

A photograph of a large, multi-story building with a red-tiled roof and arched windows, likely a Stanford University building. The building is set against a dark, overcast sky. In the foreground, there is a green lawn and a paved path. The text is overlaid on the image.

Rad229 – MRI Signals and Sequences

Daniel Ennis & Brian Hargreaves

dbe@stanford.edu –or– bah@stanford.edu

A wide-angle photograph of the Stanford University Main Quad, featuring the central tower and surrounding buildings with red-tiled roofs and arched windows, set against a dark, overcast sky. The foreground is a large, green lawn with a paved walkway leading towards the buildings.

Lecture-07A — Signal-to-Noise Ratio

Single-Channel Noise and SNR Measurement

Brian Hargreaves
bah@stanford.edu

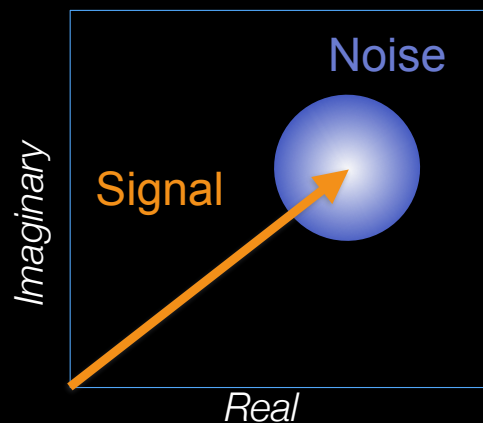
Learning Objectives

- Understand noise statistics in k-space, complex images, and magnitude images
- Explain when the distribution is Gaussian, Rayleigh and Rician
- Know basic methods to measure SNR



SNR: Signal-to-Noise Ratio

- Signal (desired) vs Noise (interference)
- Thermal noise, depends on coil, patient size



Low SNR



High SNR



Origins of SNR

- Body noise dominance
- $SNR = C f(\text{Ob}) (\text{Im})$
 - $C = \text{constants}$
 - $f(\text{Ob}) = \text{function of object}$
 - $\text{Im} = \text{Imaging parameters}$

$\omega_0 = \text{frequency}$

$V_{\text{voxel}} = \text{voxel volume}$

$T_{\text{acq}} = \text{A/D time}$



$$SNR = \left[\frac{2\chi\sqrt{\rho}}{\gamma\mu_0\sqrt{KT\pi}} \right] \left[\frac{1}{r_0^2\sqrt{l}} \right] \left[\omega_0 V_{\text{voxel}} \sqrt{T_{\text{acq}}} \right]$$



Noise and the Signal Equation

- Noise is zero-mean, complex, additive
- Recall **signal equation** from lecture 2:

$$S(\vec{k}) = \int_{\text{object}} M(\vec{r}) e^{-i2\pi\vec{k}\cdot\vec{r}} d\vec{r} + n_c(0,\sigma)$$

- Additive **complex, gaussian noise**: $n_c = n_r + i * n_i$
- **Probability density function** $P(n_r, n_i)$ is a simple product of gaussian distributions for **real** and imaginary:

$$P(n_r, n_i) = \left(\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{n_r^2}{2\sigma^2}} \right) \left(\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{n_i^2}{2\sigma^2}} \right)$$

Noise is complex, gaussian and additive, with zero mean and variance σ^2 (both real and imaginary)



