[],30)
bbb =
0.6816 2.1015 2.6694 0.9113 -0.1218
aaa =
1.0000 3.4676 7.4060 6.2102 2.5413 0.0001

```

\section*{Example 2}

Suppose you have two vectors, mag and phase, that contain magnitude and phase data gathered in a laboratory, and a third vector w of frequencies. Y ou can convert the data into a continuous-time transfer function using invfreqs.
```

[b,a] = invfreqs(mag.*exp(j*phase),w,2,3);

```

\section*{Algorithm}

By default, invfreqs uses an equation error method to identify the best model from the data. This finds \(b\) and \(a\) in
\[
\min _{b, a} \sum_{k=1}^{11} w t(k)|h(k) A(w(k))-B(w(k))|^{2}
\]
by creating a system of linear equations and solving them with MATLAB's \} operator. Here \(A(w(k))\) and \(B(w(k))\) are the Fourier transforms of the polynomials a and \(b\), respectively, at the frequency \(w(k)\), and \(n\) is the number of frequency points (the length of \(h\) and w). This algorithm is based on Levi [1]. Several variants have been suggested in the literature, where the weighting function wt gives less attention to high frequencies.

\section*{invfreqs}

The superior ("output-error") al gorithm uses the damped Gauss-N ewton method for iterative search [2], with the output of the first algorithm as the initial estimate. This solves the direct problem of minimizing the weighted sum of the squared error between the actual and the desired frequency response points.
\[
\min _{b, a} \sum_{k=1}^{11} w t(k)\left|h(k)-\frac{B(w(k))}{A(w(k))}\right|^{2}
\]

See Also freqs, freqz, invfreqz, prony

\section*{References}
[1] Levi, E.C., "Complex-Curve Fitting," IRE Trans. on Automatic Control, Vol. AC-4 (1959), pp. 37-44.
[2] Dennis, J .E., J r., and R.B. Schnabel. Numerical Methods for Unconstrained Optimization and Nonlinear Equations. Englewood Cliffs, NJ : Prentice-Hall, 1983.

\section*{Purpose}

Syntax

\section*{Description}

Identify discrete-time filter parameters from frequency response data
```

[b,a] = invfreqz(h,w,n,m)
[b,a] = invfreqz(h,w,n,m,wt)
[b,a] = invfreqz(h,w,n,m,wt,iter)
[b,a] = invfreqz(h,w,n,m,wt,iter,tol)
[b,a] = invfreqz(h,w,n,m,wt,iter,tol,'trace')
[b,a] = invfreqz(h,w,'complex',n,m,...)

```
invfreqz is the inverse operation of freqz; it finds a discrete-time transfer function that corresponds to a given complex frequency response. From a laboratory analysis standpoint, invfreqz can be used to convert magnitude and phase data into transfer functions.
\([b, a]=\operatorname{invfreqz(h,w,n,m)}\) returns the real numerator and denominator coefficients in vectors \(b\) and \(a\) of the transfer function
\[
H(z)=\frac{B(z)}{A(z)}=\frac{b(1)+b(2) z^{-1}+\cdots+b(n+1) z^{-n}}{a(1)+a(2) z^{-1}+\cdots+a(m+1) z^{-m}}
\]
whose complex frequency response is given in vector \(h\) at the frequency points specified in vector \(w\). Scalars \(n\) and \(m\) specify the desired orders of the numerator and denominator polynomials.

Frequency is specified in radians between 0 and \(\pi\), and the length of \(h\) must be the same as the length of w. invfreqz uses conj (h) at -w to ensure the proper frequency domain symmetry for a real filter.
\([b, a]=\operatorname{invfreqz}(h, w, n, m, w t)\) weights the fit-errors versus frequency, where wt is a vector of weighting factors the same length as \(w\).
[b,a] = invfreqz(h,w,n,m,wt,iter) and
[b,a] = invfreqz(h,w,n,m,wt,iter,tol) providea superior algorithm that guarantees stability of the resulting linear system and searches for the best fit using a numerical, iterative scheme. The iter parameter tells invfreqz to end the iteration when the solution has converged, or after iter iterations, whichever comes first. invfreqz defines convergence as occurring when the norm of the (modified) gradient vector is less than tol, where tol is an optional parameter that defaults to 0.01 . To obtain a weight vector of all ones, use
```

invfreqz(h,w, n, m, [],iter, tol)

```
[b, a] = invfreqz(h,w, n,m,wt,iter,tol,'trace') displays a textual progress report of the iteration.
[b,a] = invfreqz (h,w, 'complex', n,m,...) creates a complex filter. In this case no symmetry is enforced, and the frequency is specified in radians between \(-\pi\) and \(\pi\).

\section*{Examples}

Convert a simple transfer function to frequency response data and then back to the original filter coefficients.
```

a = [1 2 3 2 1 4]; b = [1 2 3 2 3];
[h,w] = freqz(b,a,64);
[bb,aa] = invfreqz(h,w,4,5)
bb =
1.0000 2.0000 3.0000 2.0000 3.0000
aa =

| 1.0000 | 2.0000 | 3.0000 | 2.0000 | 1.0000 | 4.0000 |
| :--- | :--- | :--- | :--- | :--- | :--- |

```

Notice that bb and aa are equivalent to b and a , respectively. However, aa has poles outside the unit circle and thus the system is unstable. Use invfreqz's iterative al gorithm to find a stable approximation to the system.
```

[bbb,aaa] = invfreqz(h,w,4,5,[],30)
bbb =
0.2427 0.2788 0.0069 0.0971 0.1980
aaa =
1.0000 -0.8944 0.6954 0.9997 -0.8933 0.6949

```

\section*{Algorithm}

\section*{See Also}

References

By default, invfreqz uses an equation error method to identify the best model from the data. This finds \(b\) and \(a\) in
\[
\min _{b, a} \sum_{k=1}^{n} w t(k)|h(k) A(\omega(k))-B(\omega(k))|^{2}
\]
by creating a system of linear equations and solving them with MATLAB's \} operator. Here \(A(\omega(k))\) and \(B(\omega(k))\) are the Fourier transforms of the polynomials a and \(b\), respectively, at the frequency \(\omega(k)\), and \(n\) is the number of frequency points (the length of \(h\) and \(w\) ). This al gorithm is a based on Levi [1].

The superior ("output-error") al gorithm uses the damped Gauss-Newton method for iterative search [2], with the output of the first algorithm as the initial estimate. This solves the direct problem of minimizing the weighted sum of the squared error between the actual and the desired frequency response points.
\[
\min _{b, a} \sum_{k=1} w t(k)\left|h(k)-\frac{B(\omega(k))}{A(\omega(k))}\right|^{2}
\]
freqs, freqz, invfreqz, prony
[1] Levi, E.C., "Complex-Curve Fitting," IRE Trans. on Automatic Control, Vol. AC-4 (1959), pp. 37-44.
[2] Dennis, J .E., J r., and R.B. Schnabel, Numerical Methods for Unconstrained Optimization and Nonlinear Equations, Prentice-Hall, 1983.

Purpose Convert inverse sine parameters to reflection coefficients

\section*{Syntax \\ k = is2rc(isin)}

Description
\(k=\) is2rc(isin) returns a vector of reflection coefficients \(k\) from a vector of inverse sine parameters isin.

\section*{Examples}

See Also ac2rc, lar2rc, poly2rc, rc2is
References
```

isin = [0.2000 0.8727 0.0020 0.0052 -0.0052];
k = is2rc(isin)
k =
0.3090 0.9801 0.0031 0.0082 -0.0082

```
[1] Deller, J .R., J .G. Proakis, and J.H.L. Hansen, "Discrete-TimeProcessing of Speech Signals," Prentice-H all, 1993.

\section*{Purpose Compute a Kaiser window}

\section*{Syntax}
w = kaiser(n,beta)
Description
\(\mathrm{w}=\operatorname{kaiser}\left(\mathrm{n}\right.\), beta) returns an n-point Kaiser ( \(I_{0}\) - sinh \()\) window in the column vector \(w\). beta is the Kaiser window \(\beta\) parameter that affects the sidelobe attenuation of the F ourier transform of the window.

To obtain a Kaiser window that designs an FIR filter with sidel obe height \(-\alpha \mathrm{dB}\), use the following \(\beta\).
\[
\beta= \begin{cases}0.1102(\alpha-8.7), & \alpha>50 \\ 0.5842(\alpha-21)^{0.4}+0.07886(\alpha-21), & 50 \geq \alpha \geq 21 \\ 0, & \alpha<21\end{cases}
\]

Increasing beta widens the main lobe and decreases the amplitude of the sidel obes (increases the attenuation).

\section*{Example}
```

N=200;
w = kaiser(N,0.5);
plot(w);
title('Kaiser Window, beta = .5')

```

See Also barthannwin, bartlett, blackman, blackmanharris, bohmanwin, chebwin, gausswin, hamming, hann, kaiserord, nuttallwin, rectwin, triang, tukeywin, window
References [1] K aiser, J .F., "Nonrecursive Digital Filter Design Using the \(I_{0}\) - sinhWindow Function," Proc. 1974 IEEE Symp. Circuits and Systems, (April 1974),pp. 20-23.
[2] Selected Papers in Digital Signal Processing II, IEEE Press, New York,1975.
[3] Oppenheim, A.V., and R.W. Schafer, Discrete-TimeSignal Processing, Prentice-Hall, 1989, p. 453.

\section*{Purpose}

\section*{Syntax}

\section*{Description}

Estimate parameters for an FIR filter design with a Kaiser window
```

[n,Wn,beta,ftype] = kaiserord(f,a,dev)
[n,Wn,beta,ftype] = kaiserord(f,a,dev,fs)
c = kaiserord(f,a,dev,fs,'cell')

```
kaiserord returns a filter order \(n\) and beta parameter to specify a K aiser window for use with the fir1 function. Given a set of specifications in the frequency domain, kaiserord estimates the minimum FIR filter order that will approximately meet the specifications. kaiserord converts the given filter specifications into passband and stopband ripples and converts cutoff frequencies into the form needed for windowed FIR filter design.
[ \(n, W n\), beta,ftype] = kaiserord(f,a, dev) finds the approximate order n, normalized frequency band edges Wn , and weights that meet input specifications \(f, a\), and dev. \(f\) is a vector of band edges and a is a vector specifying the desired amplitude on the bands defined by \(f\). The length of \(f\) is twice the length of a, minus 2. Together, f and a define a desired piecewise constant response function. dev is a vector the same size as a that specifies the maximum allowable error or deviation between the frequency response of the output filter and its desired amplitude, for each band. The entries in dev specify the passband ripple and the stopband attenuation. You specify each entry in dev as a positive number, representing absolute filter gain (not in decibels).

Note If, in the vector dev, you specify unequal deviations across bands, the minimum specified deviation is used, since the Kaiser window method is constrained to produce filters with minimum deviation in all of the bands.
fir1 can use the resulting order n, frequency vector \(W n\), multiband magnitude type ftype, and the Kaiser window parameter beta. The ftype string is intended for use with fir1; it is equal to 'high' for a highpass filter and 'stop ' for a bandstop filter. For multiband filters, it can be equal to 'dc-0' when the first band is a stopband (starting at \(\mathrm{f}=0\) ) or ' \(\mathrm{dc}-1\) ' when the first band is a passband.

To design an FIR filter b that approximately meets the specifications given by kaiser parameters \(f, a\), and dev, use the following command.
\[
b=f i r 1(n, W n, \text { kaiser }(n+1, b e t a), f t y p e, ' n o s c a l e ')
\]
[ \(n\),Wn, beta,ftype] = kaiserord(f,a,dev,fs) uses a sampling frequency fs in Hz. If you don't specify the argument fs, or if you specify it as the empty vector [ ], it defaults to 2 Hz , and the Nyquist frequency is 1 Hz . Y ou can use this syntax to specify band edges scaled to a particular application's sampling frequency. The frequency band edges in f must be from 0 to fs/2.
\(c=k a i s e r o r d(f, a, d e v, f s, ' c e l l ')\) is a cell-array whose elements are the parameters to fir1.

> Note In some cases, kaiserord underestimates or overestimates the order n. If the filter does not meet the specifications, try a higher order such as \(n+1, n+2\), and so on, or a try lower order.

Results are inaccurate if the cutoff frequencies are near 0 or the Nyquist frequency, or if dev is large (greater than 10\%).

\section*{Remarks}

\section*{Examples}

Be careful to distinguish between the meanings of filter length and filter order. The filter length is the number of impulse response samples in the FIR filter. Generally, the impulse response is indexed from \(n=0\) ton \(=L-1\), where \(L\) is the filter length. The filter order is the highest power in a z-transform representation of the filter. F or an FIR transfer function, this representation is a polynomial in \(z\), where the highest power is \(z^{L-1}\) and the lowest power is \(z^{0}\). The filter order is one less than the length (L-1) and is al so equal to the number of zeros of the \(z\) polynomial.

\section*{Example 1}

Design a lowpass filter with passband defined from 0 to 1 kHz and stopband defined from 1500 Hz to 4 kHz . Specify a passband ripple of 5\% and a stopband attenuation of 40 dB .
```

fsamp = 8000;
fcuts = [1000 1500];
mags = [1 0];

```
```

devs = [0.05 0.01];
[n,Wn,beta,ftype] = kaiserord(fcuts,mags,devs,fsamp);
hh = fir1(n,Wn,ftype,kaiser(n+1,beta),'noscale');
freqz(hh)

```



\section*{Example 2}

Design an odd-length bandpass filter (note that odd length means even order, so the input to fir1 must be an even integer).
```

fsamp = 8000;
fcuts = [1000 1300 2210 2410];
mags = [0 1 0];
devs = [0.01 0.05 0.01];
[n,Wn,beta,ftype] = kaiserord(fcuts,mags,devs,fsamp);
n = n + rem(n,2);
hh = fir1(n,Wn,ftype,kaiser(n+1,beta),'noscale');
[H,f] = freqz(hh,1,1024,fsamp);
plot(f,abs(H)), grid on

```


\section*{Example 3}

Design a lowpass filter with a passband cutoff of 1500 Hz , a stopband cutoff of 2000 Hz , passband ripple of 0.01 , stopband ripple of 0.1 , and a sampling frequency of 8000 Hz .
```

[n,Wn,beta,ftype] = kaiserord([1500 2000],[1 0],...
[0.01 0.1],8000);
b = fir1(n,Wn,ftype,kaiser(n+1,beta),'noscale');

```

This is equivalent to
```

c = kaiserord([1500 2000],[1 0],[0.01 0.1],8000,'cell');
b = fir1(c{:});

```

Algorithm
kaiserord uses empirically derived formulas for estimating the orders of lowpass filters, as well as differentiators and Hilbert transformers. Estimates for multiband filters (such as bandpass filters) are derived from the lowpass design formulas.

The design formulas that underlie the Kaiser window and its application to FIR filter design are
\[
\beta= \begin{cases}0.1102(\alpha-8.7), & \alpha>50 \\ 0.5842(\alpha-21)^{0.4}+0.07886(\alpha-21), & 50 \geq \alpha \geq 21 \\ 0, & \alpha<21\end{cases}
\]
where \(\alpha=-20 \log _{10} \delta\) is the stopband attenuation expressed in decibels (recall that \(\delta_{p}=\delta_{s}\) is required).
The design formula is
\[
\mathrm{n}=\frac{\alpha-7.95}{2.285(\Delta \omega)}
\]
wheren is the filter order and \(\Delta \omega\) is the width of the smallest transition region.

\section*{See Also}

References
fir1, kaiser, remezord
[1] Kaiser, J .F., "Nonrecursive Digital Filter Design Using the \(I_{0}\) - sinh Window Function," Proc. 1974 IEEE Symp. Circuits and Systems, (April 1974), pp. 20-23.
[2] Selected Papers in Digital Signal Processing II, IEEE Press, New Y ork, 1975, pp. 123-126.
[3] Oppenheim, A.V., and R.W. Schafer, DiscreteTimeSignal Processing, Prentice-H all, 1989, pp. 458-562.

Purpose Convert log area ratio parameters to reflection coefficients
Syntax \(\quad k=\operatorname{lar2rc}(g)\)

Description

Examples

See Also
References
\(\mathrm{k}=\operatorname{lar2rc}(\mathrm{g})\) returns a vector of reflection coefficients k from a vector of log area ratio parameters g .
\[
\begin{array}{lllll}
\mathrm{g}= & {[0.6389} & 4.5989 & 0.0063 & 0.0163 \\
\mathrm{k}= & \operatorname{lar} 2 \mathrm{rc}(\mathrm{~g}) & & & -0.0163] ; \\
\mathrm{k}= & & & & \\
& 0.3090 & 0.9801 & 0.0031 & 0.0081
\end{array}
\]
ac2rc, is2rc, poly2rc, rc2lar
[1] Deller, J.R., J .G. Proakis, and J .H.L. Hansen, "Discrete-TimeProcessing of Speech Signals," Prentice-H all, 1993.

\section*{Purpose \\ Convert lattice filter parameters to transfer function form}
```

Syntax

```

Description

See Also latcfilt, tf2latc
Purpose Lattice and lattice-ladder filter implementation
Syntax \(\quad\)\begin{tabular}{l}
{\([f, g]=\operatorname{latcfilt}(k, x)\)} \\
{\([f, g]=\operatorname{latcfilt}(k, v, x)\)} \\
{\([f, g]=\operatorname{latcfilt}(k, 1, x)\)} \\
{\([f, g, z f]=\operatorname{latcfilt}\left(\ldots\right.\), ic \(\left.^{\prime}, z i\right)\)}
\end{tabular}

\section*{Description \\ When filtering data, lattice coefficients can be used to represent:}
- FIR filters
- All-pole IIR filters
- Allpass IIR filters
- General IIR filters
[ \(\mathrm{f}, \mathrm{g}\) ] = latcfilt( \(\mathrm{k}, \mathrm{x}\) ) filters x with the FIR lattice coefficients in the vector \(k\). \(f\) is the forward lattice filter result and \(g\) is the backward filter result. If \(|\mathrm{k}| \leq 1\), f corresponds to the minimum-phase output, and g corresponds to the maximum-phase output.

If \(k\) and \(x\) are vectors, the result is a (signal) vector. Matrix arguments are permitted under the following rules:
- If x is a matrix and k is a vector, each column of x is processed through the lattice filter specified by \(k\).
- If \(x\) is a vector and \(k\) is a matrix, each column of \(k\) is used to filter \(x\), and a signal matrix is returned.
- If \(x\) and \(k\) are both matrices with the same number of columns, then the ith column of \(k\) is used to filter the ith column of \(x\). A signal matrix is returned.
\([f, g]=\) latcfilt ( \(k, v, x\) ) filters \(x\) with the IIR lattice coefficients \(k\) and ladder coefficients \(v . k\) and \(v\) must be vectors, while \(x\) can be a signal matrix.
\([f, g]=\operatorname{latcfilt}(k, 1, x)\) filters \(x\) with theIIR lattice specified by \(k\), where \(k\) and \(x\) can be vectors or matrices. \(f\) is theall-polelattice filter result and \(g\) is the all pass filter result.
[f,g,zf] = latcfilt(...,'ic', zi) accepts a length-k vector zi specifying the initial condition of the lattice states. Output \(z f\) is a length-k vector specifying the final condition of the lattice states.

\section*{Purpose Compute the Levinson-Durbin recursion}

\section*{Syntax}

Description

\section*{Algorithm}
levinson solves the symmetric Toeplitz system of linear equations
\[
\left[\begin{array}{cccc}
r(1) & r(2)^{*} & \cdots & r(p)^{*} \\
r(2) & r(1) & \cdots & r(p-1)^{*} \\
\vdots & \ddots & \ddots & \vdots \\
r(p) & \cdots & r(2) & r(1)
\end{array}\right]\left[\begin{array}{c}
a(2) \\
a(3) \\
\vdots \\
a(p+1)
\end{array}\right]=\left[\begin{array}{c}
-r(2) \\
-r(3) \\
\vdots \\
-r(p+1)
\end{array}\right]
\]
where \(r=[r(1) \ldots r(p+1)]\) is the input autocorrelation vector, and \(r(i)^{*}\) denotes the complex conjugate of \(r(i)\). The al gorithm requires \(O\left(p^{2}\right)\) flops and is thus much more efficient than the MATLAB \command for large p. However, the levinson function uses \for low orders to provide the fastest possible execution.

\section*{levinson}

\author{
See Also lpc, prony, rlevinson, schurrc, stmcb \\ References [1] Ljung, L., System Identification: Theory for the User, Prentice-H all, 1987, pp. 278-280.
}

\section*{Purpose Transform lowpass analog filters to bandpass}
\begin{tabular}{ll} 
Syntax & {\([b t, a t]=\operatorname{lp2bp}(b, a, W o, B w)\)} \\
& {\([A t, B t, C t, D t]=\operatorname{lp2bp}(A, B, C, D, W o, B w)\)}
\end{tabular}

\section*{Description}
lp2bp transforms analog lowpass filter prototypes with a cutoff frequency of \(1 \mathrm{rad} / \mathrm{s}\) into bandpass filters with desired bandwidth and center frequency. The transformation is one step in the digital filter design process for the butter, cheby 1 , cheby 2 , and ellip functions.
lp2bp can perform the transformation on two different linear system representations: transfer function form and state-space form. In both cases, the input system must be an analog filter prototype.

\section*{Transfer Function Form (Polynomial)}
[bt,at] = lp2bp(b,a,Wo, Bw) transforms an analog lowpass filter prototype given by polynomial coefficients into a bandpass filter with center frequency wo and bandwidth Bw. Row vectors b and a specify the coefficients of the numerator and denominator of the prototype in descending powers of \(s\).
\[
\frac{b(s)}{a(s)}=\frac{b(1) s^{n}+\cdots+b(n) s+b(n+1)}{a(1) s^{m}+\cdots+a(m) s+a(m+1)}
\]

Scalars Wo and Bw specify the center frequency and bandwidth in units of rad/s. For a filter with lower band edge w1 and upper band edge w2, use Wo = sqrt (w1*w2) and Bw =w2-w1.
lp2bp returns the frequency transformed filter in row vectors bt and at.

\section*{State-Space Form}
[At, Bt, Ct, Dt] = lp2bp(A, B, C, D, Wo, Bw) converts the continuous-time state-space lowpass filter prototype in matrices \(A, B, C, D\) shown below
\[
\begin{aligned}
& x=A x+B u \\
& y=C x+D u
\end{aligned}
\]
into a bandpass filter with center frequency Wo and bandwidth Bw. For a filter with lower band edge w1 and upper band edge w2, use Wo \(=\operatorname{sqrt}(w 1 * w 2)\) and \(\mathrm{B} w=\mathrm{w} 2-\mathrm{w} 1\).

The bandpass filter is returned in matrices \(\mathrm{At}, \mathrm{Bt}, \mathrm{Ct}, \mathrm{Dt}\).

\section*{Algorithm}
lp2bp is a highly accurate state-space formulation of the classic analog filter frequency transformation. Consider the state-space system
\[
\begin{aligned}
& x=A x+B u \\
& y=C x+D u
\end{aligned}
\]
where u is the input, x is the state vector, and y is the output. The Laplace transform of the first equation (assuming zero initial conditions) is
\[
s X(s)=A X(s)+B U(s)
\]

Now if a bandpass filter is to have center frequency \(\omega_{0}\) and bandwidth \(\mathrm{B}_{w}\), the standard s-domain transformation is
\[
s=Q\left(p^{2}+1\right) / p
\]
where \(\mathrm{Q}=\omega_{0} / \mathrm{B}_{w}\) and \(\mathrm{p}=\mathrm{s} / \omega_{0}\). Substituting this for s in the Laplace transformed state-space equation, and considering the operator \(p\) as \(d / d t\) results in
\[
\mathrm{Qx}+\mathrm{Qx}=\dot{\mathrm{A}} \mathrm{x}+\mathrm{Bu}
\]
or
\[
Q x-A \dot{x}-B u=-Q x
\]

Now define
\[
\mathrm{Q} \dot{\omega}=-\mathrm{Qx}
\]
which, when substituted, leads to
\[
\mathrm{Q} \dot{x}=\mathrm{Ax}+\mathrm{Q} \omega+\mathrm{Bu}
\]

The last two equations give equations of state. Write them in standard form and multiply the differential equations by \(\omega_{0}\) to recover the time/frequency scaling represented by \(p\) and find state matrices for the bandpass filter.
```

Q = Wo/Bw; [ma,m] = size(A);
At = Wo*[A/Q eye(ma,m);-eye(ma,m) zeros(ma,m)];
Bt = Wo*[B/Q; zeros(ma,n)];
Ct = [C zeros(mc,ma)];
Dt = d;

```

If the input to lp2bp is in transfer function form, the function transforms it into state-space form before applying this algorithm.

\author{
See Also bilinear, impinvar, lp2bs, lp2hp, 1p2lp
}

\section*{Purpose Transform lowpass analog filters to bandstop}
\begin{tabular}{ll} 
Syntax & {\([b t, a t]=\operatorname{lp2bs}(b, a\), Wo,\(B w)\)} \\
& {\([A t, B t, C t, D t]=\operatorname{lp2bs}(A, B, C, D, W o, B w)\)}
\end{tabular}

\section*{Description}
lp2bs transforms analog lowpass filter prototypes with a cutoff frequency of \(1 \mathrm{rad} / \mathrm{s}\) into bandstop filters with desired bandwidth and center frequency. The transformation is one step in the digital filter design process for the butter, cheby1, cheby2, and ellip functions.
lp2bs can perform the transformation on two different linear system representations: transfer function form and state-space form. In both cases, the input system must be an analog filter prototype.

\section*{Transfer Function Form (Polynomial)}
[bt,at] = lp2bs(b,a,Wo, Bw) transforms an analog lowpass filter prototype given by polynomial coefficients into a bandstop filter with center frequency wo and bandwidth Bw. Row vectors b and a specify the coefficients of the numerator and denominator of the prototype in descending powers of \(s\).
\[
\frac{b(s)}{a(s)}=\frac{b(1) s^{n}+\cdots+b(n) s+b(n+1)}{a(1) s^{m}+\cdots+a(m) s+a(m+1)}
\]

Scalars Wo and Bw specify the center frequency and bandwidth in units of radians/second. For a filter with lower band edge w1 and upper band edge w2, use Wo = sqrt ( w 1 *w2) and \(\mathrm{Bw}=\mathrm{w} 2-\mathrm{w} 1\).
lp2bs returns the frequency transformed filter in row vectors bt and at.

\section*{State-Space Form}
[At, Bt, Ct, Dt] = lp2bs(A, B, C, D, Wo, Bw) converts the continuous-time state-space lowpass filter prototype in matrices \(A, B, C, D\) shown below
\[
\begin{aligned}
& x=A x+B u \\
& y=C x+D u
\end{aligned}
\]
into a bandstop filter with center frequency wo and bandwidth Bw. For a filter with lower band edge w1 and upper band edge w2, use Wo \(=\operatorname{sqrt}(w 1 * w 2)\) and Bw =w2-w1.

The bandstop filter is returned in matrices \(\mathrm{At}, \mathrm{Bt}, \mathrm{Ct}, \mathrm{Dt}\).

\section*{Algorithm}
lp2bs is a highly accurate state-space formulation of the classic analog filter frequency transformation. If a bandstop filter is to have center frequency \(\omega_{0}\) and bandwidth \(\mathrm{B}_{w}\), the standard s-domain transformation is
\[
s=\frac{p}{Q\left(p^{2}+1\right)}
\]
where \(\mathrm{Q}=\omega_{0} / \mathrm{B}_{w}\) and \(\mathrm{p}=\mathrm{s} / \omega_{0}\). The state-space version of this transformation is
```

Q = Wo/Bw;
At = [Wo/Q*inv(A) Wo*eye(ma);-Wo*eye(ma) zeros(ma)];
Bt = -[Wo/Q*(A B); zeros(ma,n)];
Ct = [C/A zeros(mc,ma)];
Dt = D - C/A*B;

```

See lp2bp for a derivation of the bandpass version of this transformation.
See Also
bilinear, impinvar, lp2bp, lp2hp, lp2lp

\section*{Purpose Transform lowpass analog filters to highpass}
\begin{tabular}{ll} 
Syntax & {\([b t, a t]=\operatorname{lp2hp}(b, a, W o)\)} \\
& {\([A t, B t, C t, D t]=\operatorname{lp2hp}(A, B, C, D, W o)\)}
\end{tabular}

\section*{Description}
lp2hp transforms analog lowpass filter prototypes with a cutoff frequency of 1 rad/s into highpass filters with desired cutoff frequency. The transformation is one step in the digital filter design process for the butter, cheby1, cheby2, and ellip functions.

The lp2hp function can perform the transformation on two different linear system representations: transfer function form and state-space form. In both cases, the input system must be an analog filter prototype.

\section*{Transfer Function Form (Polynomial)}
[bt,at] = lp2hp(b,a, Wo) transforms an analog lowpass filter prototype given by polynomial coefficients into a highpass filter with cutoff frequency Wo. Row vectors b and a specify the coefficients of the numerator and denominator of the prototype in descending powers of \(s\).
\[
\frac{b(s)}{a(s)}=\frac{b(1) s^{n}+\cdots+b(n) s+b(n+1)}{a(1) s^{m}+\cdots+a(m) s+a(m+1)}
\]

Scalar Wo specifies the cutoff frequency in units of radians/second. The frequency transformed filter is returned in row vectors bt and at.

\section*{State-Space Form}
[At, Bt, Ct, Dt] = lp2hp(A, B, C, D, Wo) converts the continuous-time state-space lowpass filter prototype in matrices A, B, C, D below
\[
\begin{aligned}
& x=A x+B u \\
& y=C x+D u
\end{aligned}
\]
into a highpass filter with cutoff frequency wo. The highpass filter is returned in matrices At, Bt, Ct, Dt.
lp2hp is a highly accurate state-space formulation of the classic analog filter frequency transformation. If a highpass filter is to have cutoff frequency \(\omega_{0}\), the standard s-domain transformation is
\[
\mathrm{s}=\frac{\omega_{0}}{\mathrm{p}}
\]

The state-space version of this transformation is
\[
\begin{aligned}
& \mathrm{At}=\mathrm{Wo*inv}(\mathrm{~A}) ; \\
& \mathrm{Bt}=-\mathrm{Wo}^{*}(\mathrm{~A} \backslash \mathrm{~B}) ; \\
& \mathrm{Ct}=\mathrm{C} / \mathrm{A} ; \\
& \mathrm{Dt}=\mathrm{D}-\mathrm{C} / \mathrm{A} * \mathrm{~B} ;
\end{aligned}
\]

See lp2bp for a derivation of the bandpass version of this transformation.
See Also
bilinear, impinvar, lp2bp, lp2bs, 1p2lp

\section*{Purpose Change the cut-off frequency for a lowpass analog filter}
\begin{tabular}{ll} 
Syntax & {\([b t, a t]=\operatorname{lp2lp}(b, a, W o)\)} \\
& {\([A t, B t, C t, D t]=\operatorname{lp2lp}(A, B, C, D, W o)\)}
\end{tabular}

\section*{Description}
lp2lp transforms an analog lowpass filter prototype with a cutoff frequency of \(1 \mathrm{rad} / \mathrm{s}\) into a lowpass filter with any specified cutoff frequency. The transformation is one step in the digital filter design process for the butter, cheby1, cheby2, and ellip functions.

The lp2lp function can perform the transformation on two different linear system representations: transfer function form and state-space form. In both cases, the input system must be an analog filter prototype.

\section*{Transfer Function Form (Polynomial)}
[bt,at] = lp2lp(b,a, Wo) transforms an analog lowpass filter prototype given by polynomial coefficients into a lowpass filter with cutoff frequency Wo. Row vectors b and a specify the coefficients of the numerator and denominator of the prototype in descending powers of \(s\).
\[
\frac{b(s)}{a(s)}=\frac{b(1) s^{n}+\cdots+b(n) s+b(n+1)}{a(1) s^{m}+\cdots+a(m) s+a(m+1)}
\]

Scalar Wo specifies the cutoff frequency in units of radians/second. lp2lp returns the frequency transformed filter in row vectors bt and at.

\section*{State-Space Form}
[At, Bt, Ct, Dt] = lp2lp(A, B, C, D, Wo) converts the continuous-time state-space lowpass filter prototype in matrices A, B, C, D below
\[
\begin{aligned}
& x=A x+B u \\
& y=C x+D u
\end{aligned}
\]
into a lowpass filter with cutoff frequency Wo. 1p2lp returns the lowpass filter in matrices At, Bt, Ct, Dt.

\section*{Algorithm}
lp2lp is a highly accurate state-space formulation of the classic analog filter frequency transformation. If a lowpass filter is to have cutoff frequency \(\omega_{0}\), the standard s-domain transformation is
\[
\mathrm{s}=\mathrm{p} / \omega_{0}
\]

The state-space version of this transformation is
\[
\begin{aligned}
& \mathrm{At}=\mathrm{Wo} \mathrm{~A}_{\mathrm{A}} ; \\
& \mathrm{Bt}=\mathrm{Wo}{ }^{*} ; \\
& \mathrm{Ct}=\mathrm{C} ; \\
& \mathrm{Dt}=\mathrm{D} ;
\end{aligned}
\]

See lp2bp for a derivation of the bandpass version of this transformation.
See Also bilinear, impinvar, lp2bp, lp2bs, lp2hp

\section*{Purpose \\ Compute linear prediction filter coefficients}

\section*{Syntax \\ \([\mathrm{a}, \mathrm{g}]=\operatorname{lpc}(\mathrm{x}, \mathrm{p})\)}

\section*{Description}

Examples
lpc determines the coefficients of a forward linear predictor by minimizing the prediction error in the least squares sense. It has applications in filter design and speech coding.
[a,g] = lpc(x,p) finds the coefficients of a pth-order linear predictor (FIR filter) that predicts the current value of the real-valued time series \(x\) based on past samples.
\[
\hat{x}(n)=-a(2) x(n-1)-a(3) x(n-2)-\cdots-a(p+1) x(n-p)
\]
\(p\) is the order of the prediction filter polynomial, \(a=\left[\begin{array}{ll}1 & a(2)\end{array} \ldots a(p+1)\right]\). If \(p\) is unspecified, lpc uses as a default \(p=\) length \((x)-1\). If \(x\) is a matrix containing a separate signal in each column, lpc returns a model estimate for each column in the rows of matrix a and a row vector of prediction error variances g .

Estimate a data series using a third-order forward predictor, and compare to the original signal.

First, create the signal data as the output of an autoregressive process driven by white noise. Use the last 4096 samples of the AR process output to avoid start-up transients.
```

randn('state',0);
noise = randn(50000,1); % Normalized white Gaussian noise
x = filter(1,[1 1/2 1/3 1/4],noise);
x = x(45904:50000);

```

Compute the predictor coefficients, estimated signal, prediction error, and autocorrelation sequence of the prediction error.
```

a = lpc(x,3);
est_x = filter([0 -a(2:end)],1,x); % Estimated signal
e = x - est_x; % Prediction error
[acs,lags] = xcorr(e,'coeff'); % ACS of prediction error

```

The prediction error, e(n), can be viewed as the output of the prediction error filter \(A(z)\) shown below, where \(H(z)\) is the optimal linear predictor, \(x(n)\) is the input signal, and \(\hat{x}(\mathrm{n})\) is the predicted signal.


Compare the predicted signal to the original signal.
```

plot(1:97,x(4001:4097),1:97,est_x(4001:4097),' --');
title('Original Signal vs. LPC Estimate');
xlabel('Sample Number'); ylabel('Amplitude'); grid;
legend('Original Signal','LPC Estimate')

```


Look at the autocorrelation of the prediction error.
```

plot(lags,acs);
title('Autocorrelation of the Prediction Error');
xlabel('Lags'); ylabel('Normalized Value'); grid;

```

The prediction error is approximately white Gaussian noise, as expected for a third-order AR input process.


\section*{Algorithm}
lpc uses the autocorrelation method of autoregressive (AR) modeling to find the filter coefficients. The generated filter might not model the process exactly even if the data sequence is truly an AR process of the correct order. This is because the autocorrelation method implicitly windows the data, that is, it assumes that signal samples beyond the length of \(x\) are 0 .
lpc computes the least squares solution to
\[
X a \approx b
\]
where
\[
X=\left[\begin{array}{cccc}
x(1) & 0 & \cdots & 0 \\
x(2) & x(1) & \ddots & \vdots \\
\vdots & x(2) & \ddots & 0 \\
x(m) & \vdots & \ddots & x(1) \\
0 & x(m) & \ddots & x(2) \\
\vdots & \ddots & \ddots & \vdots \\
0 & \cdots & 0 & x(m)
\end{array}\right], \quad a=\left[\begin{array}{c}
1 \\
a(2) \\
\vdots \\
a(p+1)
\end{array}\right], \quad b=\left[\begin{array}{c}
1 \\
0 \\
\vdots \\
0
\end{array}\right]
\]
and \(m\) is the length of \(x\). Solving the least squares problem via the normal equations
\[
x^{H} X a=X^{H} b
\]
leads to the Yule-Walker equations
\[
\left[\begin{array}{cccc}
r(1) & r(2)^{*} & \cdots & r(p)^{*} \\
r(2) & r(1) & \ddots & \vdots \\
\vdots & \ddots & \ddots & r(2)^{*} \\
r(p) & \cdots & r(2) & r(1)
\end{array}\right]\left[\begin{array}{c}
a(2) \\
a(3) \\
\vdots \\
a(p+1)
\end{array}\right]=\left[\begin{array}{c}
-r(2) \\
-r(3) \\
\vdots \\
-r(p+1)
\end{array}\right]
\]
where \(r=[r(1) r(2) \ldots r(p+1)]\) is an autocorrelation estimate for \(x\) computed using xcorr. The Yule-Walker equations are solved in \(O\left(p^{2}\right)\) flops by the Levinson-Durbin algorithm (see levinson).

\section*{See Also}

References
aryule, levinson, prony, pyulear, stmcb
[1] J ackson, L.B., Digital Filters and Signal Processing, Second Edition, Kluwer Academic Publishers, 1989. pp. 255-257.
\begin{tabular}{|c|c|}
\hline Purpose & Convert line spectral frequencies to prediction filter coefficients \\
\hline Syntax & \(\mathrm{a}=1 \mathrm{sf} 2 \mathrm{poly}\) (lsf) \\
\hline Description & a = lsf2poly(lsf) returns a vector a containing the prediction filter coefficients from a vector lsf of line spectral frequencies (also known as line spectrum pairs). \\
\hline Examples & \[
\begin{array}{lllll}
\text { lsf }=\left[\begin{array}{lll}
0.7842 & 1.5605 & 1.8776 \\
a=1 s f 2 p o l y(l s f)
\end{array}\right. & 1.8984 & 2.3593] ; \\
a=1 & &
\end{array}
\] \\
\hline & \[
\begin{array}{llllll}
a= & & & \\
1.0000 & 0.6148 & 0.9899 & 0.0001 & 0.0031 & -0.0081
\end{array}
\] \\
\hline See Also & ac2poly, poly2lsf, rc2poly \\
\hline References & [1] Deller, J .R., J .G. Proakis, and J.H.L. Hansen, "DiscreteTime Processing of Speech Signals," Prentice-H all, 1993. \\
\hline & [2] Rabiner, L.R., and R.W. Schafer, "Digital Processing of Speech Signals," Prentice-Hall, 1978. \\
\hline
\end{tabular}

Purpose
Syntax

\section*{Examples}

Description \([b, a]=,\operatorname{maxflat}(n, m, W n)\) is a lowpass Butterworth filter with numerator and denominator coefficients \(b\) and a of orders \(n\) and \(m\) respectively. Wn is the normalized cutoff frequency at which the magnitude response of the filter is equal to \(1 / \sqrt{2}\) (approx. -3 dB ). Wn must be between 0 and 1 , where 1 corresponds to the \(N\) yquist frequency.
b = maxflat( n, 'sym', Wn) is a symmetric FIR Butterworth filter. n must be even, and \(W n\) is restricted to a subinterval of \([0,1]\). The function raises an error if Wn is specified outside of this subinterval.
\([b, a, b 1, b 2]=\operatorname{maxflat}(n, m, W n)\) returns two polynomials \(b 1\) and b2 whose product is equal to the numerator polynomial \(b\) (that is, \(b=\operatorname{conv}(b 1, b 2)\) ).
b1 contains all the zeros at \(z=-1\), and b2 contains all the other zeros.
[...] = maxflat(n,m,Wn, 'design_flag') enables you to monitor the filter design, where 'design_flag' is:
- 'trace', for a textual display of the design table used in the design
- 'plots ', for plots of the filter's magnitude, group delay, and zeros and poles
- 'both ', for both the textual display and plots

Generalized digital Butterworth filter design
```

[b,a,] = maxflat(n,m,Wn)

```
[b,a,] = maxflat(n,m,Wn)
b = maxflat(n,'sym',Wn)
b = maxflat(n,'sym',Wn)
[b,a,b1,b2] = maxflat(n,m,Wn)
[b,a,b1,b2] = maxflat(n,m,Wn)
[...] = maxflat(n,m,Wn,'design_flag')
```

