EE392m
Fault Diagnostics Systems
Introduction

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Course Subject

• Engineering of fault diagnostics systems
• Embedded computer interacting with real world
  – Detect abnormal operation
  – Fault tolerance: more than 80% of critical control code
• Operations and maintenance
  – More than 50% of the system lifetime costs
  – Troubleshooting support
  – Condition-based maintenance – CBM
Prerequisites and Course Place

• The subject is not covered in other courses
• Prerequisites (helpful but not necessary)
  – Stat 116; EE263 or Eng 207a; EE278 or Eng 207b
• The course is about technical approaches that are actually used in fault diagnostics applications
  – Survived demands of real life
  – Used and supported by BS-level engineers in industry
  – Should be accessible to a Stanford grad student
Course Mechanics

• Class website: www.stanford.edu/class/ee392M/
• Weekly seminars
  – Follow website announcements
• Guest lecturers from diverse industries
  – Co-sponsored by NASA
    • Travel support for lecturers
  – Lecture notes will be posted as available
• Attendance
• Reference texts
  – Isermann; Chiang, Russel, & Braatz; Patton, Clark & Frank
  – Different coverage
  – Contact me if you have a specific interest
On-line (Embedded) Functions

• Embedded system, anomaly warnings
  – BIT – Built-in-Test
  – BITE – Built-in-Test Equipment
• FDIR
  – Fault Detection Identification and Recovery
• FT-RM
  – Fault Tolerance and Redundancy Management
Off-line Functions

• Reliability
  – FMECA- Failure Mode, Effects, and Criticality Analysis
  – Design time analysis – open loop

• Maintenance and Support
  – Diagnostics for maintenance
  – Troubleshooting support
  – Test equipment
  – CBM – Condition Based Maintenance
  – Pre-testing – disk drives
Fault Diagnostics in Industry

- Space systems
- Defense systems: aviation, marine, and ground
- Commercial aerospace
  - Aircraft, jet engines
- Ground vehicles
  - Locomotives, trucks, cars
- High-tech
  - Networks and IT systems
  - Disk drives
  - Server farms
- Process control
  - IC Manufacturing
  - Refineries
  - Power plants
- Oil and gas drilling
# Guest Lecture Overview

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Diagnostics Methods Overview

• **Shewhart chart (Control chart)**
• Multivariable SPC, $T^2$
• Model-based estimation
  – Least squares estimation
• Integrated diagnostics
  – Cascaded design
Abnormality Detection - SPC

• SPC - Statistical Process Control
  – monitoring of manufacturing processes
  – warning for off-target quality

• Main SPC method
  – Shewhart Chart (1920s)

• Also see
  – EWMA (1940s)
  – CuSum (1950s)
  – Western Electric Rules (1950s)
SPC: Shewhart Control Chart

- W. Shewhart, Bell Labs, 1924
- Statistical Process Control (SPC)
- UCL = mean + 3·σ
- LCL = mean - 3·σ

Walter Shewhart (1891-1967)
Shewhart Chart, cont’d

- Quality variable assumed randomly changing around a steady state value
- Detection: $y(t) > UCL = \text{mean} + 3\cdot\sigma$
- For normal distribution, false alarm probability is less than 0.27%

$$e(t) = \frac{y(t) - \mu_0}{\sigma}$$

$$P(e > 3) = 1 - \Phi(3) = 0.1350 \cdot 10^{-2}$$

$$P(e < 3) = \Phi(-3) = 0.1350 \cdot 10^{-2}$$
Shewhart Chart – Hypothesis Test

• Null hypothesis
  – given mean and covariance

\[ H_0 : y(t) \sim N(\mu_0, \sigma^2) \quad P(H_0) = p_0 \]

• Fault hypothesis
  – a different mean

\[ H_1 : y(t) \sim N(\mu_1 \neq \mu_0, \sigma^2) \quad P(H_1) = p_1 \]

• Hypothesis testing

\[
\text{given } Y = y(t) \\
\text{find } X \in \{H_0, H_1\}
\]
Bayesian Formulation