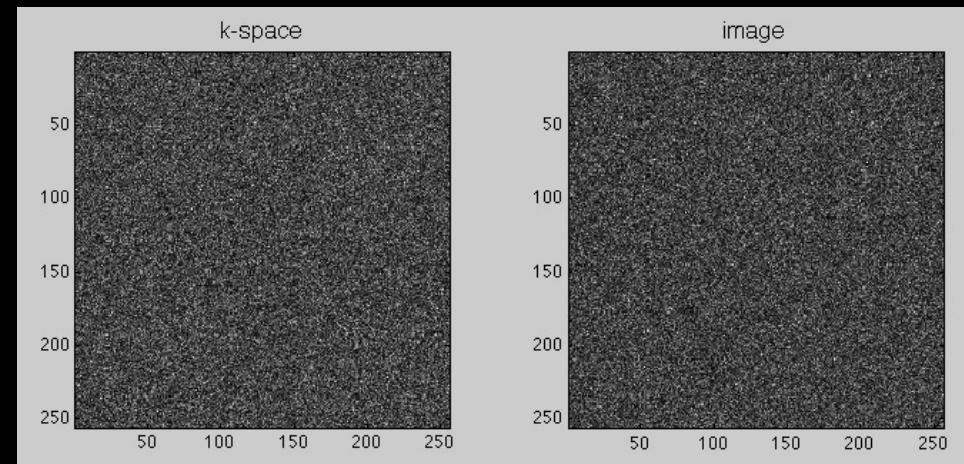
Gaussian Noise in (Discrete) Image Space and k-Space

- Assume equally scaled FFT / iFFT:
 - Equations are 1D!
- Noise statistics preserved ($M_n \Leftrightarrow S_k$)
 - additive complex noise
 - gaussian, zero-mean

$$S_k = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} M_n e^{-i2\pi kn/N}$$

$$M_n = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} S_k e^{i2\pi kn/N}$$

$$\sigma = \sigma_r = \sigma_i$$



Complex, zero-mean gaussian noise in k-space transforms to complex gaussian noise in image space, both same variance σ^2



Example: Verifying Noise Properties

- Make k-space noise, Fourier transform, calculate statistics for varying signal:

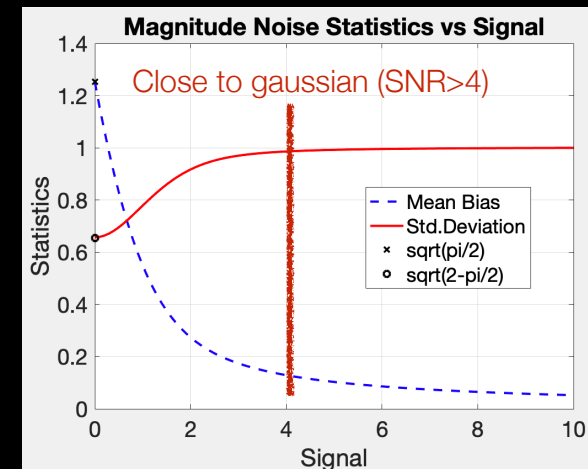
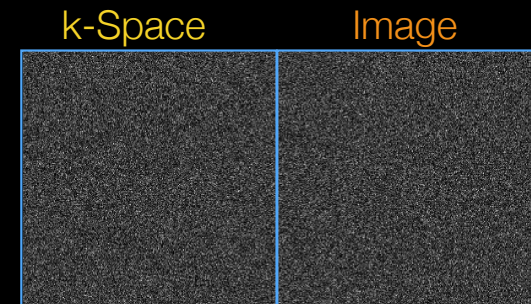
```
nsig = 1;          % Noise sigma parameter (real and imaginary)
N = 256;          % Image/k-space size.

kr = randn([N,N])*nsig;      % Generate gaussian noise (real part)
ki = randn([N,N])*nsig;      % Generate gaussian noise (imag part, same)
k = kr+i*ki;                % Combine

im = N * ift(k);            % iFFT with scaling of sqrt(N*N)=N
[std(real(im(:))),std(imag(im(:)))]

% -- Calculate noise as a function of SNR, with magnitude images

s=[0:0.1:10];              % s = Signal, so same as SNR if nsig==1
for p=1:length(s)
    mn(p) = mean(abs(im(:)+s(p)));      % Mean of magnitude signal
    sd(p) = std(abs(im(:)+s(p)));      % Std.deviation of magnitude
end;
```