[...] = maxflat(n,m,Wn,'design_flag')

```
```

n = 10; na = 2; Wn = 0.2;
[b,a,b1,b2] = maxflat(n,m,Wn,'plots')

```


\section*{Algorithm}

\section*{See Also butter, filter, freqz}

References transformation of polynomial roots.

The method consists of the use of formulae, polynomial root finding, and a
[1] Selesnick, I.W., and C.S. Burrus, "Generalized Digital Butterworth Filter Design," Proceedings of the IEEE Int. Conf. Acoust., Speech, Signal Processing, Vol. 3 (May 1996).

Description

See Also
References

Purpose

One-dimensional median filtering

Syntax
Syntax \(\quad\)\begin{tabular}{rl}
\(y\) & \(=\operatorname{medfilt} 1(x, n)\) \\
\(y\) & \(=\operatorname{medfilt} 1(x, n, b l k s z)\) \\
\(y\) & \(=\operatorname{medfilt} 1(x, n, b l k s z, \operatorname{dim})\)
\end{tabular}
\(\mathrm{y}=\) medfilt1 \((\mathrm{x}, \mathrm{n})\) applies an order n one-dimensional median filter to vector x ; the function considers the signal to be 0 beyond the end points. Output \(y\) has the same length as \(x\).

For \(n\) odd, \(y(k)\) is the median of \(x(k-(n-1) / 2: k+(n-1) / 2)\).
For \(n\) even, \(y(k)\) is the median of \(x(k-n / 2), x(k-(n / 2)+1), \ldots, x(k+(n / 2)-1)\). In this case, medfilt1 sorts the numbers, then takes the average of the \((n-1) / 2\) and \(((n-1) / 2)+1\) elements.

The default for \(n\) is 3 .
\(\mathrm{y}=\) medfilt1( \(\mathrm{x}, \mathrm{n}, \mathrm{blksz}\) ) uses a for-loop to compute blksz (block size) output samples at a time. Use blksz <<length (x) if you are low on memory, since medfilt1 uses a working matrix of size n-by-blksz. By default, blksz = length \((x)\); this provides the fastest execution if you have sufficient memory.

If \(x\) is a matrix, medfilt1 median filters its columns using
\[
y(:, i)=\operatorname{medfilt1}(x(:, i), n, b l k s z)
\]
in a loop over the columns of \(x\).
\(\mathrm{y}=\) medfilt1( \(\mathrm{x}, \mathrm{n}, \mathrm{blksz}\), dim) specifies the dimension, dim, along which the filter operates.
filter, medfilt2, median
[1] Pratt, W.K., Digital Image Processing, J ohn Wiley \& Sons, 1978, pp. 330-333.
Purpose Modulation for communications simulation
Syntax

y = modulate(x,fc,fs,'method')

\(y=\) modulate(x,fc,fs,'method',opt)

[y,t] = modulate(x,fc,fs)

\section*{Description}
y = modulate(x,fc,fs,'method') and
\(\mathrm{y}=\) modulate(x,fc,fs,'method',opt) modulate the real message signal x with a carrier frequency fc and sampling frequency \(f s\), using one of the options listed below for 'method'. Note that some methods accept an option, opt.
amdsb-sc Amplitude modulation, double sideband, suppressed carrier.
or \(\quad\) Multiplies \(x\) by a sinusoid of frequency fc.
am
\[
y=x \cdot * \cos \left(2 * p i * f c^{*} t\right)
\]
amdsb-tc Amplitude modulation, double sideband, transmitted carrier. Subtracts scalar opt from \(x\) and multiplies the result by a sinusoid of frequency fc.
\[
y=(x-o p t) \cdot * \cos (2 * p i * f c * t)
\]
If the opt parameter is not present, modulate uses a default of \(\min (\min (x))\) so that the message signal ( \(x\)-opt) is entirely nonnegative and has a minimum value of 0 .
amssb Amplitude modulation, single sideband. Multiplies \(x\) by a sinusoid of frequency fc and adds the result to the Hilbert transform of \(x\) multiplied by a phase shifted sinusoid of frequency fc .
```

y =
x.*cos(2*pi*fc*t)+imag(hilbert(x)).*sin(2*pi*fc*t)

```
This effectively removes the upper sideband.
fm Frequency modulation. Creates a sinusoid with instantaneous frequency that varies with the message signal \(x\).
```

y = cos(2*pi*fc*t + opt*cumsum(x))

```
cumsum is a rectangular approximation to the integral of \(x\). modulate uses opt as the constant of frequency modulation. If opt is not present, modulate uses a default of
```

opt = (fc/fs)*2*pi/(max(max(x)))

```
so the maximum frequency excursion from fc is fc Hz .
Phase modulation. Creates a sinusoid of frequency fc whose phase varies with the message signal \(x\).
```

y = cos(2*pi*fc*t + opt*x)

```
modulate uses opt as the constant of phase modulation. If opt is not present, modulate uses a default of
```

opt = pi/(max(max(x)))

```
so the maximum phase excursion is \(\pi\) radians.

Pulse-width modulation. Creates a pulse-width modulated signal from the pulse widths in x . The elements of x must be between 0 and 1 , specifying the width of each pulse in fractions of a period. The pulses start at the beginning of each period, that is, they are left justified.
```

modulate(x,fc,fs,'pwm','centered')

```
yields pulses centered at the beginning of each period. \(y\) is length length (x)*fs/fc.

Pulse-position modulation. Creates a pulse-position modulated signal from the pulse positions in \(x\). The elements of \(x\) must be between 0 and 1 , specifying the left edge of each pulse in fractions of a period. opt is a scalar between 0 and 1 that specifies the length of each pulse in fractions of a period. The default for opt is 0.1 . \(y\) is length length \((x) * f s / f c\).

Quadrature amplitude modulation. Creates a quadrature amplitude modulated signal from signals \(x\) and opt.
```

y = x.*cos(2*pi*fc*t) + opt.*sin(2*pi*fc*t)

```
opt must be the same size as \(x\).

If you do not specify 'method', then modulate assumes am. Except for the pwm and ptm cases, y is the same size as x .

If \(x\) is an array, modulate modulates its columns.
[ \(\mathrm{y}, \mathrm{t}]=\) modulate \((\mathrm{x}, \mathrm{fc}, \mathrm{fs})\) returns theinternal time vector t that modulate uses in its computations.

\author{
See Also \\ demod, vco
}

Purpose

\section*{Syntax}

Description

\section*{Example}

Compute a minimum 4-term Blackman-Harris window, as defined by Nuttall
w = nuttallwin(n)
\(\mathrm{w}=\) nuttallwin(n) returns a minimum, n-point, 4-term Blackman-harris window in the column vector \(w\). The window is minimum in the sense that its maximum sidel obes are minimized. The coefficients for this window differ from the Blackman-harris window coefficients computed with blackmanharris and produce slightly lower sidelobes.

Compare 64-point Blackman-Harris and Nuttall's Blackman-Harris windows and plot the difference between the windows.
```

N = 64;
w = blackmanharris(N);
y = nuttallwin(N);
plot(1:N,w,1:N,y,'r--');axis([1 N 0 1]);
title('Comparison of 64-pt windows');
legend('Blackman-harris', 'Nuttall');
plot(y-w);
title('Difference between Blackman-harris and Nuttall windows')

```



The maximum difference, using max (abs \((\mathrm{y}-\mathrm{w})\) ), is 0.0099 .

\section*{Algorithm}

The equation for computing the coefficients of a minimum 4-term Blackman-harris window, according to Nuttall, is
\[
w[k+1]=a_{0}-a_{1} \cos \left(2 \pi \frac{k}{n-1}\right)+a_{2} \cos \left(4 \pi \frac{k}{n-1}\right)-a_{3} \cos \left(6 \pi \frac{k}{n-1}\right)
\]
where \(0 \leq k \leq(n-1)\).
The coefficients for this window are
\[
\begin{aligned}
& a_{0}=0.3635819 \\
& a_{1}=0.4891775 \\
& a_{2}=0.1365995 \\
& a_{3}=0.0106411
\end{aligned}
\]

See Also blackmanharris, barthannwin, bartlett, blackman, bohmanwin, chebwin, gausswin, hann, hamming, kaiser, rectwin, triang, tukeywin, window

References [1] Nuttall, Albert H. "Some Windows with Very Good Sidel obe Behavoir." IEEE Transactions on Acoustics, Speech, and Signal Processing. Vol. ASSP-29 (February 1981). pp. 84-91.
\begin{tabular}{ll} 
Purpose & Estimate the power spectral density using the Burg method \\
Syntax & \begin{tabular}{ll} 
& {\([P x=\operatorname{pburg}(x, p)\)} \\
& {\([P x, w]=\operatorname{pburg}(x, p)\)} \\
& {\([P x x, f]=\operatorname{pburg}(x, p, n f f t)\)} \\
& {\([P x x, f]=\operatorname{pburg}(x, p, n f f t, f s)\)} \\
& {\([P x x, w]=\operatorname{pburg}(x, p, n f f t, f s, ' r a n g e ')\)} \\
& \(\operatorname{pburg}(\ldots)\)
\end{tabular}
\end{tabular}

Description \(\quad \mathrm{Pxx}^{2}=\mathrm{pburg}(\mathrm{x}, \mathrm{p})\) implements the Burg algorithm, a parametric spectral estimation method, and returns Pxx, an estimate of the power spectral density (PSD) of the vector \(x\). The entries of \(x\) represent samples of a discrete-time signal, and \(p\) is the integer specifying the order of an autoregressive (AR) prediction model for the signal, used in estimating the PSD.

The power spectral density is calculated in units of power per radians per sample. Real-valued inputs produce full power one-sided (in frequency) PSDs (by default), while complex-valued inputs produce two-sided PSDs.

In general, the length of the FFT and the values of the input \(x\) determine the length of Pxx and the range of the corresponding normalized frequencies. For this syntax, the (default) FFT length is 256 . The following table indicates the length of Pxx and the range of the corresponding normalized frequencies for this syntax.

Table 7-9: PSD Vector Characteristics for an FFT Length of 256 (Default)
\begin{tabular}{l|l|l}
\hline \begin{tabular}{l} 
Real/ Complex \\
Input Data
\end{tabular} & Length of Pxx & \begin{tabular}{l} 
Range of the Corresponding \\
Normalized Frequencies
\end{tabular} \\
\hline Real-valued & 129 & {\([0, \pi]\)} \\
\hline Complex-valued & 256 & {\([0,2 \pi)\)} \\
\hline
\end{tabular}
[Pxx,w] = pburg \((x, p)\) also returns \(w\), a vector of frequencies at which the PSD is estimated. Pxx and \(w\) have the same length. The units for frequency are rad/sample.
[Pxx,w] = pburg(x, p, nfft) uses the Burg method to estimatethe PSD while specifying the length of the FFT with the integer nfft. If you specify nfft as the empty vector [ ], it takes the default value of 256 .

The length of Pxx and the frequency range for \(w\) depend on nfft and the values of the input \(x\). The following tableindicates the length of Pxx and the frequency range for \(w\) in this syntax.

Table 7-10: PSD and Frequency Vector Characteristics
\begin{tabular}{ll|l|l}
\hline \begin{tabular}{l} 
Real/ Complex \\
Input Data
\end{tabular} & nfft Even/ Odd & Length of Pxx & Range of w \\
\hline Real-valued & Even & \((n f f t / 2+1)\) & {\([0, \pi]\)} \\
\hline Real-valued & Odd & \((n f f t+1) / 2\) & {\([0, \pi)\)} \\
\hline Complex-valued & Even or odd & \(n f f t\) & {\([0,2 \pi)\)} \\
\hline
\end{tabular}
\([P x x, f]=\operatorname{pburg}(x, p, n f f t, f s)\) uses the sampling frequency fs specified as an integer in hertz ( Hz ) to compute the PSD vector ( Pxx ) and the corresponding vector of frequencies ( \(f\) ). In this case, the units for the frequency vector are in Hz . The spectral density produced is calculated in units of power per Hz. If you specify fs as the empty vector [ ], the sampling frequency defaults to 1 Hz .

The frequency range for \(f\) depends on \(n f f t, f s\), and the values of the input \(x\). The length of Pxx is the same as in the table above. The following table indicates the frequency range for \(f\) for this syntax.

Table 7-11: PSD and Frequency Vector Characteristics with fs Specified
\begin{tabular}{l|l|l}
\hline Real/ Complex Input Data & nfft Even/ Odd & Range of \(\mathbf{f}\) \\
\hline Real-valued & Even & {\([0, \mathrm{fs} / 2]\)} \\
\hline Real-valued & Odd & {\([0, \mathrm{fs} / 2)\)} \\
\hline Complex-valued & Even or odd & {\([0, \mathrm{fs})\)} \\
\hline
\end{tabular}
[Pxx,f] = pburg(x,p,nfft,fs,'range') or
[Pxx,w] = pburg(x,p,nfft,'range') specifies the range of frequency values to include in \(f\) or \(w\). This syntax is useful when \(x\) is real. ' range ' can be either:
- 'twosided': Compute the two-sided PSD over the frequency range [0,fs). This is the default for determining the frequency range for complex-valued x .
- If you specify fs as the empty vector, [ ], the frequency range is [ 0,1 ).
- If you don't specify fs, the frequency range is \([0,2 \pi)\).
- 'onesided ': Computethe one-sided PSD over thefrequency ranges specified for real x . This is the default for determining the frequency range for real-valued \(x\).

Note You can put the string argument 'range' anywhere in the input argument list after p.
pburg (. . .) with no outputs plots the power spectral density in the current figure window. The frequency range on the plot is the same as the range of output w (or f) for a given set of parameters.

\section*{Remarks}

Examples

The power spectral density is computed as the distribution of power per unit frequency.

This algorithm depends on your selecting an appropriate model order for your signal.

Because the Burg method estimates the spectral density by fitting an AR prediction model of a given order to the signal, first generate a signal from an AR (all-pole) model of a given order. You can use freqz to check the magnitude of the frequency response of your AR filter. This will give you an idea of what to expect when you estimate the PSD using pburg.
```

a = [1 -2.2137 2.9403 -2.1697 0.9606]; % AR filter coefficients
freqz(1,a) % AR filter frequency response
title('AR System Frequency Response')

```



Now generate the input signal x by filtering white noise through the AR filter. Estimatethe PSD of \(x\) based on a fourth-order AR prediction model since in this case we know that the original AR system model a has order 4.
```

randn('state',1);
x = filter(1,a,randn(256,1)); % AR system output
pburg(x,4) % Fourth-order estimate

```

Algorithm Linear prediction filters can be used to model the second-order statistical characteristics of a signal. The prediction filter output can be used to model the signal when the input is white noise.
The Burg method fits an AR linear prediction filter model of the specified order to the input signal by minimizing (using least squares) the arithmetic mean of the forward and backward prediction errors. The spectral density is then computed from the frequency response of the prediction filter. The AR filter parameters are constrained to satisfy the Levinson-Durbin recursion.
See Also arburg, lpc, pcov, peig, periodogram, pmcov, pmtm, pmusic, pwelch, psdplot, pyulear
References [1] Marple, S.L. Digital Spectral Analysis, Englewood Cliffs, NJ , Prentice-Hall, 1987, Chapter 7.
[2] Stoica, P., and R.L. Moses, Introduction to Spectral Analysis, Prentice-H all, 1997.

\title{
Purpose Estimate the power spectral density using the covariance method
}
Syntax
Description
```

Pxx = pcov(x,p)
[Pxx,w] = pcov(x,p)
[Pxx,w] = pcov(x,p,nfft)
[Pxx,f] = pcov(x,p,nfft,fs)
[Pxx,f] = pcov(x, p,nfft,fs,'range')
[Pxx,w] = pcov(x,p,nfft,'range')
pcov(...)

```

Pxx = pcov( \(x, p\) ) implements the covariance al gorithm, a parametric spectral estimation method, and returns Pxx, an estimate of the power spectral density (PSD) of the vector \(x\). The entries of \(x\) represent samples of a discrete-time signal, and wherep is the integer specifying the order of an autoregressive (AR) prediction model for the signal, used in estimating the PSD.

The power spectral density is calculated in units of power per radians per sample. Real-valued inputs produce full power one-sided (in frequency) PSDs (by default), while complex-valued inputs produce two-sided PSDs.

In general, the length of the FFT and the values of the input \(x\) determine the length of Pxx and the range of the corresponding normalized frequencies. For this syntax, the (default) FFT length is 256. The following table indicates the length of Pxx and the range of the corresponding normalized frequencies for this syntax.

Table 7-12: PSD Vector Characteristics for an FFT Length of 256 (Default)
\begin{tabular}{l|l|l}
\hline \begin{tabular}{l} 
Real/ Complex \\
Input Data
\end{tabular} & Length of Pxx & \begin{tabular}{l} 
Range of the Corresponding \\
Normalized Frequencies
\end{tabular} \\
\hline Real-valued & 129 & {\([0, \pi]\)} \\
\hline Complex-valued & 256 & {\([0,2 \pi)\)} \\
\hline
\end{tabular}
\([P x x, w]=\operatorname{pcov}(x, p)\) also returns \(w, a\) vector of frequencies at which the PSD is estimated. Pxx and whave the same length. The units for frequency are rad/sample.
[Pxx,w] = pcov(x,p,nfft) uses the covariance method to estimate the PSD while specifying the length of theFFT with theinteger nfft. If you specify nfft as the empty vector [ ], it takes the default value of 256.

The length of Pxx and the frequency range for w depend on nfft and the values of the input \(x\). The following table indicates the length of Pxx and the frequency range for \(w\) in this syntax.

Table 7-13: PSD and Frequency Vector Characteristics
\begin{tabular}{ll|l|l}
\hline \begin{tabular}{l} 
Real/ Complex \\
Input Data
\end{tabular} & nfft Even/ Odd & Length of Pxx & Range of w \\
\hline Real-valued & Even & \((n f f t / 2+1)\) & {\([0, \pi]\)} \\
\hline Real-valued & Odd & \((n f f t+1) / 2\) & {\([0, \pi)\)} \\
\hline Complex-valued & Even or odd & \(n f f t\) & {\([0,2 \pi)\)} \\
\hline
\end{tabular}
\([P x x, f]=\operatorname{pcov}(x, p, n f f t, f s)\) uses the sampling frequency fs specified as an integer in hertz ( Hz ) to compute the PSD vector ( Pxx ) and the corresponding vector of frequencies ( \(f\) ). In this case, the units for the frequency vector are in Hz . The spectral density produced is calculated in units of power per Hz. If you specify fs as the empty vector [ ], the sampling frequency defaults to 1 Hz .

The frequency range for \(f\) depends on \(n f f t, f s\), and the values of the input \(x\). The length of Pxx is the same as in the table above. The following table indicates the frequency range for \(f\) for this syntax.

Table 7-14: PSD and Frequency Vector Characteristics with fs Specified
\begin{tabular}{ll|l}
\hline Real/ Complex Input Data & nfft Even/ Odd & Range of f \\
\hline Real-valued & Even & {\([0, f s / 2]\)} \\
\hline Real-valued & Odd & {\([0, f s / 2)\)} \\
\hline Complex-valued & Even or odd & {\([0, f s)\)} \\
\hline
\end{tabular}
[Pxx,f] = pcov(x,p,nfft,fs,'range') or
\([P x x, w]=\operatorname{pcov}(x, p, n f f t\), 'range') specifies the range of frequency values to include in \(f\) or \(w\). This syntax is useful when \(x\) is real. 'range ' can be either:
- 'twosided': Compute the two-sided PSD over the frequency range [0,fs). This is the default for determining the frequency range for complex-valued \(x\).
- If you specify fs as the empty vector, [ ], the frequency range is [ 0,1 ).
- If you don't specify fs, the frequency range is [0, \(2 \pi\) ).
- 'onesided ': Compute the one-sided PSD over thefrequency ranges specified for real x . This is the default for determining the frequency range for real-valued \(x\).

Note You can put the string argument 'range' anywhere in the input argument list after p.
pcov (...) with no outputs plots the power spectral density in the current figure window. The frequency range on the plot is the same as the range of output w (or f) for a given set of parameters.

\section*{Remarks}

Examples

The power spectral density is computed as the distribution of power per unit frequency.

This algorithm depends on your selecting an appropriate model order for your signal.

Because the covariance method estimates the spectral density by fitting an AR prediction model of a given order to the signal, first generate a signal from an AR (all-pole) model of a given order. You can use freqz to check the magnitude of the frequency response of your AR filter. This will give you an idea of what to expect when you estimate the PSD using pcov.
```

a = [1 -2.2137 2.9403 -2.1697 0.9606]; % AR filter coefficients
freqz(1,a) % AR filter frequency response
title('AR System Frequency Response')

```



Now generate the input signal x by filtering white noise through the AR filter. EstimatethePSD of \(x\) based on a fourth-order AR prediction model since in this case we know that the original AR system model a has order 4.
```

randn('state',1);
x = filter(1,a,randn(256,1)); % Signal generated from AR filter
pcov(x,4) % Fourth-order estimate

```

AlgorithmSee Also arcov, lpc, pburg, peig, periodogram, pmcov, pmtm, pmusic, pwelch, psdplot,pyulear
References [1] Marple, S.L. Digital Spectral Analysis, Englewood Cliffs, NJ , Prentice-Hall,1987, Chapter 7.
[2] Stoica, P., and R.L. Moses, Introduction to Spectral Analysis, Prentice-Hall, 1997.
\begin{tabular}{|c|c|}
\hline Purpose & Estimate the pseudospectrum using the eigenvector method \\
\hline \multirow[t]{8}{*}{Syntax} & \([S, w]=\operatorname{peig}(x, p)\) \\
\hline & \([S, w]=\operatorname{peig}(\ldots, \ldots, n f f t)\) \\
\hline & \([S, f]=\operatorname{peig}(x, p, n f f t, f s)\) \\
\hline & \([\mathrm{S}, \mathrm{f}]=\operatorname{peig}\left(. . .,{ }^{\text {corr }}{ }^{\prime}\right)\) \\
\hline & [S,f] = peig(x, p, nfft,fs, nwin, noverlap) \\
\hline & [...] = peig(...,'range') \\
\hline & [...,v,e] = peig(...) \\
\hline & peig(...) \\
\hline \multirow[t]{3}{*}{Description} & \([S, w]=\operatorname{peig}(x, p)\) implements the eigenvector spectral estimation method and returns S , the pseudospectrum estimate of the input signal x , and w , a vector of normalized frequencies (in rad/sample) at which the pseudospectrum is evaluated. The pseudospectrum is calculated using estimates of the eigenvectors of a correlation matrix associated with the input data x , where x is specified as either: \\
\hline & - A row or column vector representing one observation of the signal \\
\hline & - A rectangular array for which each row of \(x\) represents a separate observation of the signal (for example, each row is one output of an array of sensors, as in array processing), such that \(\mathrm{x}^{\prime *}\) x is an estimate of the correlation matrix \\
\hline
\end{tabular}

Note You can use the output of corrmtx to generate such an array x .

You can specify the second input argument \(p\) as either:
- A scalar integer. In this case, the signal subspace dimension is \(p\).
- A two-element vector. In this case, \(p\) (2), the second element of \(p\), represents a threshold that is multiplied by \(\lambda_{\text {min }}\), the smallest estimated eigenvalue of the signal's correlation matrix. Eigenvalues below the threshold \(\lambda_{\text {min }}{ }^{*} p\) (2) are assigned to the noise subspace. In this case, \(p(1)\) specifies the maximum dimension of the signal subspace.

The extra threshold parameter in the second entry in p provides you more flexibility and control in assigning the noise and signal subspaces.
\(S\) and \(w\) have the same length. In general, the length of the FFT and the values of the input \(x\) determine the length of the computed \(s\) and the range of the corresponding normalized frequencies. Thefollowing table indicates the length of \(S\) (and w) and the range of the corresponding normalized frequencies for this syntax.

Table 7-15: S Characteristics for an FFT Length of 256 (Default)
\begin{tabular}{l|l|l}
\hline \begin{tabular}{l} 
Real/ Complex \\
Input Data
\end{tabular} & Length of S and w & \begin{tabular}{l} 
Range of the Corresponding \\
Normalized Frequencies
\end{tabular} \\
\hline Real-valued & 129 & {\([0, \pi]\)} \\
\hline Complex-valued & 256 & {\([0,2 \pi)\)} \\
\hline
\end{tabular}
\([\mathrm{S}, \mathrm{w}]=\) peig(...,nfft) specifies the length of the FFT used to estimate the pseudospectrum with the integer nfft. The default valuefor nfft (entered as an empty vector [ ] ) is 256.

The following table indicates the length of \(S\) and \(w\), and the frequency range for w for this syntax.

Table 7-16: S and Frequency Vector Characteristics
\begin{tabular}{l|l|l|l}
\hline \begin{tabular}{l} 
Real/ Complex \\
Input Data
\end{tabular} & nfft Even/ Odd & \begin{tabular}{l} 
Length of S \\
and \(\mathbf{w}\)
\end{tabular} & Range of w \\
\hline Real-valued & Even & \((n f f t / 2+1)\) & {\([0, \pi]\)} \\
\hline Real-valued & Odd & \((n f f t+1) / 2\) & {\([0, \pi)\)} \\
\hline Complex-valued & Even or odd & \(n f f t\) & {\([0,2 \pi)\)} \\
\hline
\end{tabular}
\([S, f]=p e i g(x, p, n f f t, f s))\) returns the pseudospectrum in the vector \(S\) evaluated at the corresponding vector of frequencies \(f\) (in Hz). You supply the sampling frequency fs in Hz . If you specify fs with the empty vector [ ], the sampling frequency defaults to 1 Hz .

The frequency range for \(f\) depends on \(n f f t, f s\), and the values of the input \(x\). The length of \(s\) (and f) is the same as in Table 7-16. The following table indicates the frequency range for \(f\) for this syntax.

Table 7-17: S and Frequency Vector Characteristics with fs Specified
\begin{tabular}{l|l|l}
\hline Real/ Complex Input Data & nfft Even/ Odd & Range of \(\mathbf{f}\) \\
\hline Real-valued & Even & {\([0, f s / 2]\)} \\
\hline Real-valued & Odd & {\([0, f s / 2)\)} \\
\hline Complex-valued & Even or odd & {\([0, f s)\)} \\
\hline
\end{tabular}
\([S, f]=\) peig(..., 'corr' \()\) forces the input argument \(x\) to be interpreted as a correlation matrix rather than matrix of signal data. F or this syntax x must be a square matrix, and all of its eigenvalues must be nonnegative.
\([S, f]=p e i g(x, p, n f f t, f s, n w i n, n o v e r l a p)\) allows you to specify nwin, a scalar integer indicating a rectangular window length, or a real-valued vector specifying window coefficients. Usethe scalar integer noverlap in conjunction with nwin to specify the number of input sample points by which successive windows overlap. noverlap is not used if x is a matrix. The default value for nwin is \(2 * p\) (1) and noverlap is nwin- 1 .

With this syntax, the input data \(x\) is segmented and windowed before the matrix used to estimate the correlation matrix eigenvalues is formulated. The segmentation of the data depends on nwin, noverlap, and the form of \(x\). Comments on the resulting windowed segments are described in the following table.

Table 7-18: Windowed Data Depending on \(x\) and nwin
\begin{tabular}{l|l|l}
\hline Input data \(\mathbf{x}\) & Form of nwin & Windowed Data \\
\hline Data vector & Scalar & Length is nwin \\
\hline Data vector & Vector of coefficients & Length is length (nwin) \\
\hline
\end{tabular}

Table 7-18: Windowed Data Depending on \(x\) and nwin (Continued)
\begin{tabular}{lll}
\hline Input data \(\mathbf{x}\) & Form of nw in & Windowed Data \\
\hline Data matrix & Scalar & Data is not windowed. \\
Data matrix & Vector of coefficients & \begin{tabular}{l} 
length (nwin) must be the \\
same as the column length of x, \\
and noverlap is not used.
\end{tabular} \\
\hline
\end{tabular}

See Table 7-19 for related information on this syntax.

Note The arguments nwin and noverlap are ignored when you include the string 'corr' in the syntax.
[...] = peig(...,'range') specifies therange of frequency values to include in for w. This syntax is useful when x is real. 'range ' can be either:
- 'whole': Compute the pseudospectrum over the frequency range [0,fs). This is the default for determining the frequency rangefor complex-valued \(x\).
- If you specify fs as the empty vector, [ ], the frequency range is [ 0,1 ).
- If you don't specify fs, the frequency range is \([0,2 \pi)\).
- 'half': Compute the pseudospectrum over the frequency ranges specified for real \(x\). This is the default for determining the frequency range for real-valued x .

Note You can put the string arguments 'range' or 'corr' anywhere in the input argument list after \(p\).
\([\ldots, v, e]=\) peig(...) returns the matrix v of noise eigenvectors, along with the associated eigenvalues in the vector e. The columns of \(v\) span the noise subspace of dimension size ( \(v, 2\) ). The dimension of the signal subspace is size ( \(v, 1\) )-size ( \(v, 2\) ). F or this syntax, \(e\) is a vector of estimated eigenvalues of the correlation matrix.
peig (...) with no output arguments plots the pseudospectrum in the current figure window.

\section*{Remarks \\ In the process of estimating the pseudospectrum, peig computes the noise and signal subspaces from the estimated eigenvectors \(\mathbf{v}_{j}\) and eigenvalues \(\lambda_{j}\) of the signal's correlation matrix. The smallest of these eigenvalues is used in conjunction with the threshold parameter \(p(2)\) to affect the dimension of the noise subspace in some cases. \\ The length \(n\) of the eigenvectors computed by peig is the sum of the dimensions of the signal and noise subspaces. This eigenvector length depends on your input (signal data or correlation matrix) and the syntax you use. \\ The following table summarizes the dependency of the eigenvector length on the input argument.}

Table 7-19: Eigenvector Length Depending on Input Data and Syntax
\begin{tabular}{lll}
\hline Form of Input Data \(\mathbf{x}\) & Comments on the Syntax & \begin{tabular}{l} 
Length \(\boldsymbol{n}\) of \\
Eigenvectors
\end{tabular} \\
\hline Row or column vector & \begin{tabular}{l} 
nwin is specified as a scalar \\
integer.
\end{tabular} & nwin \\
\hline Row or column vector & \begin{tabular}{l} 
nwin is specified as a \\
vector.
\end{tabular} & length (nwin) \\
\hline Row or column vector & nwin is not specified. & \(2 \star\) p (1) \\
\hline I-by-m matrix & \begin{tabular}{l} 
If nwin is specified as a \\
scalar, it is not used. If \\
nwin is specified as a \\
vector, length (nwin) must \\
equal m.
\end{tabular} & m \\
\hline \begin{tabular}{l} 
m-by-m nonnegative \\
definite matrix
\end{tabular} & \begin{tabular}{l} 
The string ' corr' is \\
specified and nwin is not \\
used.
\end{tabular} & m \\
\hline
\end{tabular}

You should specify nwin \(>p\) (1) or length (nwin) \(>p\) (1) if you want \(p(2)>1\) to have any effect.

Examples

\section*{Algorithm}

Implement the eigenvector method to find the pseudospectrum of the sum of three sinusoids in noise, using the default FFT length of 256 . Usethe modified covariance method for the correlation matrix estimate.
```

randn('state',1); n=0:99;
s=exp(i*pi/2*n)+2*exp(i*pi/4*n)+exp(i*pi/3*n)+randn(1,100);
X=corrmtx(s,12,'mod');
peig(X,3,'whole') % Uses the default NFFT of 256.

```


The eigenvector method estimates the pseudospectrum from a signal or a correlation matrix using a weighted version of the MUSIC algorithm derived from Schmidt's eigenspace analysis method [1][2]. The algorithm performs eigenspace analysis of the signal's correlation matrix in order to estimate the signal's frequency content. The eigenvalues and eigenvectors of the signal's correlation matrix are estimated using svd if you don't supply the correlation matrix. This algorithm is particularly suitable for signals that are the sum of sinusoids with additive white Gaussian noise.

The eigenvector method produces a pseudospectrum estimate given by
\[
\mathrm{P}_{\mathrm{ev}}(\mathrm{f})=\frac{1}{\left(\sum_{-}^{\mathrm{N}}\left|\mathbf{v}_{\mathrm{k}}^{\mathrm{H}} \mathbf{e}(\mathrm{f})\right|^{2}\right) / \lambda_{\mathrm{k}}}
\]
where N is the dimension of the eigenvectors and \(\mathbf{v}_{\mathrm{k}}\) is the kth eigenvector of the correlation matrix of the input signal. The integer \(p\) is the dimension of the signal subspace, so the eigenvectors \(\mathbf{v}_{\mathrm{k}}\) used in the sum correspond to the smallest eigenvalues \(\lambda_{k}\) of the correlation matrix. The eigenvectors used in the PSD estimate span the noise subspace. The vector \(\mathbf{e}(\mathrm{f})\) consists of complex exponentials, so the inner product
\[
\mathbf{v}_{\mathrm{k}}^{\mathrm{H}} \mathbf{e}(\mathrm{f})
\]
amounts to a F ourier transform. This is used for computation of the PSD estimate. The FFT is computed for each \(\mathbf{v}_{\mathrm{k}}\) and then the squared magnitudes are summed and scaled.

\footnotetext{
See Also corrmtx, pburg, periodogram, pmtm, pmusic, prony, pwelch, psdplot, rooteig, rootmusic

References [1] Marple, S.L. Digital Spectral Analysis, Englewood Cliffs, NJ , Prentice-H all, 1987, pp. 373-378.
[2] Schmidt, R.O, "Multiple Emitter Location and Signal Parameter Estimation," IEEE Trans. Antennas Propagation, Vol. AP-34 (March 1986), pp. 276-280.
[3] Stoica, P., and R.L. Moses, I ntroduction to Spectral Analysis, Prentice-Hall, 1997.
}

\section*{Purpose}

Estimate the power spectral density (PSD) of a signal using a periodogram
Syntax

\section*{Description}
```

[Pxx,w] = periodogram(x)
[Pxx,w] = periodogram(x,window)
[Pxx,w] = periodogram(x,window,nfft)
[Pxx,f] = periodogram(x,window, nfft,fs)
[Pxx,...] = periodogram(x,...,'range')
periodogram(...)

```
[Pxx,w] = periodogram(x) returns the power spectral density (PSD) estimate Pxx of the sequence \(x\) using a periodogram. The power spectral density is calculated in units of power per radians per sample. The corresponding vector of frequencies w is computed in radians per sample, and has the same length as Pxx.

A real-valued input vector x produces a full power one-sided (in frequency) PSD (by default), while a complex-valued x produces a two-sided PSD.

In general, the length \(N\) of theFFT and the values of the input \(x\) determine the length of Pxx and the range of the corresponding normalized frequencies. For this syntax, the (default) length N of the FFT is the larger of 256 and the next power of two greater than the length of \(x\). The following table indicates the length of Pxx and the range of the corresponding normalized frequencies for this syntax.

Table 7-20: PSD Vector Characteristics for an FFT Length of \(\mathbf{N}\) (Default)
\begin{tabular}{l|l|l}
\hline \begin{tabular}{l} 
Real/ Complex \\
Input Data
\end{tabular} & Length of Pxx & \begin{tabular}{l} 
Range of the Corresponding \\
Normalized Frequencies
\end{tabular} \\
\hline Real-valued & \((\mathrm{N} / 2)+1\) & {\([0, \pi]\)} \\
\hline Complex-valued & N & {\([0,2 \pi)\)} \\
\hline
\end{tabular}
[Pxx,w] = periodogram(x,window) returns the PSD estimate Pxx computed using the modified periodogram method. The vector window specifies the coefficients of the window used in computing a modified periodogram of the input signal. Both input arguments must be vectors of the same length. When you don't supply the second argument window, or set it to the empty vector [ ],
a rectangular window (rectwin) is used by default. In this case the standard periodogram is calculated.
[Pxx,w] = periodogram(x,window, nfft) uses the modified periodogram to estimate the PSD while specifying the length of theFFT with the integer nfft. If you set nfft to the empty vector [ ], it takes the default value for N listed in the previous syntax.

The length of Pxx and the frequency range for \(w\) depend on nfft and the values of the input \(x\). The following table indicates the length of Pxx and the frequency range for \(w\) for this syntax.

Table 7-21: PSD and Frequency Vector Characteristics
\begin{tabular}{l|l|l|l}
\hline \begin{tabular}{l} 
Real/ Complex \\
Input Data
\end{tabular} & nfft Even/ Odd & Length of Pxx & Range of w \\
\hline Real-valued & Even & \((n f f t / 2+1)\) & {\([0, \pi]\)} \\
\hline Real-valued & Odd & \((n f f t+1) / 2\) & {\([0, \pi)\)} \\
\hline Complex-valued & Even or odd & \(n f f t\) & {\([0,2 \pi)\)} \\
\hline
\end{tabular}

Note periodogram uses an nfft-point FFT of the windowed data ( x . *window) to compute the periodogram. If the value you specify for nfft is less than the length of \(x\), then \(x\). *window is wrapped modulo nfft. If the value you specify for nfft is greater than the length of \(x\), then \(x\). *window is zero-padded to compute the FFT.
[Pxx,f] = periodogram(x,window, nfft,fs) uses the sampling frequency fs specified as an integer in hertz (Hz) to compute the PSD vector (Pxx) and the corresponding vector of frequencies ( \(f\) ). In this case, the units for the frequency vector are in Hz . The spectral density produced is calculated in units of power per Hz . If you specify fs as the empty vector [ ], the sampling frequency defaults to 1 Hz .

The frequency range for \(f\) depends on \(n f f t, f s\), and the values of the input \(x\). The length of Pxx is the same as in the table above. The following table indicates the frequency range for \(f\) for this syntax.

Table 7-22: PSD and Frequency Vector Characteristics with fs Specified
\begin{tabular}{l|l|l}
\hline Real/ Complex Input Data & nfft Even/ Odd & Range of \(\mathbf{f}\) \\
\hline Real-valued & Even & {\([0, \mathrm{fs} / 2]\)} \\
\hline Real-valued & Odd & {\([0, \mathrm{fs} / 2)\)} \\
\hline Complex-valued & Even or odd & {\([0, \mathrm{fs})\)} \\
\hline
\end{tabular}
[Pxx,f] = periodogram(x,window, nfft,fs,'range') or
[Pxx,w] = periodogram(x,window,nfft,'range') specifies the range of frequency values to include in \(f\) or \(w\). This syntax is useful when \(x\) is real.
'range ' can be either:
- 'twosided': Compute the two-sided PSD over the frequency range [0,fs). This is the default for determining the frequency range for complex-valued \(x\).
- If you specify fs as the empty vector, [ ], the frequency range is [0,1).
- If you don't specify fs, the frequency range is [0, \(2 \pi\) ).
- 'onesided ': Compute the one-sided PSD over thefrequency ranges specified for real \(x\). This is the default for determining the frequency range for real-valued \(x\).

\section*{Note You can put the string argument 'range' anywhere in the input argument list after window.}
periodogram(...) with no outputs plots the power spectral density in dB per unit frequency in the current figure window. The frequency range on the plot is the same as the range of output w (or f) for the syntax you use.

\section*{Examples}

Compute the periodogram of a 200 Hz signal embedded in additive noise using the default window.
```

randn('state',0);
Fs = 1000;
t = 0:1/Fs:.3;
x = cos(2*pi*t*200)+0.1*randn(size(t));
periodogram(x,[],'twosided',512,Fs)

```


Algorithm
The periodogram for a sequence \(\left[x_{1}, \ldots, x_{n}\right]\) is given by the following formula.
\[
S\left(e^{j \omega}\right)=\frac{1}{n}\left|\sum_{I=1}^{\prime \prime} x_{l} e^{-j \omega l}\right|^{<}
\]

This expression forms an estimate of the power spectrum of the signal defined by the sequence \(\left[x_{1}, \ldots, x_{n}\right]\).

If you weight your signal sequence by a window \(\left[w_{1}, \ldots, w_{n}\right]\), then the weighted or modified periodogram is defined as
\[
S\left(e^{j \omega}\right)=\frac{\frac{1}{n}\left|\sum_{l=1}^{n} w_{l} x_{l} e^{-j \omega l}\right|^{2}}{\frac{1}{n} \sum_{l=1}^{n}\left|w_{l}\right|^{2}}
\]

In either case, periodogram uses an nfft-point FFT to compute the power spectral density as \(S\left(e^{j \omega}\right) / F\), where \(F\) is:
- \(2 \pi\) when you do not supply the sampling frequency
- fs when you supply the sampling frequency

See Also
References
pburg, pcov, peig, pmcov, pmtm, pmusic, pwelch, psdplot, pyulear
[1] Stoica, P., and R.L. M oses, Introduction to Spectral Analysis, Prentice-H all, 1997, pp. 24-26.
[2] Welch, P.D, "TheU se of F ast Fourier Transform for the Estimation of Power Spectra: A Method Based on Time Averaging Over Short, Modified Periodograms," IEEE Trans. Audio Electroacoustics, Vol. AU-15 (J une 1967), pp. 70-73.
[3] Oppenheim, A.V., and R.W. Schafer, Discrete-TimeSignal Processing, Prentice-Hall, 1989, pp. 730-742.

\section*{Purpose}

Estimate the power spectral density using the modified covariance method

\author{
Syntax \\ Description
}
```