- Data: $Y$ - Observation, $X$ - Underlying State

- Bayes rule

$$P(X \mid Y) = P(Y \mid X) \cdot P(X) \cdot c$$

- Observation model: $P(Y \mid X)$
- Prior model: $P(X)$
- Maximum A posteriori Probability estimate

$$X = \arg \min \left( -\log P(Y \mid X) - \log P(X) \right)$$

$L$ - log-posterior index
Hypothesis Testing

- Null hypothesis
  \[- \log P(Y \mid X) = \frac{1}{2\sigma^2} (y - \mu_0)^2 \quad \text{and} \quad - \log P(X) = - \log p_0\]

- Fault hypothesis
  \[- \log P(Y \mid X) = \frac{1}{2\sigma^2} (y - \mu_1)^2 = 0 \quad \text{and} \quad - \log P(X) = - \log p_1 \quad p_0 = 1 - p_1\]

- Log-likelihood ratio
  \[\Lambda = \log \frac{P(H_1 \mid Y)}{P(H_0 \mid Y)} = L_0 - L_1\]

- Declare fault if
  \[\Lambda = L_0 - L_1 = \frac{1}{2\sigma^2} (y - \mu_0)^2 - \log(p_0/p_1) > 0\]

\[|y - \mu_0| > \sigma \sqrt{2 \log(1 - p_1)/p_1} \quad p_1 = 0.0113 \Rightarrow 3\sigma\]
Shewhart Chart: Use Examples

- SPC in manufacturing
- Fault monitoring
- Fault tolerance – sensor integrity monitoring

\[ |\Delta y| < 3\sigma \]

Sensor \[ \rightarrow \] Reference \[ + \] \[ - \] \[ \rightarrow \] \[ |\Delta y| < 3\sigma \] \[ no \rightarrow \] Fault \[ yes \rightarrow \] Normal
Diagnostics Methods Overview

- Shewhart chart (Control chart)
- **Multivariable SPC, $T^2$**
- Model-based estimation
  - Least squares estimation
- Integrated diagnostics
  - Cascaded design
Multivariable SPC

- Univariate process

\[ z^2 = \left( \frac{y - \mu_0}{\sigma} \right)^2 \sim \chi^2 \]

\[ P\left(z^2 > c^2\right) = 1 - F(c^2, 1) = \Phi(-c) + 1 - \Phi(c) \]

- Two independent univariate processes

\[ z^2 = \left( \frac{y_1 - \mu_1}{\sigma_1} \right)^2 + \left( \frac{y_2 - \mu_2}{\sigma_2} \right)^2 \sim \chi^2 \]

\[ P\left(z^2 > c^2\right) = 1 - F(c^2; 2) \]
Multivariable SPC

- Two correlated univariate processes $y_1(t)$ and $y_2(t)$
  \[ \text{cov}(y_1, y_2) = Q, \quad Q^{-1} = L^T L \]
- Uncorrelated linear combinations
  \[ z(t) = L \cdot [y(t) - \mu] \]
  \[ \|z\|^2 = (y - \mu)^T Q^{-1} (y - \mu) \sim \chi^2_2 \]
- Declare fault (anomaly) if
  \[ (y - \mu)^T Q^{-1} (y - \mu) > c^2 \]
  \[ P(z^2 > c^2) = 1 - F(c^2;2) \]
Multivariate SPC - Hotelling's $T^2$

• Empirical parameter estimates

$$\hat{\mu} = \frac{1}{n} \sum_{t=1}^{n} y(t) \approx E(X)$$

$$\hat{Q} = \frac{1}{n} \sum_{t=1}^{n} (y(t) - \mu)(y^T(t) - \mu^T) \approx \text{cov}(y - \mu)$$

• Hotelling's $T^2$ statistics is

$$T^2 = (y(t) - \mu)^T \hat{Q}^{-1} (y(t) - \mu)$$

• $T^2$ can be trended as a univariate SPC variable

Harold Hotelling
(1895-1973)
Diagnostics Methods Overview

- Shewhart chart (Control chart)
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- **Model-based estimation**
  - Least squares estimation
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Least Squares Estimation

- Linear observation model:
  \[ Y = CX + v \]

- Fault signature model
  - Columns of \( C \) are fault signatures
  - Could be obtained from physics model
    - secant method
  - Could be identified from data:
    - regression, data mining

- Estimate
  - regularized least squares
  \[ \hat{X} = \left( C^T C + rI \right)^{-1} C^T Y \]
Bayesian Estimation