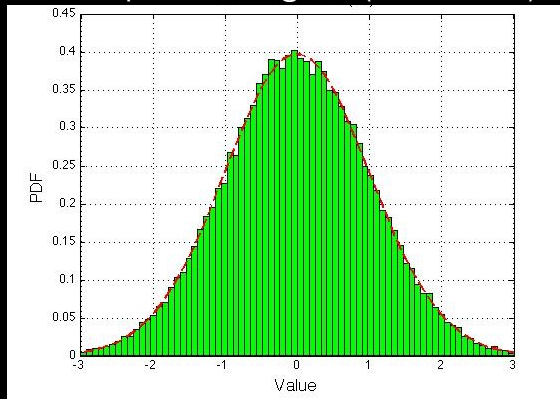


Question 1

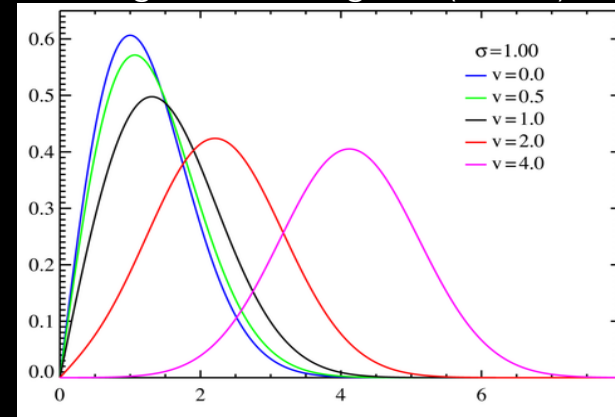


Basic Noise Distributions (Single-Channel)

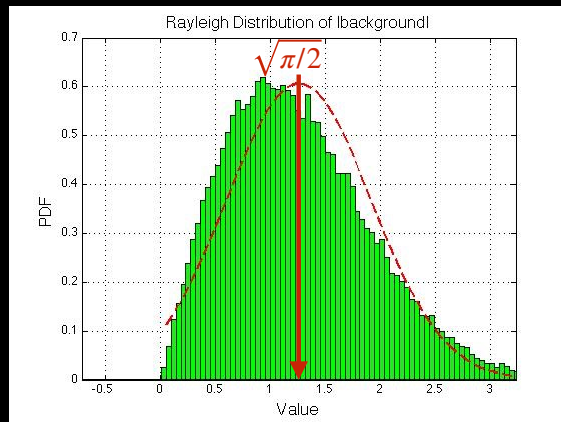
Real-part of Signal (Gaussian)



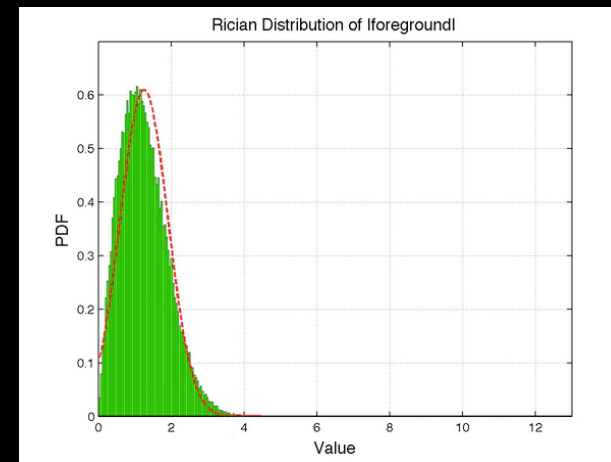
Magnitude of Signals (Rician)



Magnitude of Background (Rayleigh)



Magnitude of Signal (Varying v)



Magnitude Noise is Rayleigh for zero-mean, then Rician (Looks Gaussian above SNR ~ 4)