Pxx = pmcov(x,p)
[Pxx,w] = pmcov(x,p)
[Pxx,w] = pmcov(x,p,nfft)
[Pxx,f] = pmcov(x,p,nfft,fs)
[Pxx,f] = pmcov(x,p,nfft,fs,'range')
[Pxx,w] = pmcov(x,p,nfft,'range')
pmcov(...)

```

Pxx = pmcov ( \(\mathrm{x}, \mathrm{p}\) ) implements the modified covariance algorithm, a parametric spectral estimation method, and returns Pxx, an estimate of the power spectral density (PSD) of the vector \(x\). The entries of \(x\) represent samples of a discrete-time signal, and \(p\) is the integer specifying the order of an autoregressive (AR) prediction model for the signal, used in estimating the PSD.

The power spectral density is calculated in units of power per radians per sample. Real-valued inputs produce full power one-sided (in frequency) PSDs (by default), while complex-valued inputs produce two-sided PSDs.

In general, the length of the FFT and the values of the input \(x\) determine the length of Pxx and the range of the corresponding normalized frequencies. For this syntax, the (default) FFT length is 256. The following table indicates the length of Pxx and the range of the corresponding normalized frequencies for this syntax.

Table 7-23: PSD Vector Characteristics for an FFT Length of 256 (Default)
\begin{tabular}{l|l}
\hline \begin{tabular}{l} 
Real/ Complex \\
Input Data
\end{tabular} & Length of Pxx \\
\hline Real-valued & 129 \\
\begin{tabular}{l} 
Range of the Corresponding \\
Normalized Frequencies
\end{tabular} \\
\hline Complex-valued & 256
\end{tabular}\([0, \pi] \quad[0,2 \pi)\).
 PSD is estimated. Pxx and \(w\) have the same length. The units for frequency are rad/sample.
[Pxx,w] = pmcov(x, p,nfft) uses the covariance method to estimate the PSD while specifying the length of theFFT with the integer nfft. If you specify nfft as the empty vector [ ], it takes the default value of 256 .

The length of Pxx and the frequency range for \(w\) depend on nfft and the values of the input \(x\). The following tableindicates the length of Pxx and the frequency range for \(w\) for this syntax.

Table 7-24: PSD and Frequency Vector Characteristics
\begin{tabular}{lllll}
\hline \begin{tabular}{l} 
Real/ Complex \\
Input Data
\end{tabular} & nfft Even/ Odd & Length of Pxx & Range of w \\
\hline Real-valued & Even & \((n f f t / 2+1)\) & {\([0, \pi]\)} \\
\hline Real-valued & Odd & \((n f f t+1) / 2\) & {\([0, \pi)\)} \\
\hline Complex-valued & Even or odd & \(n f f t\) & {\([0,2 \pi)\)} \\
\hline
\end{tabular}
\([P x x, f]=\operatorname{pmcov}(x, p, n f f t, f s)\) uses the sampling frequency fs specified as an integer in hertz ( Hz ) to compute the PSD vector ( Pxx ) and the corresponding vector of frequencies ( \(f\) ). In this case, the units for the frequency vector are in Hz . The spectral density produced is calculated in units of power per Hz. If you specify fs as the empty vector [ ], the sampling frequency defaults to 1 Hz .

The frequency range for \(f\) depends on \(n f f t, f s\), and the values of the input \(x\). The length of Pxx is the same as in Table 7-24. Thefollowing table indicates the frequency range for \(f\) in this syntax.

Table 7-25: PSD and Frequency Vector Characteristics with fs Specified
\begin{tabular}{l|l|l}
\hline Real/ Complex Input Data & nfft Even/ Odd & Range of \(\mathbf{f}\) \\
\hline Real-valued & Even & {\([0, f \mathrm{fs} / 2]\)} \\
\hline Real-valued & Odd & {\([0, \mathrm{fs} / 2)\)} \\
\hline Complex-valued & Even or odd & {\([0, \mathrm{fs})\)} \\
\hline
\end{tabular}
[Pxx,f] = pmcov(x,p,nfft,fs,'range') or
[Pxx,w] = pmcov(x,p,nfft,'range') specifies the range of frequency values to include in \(f\) or \(w\). This syntax is useful when \(x\) is real. ' range' can be either:
- 'twosided': Compute the two-sided PSD over the frequency range [0,fs). This is the default for determining the frequency range for complex-valued \(x\).
- If you specify fs as the empty vector, [ ], the frequency range is [ 0,1 ).
- If you don't specify fs, the frequency range is \([0,2 \pi)\).
- 'onesided ': Computethe one-sided PSD over thefrequency ranges specified for real \(x\). This is the default for determining the frequency range for real-valued \(x\).

Note You can put the string argument 'range' anywhere in the input argument list after p.
pmcov (...) with no outputs plots the power spectral density in the current figure window. The frequency range on the plot is the same as the range of output w (or f) for a given set of parameters.

\section*{Remarks}

Examples

The power spectral density is computed as the distribution of power per unit frequency.

This algorithm depends on your selecting an appropriate model order for your signal.

Because the modified covariance method estimates the spectral density by fitting an AR prediction model of a given order to the signal, first generate a signal from an AR (all-pole) model of a given order. You can use freqz to check the magnitude of thefrequency response of your AR filter. This will give you an idea of what to expect when you estimate the PSD using pmcov.
```

a = [1 -2.2137 2.9403 -2.1697 0.9606]; % AR filter coefficients
freqz(1,a) % AR filter frequency response
title('AR System Frequency Response')

```


Now generate the input signal x by filtering white noise through the AR filter. EstimatethePSD of \(x\) based on a fourth-order AR prediction model sincein this case we know that the original AR system model a has order 4.
```

randn('state',1);
x = filter(1,a,randn(256,1)); % AR filter output
pmcov(x,4)
% Fourth-order estimate

```

Algorithm Linear prediction filters can be used to model the second-order statistical characteristics of a signal. The prediction filter output can be used to model the signal when the input is white noise.
pmcov estimates the PSD of the signal vector using the modified covariance method. This method fits an autoregressive (AR) linear prediction filter model to the signal by simultaneously minimizing the forward and backward prediction errors (based on causal observations of your input signal) in the least squares sense. The spectral estimate returned by pmcov is the magnitude squared frequency response of this AR model.
See Also armcov, lpc, pburg, pcov, peig, periodogram, pmtm, pmusic, pwelch, prony, psdplot, pyulear
References
[1] Marple, S.L. Digital Spectral Analysis, Englewood Cliffs, NJ , Prentice-Hall, 1987, Chapter 7.
[2] Stoica, P., and R.L. Moses, Introduction to Spectral Analysis, Prentice-H all, 1997.

Purpose Estimate the power spectral density using the multitaper method (MTM)
Syntax

\section*{Description}
```

[Pxx,w] $=\operatorname{pmtm}(x, n w)$
$[P x x, w]=\operatorname{pmtm}(x, n w, n f f t)$
$[P x x, f]=\operatorname{pmtm}(x, n w, n f f t, f s)$
$[P x x, P x x c, f]=\operatorname{pmtm}(x, n w, n f f t, f s)$
$[P x x, P x x c, f]=\operatorname{pmtm}(x, n w, n f f t, f s, p)$
$[P x x, P x x c, f]=\operatorname{pmtm}(x, e, v, n f f t, f s, p)$
$[P x x, P x x c, f]=p m t m\left(x, d p s s \_p a r a m s, n f f t, f s, p\right)$
[...] $=$ pmtm(...,'method')
[...] $=$ pmtm(...,'range')
pmtm(...)

```
pmtm estimates the power spectral density (PSD) of the time series x using the multitaper method (MTM) described in [1]. This method uses linear or nonlinear combinations of modified periodograms to estimate the PSD. These periodograms are computed using a sequence of orthogonal tapers (windows in thefrequency domain) specified from the discrete prolate spheroidal sequences (see dpss).
\([P x x, w]=p m t m(x, n w)\) estimates the PSD Pxx for the input signal \(x\), using \(2 *\) nw-1 discrete prolate spheroidal sequences as data tapers for the multitaper estimation method. nw is the time-bandwidth product for the discrete prolate spheroidal sequences. If you specify nw as the empty vector [ ], a default value of 4 is used. Other typical choices are \(2,5 / 2,3\), or \(7 / 2\). pmtm also returns \(w, ~ a\) vector of frequencies at which the PSD is estimated. Pxx and \(w\) have the same length. The units for frequency are rad/sample.

The power spectral density is calculated in units of power per radians per sample. Real-valued inputs produce (by default) full power one-sided (in frequency) PSDs, while complex-valued inputs produce two-sided PSDs.

In general, the length N of the FFT and the values of the input x determine the length of Pxx and the range of the corresponding normalized frequencies. For this syntax, the (default) length \(N\) of the FFT is the larger of 256 and the next power of two greater than the length of the segment. The following table
indicates the length of Pxx and the range of the corresponding normalized frequencies for this syntax.

Table 7-26: PSD Vector Characteristics for an FFT Length of N (Default)
\begin{tabular}{l|ll}
\hline \begin{tabular}{l} 
Real/ Complex \\
Input Data
\end{tabular} & Length of Pxx & \begin{tabular}{l} 
Range of the Corresponding \\
Normalized Frequencies
\end{tabular} \\
\hline Real-valued & \((\mathrm{N} / 2)+1\) & {\([0, \pi]\)} \\
Complex-valued & N & {\([0,2 \pi)\)} \\
\hline
\end{tabular}
[Pxx,w] = pmtm(x,nw, nfft) uses the multitaper method to estimate the PSD while specifying the length of theFFT with theinteger nfft. If you specify nfft as the empty vector [ ], it adopts the default value for N described in the previous syntax.

The length of Pxx and the frequency range for w depend on nfft and the values of the input \(x\). The following table indicates the length of Pxx and the frequency range for \(w\) for this syntax.

Table 7-27: PSD and Frequency Vector Characteristics
\begin{tabular}{lllll}
\hline \begin{tabular}{l} 
Real/ Complex \\
Input Data
\end{tabular} & nfft Even/ Odd & Length of Pxx & Range of w \\
\hline Real-valued & Even & \((n f f t / 2+1)\) & {\([0, \pi]\)} \\
\hline Real-valued & Odd & \((n f f t+1) / 2\) & {\([0, \pi)\)} \\
\hline Complex-valued & Even or odd & \(n f f t\) & {\([0,2 \pi)\)} \\
\hline
\end{tabular}
[Pxx,f] \(=\operatorname{pmtm}(x, n w, n f f t, f s)\) uses the sampling frequency fs specified as an integer in hertz \((\mathrm{Hz})\) to compute the PSD vector ( Pxx ) and the corresponding vector of frequencies ( f ). In this case, the units for the frequency vector fare in Hz . The spectral density produced is calculated in units of power per Hz. If you specify fs as the empty vector [ ], the sampling frequency defaults to 1 Hz .

The frequency range for \(f\) depends on \(n f f t, f s\), and the values of the input \(x\). The length of Pxx is the same as in Table 7-27. Thefollowing table indicates the frequency range for \(f\) for this syntax.

Table 7-28: PSD and Frequency Vector Characteristics with fs Specified
\begin{tabular}{l|l|l}
\hline Real/ Complex Input Data & nfft Even/ Odd & Range of \(\mathbf{f}\) \\
\hline Real-valued & Even & {\([0, \mathrm{fs} / 2]\)} \\
\hline Real-valued & Odd & {\([0, \mathrm{fs} / 2)\)} \\
\hline Complex-valued & Even or odd & {\([0, \mathrm{fs})\)} \\
\hline
\end{tabular}
[Pxx, Pxxc,f] = pmtm(x, nw, nfft,fs) returns Pxxc, the 95\% confidence interval for Pxx. Confidence intervals are computed using a chi-squared approach. Pxxc is a two-column matrix with the same number of rows as Pxx. \(\operatorname{Pxxc}(:, 1)\) is the lower bound of the confidence interval and \(\operatorname{Pxxc}(:, 2)\) is the upper bound of the confidence interval.
[Pxx, Pxxc,f] = pmtm(x, nw, nfft,fs, p) returns Pxxc, the p*100\% confidence interval for Pxx, where p is a scalar between 0 and 1. If you don't specify p, or if you specify \(p\) as the empty vector [ ], the default \(95 \%\) confidence interval is used.
[Pxx, Pxxc,f] = pmtm(x,e,v,nfft,fs,p) returns the PSD estimate Pxx, the confidence interval Pxxc, and the frequency vector f from the data tapers contained in the columns of the matrix e, and their concentrations in the vector \(v\). The length of \(v\) is the same as the number of columns in e. You can obtain the data to supply as these arguments from the outputs of dpss.

\begin{abstract}
[Pxx,Pxxc,f] = pmtm(x,dpss_params, nfft,fs,p) uses the cell array dpss_params containing the input arguments to dpss (listed in order, but excluding the first argument) to compute the data tapers. F or example, pmtm( \(x,\{3.5\), 'trace' \(\}, 512,1000\) ) calculates the prolate spheroidal sequences for \(n w=3.5\), using \(n f f t=512\), and \(\mathrm{fs}=1000\), and displays the method that dpss uses for this calculation. See dpss for other options.
\end{abstract}
[...] \(=\operatorname{pmtm}(\ldots\), 'method' \()\) specifies the algorithm used for combining the individual spectral estimates. The string 'method' can be one of the following:
- 'adapt ': Thomson's adaptive nonlinear combination (default)
- 'unity ': A linear combination of the weighted periodograms with unity weights
- 'eigen' : A linear combination of the weighted periodograms with eigenvalue weights
[...] = pmtm(...,'range') specifiestherange of frequency valuestoinclude in \(f\) or \(w\). This syntax is useful when \(x\) is real. 'range' can be either:
- 'twosided ': Compute the two-sided PSD over the frequency range [0,fs). This is the default for determining the frequency range for complex-valued x.
- If you specify fs as the empty vector, [ ], the frequency range is [ 0,1 ).
- If you don't specify fs , the frequency range is \([0,2 \pi\) ).
- 'onesided ': Computethe one-sided PSD over the frequency ranges specified for real x . This is the default for determining the frequency range for real-valued x .

Note You can put the string arguments 'range' or 'method' anywhere after the input argument nw or v .
\(\mathrm{pmtm}(\ldots)\) with no output arguments plots the PSD estimate and the confidence intervals in the current figure window. If you don't specify fs , the \(95 \%\) confidence interval is plotted. If you do specify fs, the confidence intervals plotted depend on the value of \(p\).

Examples

See Also

References

This example analyzes a sinusoid in white noise.
```

randn('state',0);
fs = 1000; t = 0:1/fs:0.3;
x = cos(2*pi*t*200) + 0.1*randn(size(t));
[Pxx,Pxxc,f] = pmtm(x,3.5,512,fs,0.99);
psdplot([Pxx Pxxc],f,'hz','db')
title('PMTM PSD Estimate with 99% Confidence Intervals')

```

dpss, pburg, pcov, peig, periodogram, pmcov, pmusic, pwelch, psdplot, pyulear
[1] Percival, D.B., and A.T. Walden, Spectral Analysis for Physical Applications: Multitaper and Conventional UnivariateTechniques, Cambridge University Press, 1993.
[2] Thomson, D.] ., "Spectrum estimation and harmonic analysis," Proceedings of theIEEE, Vol. 70 (1982), pp. 1055-1096.
```

Purpose Estimate the pseudospectrum using the MUSIC algorithm
Syntax [S,w] = pmusic (x,p)
[S,w] = pmusic(...,nfft)
[S,f] = pmusic(x,p,nfft,fs))
[S,f] = pmusic(...,'corr')
[S,f] = pmusic(x,p,nfft,fs,nwin,noverlap)
[...] = pmusic(...,'range')
[...,v,e] = pmusic(...)
pmusic(...)

```

\section*{Description \\ \([S, w]=\operatorname{pmusic}(x, p)\) implements theMUSIC (MultipleSignal Classification)}
``` al gorithm and returns \(s\), the pseudospectrum estimate of the input signal \(x\), and a vector w of normalized frequencies (in rad/sample) at which the pseudospectrum is evaluated. The pseudospectrum is calculated using estimates of the eigenvectors of a correlation matrix associated with the input data x , where x is specified as either:
- A row or column vector representing one observation of the signal
- A rectangular array for which each row of x represents a separate observation of the signal (for example, each row is one output of an array of sensors, as in array processing), such that \(\mathrm{x}^{\prime *}\) x is an estimate of the correlation matrix
```

Note You can use the output of corrmtx to generate such an array $x$.

You can specify the second input argument $p$ as either:

- A scalar integer. In this case, the signal subspace dimension is $p$.
- A two-element vector. In this case, p(2), the second element of p, represents a threshold that is multiplied by $\lambda_{\text {min }}$, the smallest estimated eigenvalue of the signal's correlation matrix. Eigenvalues below the threshold $\lambda_{\text {min }}{ }^{*} p$ (2) are assigned to the noise subspace. In this case, $p(1)$ specifies the maximum dimension of the signal subspace.

The extra threshold parameter in the second entry in p provides you more flexibility and control in assigning the noise and signal subspaces.
$S$ and $w$ have the same length. In general, the length of the FFT and the values of the input $x$ determine the length of the computed $s$ and the range of the corresponding normalized frequencies. Thefollowing table indicates the length of $s(a n d w)$ and the range of the corresponding normalized frequencies for this syntax.

Table 7-29: S Characteristics for an FFT Length of 256 (Default)

| Real/ Complex <br> Input Data | Length of S and w | Range of the Corresponding <br> Normalized Frequencies |
| :--- | :--- | :--- |
| Real-valued | 129 | $[0, \pi]$ |
| Complex-valued | 256 | $[0,2 \pi)$ |

$[S, w]=$ pmusic (..., nfft) specifies the length of the FFT used to estimate the pseudospectrum with the integer nfft. The default valuefor nfft (entered as an empty vector [ ]) is 256.

The following table indicates the length of s and $w$, and the frequency range for w in this syntax.

Table 7-30: S and Frequency Vector Characteristics

| Real/ Complex <br> Input Data | nfft Even/ Odd | Length of S <br> and w | Range of w |
| :--- | :--- | :--- | :--- |
| Real-valued | Even | $(n f f t / 2+1)$ | $[0, \pi]$ |
| Real-valued | Odd | $(n f f t+1) / 2$ | $[0, \pi)$ |
| Complex-valued | Even or odd | $n f f t$ | $[0,2 \pi)$ |

$[S, f]=p m u s i c(x, p, n f f t, f s)$ returns the pseudospectrum in the vector $S$ evaluated at the corresponding vector of frequencies $f$ (in Hz). You supply the sampling frequency fs in Hz . If you specify fs with the empty vector [ ], the sampling frequency defaults to 1 Hz .

The frequency range for $f$ depends on $n f f t, f s$, and the values of the input $x$. The length of $s$ (and f) is the same as in Table 7-30. The following table indicates the frequency range for $f$ for this syntax.

Table 7-31: S and Frequency Vector Characteristics with fs Specified

| Real/ Complex Input Data | nfft Even/ Odd | Range of $\mathbf{f}$ |
| :--- | :--- | :--- |
| Real-valued | Even | $[0, \mathrm{fs} / 2]$ |
| Real-valued | Odd | $[0, \mathrm{fs} / 2)$ |
| Complex-valued | Even or odd | $[0, \mathrm{fs})$ |

[S,f] = pmusic(..., 'corr') forces theinput argument $x$ to beinterpreted as a correlation matrix rather than matrix of signal data. For this syntax x must be a square matrix, and all of its eigenvalues must be nonnegative.
$[S, f]=$ pmusic (x, p, nfft,fs, nwin, noverlap) allows you to specify nwin, a scalar integer indicating a rectangular window length, or a real-valued vector specifying window coefficients. Usethe scalar integer noverlap in conjunction with nwin to specify the number of input sample points by which successive windows overlap. noverlap is not used if x is a matrix. The default value for nwin is $2 * p$ (1) and noverlap is nwin- 1 .

With this syntax, the input data $x$ is segmented and windowed before the matrix used to estimate the correlation matrix eigenvalues is formulated. The segmentation of the data depends on nwin, noverlap, and the form of $x$. Comments on the resulting windowed segments are described in the following table.

Table 7-32: Windowed Data Depending on $x$ and nwin

| Input data $\mathbf{x}$ | Form of nwin | Windowed Data |
| :--- | :--- | :--- |
| Data vector | Scalar | Length is nwin |
| Data vector | Vector of coefficients | Length is length (nwin) |

Table 7-32: Windowed Data Depending on $x$ and nwin (Continued)

| Input data $\mathbf{x}$ | Form of nwin | Windowed Data |
| :--- | :--- | :--- |
| Data matrix | Scalar | Data is not windowed. |
| Data matrix | Vector of coefficients | length (nwin) must be the <br> same as the column length of x, <br> and noverlap is not used. |

See Table 7-33 for related information on this syntax.

Note The arguments nwin and noverlap are ignored when you include the string 'corr ' in the syntax.
[...] = pmusic(..., 'range') specifies the range of frequency values to include in $f$ or w. This syntax is useful when $x$ is real. 'range ' can be either:

- 'whole': Compute the pseudospectrum over the frequency range [0,fs). This is the default for determining the frequency rangefor complex-valued x .
- If you specify fs as the empty vector, [ ], the frequency range is [ 0,1 ).
- If you don't specify fs, the frequency range is $[0,2 \pi)$.
- 'half': Compute the pseudospectrum over the frequency ranges specified for real $x$. This is the default for determining the frequency range for real-valued x .

Note You can put the string arguments 'range' or 'corr' anywhere in the input argument list after $p$.
$[. . ., v, e]=$ pmusic (...) returns the matrix v of noise eigenvectors, along with the associated eigenvalues in the vector $e$. The columns of $v$ span thenoise subspace of dimension size ( $v, 2$ ). The dimension of the signal subspace is size ( $v, 1$ )-size ( $v, 2$ ). F or this syntax, $e$ is a vector of estimated eigenvalues of the correlation matrix.
pmusic (...) with no output arguments plots the pseudospectrum in the current figure window.

## Remarks In the process of estimating the pseudospectrum, pmusic computes the noise and signal subspaces from the estimated eigenvectors $\mathbf{v}_{\mathrm{j}}$ and eigenvalues $\lambda_{\mathrm{j}}$ of the signal's correlation matrix. The smallest of these eigenvalues is used in conjunction with the threshold parameter $p(2)$ to affect the dimension of the noise subspace in some cases. <br> The length $n$ of the eigenvectors computed by pmusic is the sum of the dimensions of the signal and noise subspaces. This eigenvector length depends on your input (signal data or correlation matrix) and the syntax you use. <br> The following table summarizes the dependency of the eigenvector length on the input argument.

Table 7-33: Eigenvector Length Depending on Input Data and Syntax

| Form of Input Data $\mathbf{x}$ | Comments on the Syntax | Length $\mathbf{n}$ of <br> Eigenvectors |
| :--- | :--- | :--- |
| Row or column vector | nwin is specified as a scalar <br> integer. | nwin |
| Row or column vector | nwin is specified as a <br> vector. | length(nwin) |
| Row or column vector | nwin is not specified. | $2 * \mathrm{p}(1)$ |
| I-by-m matrix | If nwin is specified as a <br> scalar, it is not used. If <br> nwin is specified as a <br> vector, length (nwin) must <br> equal m. | m |
| m-by-m nonnegative <br> definite matrix | The string ' corr ' is <br> specified and nwin is not <br> used. | m |

You should specify nwin $>p(1)$ or length (nwin) $>p(1)$ if you want $p(2)>1$ to have any effect.

## Examples Example 1: pmusic with no Sampling Specified

This example analyzes a signal vector $x$, assuming that two real sinusoidal components are present in the signal subspace. In this case, the dimension of the signal subspace is 4 because each real sinusoid is the sum of two complex exponentials.

```
randn('state',0);
n = 0:199;
x = cos(0.257*pi*n) + sin(0.2*pi*n) + 0.01*randn(size(n));
pmusic(x,4)
```



## Example 2: Specifying Sampling Frequency and Subspace Dimensions

This example analyzes the same signal vector $x$ with an eigenvalue cutoff of $10 \%$ above the minimum. Setting p (1) = Inf forces the signal/noise subspace decision to be based on the threshold parameter $p$ (2). Specify the eigenvectors of length 7 using the nwin argument, and set the sampling frequency fs to 8 kHz .

```
randn('state',0);
n = 0:199;
x = cos(0.257*pi*n) + sin(0.2*pi*n) + 0.01*randn(size(n));
[P,f] = pmusic(x,[Inf,1.1],[],8000,7); % Window length = 7
```


## Example 3: Entering a Correlation Matrix

Supply a positive definite correlation matrix R for estimating the spectral density. Use the default 256 samples.

```
R = toeplitz(cos(0.1*pi*[0:6])) + 0.1*eye(7);
[P,f] = pmusic(R,4,'corr');
```


## Example 4: Entering a Signal Data Matrix Generated from corrmtx

 Enter a signal data matrix Xm generated from data using corrmtx.```
randn('state',0);
n = 0:699;
x = cos(0.257*pi*(n)) + 0.1*randn(size(n));
Xm = corrmtx(x,7,'mod');
[P,w] = pmusic(Xm,2);
```

Example 5: Using Windowing to Create the Effect of a Signal Data Matrix Use the same signal, but let pmusic form the 100-by-7 data matrix using its windowing input arguments. In addition, specify an FFT of length 512.

```
randn('state',0);
n = 0:699;
x = cos(0.257*pi*(n)) + 0.1*randn(size(n));
[PP,ff] = pmusic(x,2,512,[],7,0);
```


## Algorithm

The name MUSIC is an acronym for MUltiple SI gnal Classification. The MUSIC algorithm estimates the pseudospectrum from a signal or a correlation matrix using Schmidt's eigenspace analysis method [1]. The al gorithm performs eigenspace analysis of the signal's correlation matrix in order to estimate the signal's frequency content. This al gorithm is particularly suitable for signals that are the sum of sinusoids with additive white Gaussian noise. The eigenvalues and eigenvectors of the signal's correlation matrix are estimated if you don't supply the correlation matrix.

The MUSIC pseudospectrum estimate is given by

$$
\mathrm{P}_{\text {music }}(\mathrm{f})=\frac{1}{\mathbf{e}^{H}(\mathrm{f})\left(\begin{array}{c}
\mathrm{N} \\
\left.\mathbf{v}_{k} \mathbf{v}_{k}^{H}\right) \mathbf{e}(\mathrm{f})
\end{array}\right.}=\frac{1}{\sum_{n}^{N}\left|\mathbf{v}_{k}^{H} \mathbf{e}(f)\right|^{2}}
$$

where N is the dimension of the eigenvectors and $\mathbf{v}_{\mathrm{k}}$ is the k -th eigenvector of the correlation matrix. The integer $p$ is the dimension of the signal subspace, so the eigenvectors $\mathbf{v}_{\mathrm{k}}$ used in the sum correspond to the smallest eigenvalues and also span the noise subspace. The vector $\mathbf{e}(\mathrm{f})$ consists of complex exponentials, so the inner product

$$
\mathbf{v}_{\mathrm{k}}^{\mathrm{H}} \mathbf{e}(\mathrm{f})
$$

amounts to a F ourier transform. This is used for computation of the pseudospectrum estimate. The FFT is computed for each $\mathbf{v}_{\mathrm{k}}$ and then the squared magnitudes are summed.

See Also corrmtx, pburg, peig, periodogram, pmtm, prony, psdplot, pwelch, rooteig, rootmusic

References [1]Marple, S.L. Digital Spectral Analysis, Englewood Cliffs, NJ , Prentice-Hall, 1987, pp. 373-378.
[2] Schmidt, R.O, "Multiple E mitter Location and Signal Parameter Estimation," IEEE Trans. Antennas Propagation, Vol. AP-34 (March 1986), pp. 276-280.
[3] Stoica, P., and R.L. M oses, Introduction to Spectral Analysis, Prentice-Hall, Englewood Cliffs, NJ , 1997.

| Purpose | Convert a prediction filter polynomial to an autocorrelation sequence |
| :--- | :--- |
| Syntax | $r=\operatorname{poly2ac}(a$, efinal) | Description | $r=$ poly2ac (a, efinal) finds the autocorrelation vector $r$ corresponding to |
| :--- |
| the prediction filter polynomial a. The autocorrelation sequence produced is |
| approximately the same as that of the output of the autoregressive prediction |
| filter whose coefficients are determined by a. poly2ac also produces the final |
| length ( $r$ ) step prediction error efinal. If a(1) is not equal to 1, poly2ac |
| normalizes the prediction filter polynomial by a(1). a(1) cannot be 0. |

Purpose Convert prediction filter coefficients to line spectral frequencies
Syntax ..... lsf = poly2lsf(a)
Descriptionlsf = poly2lsf(a) returns a vector lsf of line spectral frequencies (alsoknown as line spectrum pairs) from a vector a of prediction filter coefficients.
Examples

```
    a = [ll.0000 0.6149 0.9899 0.0000 0.0031 -0.0082];
    lsf = poly2lsf(a)
    lsf =
        0.7842
        1.5605
        1.8776
        1.8984
        2.3593
```

See Also lsf2poly
References [1] Deller, J.R., J .G. Proakis, and J.H.L. Hansen, "Discrete-TimeProcessing of Speech Signals," Prentice-H all, 1993.[2] Rabiner, L.R., and R.W. Schafer, "Digital Processing of Speech Signals,"Prentice-Hall, 1978.

## Purpose

## Syntax <br> Description

## Examples

Convert a prediction filter polynomial to reflection coefficients

```
k = poly2rc(a)
[k,ro] = poly2rc(a,efinal)
```

$\mathrm{k}=$ poly2rc(a) converts the prediction filter polynomial a to the reflection coefficients of the corresponding lattice structure. a can be real or complex, and a(1) cannot be 0. If a(1) is not equal to 1 , poly2rc normalizes the prediction filter polynomial by $\mathrm{a}(1) . \mathrm{k}$ is a row vector of size length (a) -1 .
[ $\mathrm{k}, \mathrm{r} 0$ ] = poly2rc(a, efinal) returns the zero-lag autocorrelation, ro, based on the final prediction error, efinal.

A simple, fast way to check if a has all of its roots inside the unit circle is to check if each of the elements of $k$ has magnitude less than 1.

```
stable = all(abs(poly2rc(a))<1)
```

```
a = [ll.0000 0.6149 0.9899 0.0000 0.0031 -0.0082];
efinal = 0.2;
[k,r0] = poly2rc(a,efinal)
k =
    0.3090
    0.9801
    0.0031
    0.0081
    -0.0082
r0 =
```

5.6032

## Limitations

If abs(k(i)) == 1 for any $i$, finding the reflection coefficients is an ill-conditioned problem. poly2rc returns some NaNs and provide a warning message in this case.

## Algorithm

See Also ac2rc, latc2tf, latcfilt, poly2ac, rc2poly, tf2latc
References
poly2rc implements the recursive relationship

$$
\begin{aligned}
& k(n)=a_{n}(n) \\
& a_{n-1}(m)=\frac{a_{n}(m)-k(n) a_{n}(n-m)}{1-k(n)^{2}}, \quad m=1,2, \ldots, n-1
\end{aligned}
$$

This relationship is based on Levinson's recursion [1]. To implement it, poly2rc loops through a in reverse order after discarding its first element. For each loop iteration $i$, the function:

1 Sets k(i) equal to a(i)
2 Applies the second relationship above to elements 1 through i of the vector a.

$$
a=(a-k(i) * f l i p l r(a)) /\left(1-k(i)^{\wedge} 2\right) ;
$$

[1] Kay, S.M. Modern Spectral Estimation, Englewood Cliffs, NJ, Prentice-Hall, 1988.

| Purpose | Scale the roots of a polynomial |
| :--- | :--- |
| Syntax | $b=$ polyscale ( $a$, alpha) |
| Description | $\mathrm{b}=$ polyscale ( $a$, alpha) scales the roots of a polynomial in the z-plane, <br> where a is a vector containing the polynomial coefficients and alpha is the <br> scaling factor. <br> If alpha is a real valuein therange $\left[\begin{array}{ll}0 \quad 1\end{array}\right]$, then theroots of a areradially scaled <br> toward the origin in the z-plane. Complex values for alpha allow arbitrary <br> changes to the root locations. |
| Remark | By reducing the radius of the roots in an autoregressive polynomial, the <br> bandwidth of the spectral peaks in the frequency response is expanded <br> (flattened). This operation is often referred to as bandwidth expansion. |
| See Also | polystab, roots |

Purpose Stabilize polynomial
Syntax b = polystab(a)
Description
Examples
Algorithmpolystab finds the roots of the polynomial and maps those roots found outsidethe unit circle to the inside of the unit circle.

```
v = roots(a);
vs = 0.5*(sign(abs(v)-1)+1);
v = (1-vs).*v + vs./conj(v);
b = a(1)*poly(v);
```

See Also roots

## Purpose <br> Prony's method for time domain IIR filter design

## Syntax <br> [b,a] = prony (h, n, m)

Description

## Examples

## Algorithm

Recover the coefficients of a Butterworth filter from its impulse response.

```
[b,a] = butter(4,0.2)
b =
    0.0048 0.0193 0.0289 0.0193 0.0048
a =
    1.0000 -2.3695 2.3140 -1.0547 0.1874
h = filter(b,a,[1 zeros(1,25)]);
[bb,aa] = prony(h,4,4)
bb =
    0.0048 0.0193 0.0289 0.0193 0.0048
ab =
    1.0000 -2.3695 2.3140 -1.0547 0.1874
```

prony implements the method described in reference [1]. This method uses a variation of the covariance method of AR modeling to find the denominator coefficients a and then finds the numerator coefficients b for which theimpulse
response of the output filter matches exactly the first $n+1$ samples of $x$. The filter is not necessarily stable, but potentially can recover the coefficients exactly if the data sequence is truly an autoregressive moving average (ARMA) process of the correct order.

## See Also

References
butter, cheby1, cheby2, ellip, invfreqz, levinson, lpc, stmcb
[1] Parks, T.W., and C.S. Burrus, Digital Filter Design, J ohn Wiley \& Sons, 1987, pp. 226-228.

```
Purpose Plot power spectral density (PSD) data
```

```
Syntax psdplot(Pxx,w)
```

Syntax psdplot(Pxx,w)
psdplot(Pxx,w,'units')
psdplot(Pxx,w,'units')
psdplot(Pxx,w,'units','yscale')
psdplot(Pxx,w,'units','yscale')
psdplot(Pxx,w,'units','yscale','title')

```
psdplot(Pxx,w,'units','yscale','title')
```

Description
psdplot(Pxx,w) plots the power spectral density data contained in the vector $P x x$ at the frequencies specified in the vector $w$. The vectors Pxx and w must have the same length. Themagnitude of the data vector $P x x$ is plotted in dB per radians per sample versus frequency w on one plot. The units for frequency on the plots are rad/sample.
psdplot(Pxx,w, 'units') displays the frequency units according to the string 'units'. This string can be either:

- 'rad/sample' (default)
- 'Hz'
psdplot(Pxx,w, 'units', 'yscale') displays the spectral density magnitude units according to the string 'yscale'. This string can be either:
- 'db ' (default), for plotting the PSD in dB per units of frequency
- 'linear', for plotting the PSD in units of power per units of frequency
psdplot(Pxx,w, 'units', 'yscale', 'title') uses the contents of the string 'title' as the title of the plot.


## Examples

$\mathrm{t}=0: 0.001: 0.3$;
$x=\cos \left(2 *\right.$ pi*t*200 $^{*}+$ randn(size(t));
[Pxx,w] = periodogram(x, [],'twosided',512); psdplot(Pxx,w,'','','Sample PSD Plot')


See Also freqzplot, pburg, pcov, peig, periodogram, pmcov, pmusic, pwelch, pyulear

```
Purpose Generate a pulse train
Syntax y = pulstran(t,d,'func')
y = pulstran(t,d,'func',p1,p2,...)
y = pulstran(t,d,p,fs)
y = pulstran(t,d,p)
```

pulstran generates pulse trains from continuous functions or sampled prototype pulses.
$y=$ pulstran(t,d,'func') generates a pulse train based on samples of a continuous function, 'func ', where 'func' is:

- 'gauspuls', for generating a Gaussian-modulated sinusoidal pulse
- 'rectpuls', for generating a sampled aperiodic rectangle
- 'tripuls', for generating a sampled aperiodic triangle
pulstran is evaluated length (d) times and returns the sum of the evaluations $y=$ func(t-d(1)) + func(t-d(2)) $+\ldots$

The function is evaluated over the range of argument values specified in array $t$, after removing a scalar argument offset taken from the vector d. Note that func must be a vectorized function that can take an array $t$ as an argument.

An optional gain factor may be applied to each delayed evaluation by specifying d as a two-column matrix, with the offset defined in column 1 and associated gain in column 2 of d. Note that a row vector will be interpreted as specifying delays only.
pulstran(t, d, 'func', p1, p2, ...) allows additional parameters to be passed to 'func ' as necessary. For example,

```
func(t-d(1),p1,p2,...) + func(t-d(2),p1,p2,...) + ...
```

pulstran(t,d,p,fs) generates a pulse train that is the sum of multiple delayed interpolations of the prototype pulse in vector $p$, sampled at the rate fs, where p spans the time interval [0,(length(p)-1)/fs], and its samples are identically 0 outsidethis interval. By default, linear interpolation is used for generating delays.
pulstran(t, d, p) assumes that the sampling rate fs is equal to 1 Hz . pulstran(... , 'func') specifies alternative interpolation methods. See interp1 for a list of available methods.

## Examples

## Example 1

This example generates an asymmetric sawtooth waveform with a repetition frequency of 3 Hz and a sawtooth width of 0.1 s . It has a signal length of 1 s and a 1 kHz sample rate.

```
t = 0 : 1/1e3 : 1; % 1 kHz sample freq for 1 sec
d = 0 : 1/3 : 1; % 3 Hz repetition freq
y = pulstran(t,d,'tripuls',0.1,-1);
plot(t,y)
```



## Example 2

This example generates a periodic Gaussian pulse signal at 10 kHz , with $50 \%$ bandwidth. Thepulserepetition frequency is 1 kHz , samplerateis 50 kHz , and pulsetrain length is 10 msec . Therepetition amplitude should attenuateby 0.8 each time.

```
t = 0 : 1/50E3 : 10e-3;
d = [0 : 1/1E3 : 10e-3 ; 0.8.^(0:10)]';
y = pulstran(t,d,'gauspuls',10e3,0.5);
plot(t,y)
```



## Example 3

This example generates a train of 10 Hamming windows.

```
p = hamming(32);
t = 0:320; d = (0:9)'*32;
y = pulstran(t,d,p);
plot(t,y)
```



See Also
chirp, cos, diric, gauspuls, rectpuls, sawtooth, sin, sinc, square, tripuls

```
Purpose Estimate the power spectral density (PSD) of a signal using Welch's method
Syntax [Pxx,w] = pwelch(x)
[Pxx,w] = pwelch(x,window)
[Pxx,w] = pwelch(x,window,noverlap)
[Pxx,w] = pwelch(x,window,noverlap,nfft)
[Pxx,f] = pwelch(x,window,noverlap,nfft,fs)
[...] = pwelch(x,window,noverlap,...,'range')
pwelch(...)
```


## Description

```
Note pwelch computes the power spectral density, not the power spectrum. The difference between them is discussed in "Spectral Analysis" on page 3-6.
```

[Pxx,w] = pwelch(x) estimates the power spectral density Pxx of the input signal vector $x$ using Welch's averaged modified periodogram method of spectral estimation. With this syntax:

- The vector x is segmented into eight sections of equal length, each with $50 \%$ overlap.
- Any remaining (trailing) entries in $x$ that cannot be included in the eight segments of equal length are discarded.
- E ach segment is windowed with a Hamming window (see hamming) that is the same length as the segment.

The power spectral density is calculated in units of power per radians per sample. The corresponding vector of frequencies w is computed in radians per sample, and has the same length as Pxx.

A real-valued input vector x produces a full power one-sided (in frequency) PSD (by default), while a complex-valued x produces a two-sided PSD.

In general, the length $N$ of theFFT and the values of the input $x$ determine the length of Pxx and the range of the corresponding normalized frequencies. For this syntax, the (default) length $N$ of the FFT is the larger of 256 and the next power of two greater than the length of the segment. The following table
indicates the length of Pxx and the range of the corresponding normalized frequencies for this syntax.

Table 7-34: PSD Vector Characteristics for an FFT Length of $\mathbf{N}$ (Default)

| Real/ Complex <br> Input Data | Length of Pxx | Range of the Corresponding <br> Normalized Frequencies |
| :--- | :--- | :--- |
| Real-valued | $(\mathrm{N} / 2)+1$ | $[0, \pi]$ |
| Complex-valued | N | $[0,2 \pi)$ |

[Pxx,w] = pwelch(x,window) calculates the modified periodogram using either:

- The window length window for the Hamming window when window is a positive integer
- The window weights specified in window when window is a vector

With this syntax, the input vector $x$ is divided into an integer number of segments with $50 \%$ overlap, and each segment is the same length as the window. Entries in $x$ that are left over after it is divided into segments are discarded. If you specify window as the empty vector [ ], then the signal data is divided into eight segments, and a Hamming window is used on each one.
[Pxx,w] = pwelch(x,window, noverlap) divides $x$ into segments according to window, and uses the integer nover lap to specify the number of signal samples (elements of $x$ ) that are common to two adjacent segments. noverlap must be less than the length of the window you specify. If you specify noverlap as the empty vector [ ], then pwelch determines the segments of x so that there is $50 \%$ overlap (default).
[Pxx,w] = pwelch(x,window, noverlap, nfft) uses Welch's method to estimate the PSD while specifying the length of the FFT with the integer nfft. If you set nfft to the empty vector [ ], it adopts the default value for N listed in the previous syntax.

The length of Pxx and the frequency range for $w$ depend on nfft and the values of the input $x$. The following table indicates the length of $P x x$ and the frequency range for w for this syntax.

Table 7-35: PSD and Frequency Vector Characteristics

| Real/ Complex <br> Input Data | nfft Even/ Odd | Length of Pxx | Range of w |
| :--- | :--- | :--- | :--- |
| Real-valued | Even | $(n f f t / 2+1)$ | $[0, \pi]$ |
| Real-valued | Odd | $(n f f t+1) / 2$ | $[0, \pi)$ |
| Complex-valued | Even or odd | $n f f t$ | $[0,2 \pi)$ |

[Pxx,f] = pwelch(x,window, noverlap,nfft,fs) uses the sampling frequency fs specified in hertz (Hz) to compute the PSD vector (Pxx) and the corresponding vector of frequencies (f). In this case, the units for the frequency vector are in Hz . The spectral density produced is calculated in units of power per Hz. If you specify fs as the empty vector [ ], the sampling frequency defaults to 1 Hz .

The frequency range for $f$ depends on nfft, fs , and the values of the input x . The length of Pxx is the sameas in Table 7-35. The following table indicates the frequency range for $f$ for this syntax.

Table 7-36: PSD and Frequency Vector Characteristics with fs Specified

| Real/ Complex Input Data | nfft Even/ Odd | Range of $\mathbf{f}$ |
| :--- | :--- | :--- |
| Real-valued | Even | $[0, \mathrm{fs} / 2]$ |
| Real-valued | Odd | $[0, \mathrm{fs} / 2)$ |
| Complex-valued | Even or odd | $[0, \mathrm{fs})$ |

[...] = pwelch(x,window, noverlap, ...,'range') specifies the range of frequency values. This syntax is useful when x is real. The string 'range ' can be either:

- 'twosided': Compute the two-sided PSD over the frequency range [0,fs). This is the default for determining the frequency range for complex-valued $x$.
- If you specify fs as the empty vector, [ ], the frequency range is $[0,1)$.
- If you don't specify fs , the frequency range is $[0,2 \pi$ ).
- 'onesided ': Compute the one-sided PSD over the frequency ranges specified for real x . This is the default for determining the frequency range for real-valued x .

The string 'range ' can appear anywhere in the syntax after noverlap.
pwelch ( $x, \ldots$ ) with no output arguments plots the PSD estimate in dB per unit frequency in the current figure window.

## Examples

Estimate the PSD of a signal composed of a sinusoid plus noise, sampled at 1000 Hz . Use 33 -sample windows with 32 -sample overlap, and the default FFT length, and display the two-sided PSD estimate.

```
randn('state',0);
Fs = 1000; t = 0:1/Fs:.3;
x = cos(2*pi*t*200) + randn(size(t)); % 200Hz cosine plus noise
pwelch(x,33,32,[],Fs,'twosided')
```



Algorithm
pwelch calculates the power spectral density using Welch's method (see references):

1 The input signal vector x is divided into k overlapping segments according to window and noverlap (or their default values).
2 The specified (or default) window is applied to each segment of $x$.
3 An nfft-point FFT is applied to the windowed data.
4 The (modified) periodogram of each windowed segment is computed.
5 The set of modified periodograms is averaged to form the spectrum estimate $S\left(\mathrm{e}^{\mathrm{j}}\right)$.
6 The resulting spectrum estimate is scaled to compute the power spectral density as $S\left(\mathrm{e}^{\omega}\right) / \mathrm{F}$, where F is:

- $2 \pi$ when you do not supply the sampling frequency
- fs when you supply the sampling frequency

The number of segments $k$ that $x$ is divided into is calculated as:

- Eight if you don't specify window, or if you specify it as the empty vector [ ]
- $k=\frac{m-0}{1-0}$ if you specify window as a nonempty vector or a scalar In this equation, $m$ is the length of the signal vector $x$, $o$ is the number of overlapping samples (noverlap), and I is the length of each segment (the window length).

See Also pburg, pcov, peig, periodogram, pmcov, pmtm, pmusic, psdplot, pyulear
References [1] Hayes, M., Statistical Digital Signal Processing and Modeling, J ohn Wiley \& Sons, 1996.
[2] Stoica, P., and R.L. M oses, Introduction to Spectral Analysis, Prentice-H all, Englewood Cliffs, NJ, 1997, pp. 52-54.
[3] Welch, P.D, "The U se of Fast Fourier Transform for the Estimation of Power Spectra: A Method Based on Time Averaging Over Short, Modified Periodograms," IEEE Trans. Audio Electroacoustics, Vol. AU-15 (J une 1967), pp. 70-73.

| Purpose | Estimate the power spectral density using the Yule-Walker AR method |
| :--- | :--- |
| Syntax | Pxx $=\operatorname{pyulear}(x, p)$ <br> $[P x x, w]=\operatorname{pyulear}(x, p, n f f t)$ <br> $[P x x, f]=\operatorname{pyulear}(x, p, n f f t, f s)$ <br>  <br> $[P x x, f]=\operatorname{pyulear}(x, p, n f f t, f s, ' r a n g e ')$ <br>  <br> $[P x x, w]=\operatorname{pyulear}(x, p, n f f t, ' r a n g e ')$ <br>  <br> pyulear $(\ldots)$ |

Description $\quad P x x=\operatorname{pyulear}(x, p)$ implements the Yule-Walker algorithm, a parametric spectral estimation method, and returns Pxx, an estimate of the power spectral density (PSD) of the vector $x$. The entries of $x$ represent samples of a discrete-time signal. p is the integer specifying the order of an autoregressive (AR) prediction model for the signal, used in estimating the PSD.

The power spectral density is calculated in units of power per radians per sample. Real-valued inputs produce full power one-sided (in frequency) PSDs (by default), while complex-valued inputs produce two-sided PSDs.

In general, the length of the FFT and the values of the input $x$ determine the length of Pxx and the range of the corresponding normalized frequencies. For this syntax, the (default) FFT length is 256. The following table indicates the length of Pxx and the range of the corresponding normalized frequencies for this syntax.

Table 7-37: PSD Vector Characteristics for an FFT Length of 256 (Default)

| Real/ Complex <br> Input Data | Length of Pxx | Range of the Corresponding <br> Normalized Frequencies |
| :--- | :--- | :--- |
| Real-valued | 129 | $[0, \pi]$ |
| Complex-valued | 256 | $[0,2 \pi)$ |

 PSD is estimated. Pxx and $w$ have the same length. The units for frequency are rad/sample.
[Pxx,w] = pyulear (x,p,nfft) uses the Yule-walker method to estimate the PSD while specifying thelength of theFFT with the integer nfft. If you specify nfft as the empty vector [ ], it adopts the default value of 256 .

The length of Pxx and the frequency range for $w$ depend on nfft and the values of the input $x$. The following tableindicates the length of Pxx and the frequency range for $w$ for this syntax.

Table 7-38: PSD and Frequency Vector Characteristics

| Real/ Complex <br> Input Data | nfft Even/ Odd | Length of Pxx | Range of w |
| :--- | :--- | :--- | :--- |
| Real-valued | Even | $(n f f t / 2+1)$ | $[0, \pi]$ |
| Real-valued | Odd | $(n f f t+1) / 2$ | $[0, \pi)$ |
| Complex-valued | Even or odd | $n f f t$ | $[0,2 \pi)$ |

[Pxx,f] = pyulear (x, p, nfft,fs) uses the sampling frequency fs specified as an integer in hertz (Hz) to compute the PSD vector ( Pxx ) and the corresponding vector of frequencies ( f ). In this case, the units for the frequency vector are in Hz . The spectral density produced is calculated in units of power per Hz . If you specify fs as the empty vector [ ], the sampling frequency defaults to 1 Hz .

The frequency range for $f$ depends on $n f f t, f s$, and the values of the input $x$. The length of Pxx is the same as in Table 7-38. Thefollowing table indicates the frequency range for f for this syntax.

Table 7-39: PSD and Frequency Vector Characteristics with fs Specified

| Real/ Complex Input Data | nfft Even/ Odd | Range of $\mathbf{f}$ |
| :--- | :--- | :--- |
| Real-valued | Even | $[0, \mathrm{fs} / 2]$ |
| Real-valued | Odd | $[0, \mathrm{fs} / 2)$ |
| Complex-valued | Even or odd | $[0, \mathrm{fs})$ |

[Pxx,f] = pyulear(x,p,nfft,fs,'range') or
[Pxx,w] = pyulear(x,p,nfft,'range') specifies the range of frequency values to include in $f$ or $w$. This syntax is useful when $x$ is real. 'range' can be either:

- 'twosided ': Compute the two-sided PSD over the frequency range [0,fs). This is the default for determining the frequency range for complex-valued $x$.
- If you specify fs as the empty vector, [ ], the frequency range is [ 0,1 ).
- If you don't specify fs, the frequency range is [0, $2 \pi$ ).
- 'onesided ': Computethe one-sided PSD over thefrequency ranges specified for real x . This is the default for determining the frequency range for real-valued x .

Note You can put the string argument 'range' anywhere in the input argument list after p .

## Remarks

Examples

The power spectral density is computed as the distribution of power per unit frequency.

This algorithm depends on your selecting an appropriate model order for your signal.

Because the Yule-walker method estimates the spectral density by fitting an AR prediction model of a given order to the signal, first generate a signal from an AR (all-pole) model of a given order. You can use freqz to check the magnitude of the frequency response of your AR filter. This will give you an idea of what to expect when you estimate the PSD using pyulear.

```
a = [1 -2.2137 2.9403 -2.1697 0.9606]; % AR filter coefficients
freqz(1,a) % AR filter frequency response
title('AR System Frequency Response')
```




Now generate the input signal $x$ by filtering white noise through the AR filter. Estimate the PSD of $x$ based on a fourth-order AR prediction model, since in this case, we know that the original AR system model a has order 4.

```
randn('state',1);
x = filter(1,a,randn(256,1)); % AR system output
pyulear(x,4) % Fourth-order estimate
```


Algorithm Linear prediction filters can be used to model the second-order statistical characteristics of a signal. The prediction filter output can be used to model the signal when the input is white noise.
pyulear estimates the PSD of an input signal vector using the Y ule-Walker AR method. This method, al so called the autocorrelation or windowed method, fits an autoregressive (AR) linear prediction filter model to the signal by minimizing theforward prediction error (based on all observations of thein put sequence) in the least squares sense. This formulation leads to the Yule-Walker equations, which are solved by the Levinson-Durbin recursion. The spectral estimate returned by pyulear is the squared magnitude of the frequency response of this AR model.
See Also aryule, lpc, pburg, pcov, peig, periodogram, pmcov, pmtm, pmusic, prony, psdplot, pwelch

## References

[1] Marple, S.L., Digital Spectral Analysis, Prentice-Hall, 1987, Chapter 7.
[2] Stoica, P., and R.L. Moses, I ntroduction to Spectral Analysis, Prentice-Hall, 1997.

Purpose

## Syntax

Description

Examples

See Also
References

Convert reflection coefficients to an autocorrelation sequence

$$
r=r c 2 a c(k, r 0)
$$

$r=r c 2 a c(k, r 0)$ finds the autocorrelation coefficients, $r$, of the output of the discrete-time prediction error filter from the lattice-form reflection coefficients k and initial zero-lag autocorrelation ro.

```
    k = [l0.3090 0.9800 0.0031 0.0082 -0.0082];
    r0 = 0.1;
    a = rc2ac(k,r0)
    a =
        0.1000
        -0.0309
        -0.0791
        0.0787
        0.0294
        -0.0950
```

ac2rc, poly2ac, rc2poly
[1] Kay, S.M., Modern Spectral Estimation, Prentice-Hall, Englewood Cliffs, NJ, 1988.
Purpose Convert reflection coefficients to inverse sine parameters
Syntax isin = rc2is(k)
Description isin = is2rc(k) returns a vector of inverse sine parameters isin from avector of reflection coefficients $k$.
Examples

```
    k = [0.3090 0.9801 0.0031 0.0082 -0.0082];
    isin = rc2is(k)
    isin =
        0.2000 0.8728 0.0020 0.0052 -0.0052
```

See Also is2rc
References [1] Deller, J.R., J .G. Proakis, and J.H.L. Hansen, "Discrete-TimeProcessing ofSpeech Signals," Prentice-H all, 1993.

Purpose Convert reflection coefficients to log area ratio parameters

## Syntax <br> $\mathrm{g}=\operatorname{rc2lar}(\mathrm{k})$

Description
$g=\operatorname{rc2lar}(k)$ returns a vector of log area ratio parameters $g$ from a vector of reflection coefficients $k$.

Examples

```
k = [0.3090 0.9801 0.0031 0.0082 -0.0082];
g = rc2lar(k)
    g =
        0.6389 4.6002 0.0062 0.0164 -0.0164
```


## See Also lar2rc

References [1] Deller, J.R., J.G. Proakis, and J.H.L. Hansen, "DiscreteTimeProcessing of Speech Signals," Prentice-H all, 1993.

| Purpose | Convert reflection coefficients to a prediction filter polynomial |
| :---: | :---: |
| Syntax | $\begin{aligned} & a=\text { rc2poly(k) } \\ & {[a, \text { efinal] }=\text { rc2poly }(k, r o)} \end{aligned}$ |
| Description | a = rc2poly (k) converts the reflection coefficients k corresponding to the latticestructuretotheprediction filter polynomial $a$, with $a(1)=1$. Theoutput a is row vector of length length $(k)+1$. <br> [a,efinal] = rc2poly(k,ro) returnsthefinal prediction error efinal based on the zero-lag autocorrelation, ro. |
| Example | Consider a lattice IIR filter given by reflection coefficients k . $k=\left[\begin{array}{lllll} 0.3090 & 0.9800 & 0.0031 & 0.0082 & -0.0082 \end{array}\right] ;$ <br> Its equivalent prediction filter representation is given by ```a = rc2poly(k) a = 1.0000 0.6148 0.9899 0.0000 0.0032 -0.0082``` |
| Algorithm | rc2poly computes output a using Levinson's recursion [1]. The function: <br> 1 Sets the output vector a to the first element of $k$ <br> 2 Loops through the remaining elements of $k$ <br> For each loop iteration $i, a=[a+a(i-1:-1: 1) * k(i) k(i)]$. <br> 3 Implements a = [1 a] |
| See Also | ac2poly, latc2tf, latcfilt, poly2rc, rc2ac, rc2is, rc2lar, tf2latc |
| References | [1] Kay, S.M., M odern Spectral Estimation, Prentice-Hall, Englewood Cliffs, NJ, 1988. |

Purpose Real cepstrum and minimum phase reconstruction

| Syntax | $y=\operatorname{rceps}(x)$ |
| :--- | :--- |
|  | $[y, y m]=\operatorname{rceps}(x)$ |

Algorithm

See Also
References

The real cepstrum is the inverse F ourier transform of the real logarithm of the magnitude of the F ourier transform of a sequence.
rceps (x) returns the real cepstrum of the real sequence $x$. The real cepstrum is a real-valued function.
[ $y, y m$ ] = rceps $(x)$ returns both the real cepstrum $y$ and a minimum phase reconstructed version ym of the input sequence.
rceps is an $M$-file implementation of algorithm 7.2 in [2], that is,

$$
y=\operatorname{real}(i f f t(\log (\operatorname{abs}(f f t(x))))) ;
$$

Appropriate windowing in the cepstral domain forms the reconstructed minimum phase signal.

```
    w = [1; 2*ones(n/2-1,1); ones(1 - rem(n,2),1); zeros(n/2-1,1)];
    ym = real(ifft(exp(fft(w.*y))));
```

cceps, fft, hilbert, icceps, unwrap
[1] Oppenheim, A.V., and R.W. Schafer, Digital Signal Processing, Englewood Cliffs, NJ, Prentice-Hall, 1975.
[2] Programs for Digital Signal Processing, IEEE Press, New York, 1979.

## Purpose Generate a sampled aperiodic rectangle

Syntax $\quad$| $y$ | $=\operatorname{rectpuls}(t)$ |
| ---: | :--- |
| $y$ | $=\operatorname{rectpuls}(t, w)$ |

Description

See Also
chirp, cos, diric, gauspuls, pulstran, sawtooth, sin, sinc, square, tripuls
Purpose Compute a rectangular window
Syntax w = rectwin(n)
Description $\mathrm{w}=$ rectwin( n ) returns a rectangular window of length n in the columnvector $w$. This function is provided for completeness; a rectangular window isequivalent to no window at all.
Algorithm $w=$ ones $(\mathrm{n}, 1)$;
See Also barthannwin, bartlett, blackman, blackmanharris, bohmanwin, chebwin,gausswin, hamming, hann, kaiser, nuttallwin, triang, tukeywin, window
References [1] Oppenheim, A.V., and R.W. Schafer. Discrete-TimeSignal Processing.U pper Saddle River, NJ : Prentice-H all, 1999, pp. 468-471.

## Purpose Compute the Parks-McClellan optimal FIR filter design

```
Syntax
b = remez(n,f,a)
b = remez(n,f,a,w)
b = remez(n,f,a,'ftype')
b = remez(n,f,a,w,'ftype')
b = remez(...,{lgrid})
b = remez(n,f,'fresp',w)
b = remez(n,f,'fresp',w,'ftype')
b = remez(n,f,{'fresp',p1,p2,...},w)
b = remez(n,f,{'fresp',p1,p2,...},w,'ftype')
[b,delta] = remez(...)
[b,delta,opt] = remez(...)
```


## Description

remez designs a linear-phase FIR filter using the Parks-McClellan al gorithm [1]. The Parks-McClellan algorithm uses the Remez exchange algorithm and Chebyshev approximation theory to design filters with an optimal fit between the desired and actual frequency responses. The filters are optimal in the sense that the maximum error between the desired frequency response and the actual frequency response is minimized. Filters designed this way exhibit an equiripple behavior in their frequency responses and are sometimes called equiripplefilters. remez exhibits discontinuities at the head and tail of its impulse response due to this equiripple nature.
$b=r e m e z(n, f, a)$ returns row vector $b$ containing the $n+1$ coefficients of the order n FIR filter whose frequency-amplitude characteristics match those given by vectors $f$ and a.

The output filter coefficients (taps) in b obey the symmetry relation

$$
b(k)=b(n+2-k), \quad k=1, \ldots, n+1
$$

Vectors $f$ and a specify the frequency-magnitude characteristics of the filter:

- $f$ is a vector of pairs of normalized frequency points, specified in the range between 0 and 1 , where 1 corresponds to the $N$ yquist frequency. The frequencies must be in increasing order.
- a is a vector containing the desired amplitudes at the points specified in f.

The desired amplitude at frequencies between pairs of points ( $f(k), f(k+1)$ ) for $k$ odd is the line segment connecting the points ( $f(k), a(k)$ ) and (f(k+1), a(k+1)).
The desired amplitude at frequencies between pairs of points ( $f(k), f(k+1)$ ) for $k$ even is unspecified. The areas between such points are transition or "don't care" regions.

- f and a must be the same length. The length must be an even number.

The relationship between the $f$ and a vectors in defining a desired frequency response is shown in the example below.

$$
\begin{aligned}
& f=\left[\begin{array}{llllll}
0 & .3 & .4 & .6 & .7 & .9
\end{array}\right] \\
& a=\left[\begin{array}{lllll}
0 & 1 & 0 & 0 & .5 \\
.5
\end{array}\right]
\end{aligned}
$$


...... "Don't care"/transition regions
remez always uses an even filter order for configurations with a passband at the Nyquist frequency. This is because for odd orders, the frequency response at the $N$ yquist frequency is necessarily 0 . If you specify an odd-valued $n$, remez increments it by 1.
remez ( $n, f, a, w$ ) uses the weights in vector w to weight the fit in each frequency band. The length of $w$ is half the length of $f$ and $a$, sothere is exactly one weight per band.
b = remez(n,f,a,'ftype') and
b = remez(n,f,a,w,'ftype') specify a filter type, where 'ftype' is

- 'hilbert ', for linear-phase filters with odd symmetry (typelll and type IV) The output coefficients in $b$ obey the relation $b(k)=-b(n+2-k), k=1, \ldots$, $\mathrm{n}+1$. This class of filters includes the Hilbert transformer, which has a desired amplitude of 1 across the entire band.
For example,

```
h = remez(30,[0.1 0.9],[1 1],'hilbert');
```

designs an approximate FIR Hilbert transformer of length 31.

- 'differentiator', for typelll and typeIV filters, using a special weighting technique
F or nonzero amplitude bands, it weights the error by a factor of $1 / f$ so that the error at low frequencies is much smaller than at high frequencies. For FIR differentiators, which have an amplitude characteristic proportional to frequency, thesefilters minimizethe maximum relative error (the maximum of the ratio of the error to the desired amplitude).
b = remez(..., \{lgrid\}) uses the integer lgrid to control the density of the frequency grid, which has roughly (lgrid*n) / (2*bw) frequency points, where bw is the fraction of the total frequency band interval [0,1] covered by $f$. Increasing lgrid often results in filters that more exactly match an equiripple filter, but that take longer to compute. The default value of 16 is the minimum value that should be specified for lgrid. Notethat the $\{1 \mathrm{grid}\}$ argument must be a 1-by-1 cell array.
b = remez(n,f,'fresp',w) returns row vector b containing the n+1 coefficients of the order $n$ FIR filter whose frequency-amplitude characteristics best approximate the response specified by function fresp. The function is called from within remez with the following syntax.

$$
[\mathrm{dh}, \mathrm{dw}]=\operatorname{fresp}(\mathrm{n}, \mathrm{f}, \mathrm{gf}, \mathrm{w})
$$

The arguments are similar to those for remez:

- n is the filter order.
- f is the vector of normalized frequency band edges that appear monotonically between 0 and 1 , where 1 is the Nyquist frequency.
- gf is a vector of grid points that have been linearly interpolated over each specified frequency band by remez. gf determines the frequency grid at which the response function must be evaluated, and contains the same data returned by cremez in the fgrid field of the opt structure.
- w is a vector of real, positive weights, one per band, used during optimization. w is optional in the call to remez; if not specified, it is set to unity weighting before being passed to fresp.
- dh and dw are the desired complex frequency response and band weight vectors, respectively, evaluated at each frequency in grid gf.

The predefined frequency response function fresp that remez calls is remezfrf in the signal/private directory.
$\mathrm{b}=\operatorname{remez}\left(\mathrm{n}, \mathrm{f},\left\{{ }^{\prime}\right.\right.$ fresp', p1,p2,...\},w) allows you to specify additional parameters ( $\mathrm{p} 1, \mathrm{p} 2$, etc.) to pass to fresp. Note that $\mathrm{b}=\operatorname{remez}(\mathrm{n}, \mathrm{f}, \mathrm{a}, \mathrm{w})$ is a synonym for $b=\operatorname{remez}(n, f,\{' r e m e z f r f ', a\}, w)$, where $a$ is a vector containing the desired amplitudes at the points specified in $f$.
b = remez(n,f,'fresp',w,'ftype') and
b = remez(n,f,\{'fresp',p1,p2,...\},w,'ftype') design antisymmetric (odd) rather than symmetric (even) filters, where 'ftype' is either ' $d$ ' for a differentiator or ' h ' for a Hilbert transformer.

In the absence of a specification for ftype, a preliminary call is made to fresp to determine the default symmetry property sym. This call is made using the syntax.

```
sym = fresp('defaults',{n,f,[],w,p1,p2,...})
```

The arguments $n, f, w$, etc., may be used as necessary in determining an appropriate value for sym, which remez expects to be either 'even' or 'odd'. If the fresp function does not support this calling syntax, remez defaults to even symmetry.

| opt.fgrid | F requency grid vector used for the filter design optimization |
| :---: | :---: |
| opt.des | Desired frequency response for each point in opt.fgrid |
| opt.wt | Weighting for each point in opt.fgrid |
| opt.H | Actual frequency response for each point in opt.fgrid |
| opt.error | Error at each point in opt.fgrid (opt.des-opt.H) |
| opt.iextr | Vector of indices into opt.fgrid for extremal frequencies |
| opt.fextr | Vector of extremal frequencies |

## Example

Graph the desired and actual frequency responses of a 17th-order Parks-McClellan bandpass filter.

```
f = [0 0.3 0.4 0.6 0.7 1]; a = [0 0 1 1 0 0];
b = remez(17,f,a);
[h,w] = freqz(b,1,512);
plot(f,a,w/pi,abs(h))
legend('Ideal','remez Design')
```


remez is a MEX-file version of the original Fortran code from [1], altered to design arbitrarily long filters with arbitrarily many linear bands.
remez designs type I, II, III, and IV linear-phase filters. Type I and type II are the defaults for $n$ even and $n$ odd, respectively, while type III ( $n$ even) and type IV ( n odd) are obtained with the 'hilbert' and 'differentiator' flags. The different types of filters have different symmetries and certain constraints on their frequency responses (see [5] for more details).

| Linear Phase Filter Type | Filter Order | Symmetry of Coefficients | $\begin{aligned} & \text { Response } H(f), \\ & \mathbf{f}=\mathbf{0} \end{aligned}$ | Response H(f), $\mathbf{f}=\mathbf{1}$ (Nyquist) |
| :---: | :---: | :---: | :---: | :---: |
| Type I | Even | even:$b(k)=b(n+2-k), \quad k=1, \ldots, n+1$ | No restriction | No restriction |
| Type II | Odd |  | No restriction | $\mathrm{H}(1)=0$ |
| Type III | Even | odd:$b(k)=-b(n+2-k), \quad k=1, \ldots, n+1$ | $\mathrm{H}(0)=0$ | $\mathrm{H}(1)=0$ |
| Type IV | Odd |  | $\mathrm{H}(0)=0$ | No restriction |

Diagnostics

See Also butter, cheby1, cheby2, cremez, ellip, fir1,fir2, fircls, fircls1,firls, firrcos, gremez, remezord, yulewalk

References [1] Programs for Digital Signal Processing, IEEE Press, New York, 1979, Algorithm 5.1.
[2] Selected Papers in Digital Signal Processing, II, IEEE Press, New York, 1979.
[3] Parks, T.W., and C.S. Burrus, Digital Filter Design, J ohn Wiley \& Sons, New York:, 1987, p. 83.
[4] Rabiner, L.R., J .H. McClellan, and T.W. Parks, "FIR Digital Filter Design Techniques Using Weighted Chebyshev Approximations," Proc. IEEE 63 (1975).
[5] Oppenheim, A.V., and R.W. Schafer, DiscreteTimeSignal Processing, Prentice-Hall, Englewood Cliffs, NJ , 1989, pp. 256-266.

## Purpose

Syntax

Description

## Examples

Parks-McClellan optimal FIR filter order estimation

```
[n,fo,ao,w] = remezord(f,a,dev)
[n,fo,ao,w] = remezord(f,a,dev,fs)
c = remezord(f,a,dev,fs,'cell')
```

[ $n, f o, a o, w]=$ remezord(f,a, dev) finds the approximate order, normalized frequency band edges, frequency band amplitudes, and weights that meet input specifications $f, a$, and dev.

- $f$ is a vector of frequency band edges (between 0 and $f_{s} / 2$, where $f_{s}$ is the sampling frequency), and a is a vector specifying the desired amplitude on the bands defined by $f$. The length of $f$ is two less than twice the length of $a$. The desired function is piecewise constant.
- dev is a vector the same size as a that specifies the maximum allowable deviation or ripples between the frequency response and the desired amplitude of the output filter for each band.

Use remez with the resulting order $n$, frequency vector fo, amplitude response vector ao, and weights $w$ to design the filter $b$ which approximately meets the specifications given by remezord input parameters $f, a$, and dev.

$$
b=\operatorname{remez}(n, f o, a o, w)
$$

[ $n, f o, a o, w]=$ remezord(f,a,dev,fs) specifies a sampling frequency fs. fs defaults to 2 Hz , implying a Nyquist frequency of 1 Hz . You can therefore specify band edges scaled to a particular application's sampling frequency.

In some cases remezord underestimates the order n. If the filter does not meet the specifications, try a higher order such as $n+1$ or $n+2$.
$c=r e m e z o r d(f, a, d e v, f s, ' c e l l ')$ generates a cell-array whose elements are the parameters to remez.

## Example 1

Design a minimum-order lowpass filter with a 500 Hz passband cutoff frequency and 600 Hz stopband cutoff frequency, with a sampling frequency of 2000 Hz , at least 40 dB attenuation in the stopband, and less than 3 dB of ripple in the passband.

```
rp = 3; % Passband ripple
rs = 40; % Stopband ripple
fs = 2000; % Sampling frequency
f = [500 600]; % Cutoff frequencies
a = [1 0]; % Desired amplitudes
% Compute deviations
dev = [(10^(rp/20)-1)/(10^(rp/20)+1) 10^(-rs/20)];
[n,fo,ao,w] = remezord(f,a,dev,fs);
b = remez(n,fo,ao,w);
freqz(b,1,1024,fs);
title('Lowpass Filter Designed to Specifications');
```




Note that the filter falls slightly short of meeting thestopband attenuation and passband ripple specifications. Using $n+1$ in the call to remez instead of $n$ achieves the desired amplitude characteristics.

## Example 2

Design a Iowpass filter with a 1500 Hz passband cutoff frequency and 2000 Hz stopband cutoff frequency, with a sampling frequency of 8000 Hz , a maximum stopband amplitude of 0.1 , and a maximum passband error (ripple) of 0.01 .

```
[n,fo,ao,w] = remezord([1500 2000],[1 0],[0.01 0.1],8000 );
b = remez(n,fo,ao,w);
```

This is equivalent to

```
c = remezord( [1500 2000],[1 0],[0.01 0.1],8000,'cell');
b = remez(c{:});
```

Note In some cases, remezord underestimates or overestimates the order n. If the filter does not meet the specifications, try a higher order such as $n+1$ or $n+2$.

Results are inaccurate if the cutoff frequencies are near 0 or the Nyquist frequency.

| Algorithm | remezord uses the al gorithm suggested in [1]. This method is inaccurate for <br> band edges close to either 0 or the Nyquist frequency (fs /2). |
| :--- | :--- |
| See Also | buttord, cheb1ord, cheb2ord, ellipord, kaiserord, remez |
| References | [1] Rabiner, L.R., and O. Herrmann, "The Predictability of Certain Optimum <br> Finite Impulse Response Digital Filters," IEEE Trans. on Circuit Theory, <br> Vol. CT-20, No. 4 (J uly 1973), pp. 401-408. |
|  | [2] Rabiner, L.R., and B. Gold. Theory and Application of Digital Signal <br> Processing. Englewood Cliffs, NJ : Prentice-Hall, 1975, pp. 156-157. |

## Purpose Change sampling rate by any rational factor

Syntax $\quad y=\operatorname{resample}(x, p, q)$
$y=r e s a m p l e(x, p, q, n)$
$y=r e s a m p l e(x, p, q, n, b e t a)$
$y=r e s a m p l e(x, p, q, b)$
[y,b] = resample(x, $p, q$ )

## Description

$y=$ resample $(x, p, q)$ resamples the sequence in vector $x$ at $p / q$ times the original sampling rate, using a polyphase filter implementation. $p$ and $q$ must be positive integers. The length of $y$ is equal to ceil(length $(x) * p / q$ ). If $x$ is a matrix, resample works down the columns of $x$.
resample applies an anti-aliasing (lowpass) FIR filter to $x$ during the resampling process. It designs the filter using firls with a Kaiser window.
$y=$ resample $(x, p, q, n)$ uses $n$ terms on either side of the current sample, $x(k)$, to perform the resampling. The length of the FIR filter resample uses is proportional to n ; larger values of n provide better accuracy at the expense of more computation time. The default for $n$ is 10 . If you let $n=0$, resample performs a nearest-neighbor interpolation

$$
y(k)=x(\operatorname{round}((k-1) * q / p)+1)
$$

where $y(k)=0$ if the index to $x$ is greater than length $(x)$.
$y=$ resample $(x, p, q, n$, beta) uses beta as the design parameter for the Kaiser window that resample employs in designing the lowpass filter. The default for beta is 5 .
$y=$ resample $(x, p, q, b)$ filters $x$ using the vector of filter coefficients $b$.
$[y, b]=$ resample $(x, p, q)$ returns the vector $b$, which contains the coefficients of the filter applied to x during the resampling process.

Examples
Resample a simple linear sequence at $3 / 2$ the original rate.

```
fs1 = 10; % Original sampling frequency in Hz
t1 = 0:1/fs1:1; % Time vector
x = t1; % Define a linear sequence
y = resample(x,3,2); % Now resample it
t2 = (0:(length(y)-1))*2/(3*fs1); % New time vector
plot(t1,x,'*',t2,y,'o',-0.5:0.01:1.5,-0.5:0.01:1.5,':')
legend('original','resampled'); xlabel('Time')
```



Notice that the last few points of the output y are inaccurate. In its filtering process, resample assumes the samples at times before and after the given samples in $x$ are equal to zero. Thus large deviations from zero at the end points of the sequence $x$ can cause inaccuracies in $y$ at its end points. The following two plots illustrate this side effect of resample.

```
x = [1:10 9:-1:1]; y = resample(x,3,2);
subplot(2,1,1);
plot(1:19,x,'*',(0:28)*2/3 + 1,y,'o');
title('Edge Effects Not Noticeable');
legend('original','resampled');
```

```
x = [10:-1:1 2:10]; y = resample(x,3,2);
subplot(2,1,2);
plot(1:19,x,'*',(0:28)*2/3 + 1,y,'o')
title('Edge Effects Very Noticeable');
legend('original','resampled');
```



Edge Effects Very Noticeable


Algorithm
resample performs an FIR design using firls, followed by rate changing implemented with upfirdn.
decimate, downsample, firls, interp, interp1, intfilt, kaiser, spline, upfirdn, upsample

Purpose z-transform partial-fraction expansion
Syntax $\quad[r, p, k]=\operatorname{residuez}(b, a)$
$[b, a]=\operatorname{residuez}(r, p, k)$
Description residuez converts a discrete time system, expressed as the ratio of two polynomials, to partial fraction expansion, or residue, form. It also converts the partial fraction expansion back to the original polynomial coefficients.
$[r, p, k]=$ residuez ( $b, a$ ) finds the residues, poles, and direct terms of a partial fraction expansion of the ratio of two polynomials, $b(z)$ and $a(z)$.
Vectors $b$ and a specify the coefficients of the polynomials of the discrete-time system $b(z) / a(z)$ in descending powers of $z$.

$$
\begin{aligned}
& b(z)=b_{0}+b_{1} z^{-1}+b_{2} z^{-2}+\cdots+b_{m} z^{-m} \\
& a(z)=a_{0}+a_{1} z^{-1}+a_{2} z^{-2}+\cdots+a_{n} z^{-n}
\end{aligned}
$$

If there are no multiple roots and a $>\mathrm{n}-1$,

$$
\frac{b(z)}{a(z)}=\frac{r(1)}{1-p(1) z^{-1}}+\cdots+\frac{r(n)}{1-p(n) z^{-1}}+k(1)+k(2) z^{-1}+\cdots+k(m-n+1) z^{-(m-n)}
$$

The returned column vector $r$ contains the residues, column vector $p$ contains the pole locations, and row vector $k$ contains the direct terms. The number of poles is

$$
n=\text { length }(a)-1=\text { length }(r)=\text { length }(p)
$$

The direct term coefficient vector $k$ is empty if length (b) is less than length (a); otherwise

```
length(k) = length(b) - length(a) + 1
```

If $p(j)=\ldots=p(j+s-1)$ is a pole of multiplicity $s$, then the expansion includes terms of the form

$$
\frac{r(j)}{1-p(j) z^{-1}}+\frac{r(j+1)}{\left(1-p(j) z^{-1}\right)^{2}}+\cdots+\frac{r\left(j+s_{r}-1\right)}{\left(1-p(j) z^{-1}\right)^{s_{r}}}
$$

[ $b, a]=$ residuez( $r, p, k$ ) with three input arguments and two output arguments, converts the partial fraction expansion back to polynomials with coefficients in row vectors b and a .

The residue function in the standard MATLAB Ianguage is very similar to residuez. It computes the partial fraction expansion of continuous-time systems in the Laplace domain (see reference [1]), rather than discrete-time systems in the z-domain as does residuez.

## Algorithm

See Also convmtx, deconv, poly, prony, residue, roots, ss2tf, tf2ss, tf2zp, zp2ss

## residuez

References [1] Oppenheim, A.V., and R.W. Schafer, Digital Signal Processing, Prentice-Hall, Englewood Cliffs, NJ , 1975, pp. 166-170.

## Purpose Compute the reverse Levinson-Durbin recursion

Syntax $\quad$| $r=r l e v i n s o n(a, ~ e f i n a l) ~$ |  |
| ---: | :--- |
| $[r, u]=r l e v i n s o n(a, e f i n a l) ~$ |  |
|  | $[r, u, k]=r l e v i n s o n(a, e f i n a l)$ |
|  | $[r, u, k, e]=r l e v i n s o n(a, e f i n a l)$ |

## Description

The reverse Levinson-Durbin recursion implements the step-down algorithm for solving the following symmetric Toeplitz system of linear equations for $r$, where $r=[r(1) \cdots r(p+1)]$ and $r(i)^{*}$ denotes the complex conjugate of $r(i)$.

$$
\left[\begin{array}{cccc}
r(1) & r(2)^{*} & \cdots & r(p)^{*} \\
r(2) & r(1) & \cdots & r(p-1)^{*} \\
\vdots & \ddots & \ddots & \vdots \\
r(p) & \cdots & r(2) & r(1)
\end{array}\right]\left[\begin{array}{c}
a(2) \\
a(3) \\
\vdots \\
a(p+1)
\end{array}\right]=\left[\begin{array}{c}
-r(2) \\
-r(3) \\
\vdots \\
-r(p+1)
\end{array}\right]
$$

$r=r l e v i n s o n(a, e f i n a l)$ solves the above system of equations for $r$ given vector $a$, where $a=[1 a(2) \cdots a(p+1)]$. In linear prediction applications, $r$ represents the autocorrelation sequence of the input to the prediction error filter, where $\mathrm{r}(1)$ is the zero-lag element. The figure below shows the typical filter of this type, where $H(z)$ is the optimal linear predictor, $x(n)$ is the input signal, $\hat{x}(n)$ is the predicted signal, and $e(n)$ is the prediction error.


Input vector a represents the polynomial coefficients of this prediction error filter in descending powers of $z$.

$$
A(z)=1+a(2) z^{-1}+\cdots+a(n+1) z^{-p}
$$

The filter must be minimum phase to generate a valid autocorrelation sequence. efinal is the scalar prediction error power, which is equal to the variance of the prediction error signal, $\sigma^{2}(e)$.
[ $r, u]=r l e v i n s o n(a, e f i n a l)$ returns upper triangular matrix $U$ from the UDU* decomposition

$$
\mathrm{R}^{-1}=\mathrm{UE}^{-1} \mathrm{U}^{*}
$$

where

$$
R=\left[\begin{array}{cccc}
r(1) & r(2)^{*} & \cdots & r(p)^{*} \\
r(2) & r(1) & \cdots & r(p-1)^{*} \\
\vdots & \ddots & \ddots & \vdots \\
r(p) & \cdots & r(2) & r(1)
\end{array}\right]
$$

and $E$ is a diagonal matrix with elements returned in output e (seebelow). This decomposition permits the efficient evaluation of the inverse of the autocorrelation matrix, $\mathrm{R}^{-1}$.

Output matrix u contains the prediction filter polynomial, a, from each iteration of the reverse Levinson-Durbin recursion

$$
U=\left[\begin{array}{cccc}
a_{1}(1)^{*} & a_{2}(2)^{*} & \cdots & a_{p+1}(p+1)^{*} \\
0 & a_{2}(1)^{*} & \ddots & a_{p+1}(p)^{*} \\
0 & 0 & \ddots & a_{p+1}(p-1)^{*} \\
\vdots & \ddots & \ddots & \vdots \\
0 & \cdots & 0 & a_{p+1}(1)^{*}
\end{array}\right]
$$

where $a_{i}(j)$ is the jth coefficient of the ith order prediction filter polynomial (i.e., step i in the recursion). For example, the 5th order prediction filter polynomial is

$$
a 5=u(5:-1: 1,5)^{\prime}
$$

Note that $u(p+1:-1: 1, p+1)^{\prime}$ is the input polynomial coefficient vector a.

## rlevinson

[ $r, u, k]=r l e v i n s o n(a, e f i n a l)$ returns a vector $k$ of length ( $p+1$ ) containing the reflection coefficients. The reflection coefficients are the conjugates of the values in the first row of $u$.

$$
\mathrm{k}=\operatorname{conj}(\mathrm{u}(1,2: \mathrm{end}))
$$

[ $r, u, k, e]=r l e v i n s o n(a, e f i n a l)$ returns a vector of length $p+1$ containing the prediction errors from each iteration of the reverse Levinson-Durbin recursion: $\mathrm{e}(1)$ is the prediction error from the first-order model, $\mathrm{e}(2)$ is the prediction error from the second-order model, and so on.
These prediction error values form the diagonal of the matrix $E$ in the UDU* decomposition of $R^{-1}$.

$$
\mathrm{R}^{-1}=\mathrm{UE}^{-1} \mathrm{U}^{*}
$$

See Also levinson, lpc, prony, stmcb
References [1] Kay, S.M., Modern Spectral Estimation: Theory and Application, Prentice-H all, Englewood Cliffs, NJ , 1988.

```
Purpose Estimate frequency and power content using the eigenvector method
Syntax [w,pow] = rooteig(x,p)
[f,pow] = rooteig(....fs)
[w,pow] = rooteig(...,'corr')
```

Description $[w, p o w]=\operatorname{rooteig}(x, p)$ estimates the frequency content in the timesamples of a signal $x$, and returns $w$, a vector of frequencies in rad/sample, and the corresponding signal power in the vector pow in dB per rad/sample. The input signal x is specified either as:

- A row or column vector representing one observation of the signal
- A rectangular array for which each row of x represents a separate observation of the signal (for example, each row is one output of an array of sensors, as in array processing), such that $\mathrm{x}^{\prime}$ * x is an estimate of the correlation matrix

Note You can use the output of corrmtx to generate such an array x .