Question 2

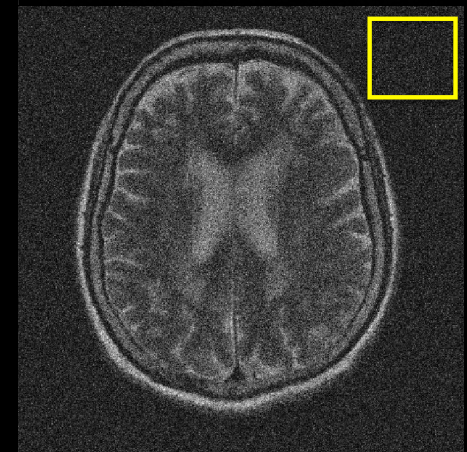
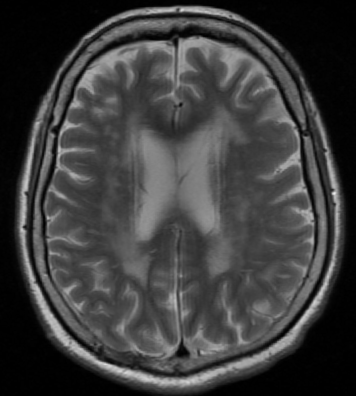


Basic SNR Measurement (1 coil)

- Measure mean in signal area ROI
- Measure std-deviation in magnitude background ROI
- Correct for Rayleigh distribution in background

$$\text{mean}_{\text{Rayleigh}} = 1.26$$
$$\sigma_{\text{Rayleigh}} = 0.65$$

$$\sigma_{\text{gaussian}} = \text{mean}_{\text{Rayleigh}} / \text{sqrt}(\pi/2) = 1.008$$
$$\sigma_{\text{gaussian}} = \sigma_{\text{Rayleigh}} / \text{sqrt}(2-\pi/2) = 0.997$$



For a single channel coil, noise can be measured from the background magnitude mean or standard deviation

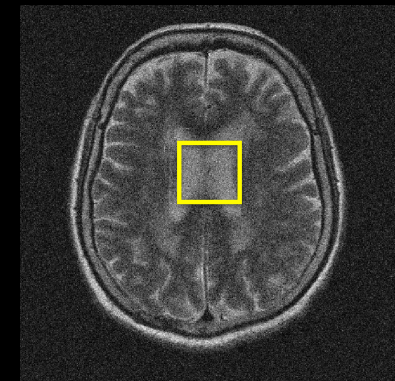


Difference Method SNR

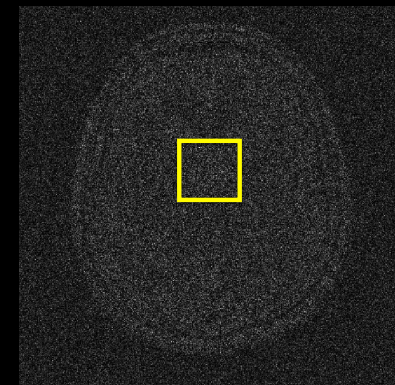
- In theory, N measurements should give you a population, and at each pixel you get a (roughly gaussian) distribution
- With 2 measurements you can still estimate mean and standard deviation (Reeder et al)
- Still want SNR > 4, or underestimate noise

$$\sigma_{\text{Mag-Diff}} = 1.394$$

$$\sigma_{\text{gaussian}} = \sigma_{\text{Mag-Diff}} / \text{sqrt}(2) \sim 1.0$$



Sum



Difference of
Magnitude Images

The difference method is a crude measure of the variation at a particular voxel



Question 3



Summary

- Noise in k-space and complex images is complex and Gaussian
- Magnitude image noise has:
 - Rician distribution (non-zero signal or mean)
 - Rayleigh in the background)
- SNR can be measured by foreground/background or the difference method (with corrections as appropriate)



How do different setup factors and sequence parameters affect SNR?

A photograph of a large, multi-story building with a red-tiled roof and arched windows, likely a Stanford University building. The building is set against a dark, overcast sky. In the foreground, there is a green lawn and a paved path. The text is overlaid on the image.

Rad229 – MRI Signals and Sequences

Daniel Ennis & Brian Hargreaves

dbe@stanford.edu –or– bah@stanford.edu