You can specify the second input argument $p$ as either:

- A scalar integer. In this case, the signal subspace dimension is $p$.
- A two-element vector. In this case, p(2), the second element of $p$, represents a threshold that is multiplied by $\lambda_{\min }$, the smallest estimated eigenvalue of the signal's correlation matrix. Eigenvalues below the threshold $\lambda_{\text {min }} * p(2)$ are assigned to the noise subspace. In this case, p(1) specifies the maximum dimension of the signal subspace.

The extra threshold parameter in the second entry in p provides you more flexibility and control in assigning the noise and signal subspaces.

The length of the vector $w$ is the computed dimension of the signal subspace. For real-valued input data $x$, the length of the corresponding power vector pow is given by

```
length(pow) = 0.5*length(w)
```

For complex-valued input data $x$, pow and $w$ have the same length.
[f, pow] = rooteig(...,fs) returns the vector of frequencies fcalculated in Hz . You supply the sampling frequency fs in Hz. If you specify fs with the empty vector [ ], the sampling frequency defaults to 1 Hz .
[w, pow] = rooteig(..., 'corr') forces the input argument $x$ to be interpreted as a correlation matrix rather than a matrix of signal data. F or this syntax, you must supply a square matrix for $x$, and all of its eigenvalues must be nonnegative.

Note You can place the string ' corr ' anywhere after $p$.

## Examples

Find the frequency content in a signal composed of three complex exponentials in noise. Use the modified covariance method to estimate the correlation matrix used by the eigenvector method.

```
randn('state',1); n=0:99;
s = exp(i*pi/2*n)+2*exp(i*pi/4*n)+exp(i*pi/3*n)+randn(1,100);
% Estimate correlation matrix using modified covariance method.
X=corrmtx(s,12,'mod');
[W,P] = rooteig(X,3)
W =
    0.7811
    1.5767
    1.0554
P =
    3.9971
    1.1362
    1.4102
```


## Algorithm

The eigenvector method used by rooteig is the same as that used by peig. The al gorithm performs eigenspace analysis of the signal's correlation matrix in order to estimate the signal's frequency content.

The difference between peig and rooteig is:

- peig returns the pseudospectrum at all frequency samples.
- rooteig returns the estimated discrete frequency spectrum, along with the corresponding signal power estimates.
roote ig is most useful for frequency estimation of signals made up of a sum of sinusoids embedded in additive white Gaussian noise.

See Also
corrmtx, peig, pmusic, rootmusic

| Purpose | Estimate frequency and power content using the root MUSIC algorithm |
| :---: | :---: |
| Syntax | $\begin{aligned} {[w, \text { pow }] } & =\operatorname{rootmusic}(x, p) \\ {[f, \operatorname{pow}] } & =\operatorname{rootmusic}(\ldots, f s) \\ {[w, \text { pow }] } & =\operatorname{rootmusic}\left(\ldots, \operatorname{corr}^{\prime}\right) \end{aligned}$ |
| Description | [w, pow] = rootmusic ( $x, p$ ) estimates the frequency content in the time samples of a signal $x$, and returns $w$, a vector of frequencies in rad/sample, and the corresponding signal power in the vector pow in dB per rad/sample. The input signal x is specified either as: <br> - A row or column vector representing one observation of the signal <br> - A rectangular array for which each row of x represents a separate observation of the signal (for example, each row is one output of an array of sensors, as in array processing), such that $x^{\prime} * x$ is an estimate of the correlation matrix |

Note You can use the output of corrmtx to generate such an array $x$.

The second input argument, p is the number of complex sinusoids in x . Y ou can specify $p$ as either:

- A scalar integer. In this case, the signal subspace dimension is $p$.
- A two-element vector. In this case, $p$ (2), the second element of $p$, represents a threshold that is multiplied by $\lambda_{\text {min }}$, the smallest estimated eigenvalue of the signal's correlation matrix. Eigenvalues below the threshold $\lambda_{\text {min }}{ }^{*} p$ (2) are assigned to the noise subspace. In this case, p(1) specifies the maximum dimension of the signal subspace.

The extra threshold parameter in the second entry in p provides you more flexibility and control in assigning the noise and signal subspaces.

The length of the vector $w$ is the computed dimension of the signal subspace. For real-valued input data $x$, the length of the corresponding power vector pow is given by

```
length(pow) = 0.5*length(w)
```

For complex-valued input data $x$, pow and $w$ have the same length.
[f, pow] = rootmusic (...,fs) returns the vector of frequencies f calculated in Hz . You supply the sampling frequency fs in Hz . If you specify fs with the empty vector [ ], the sampling frequency defaults to 1 Hz .
[w, pow] = rootmusic(..., 'corr') forces the input argument $x$ to be interpreted as a correlation matrix rather than a matrix of signal data. For this syntax, you must supply a square matrix for $x$, and all of its eigenvalues must be nonnegative.

Note You can place the string 'corr' anywhere after $p$.

## Examples

## Algorithm

Find the frequency content in a signal composed of three complex exponentials in noise. Use the modified covariance method to estimate the correlation matrix used by the MUSIC algorithm.

```
randn('state',1); n=0:99;
s = exp(i*pi/2*n)+2*exp(i*pi/4*n)+exp(i*pi/3*n)+randn(1,100);
% Estimate correlation matrix using modified covariance method.
X=corrmtx(s,12,'mod');
[W,P] = rootmusic(X,3)
W =
    1.5769
    0.7817
    1.0561
P =
    1.1358
    3.9975
    1.4102
```

The MUSIC algorithm used by rootmusic is the same as that used by pmusic. The al gorithm performs eigenspace analysis of the signal's correlation matrix in order to estimate the signal's frequency content.
The difference between pmusic and rootmusic is:

- pmusic returns the pseudospectrum at all frequency samples.
- rootmusic returns the estimated discrete frequency spectrum, along with the corresponding signal power estimates.
rootmusic is most useful for frequency estimation of signals made up of a sum of sinusoids embedded in additive white Gaussian noise.
Diagnostics If the input signal, x is real and an odd number of sinusoids, p is specified, this error message is displayed
Real signals require an even number $p$ of complex sinusoids.
See Also corrmtx, peig, pmusic, rooteig
Purpose Generate a sawtooth or triangle wave
Syntax $x=$ sawtooth(t) x = sawtooth(t,width)
DescriptionSee Alsochirp, cos, diric, gauspuls, pulstran, rectpuls, sin, sinc, square, tripuls
sawtooth ( $t$ ) generates a sawtooth wave with period $2 \pi$ for the elements of time vector $t$. sawtooth( $t$ ) is similar to sin( $t$ ), but creates a sawtooth wave with peaks of -1 and 1 instead of a sine wave. The sawtooth wave is defined to be -1 at multiples of $2 \pi$ and to increase linearly with time with a slope of $1 / \pi$ at all other times.
sawtooth( $t$, width) generates a modified triangle wave where width, a scalar parameter between 0 and 1 , determines the point between 0 and $2 \pi$ at which the maximum occurs. The function increases from -1 to 1 on the interval 0 to $2 \pi \star$ width, then decreases linearly from 1 to -1 on the interval $2 \pi *$ width to $2 \pi$. Thus a parameter of 0.5 specifies a standard triangle wave, symmetric about time instant $\pi$ with peak-to-peak amplitude of 1 . sawtooth $(t, 1)$ is equivalent to sawtooth(t).
chirp, cos, diric, gauspuls, pulstran, rectpuls, sin, sinc, square, tripuls
Purpose Compute reflection coefficients from an autocorrelation sequence
Syntax

k = schurrc(r)

$[k, e]=\operatorname{schurrc}(r)$
Description
ExamplesCreatean autocorrelation sequencefrom theMATLAB speech signal containedin mtlb.mat, and use the Schur algorithm to compute the reflection coefficientsof a lattice prediction filter for this autocorrelation sequence.

```
load mtlb
r = xcorr(mtlb(1:5),'unbiased');
k = schurrc(r(5:end))
k =
    -0.7583
    0.1384
    0.7042
    -0.3699
```

See Also levinsonReferences [1] Proakis, J. and D. Manolakis, Digital Signal Processing: Principles,Algorithms, and Applications, Third edition, Prentice-H all, 1996, pp. 868-873.

## Purpose Compute the period of a sequence

## Syntax

```
p = seqperiod(x)
[p,num] = seqperiod(x)
```


## Description

$p=$ seqperiod( $x$ ) returns the integer $p$ that corresponds to the period of the sequence in a vector $x$. The period $p$ is computed as the minimum length of a subsequence $x(1: p)$ of $x$ that repeats itself continuously every $p$ samples in $x$. The length of $x$ does not have to be a multiple of $p$, so that an incomplete repetition is permitted at the end of $x$. If the sequence $x$ is not periodic, then $p=$ length ( $x$ ).

- If $x$ is a matrix, then seqperiod checks for periodicity al ong each column of $x$. The resulting output $p$ is a row vector with the same number of columns as $x$.
- If $x$ is a multidimensional array, then seqperiod checks for periodicity along the first nonsingleton dimension of $x$. In this case:
- p is a multidimensional array of integers with a leading singleton dimension.
- The lengths of the remaining dimensions of $p$ correspond to those of the dimensions of $x$ after the first nonsingleton one.
[ $p$, num] = seqperiod $(x)$ also returns thenumber num of repetitions of $x(1: p)$ in $x$. num might not be an integer.


## Examples

$x=\left[\begin{array}{llll}4 & 0 & 1 & 6 ;\end{array}\right.$
$2027 ;$
4015 ;
$2056] ;$
$p=$ seqperiod( $x$ )
$\mathrm{p}=$
$\begin{array}{llll}2 & 1 & 4 & 3\end{array}$

The result implies:

- The first column of $x$ has period 2 .
- The second column of $x$ has period 1 .
- The third column of $x$ is not periodic, so $p(3)$ is just the number of rows of $x$.
- The fourth column of $x$ has period 3 , although the last (second) repetition of the periodic sequence is incomplete.

| Purpose | Savitzky-Golay filter design |
| :---: | :---: |
| Syntax | $\begin{aligned} & b=\operatorname{sgolay}(k, f) \\ & b=\operatorname{sgolay}(k, f, w) \\ & {[b, g]=\operatorname{sgolay}(\ldots} \end{aligned}$ |
| Description | b = sgolay ( $k, f$ ) designs a Savitzky-Golay FIR smoothing filter b . The polynomial order $k$ must be less than the frame size, $f$, which must be odd. If $\mathrm{k}=\mathrm{f}-1$, the designed filter produces no smoothing. The output, b , is an f -by- f matrix whose rows represent the time-varying FIR filter coefficients. In a smoothing filter implementation (for example, sgolayfilt), the last ( $\mathrm{f}-1$ )/2 rows (each an FIR filter) are applied to the signal during the startup transient, and the first ( $\mathrm{f}-1$ )/2 rows are applied to the signal during the terminal transient. The center row is applied to the signal in the steady state. <br> $b=\operatorname{sgolay}(k, f, w)$ specifies a weighting vector $w$ with length $f$, which contains the real, positive-valued weights to be used during the least-squares minimization. <br> [b,g] = $\operatorname{sgolay}(\ldots)$ [returns the matrix $g$ of differentiation filters. Each column of g is a differentiation filter for derivatives of order p -1 where p is the column index. Given a signal $x$ of length $f$, you can find an estimate of the $p^{\text {th }}$ order derivative, xp , of its middle value from: $\operatorname{xp}((f+1) / 2)=(f a c t o r i a l(p)) * g(:, p+1))^{*} x$ |
| Remarks | Savitzky-Golay smoothing filters (also called digital smoothing polynomial filters or least squares smoothing filters) are typically used to "smooth out" a noisy signal whose frequency span (without noise) is large. In this type of application, Savitzky-Golay smoothing filters perform much better than standard averaging FIR filters, which tend to filter out a significant portion of the signal's high frequency content along with the noise. Although Savitzky-Golay filters are more effective at preserving the pertinent high frequency components of the signal, they are less successful than standard averaging FIR filters at rejecting noise. |
|  | Savitzky-Golay filters are optimal in the sense that they minimize the least-squares error in fitting a polynomial to each frame of noisy data. |

Example
Use sgolay to smooth a noisy sinusoid and display the result and the first and second derivatives.

```
N = 4;
F = 21;
[b,g]=sgolay(N,F);
x=5*sin(.4*pi*0:.2:199);
y=x+randn(1,996); % Noisy sinusoid
for n = (F+1)/2:996-(F+1)/2,
% Zero-th order derivative (equivalent to sgolayfilt except
% that it doesn't compute transients)
    zO(n)=g(:,1)'*y(n - (F+1)/2 + 1: n + (F+1)/2 - 1)';
% 1st order derivative
    z1(n)=g(:,2)'*y(n - (F+1)/2 + 1: n + (F+1)/2 - 1)';
% 2nd order derivative
        z2(n)=2*g(:,3)'*y(n - (F+1)/2 + 1: n + (F+1)/2 - 1)';
end
plot([x(1:length(z0))',y(1:length(z0))',z0'])
legend('Noiseless sinusoid','Noisy sinusoid',...
'Smoothed sinusoid')
figure
plot([diff(x(1:length(z0)+1))',z1'])
legend('Noiseless first-order derivative',...
'Smoothed first-order derivative')
figure
plot([diff(diff(x(1:length(z0)+2)) )',z2'])
legend('Noiseless second-order derivative',...
'Smoothed second-order derivative')
```

Note The figures below are zoomed to show more detail.

Zero-th order


First derivative


Second derivative


## See Also fir1,firls,filter, sgolayfilt

References [1]Orfanidis, S.J ., Introduction toSignal Processing, Prentice-Hall, Englewood Cliffs, NJ, 1996.

| Purpose | Savitzky-Golay filtering |
| :---: | :---: |
| Syntax | $\begin{aligned} & y=\text { sgolayfilt }(x, k, f) \\ & y=\operatorname{sgolayfilt}(x, k, f, w) \\ & y=\operatorname{sgolayfilt}(x, k, f, w, \operatorname{dim}) \end{aligned}$ |
| Description | $y=$ sgolayfilt ( $x, k, f$ ) applies a Savitzky-Golay FIR smoothing filter to the data in vector $x$. If $x$ is a matrix, sgolayfilt operates on each column. The polynomial order k must be less than the frame size, $f$, which must be odd. If $\mathrm{k}=\mathrm{f}-1$, the filter produces no smoothing. <br> $y=$ sgolayfilt ( $x, k, f, w)$ specifies a weighting vector $w$ with length $f$, which contains the real, positive-valued weights to be used during the least-squares minimization. If wis not specified or if it is specified as empty, [ ], w defaults to an identity matrix. <br> $y=$ sgolayfilt(x,k,f,w,dim) specifies the dimension, dim, along which the filter operates. If dim is not specified, sgolayfilt operates along the first non-singleton dimension; that is, dimension 1 for column vectors and nontrivial matrices, and dimension 2 for row vectors. |
| Remarks | Savitzky-Golay smoothing filters (also called digital smoothing polynomial filters or least-squares smoothing filters) are typically used to "smooth out" a noisy signal whose frequency span (without noise) is large. In this type of application, Savitzky-Golay smoothing filters perform much better than standard averaging FIR filters, which tend to filter out a significant portion of the signal's high frequency content along with the noise. Although Savitzky-Golay filters are more effective at preserving the pertinent high frequency components of the signal, they are less successful than standard averaging FIR filters at rejecting noise. |
|  | Savitzky-Golay filters are optimal in the sense that they minimize the least-squares error in fitting a polynomial to frames of noisy data. |
| Example | Smooth the mtlb signal by applying a cubic Savitzky-Golay filter to data frames of length 41. |
|  | ```load mtlb % Load the data. smtlb = sgolayfilt(mtlb,3,41); % Apply the 3rd-order filter.``` |

```
subplot(2,1,1)
plot([1:2000],mtlb(1:2000)); axis([0 2000 -4 4]);
title('mtlb'); grid;
subplot(2,1,2)
plot([1:2000],smtlb(1:2000)); axis([0 2000 -4 4]);
title('smtlb'); grid;
```




## See Also

References
medfilt1, filter, sgolay, sosfilt
[1] Orfanidis, S.] ., Introduction toSignal Processing, Prentice-H all, Englewood Cliffs, NJ, 1996.

Purpose Sinc function
Syntax $\quad y=\operatorname{sinc}(x)$
Description

Example function is at integer spacings.
sinc computes the sinc function of an input vector or array, where the sinc

$$
\operatorname{sinc}(t)= \begin{cases}1, & t=0 \\ \frac{\sin (\pi t)}{\pi t}, & t \neq 0\end{cases}
$$

This function is the continuous inverse F ourier transform of the rectangular pulse of width $2 \pi$ and height 1 .

$$
\operatorname{sinc}(\mathrm{t})=\frac{1}{2 \pi} \int_{-\pi}^{\pi} \mathrm{e}^{\mathrm{j} \omega \mathrm{t}} \mathrm{~d} \omega
$$

$y=\operatorname{sinc}(x)$ returns an array $y$ the same size as $x$, whose elements are the sinc function of the elements of $x$.

The space of functions bandlimited in the frequency range $\omega \in[-\pi, \pi]$ is spanned by the infinite (yet countable) set of sinc functions shifted by integers. Thus any such bandlimited function $\mathrm{g}(\mathrm{t})$ can be reconstructed from its samples

$$
g(t)=\sum_{n=-\infty}^{\infty} g(n) \operatorname{sinc}(t-n)
$$

Perform ideal bandlimited interpolation by assuming that the signal to be interpolated is 0 outside of the given time interval and that it has been sampled at exactly the $N$ yquist frequency.

```
t = (1:10)'; % A column vector of time samples
randn('state',0);
x = randn(size(t)); % A column vector of data
ts = linspace(-5,15,600)'; % times at which to interpolate data
y = sinc(ts(:,ones(size(t))) - t(:,ones(size(ts)))')*x;
```

plot(t,x,'o',ts,y)


## See Also

chirp, cos, diric, gauspuls, pulstran, rectpuls, sawtooth, sin, square, tripuls

Purpose Convert a second-order section matrix to cell arrays

Syntax $\quad$| $c$ | $=\operatorname{sos} 2 \operatorname{cell}(m)$ |
| ---: | :--- |
| $c$ | $=\operatorname{sos} 2 \operatorname{cell}(m, g)$ |

Description

## Examples

See Also

## Purpose

## Syntax

## Description

Convert digital filter second-order section parameters to state-space form

$$
\begin{aligned}
& {[A, B, C, D]=\operatorname{sos} 2 s s(\operatorname{sos})} \\
& {[A, B, C, D]=\operatorname{sos} 2 s s(\operatorname{sos}, g)}
\end{aligned}
$$

sos2ss converts a second-order section representation of a given digital filter to an equivalent state-space representation.
[A,B,C,D] = sos2ss (sos) converts the system sos, in second-order section form, to a single-input, single-output state-space representation.

$$
\begin{array}{ll}
x[n+1] & =A x[n]+B u[n] \\
y[n] & =C x[n]+D u[n]
\end{array}
$$

The discrete transfer function in second-order section form is given by

$$
H(z)=\prod_{k=1}^{L} H_{k}(z)=\prod_{k=1}^{L} \frac{b_{0 k}+b_{1 k} z^{-1}+b_{2 k} z^{-2}}{1+a_{1 k^{2}} z^{-1}+a_{2 k} z^{-2}}
$$

sos is a L-by-6 matrix organized as

$$
\operatorname{sos}=\left[\begin{array}{cccccc}
b_{01} & b_{11} & b_{21} & 1 & a_{11} & a_{21} \\
b_{02} & b_{12} & b_{22} & 1 & a_{12} & a_{22} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
b_{0 L} & b_{1 L} & b_{2 L} & 1 & a_{1 L} & a_{2 L}
\end{array}\right]
$$

The entries of sos must be real for proper conversion to state space. The returned matrix A is size $N-b y-N$, where $N=2 L-1$, $B$ is a length $N-1$ column vector, C is a length $\mathrm{N}-1$ row vector, and D is a scalar.
$[A, B, C, D]=$ sos2ss(sos,$g)$ converts the system sos in second-order section form with gain $g$.

$$
H(z)=g \prod_{k=1} H_{k}(z)
$$

```
Example Compute the state-space representation of a simple second-order section system with a gain of 2 .
```

```
sos = [1 1 1 1 1 0 -1; -2 3 1 1 10 1];
```

sos = [1 1 1 1 1 0 -1; -2 3 1 1 10 1];
[A,B,C,D] = sos2ss(sos)
[A,B,C,D] = sos2ss(sos)
A =
A =
-10 0 10 1
-10 0 10 1
1 0}0
1 0}0
0}1010
0}1010
0
0
B =
B =
1
1
0
0
0
0
0
0
C =
C =
21 2 -16 -1
21 2 -16 -1
D =
D =
-2

```
            -2
```


## Algorithm

See Also
sos2ss first converts from second-order sections to transfer function using sos2tf, and then from transfer function to state-space using tf2ss.
sos2tf, sos2zp, ss2sos, tf2ss, zp2ss

## Purpose

## Syntax

## Description

Convert digital filter second-order section data to transfer function form

$$
\begin{aligned}
& {[b, a]=\operatorname{sos} 2 \operatorname{tf}(\operatorname{sos})} \\
& {[b, a]=\operatorname{sos} 2 t f(\operatorname{sos}, g)}
\end{aligned}
$$

sos2tf converts a second-order section representation of a given digital filter to an equivalent transfer function representation.
$[b, a]=\operatorname{sos} 2 t f(s o s)$ returns the numerator coefficients $b$ and denominator coefficients a of the transfer function that describes a discrete-time system given by sos in second-order section form. The second-order section format of $H(z)$ is given by

$$
H(z)=\prod_{k=1}^{L} H_{k}(z)=\prod_{k=1}^{L} \frac{b_{0 k}+b_{1 k} z^{-1}+b_{2 k} z^{-2}}{1+a_{1 k^{2}} z^{-1}+a_{2 k^{2}} z^{-2}}
$$

sos is an L-by-6 matrix that contains the coefficients of each second-order section stored in its rows.

$$
\text { sos }=\left[\begin{array}{cccccc}
b_{01} & b_{11} & b_{21} & 1 & a_{11} & a_{21} \\
b_{02} & b_{12} & b_{22} & 1 & a_{12} & a_{22} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
b_{0 L} & b_{1 L} & b_{2 L} & 1 & a_{1 L} & a_{2 L}
\end{array}\right]
$$

Row vectors $b$ and a contain the numerator and denominator coefficients of $\mathrm{H}(\mathrm{z})$ stored in descending powers of z .

$$
H(z)=\frac{B(z)}{A(z)}=\frac{b_{1}+b_{2} z^{-1}+\cdots+b_{n+1} z^{-n}}{a_{1}+a_{2} z^{-1}+\cdots+a_{m+1} z^{-m}}
$$

[b,a] = sos2tf(sos,g) returns the transfer function that describes a discrete-time system given by sos in second-order section form with gain g .

$$
\mathrm{H}(\mathrm{z})=\mathrm{g} \prod_{\mathrm{k}=1} \mathrm{H}_{\mathrm{k}}(\mathrm{z})
$$

```
Example Compute the transfer function representation of a simple second-order section system.
```

```
sos = [[\begin{array}{llllllllllllllll}{1}&{1}&{1}&{1}&{0}&{-1;}&{-2}&{3}&{1}&{1}&{10}&{1}\end{array}];
```

sos = [[$$
\begin{array}{llllllllllllllll}{1}&{1}&{1}&{1}&{0}&{-1;}&{-2}&{3}&{1}&{1}&{10}&{1}\end{array}
$$];
[b,a] = sos2tf(sos)
[b,a] = sos2tf(sos)
b =
b =
-2 1
-2 1
a =
a =
1
1
Algorithm
See Also
latc2tf, sos2ss, sos2zp, ss2tf, tf2sos, zp2tf

```

\section*{Purpose}

\section*{Syntax}

\section*{Description}

Convert digital filter second-order section parameters to zero-pole-gain form
```

[z,p,k] = sos2zp(sos)
[z,p,k] = sos2zp(sos,g)

```
sos2zp converts a second-order section representation of a given digital filter to an equivalent zero-pole-gain representation.
[ \(\mathrm{z}, \mathrm{p}, \mathrm{k}]=\operatorname{sos} 2 z \mathrm{p}(\mathrm{sos})\) returns the zeros z , poles p , and gain k of the system given by sos in second-order section form. The second-order section format of \(H(z)\) is given by
\[
H(z)=\prod_{k=1}^{L} H_{k}(z)=\prod_{k=1}^{L} \frac{b_{0 k}+b_{1 k^{\prime}} z^{-1}+b_{2 k} z^{-2}}{1+a_{1 k} z^{-1}+a_{2 k} z^{-2}}
\]
sos is an L-by-6 matrix that contains the coefficients of each second-order section in its rows.
\[
\operatorname{sos}=\left[\begin{array}{cccccc}
b_{01} & b_{11} & b_{21} & 1 & a_{11} & a_{21} \\
b_{02} & b_{12} & b_{22} & 1 & a_{12} & a_{22} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
b_{0 L} & b_{1 L} & b_{2 L} & 1 & a_{1 L} & a_{2 L}
\end{array}\right]
\]

Column vectors \(z\) and \(p\) contain the zeros and poles of the transfer function \(\mathrm{H}(\mathrm{z})\).
\[
H(z)=k \frac{\left(z-z_{1}\right)\left(z-z_{2}\right) \cdots\left(z-z_{n}\right)}{\left(p-p_{1}\right)\left(p-p_{2}\right) \cdots\left(p-p_{m}\right)}
\]
where the orders n and m are determined by the matrix sos.
\([z, p, k]=\operatorname{sos} 2 z p(\operatorname{sos}, g)\) returns the zeros \(z\), poles \(p\), and gain \(k\) of the system given by sos in second-order section form with gain \(g\).
\[
\mathrm{H}(\mathrm{z})=\mathrm{g} \prod_{\mathrm{k}=1} \mathrm{H}_{\mathrm{k}}(\mathrm{z})
\]
```

Example Compute the poles, zeros, and gain of a simple system in second-order section form.

```
```

sos = [11 1 1 1 1 0 0-1; -2 3 1 1 1 10 1];

```
sos = [11 1 1 1 1 0 0-1; -2 3 1 1 1 10 1];
[z,p,k] = sos2zp(sos)
[z,p,k] = sos2zp(sos)
z =
z =
    -0.5000 + 0.8660i
    -0.5000 + 0.8660i
            -0.5000 - 0.8660i
            -0.5000 - 0.8660i
            1.7808
            1.7808
            -0.2808
            -0.2808
p =
p =
            -1.0000
            -1.0000
            1.0000
            1.0000
            -9.8990
            -9.8990
            -0.1010
            -0.1010
                k =
                k =
            -2
            -2
Algorithm sos2zp finds the poles and zeros of each second-order section by repeatedly
See Also sos2ss, sos2tf, ss2zp, tf2zp, zp2sos
```


## Purpose

## Syntax

Description

See Also filter, medfilt1, sgolayfilt
References
Second-order (biquadratic) IIR digital filtering
$y=\operatorname{sosfilt}($ sos, $x)$ vector $x$. The output, $y$, is the same length as $x$. its rows.

$$
\operatorname{sos}=\left[\begin{array}{cccccc}
b_{01} & b_{11} & b_{21} & 1 & a_{11} & a_{21} \\
b_{02} & b_{12} & b_{22} & 1 & a_{12} & a_{22} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
b_{0 L} & b_{1 L} & b_{2 L} & 1 & a_{1 L} & a_{2 L}
\end{array}\right]
$$ corresponding to each column of $x$.

$y=\operatorname{sosfilt}(\operatorname{sos}, x)$ applies the second-order section digital filter sos to the
sos represents the second-order section digital filter $\mathrm{H}(\mathrm{z})$

$$
H(z)=\prod_{k=1}^{L} H_{k}(z)=\prod_{k=1}^{L} \frac{b_{0 k}+b_{1 k} z^{-1}+b_{2 k} z^{-2}}{1+a_{1 k^{2}} z^{-1}+a_{2 k} z^{-2}}
$$

by an L-by-6 matrix containing the coefficients of each second-order section in

If x is a matrix, sosfilt applies the filter to each column of x independently. Output $y$ is a matrix of the same size, containing the filtered data
[1] Orfanidis, S.] ., Introduction toSignal Processing, Prentice-Hall, Englewood Cliffs, NJ, 1996.

## Purpose Time-dependent frequency analysis (spectrogram)

Syntax

```
B = specgram(a)
B = specgram(a,nfft)
[B,f] = specgram(a,nfft,fs)
[B,f,t] = specgram(a,nfft,fs)
B = specgram(a,nfft,fs,window)
B = specgram(a,nfft,fs,window,numoverlap)
specgram(a)
B = specgram(a,f,fs,window, numoverlap)
```


## Description

specgram computes the windowed discrete-time Fourier transform of a signal using a sliding window. The spectrogram is the magnitude of this function.

B = specgram(a) calculates the windowed discrete-timeF ourier transform for the signal in vector a. This syntax uses the default values:

- nfft = min(256,length(a))
- fs = 2
- window is a periodic Hann (Hanning) window of length nfft.
- numoverlap = length(window)/2
nfft specifies the FFT Iength that specgram uses. This value determines the frequencies at which the discrete-time Fourier transform is computed. fs is a scalar that specifies the sampling frequency. window specifies a windowing function and the number of samples specgram uses in its sectioning of vector a. numoverlap is the number of samples by which the sections overlap. Any arguments that you omit from the end of the input parameter list use the default values shown above.

If a is real, specgram computes the discrete-time Fourier transform at positive frequencies only. If $n$ is even, specgram returns nfft/2+1 rows (including the zero and $N$ yquist frequency terms). If $n$ is odd, specgram returns nfft/ 2 rows. The number of columns in B is

$$
k=\text { fix((n-numoverlap)/(length(window)-numoverlap)) }
$$

If a is complex, specgram computes the discrete-time F ourier transform at both positive and negative frequencies. In this case, B is a complex matrix with nfft
rows. Time increases linearly across the columns of $B$, starting with sample 1 in column 1. Frequency increases linearly down the rows, starting at 0.
$B=$ specgram (a, nfft) uses the specified FFT length nfft in its calculations.
$[B, f]=\operatorname{specgram}(a, n f f t, f s)$ returns a vector $f$ of frequencies at which the function computes the discrete-time F ourier transform. fs has no effect on the output B; it is a frequency scaling multiplier.
$[B, f, t]=\operatorname{specgram}(a, n f f t, f s)$ returns frequency and time vectors $f$ and $t$ respectively. t is a column vector of scaled times, with length equal to the number of columns of $B . t(j)$ is the earliest time at which the jth window intersects $a . t(1)$ is always equal to 0 .
$B=$ specgram(a,nfft,fs, window) specifies a windowing function and the number of samples per section of the x vector. If you supply a scalar for window, specgram uses a Hann window of that length. The length of the window must be less than or equal to nfft.
$B=$ specgram(a, nfft,fs, window, numoverlap) overlaps the sections of $x$ by numoverlap samples.
You can use the empty matrix [ ] to specify the default value for any input argument. For example,

```
B = specgram(x,[],10000)
```

is equivalent to

```
B = specgram(x)
```

but with a sampling frequency of $10,000 \mathrm{~Hz}$ instead of the default 2 Hz .
specgram (...) with no output arguments displays the scaled logarithm of the spectrogram in the current figure window using

```
imagesc(t,f,20*log10(abs(b))), axis xy, colormap(jet)
```

The axis xy mode displays the low-frequency content of the first portion of the signal in the lower-left corner of the axes. specgram uses fs to label the axes according to true time and frequency.
$B=$ specgram(a,f,fs, window, numoverlap) computes the spectrogram at the frequencies specified in $f$, using either the chirp z-transform (for more than 20 evenly spaced frequencies) or a polyphase decimation filter bank. $f$ is a vector of frequencies in hertz; it must have at least two elements.

## Example

Display the spectrogram of a digitized speech signal.

```
load mtlb
specgram(mtlb,512,Fs,kaiser(500,5),475)
title('Spectrogram')
```



Note You can view and manipulate a similar spectrogram in the Signal Processing Tool box Demos, which you access in from the MATLAB Launch Pad.

Algorithm specgram calculates the spectrogram for a given signal as follows:
1 It splits the signal into overlapping sections and applies the window specified by the window parameter to each section.

2 It computes the discrete-time Fourier transform of each section with a length nfft FFT to produce an estimate of the short-term frequency content of the signal; these transforms make up the columns of $B$. The quantity (length(window) - numoverlap) specifies by how many samples specgram shifts the window.
3 For real input, specgram truncates the spectrogram to the first nfft/2 +1 points for nfft even and (nfft +1)/2 for nfft odd.

## Diagnostics

## See Also

References

An appropriate diagnostic message is displayed when incorrect arguments are used.

Requires window's length to be no greater than the FFT length. Requires NOVERLAP to be strictly less than the window length. Requires positive integer values for NFFT and NOVERLAP. Requires vector input.
cohere, csd, pwelch, tfe
[1] Oppenheim, A.V., and R.W. Schafer, Discrete-TimeSignal Processing, Prentice-H all, Englewood Cliffs, NJ , 1989, pp. 713-718.
[2] Rabiner, L.R., and R.W. Schafer, Digital Processing of Speech Signals, Prentice-H all, Englewood Cliffs, NJ, 1978.

Purpose Open the digital signal processing GUI (SPTool)

## Syntax sptool

Description
sptool opens SPTool, a graphical user interface (GUI) that manages a suite of four other GUIs. These GUIs provide access to many of the signal, filter, and spectral analysis functions in the toolbox. When you type sptool at the command line, the following GUI opens.


Using SPTool you can:

- Analyze signals listed in the Signals list box with the Signal Browser
- Design or edit filters with the Filter Designer (includes a Pole/Zero Editor)
- Analyzefilter responses for filters listed in theFilters list box with theFilter Viewer
- Apply filters in the Filters list box to signals in the Signals list box
- Create and analyze signal spectra with the Spectrum Viewer
- Print the Signal Browser, Filter Viewer, Filter Designer, and Spectrum Viewer

You can activate the four integrated signal processing GUI s from SPTool.

## Signal Brow ser

The Signal Browser allows you to view, measure, and analyze the time-domain information of one or more signals. To activate the Signal Browser, press the View button under the Signals list box in SPTool.

## Filter Designer

TheFilter Designer allows you to design and edit FIR and IIR filters of various lengths and types, with standard (lowpass, highpass, bandpass, bandstop, and multiband) configurations. To activate the Filter Designer, press either the New button or the Edit button under the Filters list box in SPTool.


TheFilter Designer has a Pole/ZeroE ditor you can access from the Algorithms pulldown.


## Filter Viewer

The Filter Viewer allows you to view the characteristics of a designed or imported filter, including its magnituderesponse, phaseresponse, group delay, pole-zero plot, impulse response, and step response. To activate the Filter Viewer, press the View button under the Filters list box in SPTool.


You can analyze multiple filter responses by checking several response plot options, as shown in the next figure.


## Spectrum Viewer

TheSpectrum Viewer allows you to graphically analyze frequency-domain data using a variety of methods of spectral density estimation, including the Burg method, the FFT method, the multitaper method (MTM), the MUSIC eigenvector method, Welch's method, and the YuleWalker AR method. To activate the Spectrum Viewer:

- Press the Create button under the Spectra list box to compute the power spectral density for a signal selected in the Signals list box in SPTool. You may need to press Apply to view the spectra.
- Press the View button to analyze spectra selected under the Spectra list box in SPTool.
- Press the Update button under the Spectra list box in SPT ool to modify a selected power spectral density signal.


In addition, you can right-click in any plot display area of the GUIs to modify signal properties.

SeeChapter 6, "SPTool: A Signal Processing GUI Suite," for a full discussion of how to use SPTool.

See Also fdatool
Purpose Generate a square wave
Syntax $x=$ square( $t$ )
$x=$ square(t,duty)
Description $x=$ square ( $t$ ) generates a square wave with period $2 \pi$ for the elements oftime vector $t$. square ( $t$ ) is similar to sin( $t$ ), but creates a square wave withpeaks of +1 instead of a sine wave.
$x$ = square(t, duty) generates a square wave with specified duty cycle, duty. The duty cycle is the percent of the period in which the signal is positive.
See Also chirp, cos, diric, gauspuls, pulstran, rectpuls, sawtooth, sin, square, tripuls

Purpose Convert digital filter state-space parameters to second-order sections form

```
Syntax [sos,g] = ss2sos(A,B,C,D)
[sos,g] = ss2sos(A,B,C,D,iu)
[sos,g] = ss2sos(A,B,C,D,'order')
[sos,g] = ss2sos(A,B,C,D,iu,'order')
[sos,g] = ss2sos(A,B,C,D,iu,'order','scale')
sos = ss2sos(...)
```


## Description

ss2sos converts a state-space representation of a given digital filter to an equivalent second-order section representation.
[sos,g] = ss2sos(A,B,C,D) finds a matrix sos in second-order section form with gain $g$ that is equivalent to the state-space system represented by input arguments $\mathrm{A}, \mathrm{B}, \mathrm{C}$, and D . The input system must be single output and real. sos is an L-by-6 matrix

$$
\operatorname{sos}=\left[\begin{array}{cccccc}
b_{01} & b_{11} & b_{21} & 1 & a_{11} & a_{21} \\
b_{02} & b_{12} & b_{22} & 1 & a_{12} & a_{22} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
b_{0 L} & b_{1 L} & b_{2 L} & 1 & a_{1 L} & a_{2 L}
\end{array}\right]
$$

whose rows contain the numerator and denominator coefficients $\mathrm{b}_{i k}$ and $\mathrm{a}_{i k}$ of the second-order sections of $\mathrm{H}(\mathrm{z})$.

$$
H(z)=g \prod_{k=1}^{L} H_{k}(z)=g \prod_{k=1}^{L} \frac{b_{0 k}+b_{1 k^{\prime}} z^{-1}+b_{2 k} z^{-2}}{1+a_{1 k^{-}} z^{-1}+a_{2 k} z^{-2}}
$$

[sos,g] $=\operatorname{ss2} 2 \operatorname{sos}(A, B, C, D, i u)$ specifies a scalar iu that determines which input of the state-space system $A, B, C, D$ is used in the conversion. The default for $i u$ is 1 .
$[$ sos, g$]=\mathrm{ss} 2 \operatorname{sos}\left(\mathrm{~A}, \mathrm{~B}, \mathrm{C}, \mathrm{D}, \mathrm{'order}^{\prime}\right)$ and
[sos,g] = ss2sos(A, B, C, D,iu,'order') specify the order of the rows in sos, where 'order' is:

- 'down ', to order the sections so the first row of sos contains the poles closest to the unit circle
- 'up ' , to order the sections so the first row of sos contains the poles farthest from the unit circle (default)

The zeros are always paired with the poles closest to them.
[sos, g$]=\mathrm{ss} 2 \operatorname{sos}(\mathrm{~A}, \mathrm{~B}, \mathrm{C}, \mathrm{D}, \mathrm{iu}$, 'order', 'scale') specifies the desired scaling of the gain and the numerator coefficients of all second-order sections, where 'scale' is:

- 'none ', to apply no scaling (default)
- 'inf ', to apply infinity-norm scaling
- 'two ', to apply 2-norm scaling

Using infinity-norm scaling in conjunction with up-ordering minimizes the probability of overflow in the realization. Using 2-norm scaling in conjunction with down-ordering minimizes the peak round-off noise.
sos $=$ ss2sos (...) embeds the overall system gain, $g$, in the first section, $\mathrm{H}_{1}(\mathrm{z})$, so that

$$
H(z)=\prod_{k=1}^{L} H_{k}(z)
$$

Example Find a second-order section form of a Butterworth lowpass filter.

```
[A,B,C,D] = butter(5,0.2);
sos = ss2sos(A,B,C,D)
sos =
\begin{tabular}{rrrrrr}
0.0013 & 0.0013 & 0 & 1.0000 & -0.5095 & 0 \\
1.0000 & 2.0008 & 1.0008 & 1.0000 & -1.0966 & 0.3554 \\
1.0000 & 1.9979 & 0.9979 & 1.0000 & -1.3693 & 0.6926
\end{tabular}
```

Algorithm

Diagnostics

See Also
ss2sos uses a four-step algorithm to determine the second-order section representation for an input state-space system:
1 It finds the poles and zeros of the system given by A, B, C, and D.
2 It uses the function zp2sos, which first groups the zeros and poles into complex conjugate pairs using the cp1xpair function. zp2sos then forms the second-order sections by matching the pole and zero pairs according to the following rules:
a Match the poles closest to the unit circle with the zeros closest to those poles.
b Match the poles next closest to the unit circle with the zeros closest to those poles.
c Continue until all of the poles and zeros are matched.
ss2sos groups real poles into sections with the real poles closest to them in absolute value. The same rule holds for real zeros.
3 It orders the sections according to the proximity of the pole pairs to the unit circle. ss2sos normally orders the sections with poles closest to the unit circle last in the cascade. You can tell ss2sos to order the sections in the reverse order by specifying the 'down' flag.
4 ss2sos scales the sections by the norm specified in the 'scale' argument. For arbitrary $\mathrm{H}(\omega)$, the scaling is defined by

$$
\|\mathrm{H}\|_{\mathrm{p}}=\left[\frac{1}{2 \pi} \int_{0}^{2 \pi}|\mathrm{H}(\omega)|^{\mathrm{p}} \mathrm{~d} \omega\right]^{\frac{1}{\mathrm{p}}}
$$

where p can be either $\infty$ or 2 . See the references for details. This scaling is an attempt to minimize overflow or peak round-off noise in fixed point filter implementations.

If there is more than one input to the system, ss2sos gives the following error message.
State-space system must have only one input.
cplxpair, sos2ss, ss2tf, ss2zp, tf2sos, zp2sos

References [1] J ackson, L.B., Digital Filters and Signal Processing, 3rd ed., Kluwer Academic Publishers, Boston, 1996. Chapter 11.
[2] Mitra, S.K., Digital Signal Processing: A Computer-Based Approach, McGraw-Hill, New York, 1998. Chapter 9.
[3] Vaidyanathan, P.P.,"Robust Digital Filter Structures," Handbook for Digital Signal Processing, S.K. Mitra and J.F. Kaiser, ed., J ohn Wiley \& Sons, New York, 1993, Chapter 7.

Purpose Convert state-space filter parameters to transfer function form

## Syntax $\quad[b, a]=\operatorname{ss2tf}(A, B, C, D, i u)$

Description

Algorithm

See Also
ss2tf converts a state-space representation of a given system to an equivalent transfer function representation.
$[b, a]=\operatorname{ss2tf}(A, B, C, D, i u)$ returns the transfer function

$$
H(s)=\frac{B(s)}{A(s)}=C(s l-A)^{-1} B+D
$$

of the system

$$
\begin{aligned}
& x=A x+B u \\
& y=C x+D u
\end{aligned}
$$

from the iu-th input. Vector a contains the coefficients of the denominator in descending powers of $s$. The numerator coefficients are returned in array $b$ with as many rows as there are outputs y. ss2tf also works with systems in discrete time, in which case it returns the z-transform representation.

The ss2tf function is part of the standard MATLAB Ianguage.
The ss2tf function uses poly to find the characteristic polynomial det(sl-A) and the equality

$$
H(s)=C(s l-A)^{-1} B=\frac{\operatorname{det}(s l-A+B C)-\operatorname{det}(s l-A)}{\operatorname{det}(s l-A)}
$$

latc2tf, sos2tf, ss2sos, ss2zp, tf2ss, zp2tf

## Purpose <br> Convert state-space filter parameters to zero-pole-gain form

## Syntax

$[z, p, k]=\operatorname{ss2zp}(A, B, C, D, i)$

Description

## Example

ss2zp converts a state-space representation of a given system to an equivalent zero-pole-gain representation. The zeros, poles, and gains of state-space systems represent the transfer function in factored form.
$[z, p, k]=\operatorname{ss2zp}(A, B, C, D, i)$ calculates the transfer function in factored form

$$
H(s)=\frac{Z(s)}{P(s)}=k \frac{\left(s-z_{1}\right)\left(s-z_{2}\right) \cdots\left(s-z_{n}\right)}{\left(s-p_{1}\right)\left(s-p_{2}\right) \cdots\left(s-p_{n}\right)}
$$

of the continuous-time system

$$
\begin{aligned}
& x=A x+B u \\
& y=C x+D u
\end{aligned}
$$

from the ith input (using the ith columns of $B$ and $D$ ). The column vector $p$ contains the pole locations of the denominator coefficients of the transfer function. The matrix z contains the numerator zeros in its columns, with as many columns as there are outputs y (rows in C ). The column vector k contains the gains for each numerator transfer function.
ss2zp also works for discretetime systems. The input state-space system must be real.

The ss2zp function is part of the standard MATLAB Ianguage.
Here are two ways of finding the zeros, poles, and gains of a discrete-time transfer function

$$
\begin{aligned}
& \mathrm{H}(\mathrm{z})=\frac{2+3 \mathrm{z}^{-1}}{1+0.4 \mathrm{z}^{-1}+\mathrm{z}^{-2}} \\
& \mathrm{~b}=\left[\begin{array}{ll}
2 & 3
\end{array}\right] ; \\
& \mathrm{a}=\left[\begin{array}{ll}
1 & 0.4 \\
1
\end{array}\right] ; \\
& {[\mathrm{b}, \mathrm{a}]=\text { eqtflength }(\mathrm{b}, \mathrm{a}) ;} \\
& {[\mathrm{z}, \mathrm{p}, \mathrm{k}]=\operatorname{tf2zp}(\mathrm{b}, \mathrm{a})}
\end{aligned}
$$

```
z =
    0.0000
    -1.5000
p =
    -0.2000 + 0.9798i
    -0.2000 - 0.9798i
k =
    2
[A,B,C,D] = tf2ss(b,a);
[z,p,k] = ss2zp(A,B,C,D,1)
z =
        0.0000
        -1.5000
p =
    -0.2000 + 0.9798i
    -0.2000 - 0.9798i
k =
    2
```


## Algorithm

See Also pzmap, sos2zp, ss2sos, ss2tf, tf2zp, zp2ss
References finite solutions to a generalized eigenvalue problem.

```
z = eig([A B;C D], diag([ones(1,n) 0]);
``` ss2zp interprets these large zeros as infinite.
ss2zp finds the poles from the eigenvalues of the A array. The zeros are the

In many situations this algorithm produces spurious large, but finite, zeros.
ss2zp finds the gains by solving for the first nonzero Markov parameters.
[1] Laub, A.J ., and B.C. M oore, "Calculation of Transmission Zeros Using QZ Techniques," Automatica 14 (1978), p. 557.

\section*{Purpose Compute a linear model using Steiglitz-McBride iteration}

\section*{Syntax}
```

[b,a] = stmcb(h,nb,na)
[b,a] = stmcb(y,x,nb,na)
[b,a] = stmcb(h,nb,na,niter)
[b,a] = stmcb(y,x,nb,na,niter)
[b,a] = stmcb(h,nb,na,niter,ai)
[b,a] = stmcb(y,x,nb,na,niter,ai)

```

\section*{Description}

Steiglitz-McBride iteration is an algorithm for finding an IIR filter with a prescribed time domain impulse response. It has applications in both filter design and system identification (parametric modeling).
\([b, a]=\operatorname{stmcb}(h, n b, n a)\) finds the coefficients \(b\) and \(a\) of the system \(b(z) / a(z)\) with approximate impulse response \(h\), exactly nb zeros, and exactly na poles.
\([b, a]=\operatorname{stmcb}(y, x, n b, n a)\) finds the system coefficients \(b\) and \(a\) of the system that, given \(x\) as input, has \(y\) as output. \(x\) and \(y\) must be the same length.
[b,a] = stmcb(h,nb, na, niter) and
\([b, a]=\operatorname{stmcb}(y, x, n b, n a\), niter \()\) useniter iterations. The default for niter is 5 .
\([b, a]=\operatorname{stmcb}(h, n b, n a\), niter, ai) and
[b,a] = stmcb(y,x,nb,na,niter, ai) usethevector ai as theinitial estimate of the denominator coefficients. If ai is not specified, stmcb uses the output argument from [b, ai] = prony (h, \(0, n a\) ) as the vector ai.
stmcb returns the IIR filter coefficients in length nb+1 and na+1 row vectors b and \(a\). The filter coefficients are ordered in descending powers of \(z\).
\[
H(z)=\frac{B(z)}{A(z)}=\frac{b(1)+b(2) z^{-1}+\cdots+b(n b+1) z^{-n b}}{a(1)+a(2) z^{-1}+\cdots+a(n a+1) z^{-n a}}
\]

Approximate the impulse response of a Butterworth filter with a system of lower order.
```

[b,a] = butter(6,0.2);
h = filter(b,a,[1 zeros(1,100)]);
freqz(b,a,128)

```


[bb,aa] \(=\operatorname{stmcb}(h, 4,4)\); freqz(bb, aa, 128)


\begin{tabular}{|c|c|}
\hline Algorithm & \begin{tabular}{l}
stmcb attempts to minimize the squared error between the impulse responseh of \(b(z) / a(z)\) and the input signal \(x\).
\[
\min _{a, b} \sum_{i=0}^{\infty}|x(i)-h(i)|^{2}
\] \\
stmcb iterates using two steps: \\
1 It prefilters h and x using \(1 / \mathrm{a}(\mathrm{z})\). \\
2 It solves a system of linear equations for \(b\) and \(a\) using \(\backslash\). \\
stmcb repeats this process niter times. No checking is doneto see if the b and a coefficients have converged in fewer than niter iterations.
\end{tabular} \\
\hline Diagnostics & If \(x\) and \(y\) have different lengths, stmcb produces this error message, Input signal X and output signal Y must have the same length. \\
\hline See Also & levinson, lpc, aryule, prony \\
\hline References & \begin{tabular}{l}
[1] Steiglitz, K., and L.E. McB ride, "A Techniquefor the Identification of Linear Systems," IEEE Trans. Automatic Control, Vol. AC-10 (1965), pp. 461-464. \\
[2] Ljung, L., System Identification: Theory for the User, Prentice-H all, Englewood Cliffs, NJ, 1987, p. 297.
\end{tabular} \\
\hline
\end{tabular}

\section*{Purpose Strip plot}

\section*{Syntax strips(x)}
strips( \(x, n\) )
strips( \(x\), sd,fs)
strips(x,sd,fs,scale)

Description

Example
strips (x) plots vector x in horizontal strips of length 250. If x is a matrix, strips ( \(x\) ) plots each column of \(x\). The left-most column (column 1) is the top horizontal strip.
strips ( \(x, n\) ) plots vector \(x\) in strips that are each \(n\) samples long.
strips ( \(\mathrm{x}, \mathrm{sd}, \mathrm{fs}\) ) plots vector x in strips of duration sd seconds, given a sampling frequency of fs samples per second.
strips ( \(x\), sd, fs, scale) scales the vertical axes.
If \(x\) is a matrix, \(\operatorname{strips(x,n),~strips(x,sd,fs),~and~strips(x,sd,fs,scale)~}\) plot the different columns of \(x\) on the same strip plot.
strips ignores the imaginary part of complex-valued \(x\).
Plot two seconds of a frequency modulated sinusoid in 0.25 second strips.
```

fs = 1000; % Sampling frequency
t = 0:1/fs:2; % Time vector
x = vco(sin(2*pi*t),[10 490],fs); % FM waveform
strips(x,0.25,fs)

```

Purpose Convert transfer function filter parameters to lattice filter form
Syntax

[k,v] = tf2latc(b,a)

k = tf2latc(1,a)

[k,v] = tf2latc(1,a)

k = tf2latc(b)

k = tf2latc(b,'phase')
See Also latc2tf, latcfilt, tf2sos, tf2ss, tf2zp

\section*{Description}
[ \(k, v\) ] = tf2latc \((b, a)\) finds the lattice parameters \(k\) and the ladder parameters \(v\) for an IIR (ARMA) lattice-ladder filter, normalized by a (1). Note that an error is generated if one or more of the lattice parameters are exactly equal to 1.
\(\mathrm{k}=\mathrm{tf} 2 \mathrm{latc}(1, \mathrm{a})\) finds the lattice parameters k for an IIR all-pole (AR) lattice filter.
\([k, v]=\) tf2latc (1, a) returns the scalar ladder coefficient at the correct position in vector \(v\). All other elements of \(v\) are zero.
\(k=t f 2 l a t c(b)\) finds the lattice parameters \(k\) for an FIR (MA) lattice filter, normalized by \(b(1)\).
k = tf2latc (b, 'phase') specifies the type of FIR (MA) lattice filter, where 'phase' is
- 'max', for a maximum phase filter.
- 'min', for a minimum phase filter.

\section*{Purpose}

\section*{Syntax}

\section*{Description}

Convert digital filter transfer function data to second-order sections form
```

[sos,g] = tf2sos(b,a)
[sos,g] = tf2sos(b,a,'order')
[sos,g] = tf2sos(b,a,'order','scale')
sos = tf2sos(...)

```
tf2sos converts a transfer function representation of a given digital filter to an equivalent second-order section representation.
[sos,g] = tf2sos(b,a) finds a matrix sos in second-order section form with gain \(g\) that is equivalent to the digital filter represented by transfer function coefficient vectors a and b .
\[
H(z)=\frac{B(z)}{A(z)}=\frac{b_{1}+b_{2} z^{-1}+\cdots+b_{n+1} z^{-n}}{a_{1}+a_{2} z^{-1}+\cdots+a_{m+1} z^{-m}}
\]
sos is an L-by-6 matrix
\[
\text { sos }=\left[\begin{array}{cccccc}
b_{01} & b_{11} & b_{21} & 1 & a_{11} & a_{21} \\
b_{02} & b_{12} & b_{22} & 1 & a_{12} & a_{22} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
b_{0 L} & b_{1 L} & b_{2 L} & 1 & a_{1 L} & a_{2 L}
\end{array}\right]
\]
whose rows contain the numerator and denominator coefficients \(\mathrm{b}_{i k}\) and \(\mathrm{a}_{i k}\) of the second-order sections of \(\mathrm{H}(\mathrm{z})\).
\[
H(z)=g \prod_{k=1}^{L} H_{k}(z)=g \prod_{k=1}^{\llcorner } \frac{b_{0 k}+b_{1 k^{\prime}} z^{-1}+b_{2 k} z^{-2}}{1+a_{1 k^{2}} z^{-1}+a_{2 k} z^{-2}}
\]
[sos,g] = tf2sos(b,a,'order') specifies the order of the rows in sos, where 'order' is:
- 'down ', to order the sections so the first row of sos contains the poles closest to the unit circle
- ' up ' , to order the sections so the first row of sos contains the poles farthest from the unit circle (default)
[sos,g] = tf2sos(b,a, 'order','scale') specifies the desired scaling of the gain and numerator coefficients of all second-order sections, where 'scale' is:
- 'none ', to apply no scaling (default)
- 'inf ', to apply infinity-norm scaling
- 'two ' , to apply 2-norm scaling

Using infinity-norm scaling in conjunction with up-ordering minimizes the probability of overflow in the realization. Using 2-norm scaling in conjunction with down-ordering minimizes the peak round-off noise.
sos \(=\) tf2sos (...) embeds the overall system gain, \(g\), in the first section, \(\mathrm{H}_{1}(\mathrm{z})\), so that
\[
H(z)=\prod_{k=1}^{L} H_{k}(z)
\]

Algorithm tf2sos uses a four-step algorithm to determine the second-order section representation for an input transfer function system:

1 It finds the poles and zeros of the system given by \(b\) and \(a\).
2 It uses the function zp2sos, which first groups the zeros and poles into complex conjugate pairs using the cplxpair function. zp2sos then forms the second-order sections by matching the pole and zero pairs according to the following rules:
a Match the poles closest to the unit circle with the zeros closest to those poles.
b Match the poles next closest to the unit circle with the zeros closest to those poles.
c Continue until all of the poles and zeros are matched.
tf2sos groups real poles into sections with the real poles closest to them in absolute value. The same rule holds for real zeros.
3 It orders the sections according to the proximity of the pole pairs to the unit circle. tf2sos normally orders the sections with poles closest to the unit circle last in the cascade. Y ou can tell tf2sos to order the sections in the reverse order by specifying the 'down' flag.

4 tf2sos scales the sections by the norm specified in the 'scale' argument. For arbitrary \(\mathrm{H}(\omega)\), the scaling is defined by
\[
\|H\|_{p}=\left[\frac{1}{2 \pi} \int_{0}^{2 \pi}|H(\omega)|^{p} d \omega\right]^{\frac{1}{p}}
\]
where \(p\) can be either \(\infty\) or 2 . See the references for details on the scaling. This scaling is an attempt to minimize overflow or peak round-off noise in fixed point filter implementations.

See Also cplxpair, sos2tf, ss2sos, tf2ss, tf2zp, zp2sos
References [1]J ackson, L.B., Digital Filters and Signal Processing, 3rd ed., Kluwer Academic Publishers, Boston, 1996, Chapter 11.
[2] Mitra, S.K., Digital Signal Processing: A Computer-Based Approach, McGraw-Hill, New York, 1998, Chapter 9.
[3] Vaidyanathan, P.P., "Robust Digital Filter Structures," Handbook for Digital Signal Processing, S.K. Mitra and J.F. Kaiser, ed., J ohn Wiley \& Sons, New Y ork, 1993, Chapter 7.

\section*{Purpose}

\section*{Syntax}

Description

Example

Convert transfer function filter parameters to state-space form
```

[A,B,C,D] = tf2ss(b,a)

```
tf2ss converts the parameters of a transfer function representation of a given system to those of an equivalent state-space representation.
\([A, B, C, D]=t f 2 s s(b, a)\) returns the \(A, B, C\), and \(D\) matrices of a state space representation for the single-input transfer function
\[
H(s)=\frac{B(s)}{A(s)}=\frac{b_{1} s^{n-1}+\cdots+b_{n-1} s+b_{n}}{a_{1} s^{m-1}+\cdots+a_{m-1} s+a_{m}}=C(s l-A)^{-1} B+D
\]
in controller canonical form
\[
\begin{aligned}
& x=A x+B u \\
& y=C x+D u
\end{aligned}
\]

The input vector a contains the denominator coefficients in descending powers of \(s\). The rows of the matrix \(b\) contain the vectors of numerator coefficients (each row corresponds to an output). In thediscrete-time case, you must supply b and a to correspond to the numerator and denominator polynomials with coefficients in descending powers of \(z\).

For discrete-time systems you must make b have the same number of columns as the length of \(a\). You can dothis by padding each numerator represented in b (and possibly the denominator represented in the vector a) with trailing zeros. You can use the function eqtflength to accomplish this if b and a are vectors of unequal lengths.

The tf2ss function is part of the standard MATLAB language.
Consider the system
\[
H(s)=\frac{\left[\begin{array}{c}
2 s+3 \\
s^{2}+2 s+1
\end{array}\right]}{s^{2}+0.4 s+1}
\]

To convert this system to state-space, type
```

b = [0 2 3; 1 2 1];
a = [1 0.4 1];
[A,B,C,D] = tf2ss(b,a)
A =
-0.4000 -1.0000
1.0000 0
B =
1
0
C =
2.0000 3.0000
1.6000 0
D =
0
1

```

Note There is disagreement in the literature on naming conventions for the canonical forms. It is easy, however, to generate similarity transformations that convert these results to other forms.

See Also sos2ss, ss2tf, tf2sos, tf2zp, zp2ss

Purpose

\section*{Syntax \(\quad[z, p, k]=\operatorname{tf2zp}(b, a)\)}

Description

Convert transfer function filter parameters to zero-pole-gain form
tf2zp finds the zeros, poles, and gains of a transfer function.
\([z, p, k]=t f 2 z p(b, a)\) finds the matrix of zeros \(z\), the vector of poles \(p\), and the associated vector of gains \(k\) from the transfer function parameters \(b\) and \(a\) :
- The numerator polynomials are represented as columns of the matrix \(b\).
- The denominator polynomial is represented in the vector a.

Given a SIMO continuous-time system in polynomial transfer function form
\[
H(s)=\frac{B(s)}{A(s)}=\frac{b_{1} s^{n-1}+\cdots+b_{n-1} s+b_{n}}{a_{1} s^{m-1}+\cdots+a_{m-1} s+a_{m}}
\]
or
\[
H(z)=\frac{B(z)}{A(z)}=\frac{b_{1}+b_{2} z^{-1} \cdots+b_{n-1} z^{-n}+b_{n} z^{-n-1}}{a_{1}+a_{2} z^{-1} \cdots+a_{m-1} z^{-m}+a_{m} z^{-m-1}}
\]
you can use the output of tf2zp to produce the single-input, multioutput (SIMO) factored transfer function form
\[
H(s)=\frac{Z(s)}{P(s)}=k \frac{\left(s-z_{1}\right)\left(s-z_{2}\right) \cdots\left(s-z_{m}\right)}{\left(s-p_{1}\right)\left(s-p_{2}\right) \cdots\left(s-p_{n}\right)}
\]
or
\[
H(z)=\frac{Z(z)}{P(z)}=k \frac{\left(z-z_{1}\right)\left(z-z_{2}\right) \cdots\left(z-z_{m}\right)}{\left(z-p_{1}\right)\left(z-p_{2}\right) \cdots\left(z-p_{n}\right)}
\]

The following describes the input and output arguments for tf2zp:
- The vector a specifies the coefficients of the denominator polynomial \(A(s)\) (or \(A(z)\) ) in descending powers of \(s\left(z^{-1}\right)\).
- The ith row of the matrix b represents the coefficients of the ith numerator polynomial (the ith row of \(\mathrm{B}(\mathrm{s})\) or \(\mathrm{B}(\mathrm{z})\) ). Specify as many rows of b as there are outputs.
- F or continuous-timesystems, choose the number nb of columns of \(b\) to be less than or equal to the length na of the vector a.
- F or discrete-time systems, choose the number nb of columns of \(b\) to be equal to the length na of the vector a. You can use the function eqtflength to provide equal length vectors in the case that \(b\) and a are vectors of unequal lengths. Otherwise, pad the numerators in the matrix b (and, possibly, the denominator vector a) with zeros.
- The zero locations are returned in the columns of the matrix \(z\), with as many columns as there are rows in b .
- The pole locations are returned in the column vector \(p\) and the gains for each numerator transfer function in the vector \(k\).

The tf2zp function is part of the standard MATLAB Ianguage.
Example Find the zeros, poles, and gains of the discrete-time system
```

H}(z)=\frac{2+3\mp@subsup{z}{}{-1}}{1+0.4\mp@subsup{z}{}{-1}+\mp@subsup{z}{}{-2}
b = [2 3];
a = [1 0.4 1];
[b,a] = eqtflength(b,a); % Make lengths equal.
[z,p,k] = tf2zp(b,a) % Obtain the zero-pole-gain form.

```
```

z =
0
-1.5000
p =
-0.2000 + 0.9798i
-0.2000 - 0.9798i
k =
2

```

See Also
sos2zp, ss2zp, tf2sos, tf2ss, zp2tf

\section*{Purpose \\ Estimate the transfer function from input and output}

\section*{Syntax}
```

$T x y=\operatorname{tfe}(x, y)$
Txy $=$ tfe( $x, y, n f f t)$
[Txy,f] $=t f e(x, y, n f f t, f s)$
Txy $=$ tfe(x,y,nfft,fs,window)
Txy $=$ tfe(x,y,nfft,fs,window, numoverlap)
Txy $=$ tfe(x,y,...,'dflag')
tfe(x,y)

```

\section*{Description}

Txy = tfe( \(x, y\) ) finds a transfer function estimate Txy given input signal vector \(x\) and output signal vector \(y\). The transfer function is the quotient of the cross spectrum of \(x\) and \(y\) and the power spectrum of \(x\).
\[
T_{x y}(f)=\frac{P_{x y}(f)}{P_{x x}(f)}
\]

The relationship between the input \(x\) and output \(y\) is modeled by the linear, time-invariant transfer function Txy.

Vectors \(x\) and \(y\) must be the same length. Txy \(=t f e(x, y)\) uses the following default values:
- nfft = min(256,(length(x))
- fs = 2
- window is a periodic Hann (Hanning) window of length nfft
- numoverlap = 0
nfft specifies the FFT length that tfe uses. This value determines the frequencies at which the power spectrum is estimated. fs is a scalar that specifies the sampling frequency. window specifies a windowing function and the number of samples tfe uses in its sectioning of the \(x\) and \(y\) vectors. numoverlap is the number of samples by which the sections overlap. Any arguments that are omitted from the end of the parameter list use the default values shown above.

If \(x\) is real, tfe estimates the transfer function at positive frequencies only; in this case, the output Txy is a column vector of length nfft/2+1 for nfft even and ( \(\mathrm{nfft}+1\) )/2 for nfft odd. If x or y is complex, tfe estimates the transfer function for both positive and negative frequencies and Txy has length nfft.

Txy \(=t f e(x, y, n f f t)\) uses the specified FFT length nfft in estimating the transfer function.
\([T x y, f]=t f e(x, y, n f f t, f s)\) returns a vector \(f\) of frequencies at which tfe estimates thetransfer function. \(f s\) is the sampling frequency. \(f\) is the same size as Txy, so plot ( \(\mathrm{f}, \mathrm{Txy}\) ) plots the transfer function estimate versus properly scaled frequency. fs has no effect on the output Txy; it is a frequency scaling multiplier.
\(T x y=t f e(x, y, n f f t, f s, w i n d o w)\) specifies a windowing function and the number of samples per section of the x vector. If you supply a scalar for window, Txy uses a Hann window of that length. The length of the window must be less than or equal to nfft ; tfe zero pads the sections if the length of the window exceeds nfft .

Txy = tfe(x,y,nfft,fs,window, numoverlap) overlaps the sections of \(x\) by numoverlap samples.

You can use the empty matrix [ ] to specify the default value for any input argument except x or y . For example,

Txy \(=\operatorname{tfe}(x, y,[],[], k a i s e r(128,5))\)
uses 256 as the value for \(n f f t\) and 2 as the value for fs .
Txy \(=\) tfe( \(\left.x, y, \ldots,{ }^{\prime} d f l a g '\right)\) specifies a detrend option, where 'dflag' is:
- 'linear', to remove the best straight-linefit from the prewindowed sections of \(x\) and \(y\)
- 'mean ', to remove the mean from the prewindowed sections of \(x\) and \(y\)
- ' none ', for no detrending (default)

The 'dflag ' parameter must appear last in the list of input arguments. tfe recognizes a 'dflag' string no matter how many intermediate arguments are omitted.
tfe(...) with no output arguments plots the magnitude of the transfer function estimate as decibels versus frequency in the current figure window.

\section*{Example}

Compute and plot the transfer function estimate between two col ored noise sequences \(x\) and \(y\).
```

h = fir1(30,0.2,rectwin(31));
x = randn(16384,1);
y = filter(h,1,x);
tfe(x,y,1024,[],[],512)
title('Transfer Function Estimate')

```


\section*{Algorithm}
tfe uses a four-step algorithm:
1 It multiplies the detrended sections by window.
2 It takes the length nfft FFT of each section.
3 It averages the squares of the spectra of the \(x\) sections to form Pxx and averages the products of the spectra of the \(x\) and \(y\) sections to form Pxy.
4 It calculates Txy:
Txy = Pxy./Pxx
Diagnostics An appropriate diagnostic message is displayed when incorrect arguments are used.
Requires window's length to be no greater than the FFT length.
Requires NOVERLAP to be strictly less than the window length.
Requires positive integer values for NFFT and NOVERLAP.
Requires vector (either row or column) input.
Requires inputs \(X\) and \(Y\) to have the same length.
See Also etfe, cohere, csd, pwelch, spa

\section*{Purpose Compute a triangular window}

\section*{Syntax \\ w = triang (n)}

Description triang \((\mathrm{n})\) returns an \(n\)-point triangular window in the column vector \(w\). The coefficients of a triangular window are

For n odd:
\[
w[k]= \begin{cases}\frac{2 k}{n+1}, & 1 \leq k \leq \frac{n+1}{2} \\ \frac{2(n-k+1)}{n+1}, & \frac{n+1}{2} \leq k \leq n\end{cases}
\]

For \(n\) even:
\[
w[k]= \begin{cases}\frac{2 k-1}{n}, & 1 \leq k \leq \frac{n}{2} \\ \frac{2(n-k+1)}{n}, & \frac{n}{2}+1 \leq k \leq n\end{cases}
\]

The triangular window is very similar to a Bartlett window. The Bartlett window always ends with zeros at samples 1 and \(n\), while the triangular window is nonzero at those points. For \(n\) odd, the center \(n-2\) points of triang ( \(n-2\) ) are equivalent to bartlett ( \(n\) ).

\section*{Example}
```

N=200;
w = triang(200);
plot(w);
title('Triangular Window')

```


\section*{See Also}

\section*{References}
bartlett, barthannwin, blackman, blackmanharris, bohmanwin, chebwin, gausswin, hamming, hann, kaiser, nuttallwin, rectwin, tukeywin, window
[1] Oppenheim, A.V., and R.W. Schafer, Discrete-TimeSignal Processing, Prentice-Hall, Englewood Cliffs, NJ , 1989, pp. 447-448.
Purpose Generate a sampled aperiodic triangle
Syntax y = tripuls( T )
y = tripuls( \(\mathrm{T}, \mathrm{w}\) )
y = tripuls(T,w,s)
Description \(y=\) tripuls( \(T\) ) returns a continuous, aperiodic, symmetric, unity-heighttriangular pulse at the times indicated in array T , centered about \(\mathrm{T}=0\) and witha default width of 1 .\(y=\operatorname{tripuls}(T, w)\) generates a triangular pulse of width \(w\).\(y=\operatorname{tripuls}(T, w, s)\) generates a triangular pulse with skew s, where\(-1<\mathrm{s}<1\). When s is 0 , a symmetric triangular pulse is generated.
See Also chirp, cos, diric, gauspuls, pulstran, rectpuls, sawtooth, sin, square, tripuls

\section*{Purpose \\ Compute a Tukey window}

\section*{Syntax}

Description

Example

Algorithm
w = tukeywin ( \(\mathrm{n}, \alpha\) ) a hann window.
w = tukeywin( \(n, r\) ) returns an n-point, Tukey window in column vector w. Tukey windows are cosine-tapered windows. \(\alpha\) is the ratio of taper to constant sections and is between 0 and 1 define. \(\alpha \leq 0\) is a rectwin window and \(\alpha \geq 1\) is

Compute 128-point Tukey windows with five different tapers.
```

wtuk = [];
for i = linspace(0,1,5)
wtuk = [wtuk tukeywin(128,i)];
end
plot(linspace(0,1,128),wtuk)
axis([0 1 0 1.05 ] );
legend('R=0 Rect.','R=1/4','R=1/2','R=3/4','R=1 Hanning',0);
title('Tukey Windows for Five Taper Ratio Values');

```


The equation for computing the coefficients of a Tukey window is
\[
w[k+1]= \begin{cases}1.0, & 0 \leq|k| \leq \frac{N}{2}(1+\alpha) \\ 0.5\left[1.0+\cos \left[\pi \frac{k-\frac{N}{2}(1+\alpha)}{N(1-\alpha)}\right]\right], & \frac{N}{2}(1+\alpha) \leq|k| \leq N\end{cases}
\]

\section*{See Also}

References
barthannwin, bartlett, blackman, blackmanharris, bohmanwin, chebwin, gausswin, hann, hamming, kaiser, nuttallwin, rectwin, triang, window
[1] harris, f. j. "On the Use of Windows for HarmonicAnalysis with the Discrete Fourier Transform." Proceedings of the IEEE. Vol. 66 (J anuary 1978). pp. 66-67.

Purpose Decode \(2^{n}\)-level quantized integer inputs to floating-point outputs
Syntax \(\quad\)\begin{tabular}{l}
\(y=\operatorname{udecode}(u, n)\) \\
\(y=\operatorname{udecode}(u, n, v)\) \\
\(y\)
\end{tabular}\(=\operatorname{udecode}\left(u, n, v\right.\), ' saturatemode \(\left.^{\prime}\right)\)

Description \(\quad y=\operatorname{udecode}(u, n)\) inverts the operation of uencode and reconstructs quantized floating-point values from an encoded multidimensional array of integers \(u\). The input argument \(n\) must be an integer between 2 and 32 . The integer \(n\) specifies that there are \(2^{n}\) quantization levels for the inputs, so that entries in u must be either:
- Signed integers in the range \(\left[-2^{n} / 2,\left(2^{n} / 2\right)-1\right]\)
- Unsigned integers in the range [0, \(\left.2^{\mathrm{n}}-1\right]\)

Inputs can be real or complex values of any integer data type (uint8, uint16, uint32, int8, int16, int32). Overflows (entries in u outside of the ranges specified above) are saturated to the endpoints of the range interval. The output \(y\) has the same dimensions as \(u\). Its entries have values in the range \([-1,1]\).
\(y=u d e c o d e(u, n, v)\) decodes \(u\) such that the output \(y\) has values in the range \([-v, v\) ], where the default value for \(v\) is 1 .
\(y=u d e c o d e(u, n, v, ' S a t u r a t e M o d e ')\) decodes \(u\) and treats input overflows (entries in u outside of \([-\mathrm{v}, \mathrm{v}]\) ) according to the string ' saturatemode' ', which can be one of the following:
- 'saturate' : Saturate overflows. This is the default method for treating overflows.
- Entries in signed inputs \(u\) whose values are outside of the range \(\left[-2^{n} / 2,\left(2^{n} / 2\right)-1\right]\) are assigned the value determined by the closest endpoint of this interval.
- Entries in unsigned inputs u whose values are outside of the range [ \(0,2^{\mathrm{n}}-1\) ] are assigned the value determined by the closest endpoint of this interval.
- 'wrap ': Wrap all overflows according to the following:
- Entries in signed inputs u whose values are outside of the range \(\left[-2^{n} / 2,\left(2^{n} / 2\right)-1\right]\) are wrapped back into that range using modulo \(2^{n}\) arithmetic (calculated using \(u=\bmod \left(u+2^{\wedge} n / 2,2^{\wedge} n\right)-\left(2^{\wedge} n / 2\right)\) ).
- Entries in unsigned inputs \(u\) whose values are outside of the range [ \(\left.0,2^{n}-1\right]\) are wrapped back into the required range before decoding using modulo \(2^{n}\) arithmetic (calculated using \(u=\bmod \left(u, 2^{\wedge} n\right)\) ).

\section*{Examples}

\section*{Algorithm}
```

u = int8([-1 1 2 -5]); % Create a signed 8-bit integer string.
ysat = udecode(u,3) % Decode with 3 bits.
ysat =
-0.2500 0.2500 0.5000 -1.0000

```

Notice the last entry in u saturates to 1, the default peak input magnitude. Change the peak input magnitude.
```

ysatv = udecode(u,3,6) % Set the peak input magnitude to 6.
ysatv =

```
    \(\begin{array}{llll}-1.5000 & 1.5000 & 3.0000 & -6.0000\end{array}\)

The last input entry still saturates. Try wrapping the overflows.
ywrap \(=\) udecode(u,3,6,'wrap')
ywrap =
\(\begin{array}{llll}-1.5000 & 1.5000 & 3.0000 & 4.5000\end{array}\)
Try adding more quantization levels.
```

yprec = udecode(u,5)
yprec =
-0.0625 0.0625 0.1250 -0.3125

```

The al gorithm adheres to the definition for uniform decoding specified in ITU-T Recommendation G.701. Integer input values are uniquely mapped (decoded) from one of \(2^{n}\) uniformly spaced integer values to quantized floating-point values in the range \([-v, v]\). The smallest integer input value allowed is mapped to \(-v\) and the largest integer input value allowed is mapped to \(v\).

\section*{udecode}

Values outside of the allowable input range are either saturated or wrapped, according to specification.

The real and imaginary components of complex inputs are decoded independently.

\section*{See Also uencode}

References General Aspects of Digital Transmission Systems: Vocabulary of Digital Transmission and Multiplexing, and PulseCodeModulation (PCM) Terms, International Telecommunication Union, ITU-T Recommendation G.701, March, 1993.

\section*{Purpose \\ Quantize and encode floating-point inputs to integer outputs}
```

Syntax y = uencode(u,n)
y = uencode(u,n,v)
y = uencode(u,n,v,'SignFlag')

```

Description \(\quad y=\operatorname{uencode}(u, n)\) quantizes the entries in a multidimensional array of floating-point numbers \(u\) and encodes them as integers using \(2^{\text {n }}\)-level quantization. \(n\) must be an integer between 2 and 32 (inclusive). Inputs can be real or complex, double- or single-precision. The output y and the input u are arrays of the same size. The elements of the output \(y\) are unsigned integers with magnitudes in the range [ \(0,2^{\mathrm{n}}-1\) ]. Elements of the input u outside of the range \([-1,1]\) are treated as overflows and are saturated.
- F or entries in the input u that are less than -1, the value of the output of uencode is 0 .
- F or entries in the input \(u\) that are greater than 1 , the value of the output of uencode is \(2^{\mathrm{n}}-1\).
\(y=u e n c o d e(u, n, v)\) allows the input \(u\) to have entries with floating-point values in therange [ \(-\mathrm{v}, \mathrm{v}\) ] before saturating them (the default valuefor v is 1 ). Elements of the input \(u\) outside of the range \([-v, v]\) are treated as overflows and are saturated.
- F or input entries less than \(-v\), the value of the output of uencode is 0 .
- F or input entries greater than \(v\), the value of the output of uencode is \(2^{n}-1\).
y = uencode(u,n,v,'SignFlag') maps entriesin a multidimensional array of floating-point numbers \(u\) whose entries have values in the range \([-\mathrm{v}, \mathrm{v}]\) to an integer output y . I nput entries outside this range are saturated. The integer type of the output depends on the string 'SignFlag' and the number of quantization levels \(2^{n}\). The string 'SignFlag' can be one of the following:
- 'signed': Outputs are signed integers with magnitudes in the range \(\left[-2^{n} / 2,\left(2^{n} / 2\right)-1\right]\).
- ' unsigned ' (default): Outputs are unsigned integers with magnitudes in the range \(\left[0,2^{\mathrm{n}}-1\right]\).

The output data types are optimized for the number of bits as shown in the table below.
\begin{tabular}{c|c|c}
\hline \(\mathbf{n}\) & Unsigned Integer & Signed Integer \\
\hline 2 to 8 & uint8 & int8 \\
\hline 9 to 16 & uint16 & int16 \\
\hline 17 to 32 & uint32 & int32 \\
\hline
\end{tabular}

\section*{Examples}

Map floating-point scalars in [-1, 1] to uint8 (unsigned) integers, and produce a staircase plot. N ote that the horizontal axis plots from-1 to 1 and the vertical axis plots from 0 to \(7\left(2^{\wedge} 3-1\right)\).
```

u = [-1:0.01:1];
y = uencode(u,3);
plot(u,y,'.')

```


Now look at saturation effects when you under specify the peak value for the input.
```

u = [-2:0.5:2];
y = uencode(u,5,1)
y =
0

```

Now look at the output for
\(u=[-2: 0.5: 2] ;\)
\(y=\) uencode(u, 5, 2, 'signed')
\(y=\)
\(\begin{array}{lllllllll}-8 & -4 & 0 & 4 & 8 & 12 & 16 & 20 & 23\end{array}\)

Algorithm

See Also udecode
References General Aspects of Digital Transmission Systems: Vocabulary of Digital Transmission and Multiplexing, and PulseCodeModulation (PCM) Terms, International Telecommunication Union, ITU-T Recommendation G.701, March, 1993.
Purpose Unwrap phase angles
Syntax ..... \(p=\operatorname{unwrap}(p)\)
Description \(p=\) unwrap \((p)\) corrects the phase angles in vector \(p\) by adding multiples of\(\pm 2 \pi\), where needed, to smooth the transitions across branch cuts. When \(p\) is amatrix, unwrap corrects the phase angles down each column. The phase mustbe in radians.
The unwrap function is part of the standard MATLAB Ianguage.
Limitations unwrap tries to detect branch cut crossings, but it can be fooled by sparse, rapidly changing phase values.
See Also ..... abs, angle
\begin{tabular}{ll} 
Purpose & Upsample, apply an FIR filter, and downsample \\
Syntax & \begin{tabular}{l} 
yout \(=\operatorname{upfirdn}(x i n, h)\) \\
\\
yout \(=\operatorname{upfirdn}(\operatorname{xin}, h, p)\) \\
\\
\\
\\
\\
\\
\end{tabular} yout \(=\operatorname{upfirdn}(x i n, h, p, q)\)
\end{tabular}

\section*{Description}
upfirdn performs a cascade of three operations:
1 Upsampling the input data in the matrix xin by a factor of the integer \(p\) (inserting zeros)
2 FIR filtering the upsampled signal data with theimpulseresponse sequence given in the vector or matrix \(h\)
3 Downsampling the result by a factor of the integer q (throwing away samples)
upfirdn has been implemented as a MEX-file for maximum speed, so only the outputs actually needed are computed. The FIR filter is usually a lowpass filter, which you must design using another function such as remez or fir1.

Note The function resample performs an FIR design using firls, followed by rate changing implemented with upfirdn.
yout \(=\) upfirdn(xin, h) filters the input signal xin with theFIR filter having impulse response \(h\). If xin is a row or column vector, then it represents a single signal. If xin is a matrix, then each column is filtered independently. If h is a row or column vector, then it represents one FIR filter. If h is a matrix, then each column is a separate FIR impulse response sequence. If yout is a row or column vector, then it represents one signal. If yout is a matrix, then each column is a separate output. No upsampling or downsampling is implemented with this syntax.
yout \(=\) upfirdn(xin, \(h, p\) ) specifies the integer upsampling factor \(p\), where \(p\) has a default value of 1 .
yout \(=\) upfirdn(xin, h, p,q) specifies the integer downsampling factor q, where \(q\) has a default value of 1 .
[yout, zf] = upfirdn(xin, h, ...,zi) specifies initial state conditions in the vector zi.

The size of the initial condition vector zi must be the sameas length (h) - 1 , the number of delays in the FIR filter.

When xin is a vector, the size of the final condition vector \(z f\) is length \((h)-1\), the number of delays in the filter. When xin is a matrix, zf is an matrix with (length(h)-1) rows and (size(xin,2)) columns.

Note Since upfirdn performs convolution and rate changing, the yout signals have a different length than xin. The number of rows of yout is approximately \(\mathrm{p} / \mathrm{q}\) times the number of rows of xin.

\section*{Remarks}

Usually the inputs xin and the filter \(h\) are vectors, in which case only one output signal is produced. However, when these arguments are arrays, each column is treated as a separate signal or filter. Valid combinations are:

1 xin is a vector and h is a vector.
There is one filter and one signal, so the function convolves xin with \(h\). The output signal yout is a row vector if xin is a row; otherwise, yout is a column vector.

2 xin is a matrix and h is a vector.
There is one filter and many signals, so the function convolves \(h\) with each column of xin. The resulting yout will be an matrix with the same number of columns as xin.
3 xin is a vector and \(h\) is a matrix.
There are many filters and onesignal, so the function convolves each column of \(h\) with xin. The resulting yout will be an matrix with the same number of columns as \(h\).
\(4 x\) in is a matrix and \(h\) is a matrix, both with the same number of columns. There are many filters and many signals, so the function convolves corresponding columns of xin and h . The resulting yout is an matrix with the same number of columns as \(x i n\) and \(h\).

\section*{Examples}

Algorithm

\section*{Diagnostics}

If both \(p\) and \(q\) are equal to 1 (that is, there is no rate changing), the result is ordinary convolution of two signals (equivalent to conv).
\[
y y=\operatorname{upfirdn}(x x, h h) ;
\]

This example implements a seven-channel filter bank by convolving seven different filters with one input signal, then downsamples by five.
```

% Assume that hh is an L-by-7 array of filters.
yy = upfirdn(xx,hh,1,5);

```

Implement a rate change from 44.1 kHz (CD sampling rate) to 48 kHz (DAT rate), a ratio of 160/147. This requires a lowpass filter with cutoff frequency at \(\omega_{C}=2 \pi / 160\).
```

% Design lowpass filter with cutoff at 1/160th of fs.
hh = fir1(300,2/160); % Need a very long lowpass filter
yy = upfirdn(xx,hh,160,147);

```

In this example, the filter design and resampling are separate steps. Note that resample would do both steps as one.
upfirdn uses a polyphase interpolation structure. The number of multiply-add operations in the polyphase structure is approximately \(\left(L_{h} L_{x}-L_{x}\right) / q\) where \(L_{h}\) and \(L_{x}\) are the lengths of \(h[n]\) and \(x[n]\), respectively.

A more accurate flops count is computed in the program, but the actual count is still approximate. For long signals \(x[n]\), the formula is often exact.

If \(p\) and \(q\) are large and do not have many common factors, you may see this message
```

Filter length is too large - reduce problem complexity.

```

Instead, you should use an interpolation function, such as interp1, to perform the resampling and then filter the input.

\author{
See Also conv, decimate, downsample, filter, interp, intfilt, resample, upsample \\ References [1] Crochiere, R.E., and L.R. Rabiner, Multi-RateSignal Processing, Prentice-Hall, Englewood Cliffs, NJ , 1983, pp. 88-91. \\ [2] Crochiere, R.E., "A General Program to Perform Sampling RateConversion of Data by Rational Ratios," Programs for Digital Signal Processing, IEEE Press, New York, 1979, pp. 8.2-1 to 8.2-7.
}

\section*{Purpose Increase the sampling rate of the input signal}

\section*{Syntax \\ \(y=u p s a m p l e(x, n)\) \\ \(y=u p s a m p l e(x, n\), phase \()\)}

Description
\(y=u p s a m p l e(x, n)\) increases the sampling rate of \(x\) by inserting \(n-1\) zeros between samples. \(x\) can be a vector or a matrix. If \(x\) is a matrix, each column is considered a separate sequence. The upsampled y has \(\mathrm{x}^{*} \mathrm{n}\) samples.
\(\mathrm{y}=\) upsample( \(\mathrm{x}, \mathrm{n}\), phase) specifies the number of samples by which to offset the upsampled sequence. phase must be an integer from 0 to \(n-1\).

Examples Increase the sampling rate of a sequence by 3.
```

x = [1 2 3 4];
y = upsample(x,3);
x,y
x =
1 2 3 4
y =
1}0

```

Increase the sampling rate of the sequence by 3 and add a phase offset of 2.
```

x = [1 2 3 4];
y = upsample(x,3,2);
x,y
x =
1 2 3 4
y =
0

```

Increase the sampling rate of a matrix by 3.
\[
\begin{aligned}
& \mathrm{x}=[12 ; 34 ; 56 ;] ; \\
& y=\text { upsample(x,3); } \\
& x, y \\
& x= \\
& 12 \\
& 34 \\
& 56 \\
& y= \\
& 12 \\
& 00 \\
& 00 \\
& 34 \\
& 00 \\
& 0 \quad 0 \\
& 56 \\
& 00 \\
& 00
\end{aligned}
\]

\section*{See Also}
decimate, downsample, interp, interp1, resample, spline, upfirdn

\section*{Purpose Voltage controlled oscillator}

\section*{Syntax \\ \(y=v c o(x, f c, f s)\) \\ \(y=\operatorname{vco}(x,[F m i n\) Fmax \(], f s)\)}

\section*{Description}

\section*{Example}
\(y=v c o(x, f c, f s)\) creates a signal that oscillates at a frequency determined by the real input vector or array x with sampling frequency \(\mathrm{fs} . \mathrm{fc}\) is the carrier or reference frequency; when x is \(0, \mathrm{y}\) is an fc Hz cosine with amplitude 1 sampled at fs Hz . \(x\) ranges from -1 to 1 , where \(x=-1\) corresponds to 0 frequency output, \(\mathrm{x}=0\) corresponds to fc , and \(\mathrm{x}=1\) corresponds to \(2 * \mathrm{fc}\). Output y is the same size as x .
\(y=\operatorname{vco}(x,[F m i n ~ F m a x], f s)\) scales the frequency modulation range so that \(\pm 1\) values of \(x\) yield oscillations of Fmin Hz and Fmax Hz respectively. For best results, Fmin and Fmax should be in the range 0 to fs \(/ 2\).

By default, fs is 1 and fc is \(\mathrm{fs} / 4\).
If \(x\) is a matrix, vco produces a matrix whose columns oscillate according to the columns of \(x\).

Generate two seconds of a signal sampled at 10,000 samples/second whose instantaneous frequency is a triangle function of time.
```

fs = 10000;
t = 0:1/fs:2;
x = vco(sawtooth(2*pi*t,0.75),[0.1 0.4]*fs,fs);

```

Plot the spectrogram of the generated signal.
specgram(x,512,fs,kaiser(256,5),220)


Algorithm

See Also

Diagnostics If any values of \(x\) lie outside [-1, 1], vco gives the following error message. \(X\) outside of range [-1,1].
vco performs FM modulation using the modulate function.
demod, modulate
```

Purpose Compute a specific window
Syntax w = window(fhandle,n)
w = window(fhandle,n,winopt)
w = window(fhandle,n,sidelobe)
Description w = window(fhandle, $n$ ) returns the $n$-point window, specified by its function handle, fhandle, in column vector w. Function handles are window function names preceded by an @.

| @barthannwin | @hamming |
| :--- | :--- |
| @bartlett | @hann |
| @blackman | @kaiser |
| @blackmanharris | @nuttallwin |
| @bohmanwin | @rectwin |
| @chebwin | @triang |
| @gausswin | @tukeywin |

Note For more information on each window function and its option(s), refer to its reference page.
$\mathrm{w}=$ window(fhandle, N , winopt) returns the window specified by its function handle, fhandle, and its option value or string in winopt. Only blackman, chebwin, gausswin, hamming, hann, and tukeywin windows take an option.
w = window(fhandle, N , sidelobe) returns the window specified by its function handle, fhandle. If fhandle is either @chebwin or akaiser, a second numerical parameter must beentered. For Chebyshev sidelobe is the number of decibels that the sidel obe magnitude is below the mainlobe; for Kaiser sidelobe is the beta value.
Example Create and plot three windows.

$$
N=65 ;
$$

```
```

w = window(@blackmanharris,N);
w1 = window(@hamming,N);
w2 = window(@gausswin,N,2.5);
plot(1:N,[w,w1,w2]); axis([1 N 0 1]);
legend('Blackman-Harris','Hamming','Gaussian');

```


\section*{See Also}
barthannwin, bartlett, blackman, blackmanharris, bohmanwin, chebwin, gausswin, hamming, hann, kaiser, nuttallwin, rectwin, triang, tukeywin

\section*{Purpose Estimate the cross-correlation function}

\section*{Syntax}
```

c = xcorr(x,y)
c = xcorr(x)
c = xcorr(x,y,'option')
c = xcorr(x,'option')
c = xcorr(x,y,maxlags)
c = xcorr(x,maxlags)
c = xcorr(x,y,maxlags,'option')
c = xcorr(x,maxlags,'option')
[c,lags] = xcorr(...)

```

\section*{Description}
xcorr estimates the cross-correlation sequence of a random process. Autocorrelation is handled as a special case.

The true cross-correlation sequence is
\[
R_{x y}(m)=E\left\{x_{n+m} y^{*} n\right\}=E\left\{x_{n} y^{*} n-m\right\}
\]
where \(\mathrm{x}_{n}\) and \(\mathrm{y}_{n}\) are jointly stationary random processes, \(-\infty<\mathrm{n}<\infty\), and \(\mathrm{E}\}\) is the expected value operator. xcorr must estimate the sequence because, in practice, only a finite segment of one realization of the infinite-length random process is available.
\(\mathrm{c}=\mathrm{xcorr}(\mathrm{x}, \mathrm{y})\) returns the cross-correlation sequence in a length \(2 * \mathrm{~N}-1\) vector, where \(x\) and \(y\) are length \(N\) vectors ( \(N>1\) ). If \(x\) and \(y\) are not the same length, the shorter vector is zero-padded to the length of the longer vector.

By default, xcorr computes raw correlations with no normalization.
\[
\hat{R}_{x y}(m)= \begin{cases}\sum_{n=0}^{N-m-1} x_{n+m} y_{n}^{*} & m \geq 0 \\ \hat{R}_{y x(-m)}^{*} & m<0\end{cases}
\]

The output vector \(c\) has elements given by \(c(m)=c_{x y}(m-N), m=1, \ldots, 2 N-1\).
In general, the correlation function requires normalization to produce an accurate estimate (see below).
\(c=x \operatorname{corr}(x)\) is the autocorrelation sequence for the vector \(x\). If \(x\) is an \(N\)-by-P matrix, c is a matrix with \(2 N-1\) rows whose \(P^{2}\) columns contain the cross-correlation sequences for all combinations of the columns of \(x\). F or more information on matrix processing with xcorr, see "Multiple Channels" on page 3-5.
c = xcorr(x,y,'option') specifies a normalization option for the cross-correlation, where 'option' is:
- 'biased ': Biased estimate of the cross-correlation function
\[
c_{x y, \text { biased }}(m)=\frac{1}{N} c_{x y}(m)
\]
- 'unbiased ': Unbiased estimate of the cross-correlation function
\[
c_{x y, \text { unbiased }}(m)=\frac{1}{N-|m|} c_{x y}(m)
\]
- 'coeff': N ormalizes the sequence so the autocorrelations at zerolag are identically 1.0
- 'none ', to use the raw, unscaled cross-correlations (default)

See reference[1] for more information on the properties of biased and unbiased correlation estimates.
c \(=x \operatorname{corr}(x\), ' option' \()\) specifies one of the above normalization options for the autocorrelation.
\(c=x \operatorname{corr}(x, y\), maxlags) returns the cross-correlation sequence over the lag range [-maxlags:maxlags]. Output c has length \(2 *\) maxlags +1 .
\(c=x \operatorname{corr}(x\), maxlags \()\) returns the autocorrelation sequence over the lag range [-maxlags:maxlags]. Output chas length \(2 *\) maxlags +1 . If \(x\) is an \(N\)-by-P matrix, c is a matrix with \(2 *\) maxlags +1 rows whose \(P^{2}\) columns contain the autocorrelation sequences for all combinations of the columns of \(x\).
c = xcorr(x,y,maxlags, 'option') specifies both a maximum number of lags and a scaling option for the cross-correlation.
c = xcorr(x,maxlags,'option') specifies both a maximum number of lags and a scaling option for the autocorrelation.
[c,lags] = xcorr(...) returns a vector of the lag indices at which c was estimated, with the range [-maxlags:maxlags]. When maxlags is not specified, the range of lags is \([-N+1: N-1]\).

In all cases, the cross-correlation or autocorrelation computed by xcorr has the zeroth lag in the middle of the sequence, at element or row maxlags+1 (element or row N if maxlags is not specified).

\section*{Examples}

The second output, lags, is useful for plotting the cross-correlation or autocorrelation. F or example, the estimated autocorrelation of zero-mean Gaussian white noise \(\mathrm{c}_{\mathrm{ww}}(\mathrm{m})\) can be displayed for \(-10 \leq \mathrm{m} \leq 10\) using
```

ww = randn(1000,1);
[c_ww,lags] = xcorr(ww,10,'coeff');
stem(lags,c_ww)

```

Swapping the \(x\) and \(y\) input arguments reverses (and conjugates) the output correlation sequence. F or row vectors, the resulting sequences are reversed left to right; for column vectors, up and down. The following example illustrates this property (mat2str is used for a compact display of complex numbers).
```

x = [1,2i,3]; y = [4,5,6];
[c1,lags] = xcorr(x,y);
c1 = mat2str(c1,2), lags
c1 =
[6-i*8.9e-016 5+i*12 22+i*10 15+i*8 12+i*8.9e-016]
lags =
-2
c2 = conj(fliplr(xcorr(y,x)));
c2 = mat2str(c2,2)
c2 =
[6-i*8.9e-016 5+i*12 22+i*10 15+i*8 12+i*8.9e-016]

```

For the case where input argument \(x\) is a matrix, the output columns are arranged so that extracting a row and rearranging it into a square array produces the cross-correlation matrix corresponding to the lag of the chosen row. For example, the cross-correlation at zero lag can be retrieved by
```

randn('state',0)
X = randn(2,2);
[M,P] = size(X);
c = xcorr(X);

```
```

cO = zeros(P); cO(:) = c(M,:) % Extract zero-lag row
cO =
2.9613 -0.5334
-0.5334 0.0985

```

You can calculate the matrix of correlation coefficients that the MATLAB function corrcoef generates by substituting
```

c = xcov(X,'coef')

```
in the last example. The function xcov subtracts the mean and then calls xcorr.

Usefftshift to move the second half of the sequence starting at the zeroth lag to the front of the sequence. fftshift swaps the first and second halves of a sequence.

Algorithm For more information on estimating covariance and correlation functions, see [1].

See Also conv, corrcoef, cov, xcorr2, xcov
References [1] Orfanidis, S.J ., Optimum Signal Processing. An Introduction. 2nd Edition, Prentice-H all, Englewood Cliffs, NJ , 1996.

\section*{Purpose Estimate the two-dimensional cross-correlation}
Syntax \(\quad\)\begin{tabular}{rl}
\(C\) & \(=x \operatorname{corr} 2(A)\) \\
\(C\) & \(=x \operatorname{corr} 2(A, B)\)
\end{tabular}

Description

See Also conv2, filter2, xcorr

\section*{Purpose}

Estimate the cross-covariance function (mean-removed cross-correlation)

\section*{Syntax}
```

v = xcov(x,y)
v = xcov(x)
v = xcov(x,'option')
[c,lags] = xcov(x,y,maxlags)
[c,lags] = xcov(x,maxlags)
[c,lags] = xcov(x,y,maxlags,'option')

```

\section*{Description xcov estimates the cross-covariance sequence of random processes.}

Autocovariance is handled as a special case.
The true cross-covariance sequence is the cross-correlation of mean-removed sequences
\[
\phi_{\mathrm{xy}}(\mu)=\mathrm{E}\left\{\left(\mathrm{x}_{\mathrm{n}+\mathrm{m}}-\mu_{\mathrm{x}}\right)\left(\mathrm{y}_{\mathrm{n}}-\mu_{\mathrm{y}}\right)^{*}\right\}
\]
where \(\mu_{x}\) and \(\mu_{y}\) are the mean values of the two stationary random processes, and \(E\}\}\) is the expected value operator. xcov estimates the sequence because, in practice, access is available to only a finite segment of the infinite-length random process.
\(v=x \operatorname{cov}(x, y)\) returns the cross-covariance sequence in a length \(2 N-1\) vector, where \(x\) and \(y\) are length \(N\) vectors. For information on how arrays are processed with xcov, see "Multiple Channels" on page 3-5.
\(v=x \operatorname{cov}(x)\) is the autocovariance sequence for the vector \(x\). Where \(x\) is an \(N\)-by-P array, \(v=x \operatorname{cov}(x)\) returns an array with \(2 N-1\) rows whose \(P^{2}\) columns contain the cross-covariance sequences for all combinations of the columns of \(x\).

By default, xcov computes raw covariances with no normalization. For a length N vector
\[
c_{x y}(m)= \begin{cases}\sum_{n=0}^{N-|m|-1}\left(x(n+m)-\frac{1}{N} \sum_{i=0}^{N-1} x_{i}\right)\left(y_{n}^{*}-\frac{1}{N} \sum_{i=0}^{N-1} y_{i}^{*}\right) & m \geq 0 \\ c_{y x}^{*}(-m) & m<0\end{cases}
\]

The output vector c has elements given by \(\mathrm{c}(\mathrm{m})=\mathrm{c}_{\mathrm{xy}}(\mathrm{m}-\mathrm{N}), \mathrm{m}=1, \ldots, 2 \mathrm{~N}-1\).
The covariance function requires normalization to estimate the function properly.
v = xcov(x, option') specifies a scaling option, where 'option' is:
- 'biased', for biased estimates of the cross-covariance function
- 'unbiased ', for unbiased estimates of the cross-covariance function
- ' coeff', to normalize the sequence so the auto-covariances at zero lag are identically 1.0
- 'none ', to use the raw, unscaled cross-covariances (default)

See [1] for more information on the properties of biased and unbiased correlation and covariance estimates.
[ \(c\), lags] \(=x \operatorname{cov}(x, y\), maxlags \()\) where \(x\) and \(y\) are length \(m\) vectors, returns the cross-covariance sequence in a length \(2 *\) maxlags +1 vector c . lags is a vector of the lag indices where c was estimated, that is, [-maxlags: maxlags].
[c,lags] = xcov(x,maxlags) is the autocovariance sequence over the range of lags [-maxlags:maxlags].
[c,lags] \(=x \operatorname{cov}(x\), maxlags \()\) where \(x\) is an m-by-p array, returns array \(c\) with \(2 *\) maxlags +1 rows whose \(P^{2}\) columns contain the cross-covariance sequences for all combinations of the columns of \(x\).
[c,lags] \(=x \operatorname{cov}(x, y\), maxlags,'option') specifies a scaling option, where 'option' is the last input argument.

In all cases, xcov gives an output such that the zeroth lag of the covariance vector is in the middle of the sequence, at element or row maxlag+1 or at m .

\section*{Examples}

The second output lags is useful when plotting. For example, the estimated autocovariance of uniform white noise \(c_{w w}(m)\) can be displayed for \(-10 \leq m \leq 10\) using
```

ww = randn(1000,1); % Generate uniform noise with mean = 1/2.
[cov_ww,lags] = xcov(ww,10,'coeff');
stem(lags,cov_ww)

```

Algorithm

Diagnostics

See Also conv, corrcoef, cov, xcorr, xcorr2
References functions, see [1].
xcov computes the mean of its inputs, subtracts the mean, and then calls xcorr. F or more information on estimating covariance and correlation
xcov does not check for any errors other than the correct number of input arguments. Instead, it relies on the error checking in xcorr.
[1] Orfanidis, S.J ., Optimum Signal Processing. An Introduction. 2nd Edition, Prentice-Hall, Englewood Cliffs, NJ , 1996.

\section*{Purpose \\ Recursive digital filter design}

\section*{Syntax \\ [b,a] = yulewalk(n,f,m)}

\section*{Description}

\section*{Example}
yulewalk designs recursive IIR digital filters using a least-squares fit to a specified frequency response.
[b,a] = yulewalk( \(n, f, m\) ) returns row vectors \(b\) and a containing the \(n+1\) coefficients of the order n IIR filter whose frequency-magnitude characteristics approximately match those given in vectors \(f\) and \(m\) :
- f is a vector of frequency points, specified in the range between 0 and 1 , where 1 corresponds to half the sample frequency (the Nyquist frequency). The first point of f must be 0 and the last point 1 , with all intermediate points in increasing order. Duplicate frequency points are allowed, corresponding to steps in the frequency response.
- \(m\) is a vector containing the desired magnitude response at the points specified in f.
- \(f\) and \(m\) must be the same length.
- plot(f,m) displays the filter shape.

The output filter coefficients are ordered in descending powers of \(z\).
\[
\frac{B(z)}{A(z)}=\frac{b(1)+b(2) z^{-1}+\cdots+b(n+1) z^{-n}}{a(1)+a(2) z^{-1}+\cdots+a(n+1) z^{-n}}
\]

When specifying the frequency response, avoid excessively sharp transitions from passband to stopband. You may need to experiment with the slope of the transition region to get the best filter design.

Design an 8th-order lowpass filter and overplot the desired frequency response with the actual frequency response.
```

f = [0 0.6 0.6 1];

```
f = [0 0.6 0.6 1];
m = [1 1 0 0];
m = [1 1 0 0];
[b,a] = yulewalk(8,f,m);
[b,a] = yulewalk(8,f,m);
[h,w] = freqz(b,a,128);
[h,w] = freqz(b,a,128);
plot(f,m,w/pi,abs(h),'--')
plot(f,m,w/pi,abs(h),'--')
legend('Ideal','yulewalk Designed')
legend('Ideal','yulewalk Designed')
title('Comparison of Frequency Response Magnitudes')
```

title('Comparison of Frequency Response Magnitudes')

```


\footnotetext{
\section*{Algorithm}

See Also butter, cheby1, cheby2, ellip, fir2, firls, maxflat, remez
References
yulewalk performs a least-squares fit in the time domain. It computes the denominator coefficients using modified Yule-Walker equations, with correlation coefficients computed by inverse Fourier transformation of the specified frequency response. To compute the numerator, yulewalk takes the following steps:

1 Computes a numerator polynomial corresponding to an additive decomposition of the power frequency response.
2 Evaluates the complete frequency response corresponding to the numerator and denominator polynomials.
3 Uses a spectral factorization technique to obtain the impulseresponse of the filter.
4 Obtains the numerator polynomial by a least-squares fit to this impulse response.
[1] Friedlander, B., and B. Porat, "The Modified Yule-Walker Method of ARMA Spectral Estimation,"IEEE Transactions on Aerospace Electronic Systems, AES-20, No. 2 (March 1984), pp. 158-173.
}

\section*{Purpose}

Convert digital filter zero-pole-gain parameters to second-order sections form

\section*{Syntax}

Description
```

[sos,g] = zp2sos(z,p,k)
[sos,g] = zp2sos(z,p,k,'order')
[sos,g] = zp2sos(z,p,k,'order','scale')
sos = zp2sos(...)

```
zp2sos converts a discrete-time zero-pole-gain representation of a given digital filter to an equivalent second-order section representation.

Use [sos, \(g\) ] = zp2sos( \(z, p, k\) ) to obtain a matrix sos in second-order section form with gain g equivalent to the discrete-time zero-pole-gain filter represented by input arguments \(z, p\), and \(k\). Vectors \(z\) and p contain the zeros and poles of the filter's transfer function \(\mathrm{H}(\mathrm{z})\), not necessarily in any particular order.
\[
H(z)=k \frac{\left(z-z_{1}\right)\left(z-z_{2}\right) \cdots\left(z-z_{n}\right)}{\left(z-p_{1}\right)\left(z-p_{2}\right) \cdots\left(z-p_{m}\right)}
\]
where \(n\) and \(m\) are the lengths of \(z\) and \(p\), respectively, and \(k\) is a scalar gain. The zeros and poles must be real or complex conjugate pairs. sos is an L-by-6 matrix
\[
\text { sos }=\left[\begin{array}{cccccc}
b_{01} & b_{11} & b_{21} & 1 & a_{11} & a_{21} \\
b_{02} & b_{12} & b_{22} & 1 & a_{12} & a_{22} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
b_{0 L} & b_{1 L} & b_{2 L} & 1 & a_{1 L} & a_{2 L}
\end{array}\right]
\]
whose rows contain the numerator and denominator coefficients \(\mathrm{b}_{i k}\) and \(\mathrm{a}_{i k}\) of the second-order sections of \(\mathrm{H}(\mathrm{z})\).
\[
H(z)=g \prod_{k=1}^{L} H_{k}(z)=g \prod_{k=1}^{L} \frac{b_{0 k}+b_{1 k} z^{-1}+b_{2 k} z^{-2}}{1+a_{1 k^{2}} z^{-1}+a_{2 k^{2}} z^{-2}}
\]

The number \(L\) of rows of the matrix sos is the closest integer greater than or equal to the maximum of \(n / 2\) and \(m / 2\).
[sos,g] \(=\) zp2sos(z, p,k,'order') specifies the order of the rows in sos, where 'order' is:
- 'down ' , to order the sections so the first row of sos contains the poles closest to the unit circle
- ' up ' , to order the sections so the first row of sos contains the poles farthest from the unit circle (default)
[sos,g] = zp2sos(z,p,k,'order','scale') specifies the desired scaling of the gain and the numerator coefficients of all second-order sections, where 'scale' is:
- 'none ' , to apply no scaling (default)
- 'inf ', to apply infinity-norm scaling
- 'two ' , to apply 2-norm scaling

Using infinity-norm scaling in conjunction with up-ordering minimizes the probability of overflow in the realization. Using 2-norm scaling in conjunction with down-ordering minimizes the peak round-off noise.
sos \(=\) zp2sos(...) embeds the overall system gain, \(g\), in the first section, \(\mathrm{H}_{1}(z)\), so that
\[
H(z)=\prod_{k=1} H_{k}(z)
\]

\section*{Example}

Find a second-order section form of a Butterworth lowpass filter.
```

[z,p,k] = butter(5,0.2);
sos = zp2sos(z,p,k);

```

\section*{Algorithm}

See Also
zp2sos uses a four-step algorithm to determine the second-order section representation for an input zero-pole-gain system:

1 It groups the zeros and poles into complex conjugate pairs using the cplxpair function.
2 It forms the second-order section by matching the pole and zero pairs according to the following rules:
a Match the poles closest to the unit circle with the zeros closest to those poles.
b Match the poles next closest to the unit circle with the zeros closest to those poles.
c Continue until all of the poles and zeros are matched.
zp2sos groups real poles into sections with the real poles closest to them in absolute value. The same rule holds for real zeros.
3 It orders the sections according to the proximity of the pole pairs to the unit circle. zp2sos normally orders the sections with poles closest to the unit circle last in the cascade. Y ou can tell zp2sos to order the sections in the reverse order by specifying the down flag.
4 zp2sos scales the sections by the norm specified in the 'scale' argument. For arbitrary \(\mathrm{H}(\omega)\), the scaling is defined by
\[
\|H\|_{p}=\left[\frac{1}{2 \pi} \int_{0}^{2 \pi}|H(\omega)|^{p} d \omega\right]^{\frac{1}{p}}
\]
where \(p\) can be either \(\infty\) or 2 . See the references for details on the scaling. This scaling is an attempt to minimize overflow or peak round-off noise in fixed point filter implementations.
cplxpair, filternorm, sos2zp, ss2sos, tf2sos, zp2ss, zp2tf

\author{
References [1] J ackson, L.B., Digital Filters and Signal Processing, 3rd ed., Kluwer Academic Publishers, Boston, 1996, Chapter 11. \\ [2] Mitra, S.K., Digital Signal Processing: A Computer-Based Approach, McGraw-Hill, New York, 1998, Chapter 9. \\ [3] Vaidyanathan, P.P., "Robust Digital Filter Structures," Handbook for Digital Signal Processing, S.K. Mitra and J.F. Kaiser, ed., J ohn Wiley \& Sons, New York, 1993, Chapter 7.
}

\section*{Purpose}

\section*{Syntax}

Description

Algorithm

See Also

Convert zero-pole-gain filter parameters to state-space form
```

[A,B,C,D] = zp2ss(z,p,k)

```
zp2ss converts a zero-pole-gain representation of a given system to an equivalent state-space representation.
\([A, B, C, D]=z p 2 s s(z, p, k)\) finds a single input, multiple output, state-space representation
\[
\begin{aligned}
& x=A x+B u \\
& y=C x+D u
\end{aligned}
\]
given a system in factored transfer function form.
\[
H(s)=\frac{Z(s)}{P(s)}=k \frac{\left(s-z_{1}\right)\left(s-z_{2}\right) \cdots\left(s-z_{n}\right)}{\left(s-p_{1}\right)\left(s-p_{2}\right) \cdots\left(s-p_{n}\right)}
\]

Column vector \(p\) specifies the pole locations, and matrix \(z\) the zero locations with as many columns as there are outputs. The gains for each numerator transfer function are in vector k. The A, B, C, and D matrices are returned in controller canonical form.

Inf values may be used as place holders in z if some columns havefewer zeros than others.
zp2ss, for single-input systems, groups complex pairs together into two-by-two blocks down the diagonal of the A matrix. This requires the zeros and poles to be real or complex conjugate pairs.
sos2ss, ss2zp, tf2ss, zp2sos, zp2tf

Purpose Convert zero-pole-gain filter parameters to transfer function form

\section*{Syntax \(\quad[b, a]=z p 2 t f(z, p, k)\)}

Description

\section*{Algorithm}

\section*{See Also}
zp2tf forms transfer function polynomials from thezeros, poles, and gains of a system in factored form.
\([b, a]=z p 2 t f(z, p, k)\) finds a rational transfer function
\[
\frac{\mathrm{B}(\mathrm{~s})}{\mathrm{A}(\mathrm{~s})}=\frac{\mathrm{b}_{1} \mathrm{~s}^{(\mathrm{n}-1)}+\cdots+\mathrm{b}_{(\mathrm{n}-1)} \mathrm{s}+\mathrm{b}_{\mathrm{n}}}{\mathrm{a}_{1} \mathrm{~s}^{(\mathrm{m}-1)}+\cdots+\mathrm{a}_{(\mathrm{m}-1)} \mathrm{s}+\mathrm{a}_{\mathrm{m}}}
\]
given a system in factored transfer function form
\[
H(s)=\frac{Z(s)}{P(s)}=k \frac{\left(s-z_{1}\right)\left(s-z_{2}\right) \cdots\left(s-z_{m}\right)}{\left(s-p_{1}\right)\left(s-p_{2}\right) \cdots\left(s-p_{n}\right)}
\]

Column vector p specifies the pole locations, and matrix z specifies the zero locations, with as many columns as there are outputs. The gains for each numerator transfer function are in vector \(k\). The zeros and poles must be real or come in complex conjugate pairs. The polynomial denominator coefficients are returned in row vector a and the polynomial numerator coefficients are returned in matrix \(b\), which has as many rows as there are columns of \(z\).

Inf values can be used as place hol ders in z if some columns have fewer zeros than others.

The system is converted to transfer function form using poly with \(p\) and the columns of \(z\).
sos2tf, ss2tf, tf2zp, zp2sos, zp2ss
\begin{tabular}{ll} 
Purpose & Zero-pole plota \\
Syntax & zplane \((z, p)\) \\
& zplane \((b, a)\) \\
& {\([h z, h p, h t]=\) zplane \((z, p)\)}
\end{tabular}

Description This function displays the poles and zeros of discrete-time systems.
zplane(z,p) plots the zeros specified in column vector \(z\) and the poles specified in column vector \(p\) in the current figure window. The symbol ' 0 ' represents a zero and the symbol ' \(x\) ' represents a pole. The plot includes the unit circle for reference. If \(z\) and \(p\) are arrays, zplane plots the poles and zeros in the columns of \(z\) and \(p\) in different colors.

You can override the automatic scaling of zplane using
```

axis([xmin xmax ymin ymax])
set(gca,'ylim',[ymin ymax])
set(gca,'xlim',[xmin xmax])

```
or
or
after calling zplane. This is useful in the case where one or a few of the zeros or poles have such a large magnitude that the others are grouped tightly around the origin and are hard to distinguish.
zplane ( \(b, a\) ) where \(b\) and a are row vectors, first uses roots to find the zeros and poles of the transfer function represented by numerator coefficients b and denominator coefficients a.
[hz,hp,ht] = zplane(z,p) returns vectors of handles to the zerolines, hz, and the pole lines, \(h p\). ht is a vector of handles to the axes/unit circle line and to text objects, which are present when there are multiple zeros or poles. If there are no zeros or no poles, hz or hp is the empty matrix [ ].

Examples
For data sampled at 1000 Hz , plot the poles and zeros of a 4th-order elliptic lowpass digital filter with cutoff frequency of \(200 \mathrm{~Hz}, 3 \mathrm{~dB}\) of ripple in the passband, and 30 dB of attenuation in the stopband.
```

[z,p,k] = ellip(4,3,30,200/500);
zplane(z,p);
title('4th-Order Elliptic Lowpass Digital Filter');

```


To generate the same plot with a transfer function representation of the filter, use the following commands.
```

[b,a] = ellip(4,3,30,200/500); % Transfer function
zplane(b,a)

```

\section*{See Also freqz}

\section*{Numerics}

2-norm 7-181

\section*{A}

A/D conversion 7-459
abs 7-26
ac2poly 7-27
ac2rc 7-28
aliased sinc functions 1-13
command for 7-145
aliasing
impulse invariance 2-42
preventing 4-23
reducing 4-40
all-pole filters. SellR filters
all-zero filters. SeFIR filters
am 4-31
AM. Seeamplitude modulation
amdsb-sc 4-31, 7-293
amdsb-tc 4-31, 7-293
amplitude demodulation
double side-band, suppressed carrier 7-142
double side-band, transmitted carrier 7-142
single side-band 7-142
amplitude modulation 4-31
double side-band, suppressed carrier 7-293
double side-band, transmitted carrier 7-293
quadrature 4-32
single side-band 7-293
amssb 4-32, 7-293
analog filters 2-39
bandpass 7-276
bandstop 7-279
Bessel 2-12, 2-39, 7-38, 7-39
bilinear transformation 2-43
Butterworth 2-9, 2-39, 7-64, 7-65, 7-66

Chebyshev 2-39
Chebyshev Type I 2-10, 7-78, 7-90
Chebyshev Type II 2-11, 7-96
converting to digital 2-42, 7-246
design 2-8
discretization 2-42
elliptic 2-39, 7-155
frequency response 1-27, 2-13, 7-206
highpass 7-281
impulse invariance 2-42
inverse 7-255
lowpass 7-283
order estimation
Butterworth 7-71
Chebyshev Typel 7-80, 7-85
Chebyshev Type II 7-85
elliptic 7-163
plotting 2-13
representational models 1-42
Sealso IIR filters
analog frequency \(x \times v i\)
analog signals. Sesignals
analytic signals 7-238
angle 7-29
anti-symmetric filters 2-26
AR filters, stability check 7-341
AR models. See autoregressive (AR) models
arburg 4-13, 7-30
arcov 4-13, 7-31
ARMA filters 1-16, 4-15, 4-17
Prony's method 4-15
Steiglitz-McBride method 4-17
Seealso IIR filters
armcov 4-13, 7-32
ARX models 4-15
aryule 4-13, 7-33

ASCII files, importing 1-14
autocorrelation 7-339, 7-474
autocorrelation sequences
converting from reflection coefficients 7-364
estimation, variance 3-4
filter coefficients
converting to and from 7-27, 7-28, 7-339
filters, multiple channels 3-5
two-dimensional 7-477
autocovariance 7-478
multiple channels 3-5
autoregressive (AR) models 1-16
Burg method 7-30, 7-299, 7-303
covariance method 7-31, 7-304
modified covariance method 7-32, 7-321, 7-325
Yule-Walker AR method 7-33, 7-359, 7-363
See also IIR filters
autoregressive moving average (ARMA) filters. SeeARMA filters
averaging filters 1-15
axis labels 6-50
axis parameters
Filter Viewer 6-50
Spectrum Viewer 6-50

\section*{B}
band edges, prewarping 2-44
bandlimited interpolation 7-406
bandpass filters 7-71, 7-80, 7-85, 7-163
Bessel 7-39
Butterworth 7-65
Chebyshev Type I 7-90, 7-92
Chebyshev Type II 7-95
design 2-7
elliptic 7-155
example, Chebyshev Type I 2-40
FIR 2-22, 7-188
impulse invariance 2-42
transformation from lowpass to 7-276
bandstop filters 2-7, 7-71, 7-80, 7-85, 7-163
Bessel 7-39
Butterworth 7-66
Chebyshev Type I 7-91
Chebyshev Type II 7-95
elliptic 7-156
FIR 2-22, 7-187
transformation from lowpass to 7-279
bandwidth 2-41
barthannwin 4-3, 7-34
bartlett 4-3, 7-36
example 4-4
triang, comparison to 7-36
Bartlett windows 4-4
coefficients 7-36
Bartlett-Hanning 7-34
Bessel filters 2-12, 2-39, 7-38
bandpass 7-39
bandstop 7-39
characteristics 2-12
highpass 7-39
limitations 7-41
lowpass 7-39
roots 7-38
besselap 2-6, 7-38
example 2-12
besself 2-6, 2-7, 7-39
bias
correlation 3-4, 4-14
power spectral density 3-17, 3-18, 3-23
variance trade-off 3-4
bilinear 2-6, 2-42, 2-43, 7-42
bilinear transformations 2-43, 2-44, 7-42
output representation 7-43
prewarping 2-44, 7-42
bit reversal 7-47
bitrevorder 7-47
blackman 4-3, 7-49
Blackman windows 4-5, 7-49
Blackman-Harris 7-51
blackmanharris 4-3, 7-51
Blackman-Harris windows 7-296
Bohman 7-53
bohmanwin 4-3, 7-53
boxcar 7-55
boxcar windows. Serectangular windows
brackets, indicating closed interval xxvi
buffer 7-55
buffering 7-55
Burg method 3-8, 3-9, 3-33
example 3-34
Welch's method, comparison 3-35
buttap 2-6, 7-64
example 2-9
butter 2-6, 2-7, 7-65
Butterworth filters 2-9, 2-39, 7-64
bandpass 7-65
bandstop 7-66
characteristics 2-9
design 7-65
generalized 2-15
highpass 7-66
limitations 7-69
lowpass 7-65
order estimation 2-8, 7-70
buttord 2-6, 7-70

\section*{C}
canonical forms 1-18, 7-443
carrier frequency 4-31, 7-293, 7-469
carrier signals 4-31, 7-142
cascade, filters 1-38
Cauer filters. See elliptic filters
cceps 4-25, 4-27, 7-75
example 4-25
cell2sos 7-77
center frequency 2-41
central features 1-2
cepstrum
analysis 4-25
applications 4-25
complex 4-25
inverse 4-25, 4-27
overview 4-25
real 4-25, 4-26, 7-368
reconstructing signals (minimum-phase) 4-27
cheb1ap 2-6, 7-78
example 2-10, 2-40
cheb1ord 2-6, 7-79
cheb2ap 2-6, 7-83
example 2-11
cheb2ord 2-6, 7-84
chebwin 4-3, 7-89, 7-116
cheby1 2-6, 2-7, 7-90
example 2-45
cheby2 2-6, 2-7, 7-95
Chebyshev error minimization 2-23, 7-371
Chebyshev Type I filters 2-10, 2-39, 7-78, 7-90
bandpass 7-90, 7-92
bandstop 7-91
characteristics 2-10
design 7-90
highpass 7-91
lowpass 7-90
order estimation 2-8, 7-79
Chebyshev Type II filters 2-39, 7-95
bandpass 7-95
bandstop 7-95
characteristics 2-11
highpass 7-95
limitations 7-94
lowpass 7-95
order estimation 2-8
Chebyshev windows 4-10, 7-89
frequency response 4-10
chirp 1-10, 7-100
chirp signals 1-10
chirp z-transforms (CZT) 4-36, 7-133
discrete Fourier transforms, comparison 4-36
frequency analysis, narrowband 7-133
coding, PCM 7-459
coefficients
correlation 7-115
filter 1-16, 6-34, 7-27, 7-339, 7-341, 7-367
linear prediction 7-285
reflection 1-38, 7-28, 7-341, 7-364, 7-367
sequence 7-364
cohere 3-9, 7-106
linearly dependent data 3-30
cohere 3-29
coherence 3-29, 7-106
linearly dependent data 3-30
colors, SPTool 6-50
communications 4-12, 4-31, 7-293
See al so modulation, demodulation, voltage controlled oscillation
communications simulation 7-142
compact disc standards 4-22
compaction 4-39
complex conjugate 7-120
complex envel ope. SeeHilbert transforms
complex numbers, grouping by conjugate 7-120
confidence intervals
cross spectral density 3-27
power spectral density 3-27
warnings 3-27
context-sensitive help 6-7
continuous signals. Sesignals
continuous-time filters. See anal og filters
control systems 1-36
Control Systems Tool box 1-36
conv 1-15, 1-21, 7-110
conv2 1-15, 7-111
conversions
autocorrelation sequences to and from filter coefficients 7-27
autocorrel ation sequences to and from reflection coefficients 7-28
errors in 1-43, 5-15
filter coefficients to autocorrelation sequences 7-339
filter coefficients to reflection coefficients 7-341, 7-367
functions (table) 1-43
reflection coefficients to autocorrelation sequences 7-364
second-order section forms to state-space forms 7-409
second-order section forms to transfer functions 7-411
second-order section forms to zero-pol e-gain forms 7-413
state-space forms to second-order section forms 7-426
state-space forms to zero-pole-gain forms 7-431
transfer functions to lattice forms 7-438
transfer functions to second-order section forms 7-439
transfer functions to state-space forms 7-442
zero-pole-gain forms to second-order section forms 7-483
zero-polegain forms to state-space forms 7-487
convmtx 1-41, 1-43, 7-113
convolution 7-110
cross-correlation 3-3
example 1-15
filtering 1-15, 7-180
matrices for 1-41, 1-43, 7-113
example 7-113
two-dimensional 7-111
corrcoef 7-115
correlation 3-2
bias 3-4, 4-14
coefficient matrices 7-115
cross-correlation 7-473
matrices
covariance method 7-116
modified covariance method 7-116
See al so autocorrelation sequences, cross-correlation sequences
correlation matrices 7-116
corrmtx 7-116
cosine windows 4-5
cov 7-119
covariance 3-2
matrices 7-119
See also autocovariance, cross-covariance
covariance method 3-9, 3-36, 7-308
example 3-36
See also modified covariance method
cplxpair 7-120
cremez 2-17, 7-121
cross spectral density 3-27, 7-129
confidence intervals 3-27

Seealso power spectral density, spectral estimation
cross-correlation sequences 3-3
estimation 7-473
biased 3-4
unbiased 3-4
filters, multiple channels 3-5
normalization 3-5
two-dimensional 7-477
cross-covariance 3-3, 7-478
multiple channels 3-5
csd 3-9, 3-27, 7-129
cutoff frequency 2-39, 7-39
czt 4-37, 7-133
CZT. Sechirp z-transforms

\section*{D}
D.C. component suppression 1-47
data
multichannel 1-5, 1-8
vectors 1-7
data compression 4-12
data matrices 1-5, 1-8
data vectors 1-5
dct 4-38, 7-136
example 4-39
decimate 7-138
decimation 7-138
FIR filter for 7-253
decoding 7-456
deconv 4-35, 7-141
example 4-35
deconvolution 4-35, 7-141
default session file 6-50
delays
group 1-29
noninteger 2-27
phase 1-29
signals 2-27
demod 4-31, 4-32, 7-142
example 4-32
demodulation 4-32, 7-142
amplitude, quadrature 7-143
example 4-32
methods 4-32, 7-142
phase 7-143
pulse position 7-143
pulse width 7-143
DFT. See discrete Fourier transforms
dftmtx 7-144
difference equations 1-33
differentiators 2-27, 7-200, 7-373
digital audio tape standards 4-22
digital filters
anti-causal 1-21
Butterworth 7-65
cascade 1-38
Chebyshev Type II 7-95
coefficients 1-16
convolution matrices 1-41
design 2-3
elliptic 7-155
FIR 2-17
IIR, comparison to 2-17
fixed-point implementation 1-38
frequency data, identification from 7-259
frequency response 1-25
group delay 1-29, 7-231
IIR 2-5
FIR filters, comparison to 2-5
implementation 1-15, 7-174, 7-177
convolution 1-15
FFT-based (FIR) 7-174
filter 1-17
overlap-add method 1-23
impulse response 1-15, 1-24, 7-248
initial conditions 1-18
linear models 1-33
models 1-33
names 1-16
order 1-16
state-space representation 1-35
order estimation
Butterworth 7-70, 7-79, 7-84
Chebyshev Type I 7-79, 7-84
Chebyshev Type II 7-84
elliptic 7-162
equiripple FIR 7-378
phase delays 1-29, 7-231
poles 1-31, 1-34
second-order sections 1-38
specifications 2-8
startup transients 1-22
structures
lattice/ladder 1-38
transposed direct form II 1-18
time-domain representation 1-17
transfer functions representation 1-16
transients 1-23
two-dimensional 7-180
zero-phase 1-21, 7-183
zeros 1-31, 1-34
Sealso FIR filters, IIR filters
digital frequency xxvi
direct design 2-6
diric 7-145
Dirichlet functions 1-13
command for 7-145
discrete cosine transforms (DCT) 7-136 applications 4-38
energy compaction property 4-39
example 4-39
inverse 4-38, 7-243
signals, reconstructing 4-39
discrete F ourier transforms (DFT) 1-3, 1-45, 2-27, 7-170
algorithms 1-46
applications 7-170
eigenvector equivalent 3-38
example 1-46
goertzel 1-47
IIR filter implementation 1-23
inverse 1-45, 7-244
matrices 7-144
two-dimensional 1-47, 7-245
magnitude 1-46
matrices 7-144
phase 1-46
signal length dependencies 1-46
spectral analysis 3-6, 3-10
time-dependent 4-29
two-dimensional 1-47, 7-173
See also fast Fourier transforms (FFT), fft
discrete prolate spheroidal sequences
Se DPSS
discretization 7-246
bilinear transformations 2-43
prewarping 2-44
impulse invariance 2-42
discretization, filters 2-42
disk, loading variables from 6-43
division, polynomials 7-141
DPSS
direct method 7-149
interpolation 7-148
dpss 7-148
dpss.mat 3-26
dpssclear 3-26, 7-151
dpssdir 3-26, 7-152
dpssload 3-26, 7-153
dpsssave 3-26, 7-154
duty cycles 1-9

\section*{E}
echoes, detection 4-25
edge effects 1-23
eigenanalysis 3-37
frequency estimation 3-37
eigenvector method 3-8, 3-36, 7-309
root MUSIC 7-390
Sealso multiple signal classification method
ellip 2-6, 2-7, 7-155
ellipap 2-6, 7-161
example 2-11
ellipord 2-6, 7-162, 7-167
elliptic filters 2-39, 7-155
bandpass 7-155
bandstop 7-156
characteristics 2-11
highpass 7-156
limitations 7-159
Iowpass 7-155
order estimation 2-8, 7-162, 7-167
encoding
PCM 7-459
uniform 7-459
eqtflength 7-167
equiripple characteristics
Chebyshev Type I filters (passband) 2-10
Chebyshev Type II filters (stopband) 2-11
Chebyshev windows 4-10
elliptic filters 2-11, 7-155, 7-161
Parks-McClellan design 7-371
equiripple filters 2-23
error minimization
desired and actual response, between 2-23
frequency bands, weighting 2-26
minimax 2-23
estimation
cross spectral density 3-27
nonparametric
multiple signal classification method (MUSIC) 3-8
multitaper method (MTM) 3-8
Welch's method 3-8
parametric 3-8
Burg method 7-30
covariance method 7-31
modified covariance method 7-32
Yule-Walker method 7-33
spectral density 3-8, 3-10
transfer functions 3-28
See also parametric modeling

\section*{F}
fast Fourier Transforms (FFT)
Goertzel algorithm 7-226
fast Fourier transforms (FFT) 1-23, 1-45
fft 1-23
frequency response 1-25
radix-2 algorithm 7-172
signal processing, role in 1-45
two-dimensional 7-173
fdatool 7-168
fdatool 5-1
help on 6-7
opening 5-6
fft 1-3, 1-23, 1-45, 7-170
example 1-46
execution time 1-46
number of samples 1-46
output 1-47, 7-176
radix-2 al gorithm 7-172
FFT filtering 1-23
FFT. Seefast Fourier transforms
fft2 1-47, 1-47, 7-173
output 1-47
fftfilt 1-20, 7-174
filter, comparison to 7-174
fftshift 1-47, 1-47, 7-176
filter
coefficients 1-16
median 4-30
order 1-16
filter 1-3, 1-17, 1-21, 7-177
fftfilt, comparison to 7-174
filtfilt, comparison 1-22
final condition parameters 1-18
implementation 1-18
initial condition parameters 1-18
initial conditions 7-184
filter coefficients
reflection coefficients, conversions to 7-341, 7-367
filter design GUI 5-2
analysis buttons 5-13
analysis functions 5-13
computing coefficients 5-12
design methods 5-8
design sessions
opening 5-25
saving 5-25
exporting filters 5-21
filter design specification 5-9
filter order specification 5-11
filter type 5-7
filters
architecture 5-15
implementation 5-15
realization 5-15
structure 5-15
frequency response specification 5-9
group delay 5-13
importing coefficients 5-17
importing filters 5-17
impulse response 5-13
magnitude response 5-13
magnitude response specs 5-10
opening 5-6
phase delay 5-13
phase response 5-13
pole-zero plots 5-13
saving coefficients 5-21
step response 5-13
Filter Designer 6-11, 7-421
FFT length 6-50
filter types 6-11
filters
editing 6-41
redesigning 6-49
saving 6-33
FIR filters 6-11
FIR methods 6-11
grid lines 6-50
IIR methods 6-11
opening 6-12, 6-22
overview 6-11
plots
customizing 6-50
magnitude 6-49
Pole/Zero Editor 6-46
sample frequency 6-34
spectra, overlaying 6-12
zooming 6-50
filter parameters 6-50
Filter Viewer 6-14, 7-422
axis parameters 6-50
filter parameters 6-50
measurements 6-52
opening 6-14
overview 6-14
preferences, tiling 6-50
printing 6-27
rulers 6-52
zooming 6-50
filter2 7-180
filternrom 7-181
filters 1-3
analog 2-9, 2-12, 7-38, 7-64, 7-78
anti-causal 1-21
anti-symmetric 2-26
averaging 1-15
bandpass
Butterworth 7-70
Chebyshev Typel 7-79
Chebyshev Type II 7-84
elliptic 7-162
bandstop
Butterworth 7-70
Chebyshev Typel 7-79
Chebyshev Type II 7-84
elliptic 7-162
Butterworth 2-8, 7-65
generalized 2-15
Chebyshev 2-8
Typel 7-90
Type II 7-95
coefficients 1-17, 1-33, 2-18, 6-34
bit reversal 7-47
converting to autocorrelation sequence 7-339
export to C header file 5-22
export to text file 5-22
export to workspace 5-21
convolution 1-15
creating 2-8
design 6-11
Filter Designer 6-11
FIR 2-23
generalized 2-6
discretization 2-42
elliptic 2-8, 7-155
equiripple 2-23
FIR 7-371
single band 2-21
frequency data, identification from 7-255
frequency domain 1-23
frequency transformation functions 2-39, 2-40
highpass
Butterworth 7-70
Chebyshev Typel 7-79
Chebyshev Type II 7-84
elliptic 7-162
implementation 1-23, 7-174, 7-177
initial conditions 1-18, 1-19
inverse 7-255, 7-259
lattice/ladder 1-38
linear phase 2-17, 2-18
linear time-invariant digital 1-3
lowpass
Butterworth 7-70
Chebyshev Typel 7-79
Chebyshev Type II 7-84
elliptic 7-162
measurements 6-52
median 7-292
minimax 2-23
minimum phase 7-344
names 1-16
norm 7-181
order 1-16, 2-8, 7-70, 7-79, 7-162, 7-167
order estimation 2-8
phase, modulation 4-27
prediction 4-14
quantized, state vectors 7-178
Savitzky-Golay 7-400, 7-404
Schur realizations 7-397
second-order section forms 1-38, 1-44, 7-415
specifications 2-8
SPTool 6-39
transposed direct form II structure 1-18
two-dimensional 7-180
types 2-18
zero-phase 1-21, 7-183
Se also FIR filters, IIR filters, digital filters, analog filters
filtfilt 1-20, 1-21, 2-5, 7-183
example 1-21
filter, comparison 1-22
initial conditions 1-22
filtic 1-19, 7-184
FIR filters 1-16, 2-17
decimation 7-253
differentiators 2-27, 7-200, 7-373
equiripple 2-17, 2-23, 2-24
example 6-20
Filter Designer 6-11
frequency domain 1-20
frequency response 7-190
Hilbert transformers 2-26, 7-200, 7-373
IIR filters, comparison 2-17
implementation 1-18, 7-177

FFT-based 1-23, 7-174
overlap-add method 1-23, 7-174
interpolation 7-253
Kaiser windows 4-8
lattice/ladder 1-38
least squares 2-17, 2-24, 7-199
constrained 2-17, 2-28
equiripple, comparison 2-24
linear phase 2-29
multiband 2-29, 2-30
weighted 2-31
linear phase 2-18, 2-23, 7-199, 7-371
multiband 2-17, 2-22, 2-23
order estimation, remez 7-378
overlap-add method 7-174
Parks-McClellan method 2-23, 7-371
raised cosine method 2-17
resampling 1-20
responses 2-32
complex filters 2-17, 7-121
delays, reducing 2-35
nonlinear phase 2-17, 7-121
standard band 2-21
types 7-202, 7-376
windowing method 2-17
windows 2-19, 7-186
fir1 2-17, 2-21
fir2 2-17, 2-21
fircls 2-17, 7-193
fircls1 2-17, 7-196
firls 2-17, 2-23, 7-199
differentiators 2-27
filter characteristics 7-202
remez, comparison to 2-24
weight vectors 2-26
firrcos 2-17, 7-204
fixed-point implementation, digital filters 1-38
fm 4-32
FM. Sefrequency modulation fopen 1-14
Fourier transforms. See discrete Fourier transforms, fast Fourier transforms
fread 1-14
freqs 1-27, 7-206
freqspace 7-208
frequency 7-372
analog xxvi
angular 2-3
carrier 4-31, 7-293, 7-469
center 2-41
cutoff 2-39
digital xxvi
estimation
eigenanalysis 3-37
eigenvector (EV) method 3-37
multiple signal classification (MUSIC) method 3-37
normalization 2-3
Nyquist xxvi, 2-3
prewarping 7-42
vectors 2-25, 7-190, 7-193, 7-481
frequency analysis, time-dependent 7-416
frequency demodulation 7-143
frequency domain
duality with time-domain 1-23
filters 1-23
FIR filtering 1-20
transformation functions 2-39, 7-276, 7-279, 7-281, 7-283
example 2-41
lowpass to bandpass 7-276
lowpass to bandstop 7-279
lowpass to highpass 7-281
frequency domain based modeling. See parametric modeling
frequency modulation 7-294
frequency response 1-25, 2-14, 7-190
Bessel filters 2-12
Butterworth filters 2-9
Chebyshev Type I filters 2-10
Chebyshev Type II filters 2-11
Chebyshev windows 4-10
elliptic filters 2-11
error minimization 2-23
evaluating 1-25
example 1-26
inverse 7-255
Kaiser window 4-7
linear phase 2-18
magnitude 1-27
monotonic 2-9
multiband 2-14
phase 1-27
unwrapping 1-28
plotting 1-26, 7-213
samples, spacing 7-208
sampling frequency 1-25
frequency vectors 7-372
freqz 1-25, 7-209
sampling frequencies 1-25
sampling frequency 1-25
spacing 7-208
freqzplot 7-213
From Disk radio button 6-43
fscanf 1-14

\section*{G}
gains, scalar 1-34
gauspuls 1-10, 1-11, 7-220

Gaussian monopulse 7-224
Gauss-Newton method 7-258, 7-261
gausswin 4-3
generalized Butterworth filters 2-15
generalized cosine windows 4-5
generalized filters 2-6
Gibbs effect 2-20
reduced by window 4-3
gmonopuls 7-224
goertzel 7-226
graphical user interface (GUI) 1-4
Sealso interactive tools, SPTool
grid lines 6-50
group delay 1-29, 2-18, 7-231
example 1-30
passband 2-12
grpdelay 1-29, 7-231
GUI-based tools. See interactive tools

\section*{H}
hamming 4-3, 7-234
Hamming windows 2-20, 3-18, 4-5, 7-234
hann 4-3
hann 7-236
Hann windows 7-236
Hanning windows 4-5, 7-236
hanning. Sehann
highpass filters 2-7, 7-71, 7-80, 7-85, 7-163

> Bessel 7-39

Butterworth 7-66
Chebyshev Type I 7-91
Chebyshev Type II 7-95
elliptic 7-156
FIR 2-22, 7-188
lowpass, transformation from 7-281
hilbert 2-27, 4-40
example 4-40
Hilbert transformers 7-200, 7-373
Hilbert transforms 4-36, 4-40, 7-238
analytic signals, of 2-27
example 4-40
instantaneous attributes 4-41
homomorphic systems 4-25
Hz 7-300, 7-305, 7-322, 7-360

\section*{I}
icceps 4-25, 4-27, 7-242
example 4-28
idct 4-38, 7-243
ideal lowpass filters 2-19
See also lowpass filters
ifft 1-45, 7-244
samples, specifying 1-47
ifft2 1-47, 7-245
IIR filters 2-5, 2-6, 2-8, 2-9, 2-14
Bessel 2-12
Butterworth 2-8, 2-9
Butterworth, generalized 2-15
Chebyshev 2-8, 2-10, 2-11
Chebyshev Typel 2-10
Chebyshev Type II 2-11
design 2-7, 2-38
elliptic 2-8, 2-11
Filter Designer 6-11
filter types, comparison 2-9
FIR filters, comparison to 2-5
frequency response 2-14
implementation 7-177
frequency domain 1-23
zero-phase 1-21
lattice/ladder 1-38
Levinson-Durbin recursion 7-274
maximally flat 2-15
multiband 2-14
order estimation 2-8
plotting responses 2-13
Prony's method 7-345
specifications 2-8
Steiglitz-McBride iteration 7-433
Yule-Walker 2-14, 7-481
Sealso direct design
image processing 1-47, 7-111
impinvar 2-6, 2-42, 7-246
Import dialog box
From Disk radio button 6-43
Workspace Contents list 6-21
impulse invariance 2-42, 7-246
limitations 2-42
impulse response 1-24, 7-248
computing with filter 1-24
computing with impz 1-24
example 1-24
impulse invariance 2-42
lowpass filters, ideal 2-19
impz 7-248
example 1-24
indexing 1-16
inf-norm 7-181
initial conditions 1-18, 1-19, 1-22, 7-184
instantaneous attributes 4-41
interactive tools 1-4, 6-3
example 6-20
Filter Design and Analysis Tool 5-2
Filter Designer 6-11, 7-421
Filter Viewer 7-422
Signal Browser 7-421
Spectrum Viewer 6-17, 7-424
SPTool 7-420
interp 7-251
interpolation 7-251
bandlimited 7-406
FIR filters 7-253
interval notation xxvi
intfilt 7-253
inverse cepstrum, complex 4-27
inverse discrete cosine transforms 7-243
accuracy of signal reconstruction 4-40
inverse discrete Fourier transforms 1-45, 7-244
ifft 1-45
matrices 7-144
two-dimensional 1-47, 7-245
inverse filters 7-259, 7-345
analog 7-255
digital 7-259
inverse Fourier transforms, continuous. Seesinc
inverse-sine parameters
reflection coefficients, transformations from 7-262
reflection coefficients, transformations to 7-365
invfreqs 2-6, 4-13, 4-19, 7-255
invfreqz 2-6, 4-13, 4-19, 7-259
is2rc 7-262

\section*{K}
kaiser 4-3, 7-263
example 4-6
Kaiser window 3-20
Kaiser windows 4-6, 7-263
beta parameter 4-6, 7-263
example 4-6
FIR filters 4-8
frequency response 4-7
kaiserord 2-17, 7-265

\section*{L}
ladder filters. Selattice/ladder filters
Lagrange interpolation filter 7-253
Laplace transforms 1-42
state-space forms 1-42
lar2rc 7-270
latc2tf 1-41, 1-43, 7-271
latcfilt 1-20, 1-41, 7-272
lattice/ladder filters 1-38, 1-39, 1-43
coefficients 1-39
latcfilt 1-41
Schur al gorithm 7-397
transfer functions, conversions from 7-438
least squares method, FIR filters 7-199, 7-202
levinson 4-13, 7-274, 7-387
parametric modeling 4-14
Levinson-Durbin recursion 4-14, 7-274, 7-387
line spectral frequencies
prediction polynomial coefficients, transformation from 7-340
prediction polynomial coefficients, transformation to 7-289
line style, SPTool 6-50
linear models. Se models
linear phase 2-17, 2-18, 7-199
characteristics 2-18
filters 7-371
linear prediction coefficients 7-285
linear prediction modeling 4-14
linear predi ctive coding 4-14
linear system transformations. See conversions load 1-14
log area ration parameters
reflection coefficients, transformations from 7-270
reflection coefficients, transformations to 7-366
lowpass filters 2-7, 7-71, 7-80, 7-85, 7-163

Bessel 7-39
Butterworth 7-65
Chebyshev Type I 7-90
Chebyshev Type II 7-95
cutoff frequency, translation of 7-283
decimation 7-138
elliptic 7-155
FIR 2-22
ideal 2-19
impulse invariance 2-42
impulse response 2-19
interpolation 7-251
lp2bp 2-6, 2-40, 7-276
example 2-41
lp2bs 2-6, 2-40, 7-279
lp2hp 2-6, 2-40, 7-281
lp2lp 2-6, 2-40, 7-283
lpc 2-6, 4-13, 7-285
See also linear predictive coding, Prony's method
LPC. Seelinear prediction coefficients
Ise 7-224
lsf2poly 7-289

\section*{M}
magnitude
F ourier transforms 1-46
frequency response 1-27
plots 6-49
transfer functions 3-28
vectors 2-25, 7-190, 7-193, 7-481
manufacturing 4-12
match frequency (for prewarping) 7-42
MAT-files
dpss.mat 3-26
format, converting to 1-14
importing 1-14
SPTool 6-43
matrices
convol ution 1-41, 7-113
correlation coefficient 7-115
covariance 7-119
data 1-5, 1-8
discrete F ourier transforms 7-144
inverse discrete F ourier transforms 7-144
matrix forms. Se state-space forms
maxflat 2-6, 2-15, 7-290
maximally flat filters 2-15
medfilt1 4-30, 7-292
median filters 4-30, 7-292
MEX-files 1-14
M-files 1-4
minimax method, FIR filters 2-23
Seealso Parks-McClellan method
minimum phase 7-344
models 1-33
autoregressi ve 7-30, 7-31, 7-32, 7-33
Burg method 7-299, 7-303
covariance method 7-304
modified covariance method 7-321, 7-325
Yule-Walker AR method 7-359, 7-363
bilinear transformations 2-44
transformations, discrete/continuous 2-44
modified covariance method 3-36
example 3-36
modulate 4-31, 4-32, 7-293
example 4-32
method flags 4-31
modulation 4-31, 7-293
amplitude 4-31
Sealso amplitude modulation
example 4-32
frequency 4-32
phase 4-32
pulse position 4-32
pulse width 4-32
quadrature amplitude 4-32
results of 4-32
signals 4-31, 7-293
moving average (MA) filters 1-16
See also FIR filters
MTM. Semultitaper method multiband filters

FIR 2-22
FIR, with transition bands 2-23
IIR 2-14
multichannel data 1-8
multiple signal dassification method (MUSIC) 3-8, 3-9, 3-36, 7-331, 7-337
correlation matrices 7-116
eigenvector method 7-309, 7-314
root music 7-393
multiplication, polynomials 7-110
multiplicity, of zeros and poles 6-47
multirate filters 1-20
banks 1-20
multitaper method (MTM) 3-8, 3-9, 3-24
average power, conservation of 3-26
example 3-25
Welch's method, comparison to 3-26
MUSIC algorithm. Seemultiple signal classification method

\section*{N}
nonrecursive filters. SeFIR filters
normalization 3-4
correlation 3-5, 7-473, 7-474
power spectral density 3-17, 3-18, 3-23
Nuttall windows 7-296
nuttallwin 4-3, 7-296
Nyquist frequency xxvi, 2-3, 7-155
Nyquist interval 7-155

\section*{0}
order
estimation 2-8, 7-378
Butterworth 7-70
Chebyshev Type I 7-79
elliptic 7-162, 7-167
filters, of 1-16, 2-8
oscillators, voltage controlled 7-469
overlap-add method
FIR filter implementation 1-23
FIR filters 7-174

\section*{P}

Panner check box, Signal Browser 6-50
parametric modeling 4-12, 7-259
applications 4-12
frequency domain based 4-19
summary 2-6
techniques 4-12
time-domain based 4-14
Burg method 7-30
covariance method 7-31
linear predictive coding 4-14, 4-15
modified covariance method 7-32
Steiglitz-McBride method 4-17
Yule-Walker method 7-33
parentheses, indicating open interval xxvi
Parks-McClellan method 2-23, 7-371
partial fraction expansion 1-36, 1-42, 1-43, 7-384
determining with residue 1-42
example 1-36
passband 7-70, 7-79, 7-84, 7-162
equiripple 2-10, 2-11
group delay 2-12
pburg 3-9, 3-34, 7-299
example 3-34
PCM 7-459
pcov 3-9, 3-36, 7-304
example 3-36
peig 3-36
peig 7-309
period, finding in a sequence 7-398
periodic sinc functions 7-145
See also Dirichlet functions
periodogram 7-316
periodograms 3-10, 7-316, 7-320
phase
computing 7-29
delays 1-29, 2-18, 7-231
example 1-30
demodulation 7-143
distortion
eliminating 1-20, 1-21
FIR filters 1-21
IIR filters 1-21
Fourier transforms 1-46
frequency response 1-27
modulation 4-32, 7-294
filters 4-27
transfer functions, of 3-28
unwrapping 1-28, 7-462
plots
analog filters 2-13
cepstrum, complex 4-26
coherence function 3-29
DFT 1-46
frequency response 1-26
functions for 7-347
group delay 1-30
magnitude 1-27, 6-49
phase 1-27
delays 1-30
strip plots 7-436
transfer functions 3-28
zero-pole 1-31, 7-489
plotting functions 7-213
plug-ins 6-50
pm 4-32
pmcov 3-9, 3-36, 7-321
example 3-36
p-model. Se parametric modeling
pmtm 3-9, 7-326
example 3-25
pmusic 3-9, 3-36, 7-331
Pole/Zero Editor 6-46
pole-zero filters. SeIIR filters
poly 1-34, 1-43
poly2ac 7-339
poly21sf 7-340
poly2rc 7-341
polynomials
division 4-35, 7-141
multiplication 7-110
roots 1-34, 1-43
scaling 7-344
stability check 7-341
stabilization 7-343
polyphase filtering techniques 1-20
polyscale 7-343
polystab 7-343, 7-344
power spectral density 3-6
bias 3-17, 3-18, 3-23
confidence intervals 3-27
estimation
Burg method 3-9, 3-33, 7-299
covariance method 3-9, 3-36, 7-304
modified covariance method 3-9, 7-321
multitaper method 3-24, 7-326
MUSIC method 3-37, 7-331
root music 7-390, 7-393
Welch's method 3-9, 3-20, 3-23
Yule-Walker AR method 3-9, 3-32, 7-359
multitaper method 3-9
MUSIC method 3-9
normalization 3-17, 3-18, 3-23
plots 6-17
Spectrum Viewer 6-17
SPTool 6-41
units of 3-7
ppm 4-32
prediction filters 4-14
prediction polynomials
line spectral frequencies, transformations from 7-289
line spectral frequencies, transformations to 7-340
Preferences menu item 6-50
prewarping 7-42
Print dialog box 6-28, 6-30
Print Preview window
Signal Browser preferences 6-28
Spectrum Viewer 6-30
printing, Spectrum Viewer 6-53
prolate-spheroidal windows 4-6
prony 2-6, 4-13, 4-15, 7-345
Prony's method 4-15, 7-345
modeling 4-15
psdplot 7-347
pseudospectrum 7-337
eigenvector method 7-309, 7-314
MUSIC algorithm 7-337
pulse position demodulation 7-143
pulse position modulation 4-32
pulse time modulation 7-294
pulse train generator 7-349
pulsetrains
generating 1-11
pulstran 1-11
pulse width demodulation 7-143
pulse width modulation 4-32, 7-294
pulstran 1-11, 7-349
pwelch 3-9, 3-20, 7-353
pwm 4-32
pyulear 3-9, 3-32, 7-359
example 3-33, 3-34

\section*{Q}
qam 4-32
quadrature amplitude demodulation 7-143
quadrature amplitude modulation 4-32, 7-294
quantization 7-181, 7-456, 7-459
PCM 7-459
quantized filters 7-178
second-order sections
coefficients in a cell array 7-408
coefficients in a matrix 7-77

\section*{R}
radar applications 4-29
raised cosine filters 7-204
randn xxiv
random number, generation xxiv
range notation xxvi
rc2ac 7-364
rc2is 7-365
rc2lar 7-366
rc2poly 7-367
rceps 4-25, 4-27, 7-368
rebuffering 7-55
rectangular windows 2-19, 4-3, 7-370
rectpuls 7-369
rectwin 4-3
example 4-4
rectwin 7-370
recursive filters. SeIIR filters
references 1-48, 3-39, 4-42
reflection coefficients 1-38, 1-39
converting to autocorrelation sequence 7-364
filter coefficients, conversions from 7-341, 7-367
inverse sine parameters, transformation from 7-365
inverse sine parameters, transformation to 7-262
log area ratio parameters, transformation from 7-366
log area ratio parameters, transformation to 7-270
Schur algorithm 7-397
remez 2-17, 2-23, 7-371
differentiators 2-27
filter characteristics 7-376
firls, comparison to 2-24
Hilbert transformers 2-26
order estimation 7-378
weight vectors 2-26
Remez exchange algorithm 2-23, 7-371
remezord 2-17, 7-378
resample 7-381
resampling 4-22, 7-381
FIR filters 1-20
See al so decimation, interpolation
residue 1-42, 1-43, 1-43
residue forms. Seepartial fraction expansion
residuez 1-43, 7-384
rlevinson 7-387
root MUSIC 7-393
eigenvector method 7-390
rooteig 7-390
rootmusic 7-393
roots 1-34, 1-43
polynomials 1-34
rulers
positioning 6-53
Signal Browser 6-50
Spectrum Viewer 6-50

\section*{S}
sampling frequency
changing
noninteger resampling factors 4-22, 7-381
with upfirdn 1-20
decreasing 7-146
decreasing by integer factor 7-138
FIR filters 1-20
freqz 1-27
increasing 7-251, 7-467
irregularly spaced data 4-23
Nyquist interval 7-155
range 1-27
spacing 1-27
saving data
Spectrum Viewer 6-37
Savitzky-Golay filters 7-400, 7-404
sawtooth 1-9, 7-390, 7-396
sawtooth wave 1-9
scaling 7-343
schur 7-397
Schur algorithm 7-397
schurrc 7-397
second-order section forms 1-38, 1-43
filters 7-415
matrices 1-38
SPTool 6-40
state-space forms, conversions from 7-426
state-space forms, conversions to 7-409
transfer functions, conversions from 7-411, 7-439
zero-pole-gain forms, conversions from 7-483
zero-pole-gain forms, conversions to 7-413
second-order sections
coefficients in cell arrays 7-408
coefficients in matrices 7-77
seqperiod 7-398
sgolay 7-400, 7-404
sgolayfilt 7-404
Signal Browser 6-8, 7-421
axis labels 6-50
markers, preferences 6-50
opening 6-8
overview 6-8
Panner, preferences 6-50
Print Preview window 6-28
printing 6-10, 6-26, 6-27, 6-53
signals, measuring 6-52
zooming, preferences 6-50
Signal Processing Tool box 1-3
signals 2-27
adding noise 1-7
analytic 4-40, 7-238
aperiodic 1-10
applications 4-40
array 6-8
buffering 7-55
carrier 4-31, 7-142
chirp 1-10
continuous (analog) 1-3
differentiators 2-27
diric 1-13
discrete (digital) 1-3
generating 1-8
linear swept-frequency cosine. Sechirp
measurements 6-52
modulation 4-31, 7-293
multichannel 3-5
periodic 1-9
plotting 1-7
properties 4-40
pulstran 1-11
rebuffering 7-55
reconstruction
DCT coefficients, from 4-39
minimum phase 4-27, 7-368
representing 1-5
multichannel 1-5
single channel 1-5
sawtooth 1-9, 7-396
example 1-9
sinc 1-12
sinusoidal 1-7, 1-10
pulse, Gaussian-modulated 1-10
square wave 1-9, 7-425
triangle 7-396
sinc 1-12, 7-406
bandlimited interpolation example 7-406
sinc functions 1-12, 7-406
basic example 1-12
Slepian sequences. Seediscrete prolate spheroidal sequences
sonar applications 4-29
sos2cell 7-408
sos2ss 1-43, 7-409
sos2tf 1-43, 7-411
sos2zp 1-43, 7-413
sosfilt 7-415
specgram 4-29, 7-416
example 4-29, 7-469
specification lines. SeFilter Designer
specifications, filters 2-8
spectra. See spectrum
spectral analysis 3-6
cross spectral density 3-27
power spectrum 3-6
Spectrum Viewer 6-17
See also spectral estimation
spectral density 3-6
measurements 6-52
plotting functions 7-347
Spectrum Viewer 6-17
units of 3-7
See also power spectral density, cross spectral density
spectral density plots 6-17
spectral estimation 3-10
Burg method 3-9, 3-33, 7-299, 7-300
covariance method 7-304, 7-308
eigenvector method 7-309, 7-310, 7-314
modified covariance method 3-9, 7-321
multitaper method 3-9, 7-326
MUSIC algorithm 7-331, 7-337
MUSIC method 3-9, 7-332
nonparametric
multiple signal dassification method (MUSIC) 3-8
multitaper method (MTM) 3-8
Welch's method 3-8
parametric
Burg method 7-30
covariance method 7-31
modified covariance method 7-32
Yule-Walker method 7-33
periodograms 7-320
root MUSIC 7-390, 7-393
Welch's method 3-8, 3-9, 3-20, 3-23, 3-27, 7-109, 7-131, 7-353, 7-357
Yule-Walker AR method 2-14, 3-8, 3-9, 3-32, 3-33, 7-359, 7-360
spectrogram 4-29, 7-416
example 4-29, 7-469
Spectrum Viewer 6-17, 7-424
activating 6-17
axis parameters 6-50
markers, preferences 6-50
measurements 6-52
opening 6-17
overview 6-17
Print Preview 6-30
printing 6-17, 6-27, 6-53
rulers 6-52
spectra structures 6-37
spectral density plots 6-17
windows 6-18
zooming 6-50
speech processing 4-12, 4-23
spline 4-23
SPTool 6-3, 7-420
colors, customizing 6-50
context-sensitive help 6-7
customizing 6-50
data
entering 1-14
objects 6-44
sel ecting 6-44
data structures 6-3
editing 6-45
example 6-20
exporting data 1-14, 6-32
filter design 6-22
filtering 6-24
filters 6-39
coefficients 6-34
importing 6-22, 6-39
parameters 6-34
specifications 6-35
filters, saving 6-33
help on 6-7
Import dialog 6-21
importing 1-14, 6-20, 6-22, 6-39
items, sel ecting 6-44
line style, customizing 6-50
MAT-files 6-43
MATLAB workspace 6-3
multiselection of items 6-44
operation 6-3
Pole/Zero Editor 6-46
preferences 6-50
Preferences menu item 6-50
Print dialog box 6-28, 6-30
printing 6-27
filters 6-28
spectra 6-28
right-dick edit menu 6-45
rulers 6-52
sample frequency 6-34
saving 6-32
second-order section forms 6-40
Signal Browser 6-26
signals
analysis 6-26
measurements 6-52
playing 6-27
sound 6-27
spectra
analyzing 6-28
importing 6-22
spectral densities
importing 6-39, 6-41
plots 6-41
Spectrum Viewer 6-28
state-space forms 6-40
transfer functions
exporting 6-34
specifying 6-40
workspace 6-3
zero-polegain forms 6-40
sptool 7-420
square 1-9, 7-425
square wave 1-9
ss2sos 1-43, 7-426
ss2tf 1-43, 7-430
ss2zp 1-43, 7-431
stability check, polynomials 7-341
stabilization 7-344
standards, digital audio tape 4-22
startup transients, reducing 1-22, 7-183
state vectors 7-178
state-space forms 1-35, 1-42, 1-43
scalar 1-35
second-order section forms, conversions from 7-409
second-order section forms, conversions to 7-426
SPTool 6-40
transfer functions, conversions to 7-442
zero-pole-gain forms, conversions from 7-487
zero-pole-gain forms, convertions to 7-431
statistical operations 3-3
Sealso autocorrelation sequences, cross-correlation sequences, cross-covariance
Steiglitz-McBride method 4-17, 7-433
stmcb 2-6, 4-13, 4-17, 7-433
stopband 7-70, 7-79, 7-84, 7-162
equiripple 2-11
strip plots 7-436
strips 7-436
structures
converting 1-43, 5-15
lattice/ladder 1-38
transposed direct form II 7-178
structures, digital filters
lattice/ladder 1-38
transposed direct form II 1-18
swept-frequency cosine generator. Seechirp
system identification 4-15
system models. See models

\section*{T}
tapers, PSD estimates 3-24
taps 2-18
tf2latc 1-39, 1-43, 7-438
tf2sos 7-439
tf2ss 1-43, 7-442
tf2zp 1-43, 7-431, 7-444
tfe 3-9, 3-28, 7-447
tiling preferences 6-50
time series attributes 4-41
time-domain based modeling. See parametric modeling
toolboxes
Control Systems Tool box 1-36
Signal Processing Tool box 1-3
Symbolic Math Tool box 7-38
transfer functions 1-16, 1-33, 1-36, 1-43
coefficients 1-16, 6-34
estimation 7-447
using Welch's method 3-28
factoring 1-34
lattice forms, conversions to 7-438
second-order section forms, conversions from 7-411
second-order section forms, conversions to 7-439
SPTool 6-40
state-space forms, conversions to 7-442
zero-pole-gain forms 1-34
transformations
bilinear 2-43, 7-42
discrete/continuous 2-44
frequency 2-39, 7-276, 7-279, 7-281, 7-283
models, between 1-43
transforms 4-36
chirp z-transforms (CZT) 4-36, 7-133
discrete cosine 7-136
discrete F ourier 1-45, 7-170
Hilbert 4-40, 7-238
inverse discrete cosine 4-38, 7-243
inverse discrete Fourier 7-244
transients, filters 1-23
transition band 2-23
transposed direct form II 7-178
initial conditions 7-184
triang 4-3, 7-451
example 4-4
triangular windows 7-451
tripuls 7-453
Tukey 7-454
tukeywin 4-3, 7-454
two-dimensional operations
discrete Fourier transforms 1-47, 7-173
inverse discrete F ourier transforms 1-47, 7-245
See al so filters, two-dimensional
two-dimensional signal processing 1-47
typographical conventions (table) xxvii

\section*{U}
udecode 7-456
uencode 7-459
uniform encoding 7-459
unit circle 7-344
unit impulse function 1-8
unit ramp function 1-8
unit sample, multichannel representation 1-8
unit step function 1-8
units of power spectral density (PSD) 3-7
unwrap 1-28, 7-462
upfirdn 1-20, 4-23, 7-463
upsample 7-467

\section*{v}
variance, correlation sequence estimate 3-4
vco 4-31, 4-34, 7-148, 7-469
vectors
data 1-5, 1-7
frequency 2-25, 7-190, 7-193, 7-372, 7-481
indexing xxvi, 1-16
magnitude 2-25, 7-190, 7-193, 7-481
weighting 7-200
voltage controlled oscillators 4-34, 7-469

\section*{W}
waveforms. Seesignals
Welch's method 3-9, 3-20
bias 3-23
Burg method, comparison to 3-35
MTM method, comparison to 3-26
normalization 3-23
power spectral density estimation 3-8, 3-23, 3-27, 7-109, 7-131, 7-357
system identification, nonparametric 3-28

Yule-Walker AR method, comparison to 3-33
white noise 1-7
window 7-471
windows
Bartlett 4-4, 7-36
Bartlett-Hanning 7-34
Blackman 4-5, 7-49
Blackman-H arris 7-51, 7-296
blackmanharris vs. nuttallwin 7-51, 7-296
Bohman 7-53
boxcar 2-19
Chebyshev 4-10, 7-89
cosine, generalized 4-5
filters 2-19
FIR filters 2-19
bandpass 7-186
bandstop 7-187
highpass 7-187
lowpass 7-186
multiband filters 2-22
single band design 2-21
fir1 2-22
generalized cosine 4-5
Hamming 2-20, 3-18, 4-5, 7-234
Hann 7-236
Hanning 4-5, 7-236
Kaiser 3-20, 4-6, 7-263
Nuttall 7-296
periodograms 3-12, 3-18
prolate-spheroidal 4-6
rectangular 2-19, 7-370
shapes 4-3
triangular 7-451
Tukey 7-454
Workspace Contents list 6-21

\section*{X}
xcorr 3-3, 7-473
parametric modeling 4-14
xcorr2 7-477
\(x \operatorname{cov} 3-3,7-478\)
zp2tf 1-43, 7-488
zplane 1-31, 7-489
z-transforms 1-16, 1-33
chirp z-transforms (CZT) 4-36, 7-133
discrete Fourier transforms 1-45, 7-170

\section*{Y}
yulewalk 2-6, 2-14, 7-481
example 2-14
Yule-Walker AR method 3-8, 3-9, 3-32, 7-481
example 3-33, 3-34
Welch's method, comparison to 3-33
Yule-Walker equations 2-14

\section*{Z}
zero frequency component, centering 1-47
zero-order hold. Seaveraging filters
zero-phase filtering 7-183
zero-pole analysis 7-489
zero-pole plots 1-31, 7-489
zero-pole-gain forms 1-34, 1-42, 1-43
example 1-31
second-order section forms, conversions from 7-413
second-order section forms, conversions to 7-483
SPTool 6-40
state-space forms, conversions from 7-431
state-space forms, conversions to 7-487
zeros and poles
multiplicity of 6-47
transfer functions 1-34
zooming 6-50
zp2sos 1-43, 7-483
zp2ss 1-43, 7-487```


[^0]:    Note The functions prony and stmcb (described next) are more accurately described as ARX models in system identification terminology. ARMA modeling assumes noise only at the inputs, while ARX assumes an external input. prony and stmcb know the input signal: it is an impulse for prony and is arbitrary for stmcb.

[^1]:    You can access the information in these fields as you do with every MATLAB structure.

    For example, if you export an SPTool PSD estimate spect1 to the workspace, type

    ```
    spect1.P
    ```

    to obtain the vector of associated power values.

[^2]:    Tip K eep the Filter Viewer open while designing a filter with the Pole/Zero Editor. Any changes that you make to the filter transfer function in the Pole/Zero Editor are then simultaneously reflected in the response plots of the Filter Viewer.

[^3]:    See Also
    barthannwin, blackman, blackmanharris, bohmanwin, chebwin, gausswin, hamming, hann, kaiser, nuttallwin, rectwin, triang, tukeywin, window

[^4]:    See Also
    besself, butter, cheb1ap, cheb1ord, cheby2, ellip