- Observation model: $P(Y|X)$
  \[ Y = CX + \nu \quad \nu \sim N(0, Q) \]
- Prior models: $P(X)$
  \[ X \sim N(0, R) \quad -\log P(X) = \frac{1}{2} X^T R^{-1} X + ... \]
- MAP estimate:
  \[
  \hat{X} = \arg \min \underbrace{\frac{1}{2} \|Y - CX\|_Q^{-1}^2}_{-\log P(Y|X)} + \underbrace{\frac{1}{2} \|X\|_R^{-1}^2}_{-\log P(X)}
  \]
  \[
  \hat{X} = \left(C^T Q^{-1} C + R^{-1}\right)^{-1} Q^{-1} C^T Y
  \]
Model-based Residuals

- Compute model-based prediction residual
  \[ Y = Y_{raw} - f(U,X) \]
- If \( X = 0 \) (nominal case) we should have \( Y = 0 \).
- Residuals \( Y \) reflect faults
  - Sensor fault model - additive output change
  - Actuator fault model - additive input change
Example: Jet Engine Model

- Nonlinear jet engine model
  - static map

- Residuals
  \[ Y = Y_{raw} - f(U, X) \]

- Linearized model
  \[ Y = CX + \nu \]
  \[ C = -\frac{\partial f(U, X)}{\partial X} \]
  \[ X = \begin{bmatrix}
  \text{Turbine deterioration} \\
  \text{Bleed band leak} \\
  \text{EGT sensor drift}
\end{bmatrix} \]
Example: Fault Estimates

- Maintenance decision support tool

Honeywell LF507 Engine Fleet

Estimates of (fault) performance parameter deterioration

Ganguli, Deo, & Gorinevsky, IEEE CCA’04
Diagnostics Methods Overview

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• **Integrated diagnostics**
  – Cascaded design
Cascaded Design

- Increasing complexity and integration of system $\uparrow$
- Slower time scale $\uparrow$
- Simple inner loop models
- Examples
  - Control systems
  - Estimation and data fusion
  - Fault diagnostics systems
Integrated System Diagnostics

• Complex integrated systems
• Examples
  – Aerospace vehicle, e.g. B777
  – Large scale computer network
  – Medical equipment

Decision Support Interface

Integrated Diagnostic System

Subsystem 1 Diagnostics

Subsystem 2 Diagnostics

... Subsystem \( n \) Diagnostics
## Discrete Fault Signatures

Model of root cause fault $k$:

$$Y^k = B^k$$

<table>
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<th>Root Cause $\rightarrow$</th>
<th>#0 Null</th>
<th>#1</th>
<th>#2</th>
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Estimation Algorithm

• Diagnosis problem:
  Given data $Y$, diagnose root cause $k$
• Solution:

$$k = \arg \min_k \| Y - B^k \|_1$$

• Minimal Hamming distance
• Justifications
  – Case-based reasoning (table of fault cases)
  – Model-based reasoning (fault signature model)
  – Bayesian
Bayesian Justification

- Data
  \[ Y \quad X = \{ H_0 : 0, \quad H_1 : B^1, \quad \ldots, \quad H_n : B^n \} \]

- Observation model
  \[
  P(Y \mid X) = \begin{cases} 
  P(y_j = b_j^k \mid H_k) = 1 - p_1 & y_j \text{ follows the model} \\
  P(y_j \neq b_j^k \mid H_k) = p_1 & \text{deviates from the model}
  \end{cases}
  \]

  \[-\log P(Y \mid H_k) = \sum_{y_j = b_j^k} -\log(1 - p_1) + \sum_{y_j \neq b_j^k} -\log p_1 =
  \]

  \[-n \cdot \log(1 - p_1) - \sum_{j=0}^{n} |y_j - b_j^k| \cdot \left( \log p_1 - \log(1 - p_1) \right) > 0, \text{ for } p_1 < 1/2 \]

  \[-\log P(Y \mid H_k) = c + w\|y - b^k\|_1 \]
Bayesian Justification

- Prior model
  \[ P(X) \quad P(H_k) = \frac{1}{n + 1} \]
  \[ - \log P(H_k) = d \]

- MAP Estimate
  \[ k = \arg \min_k (- \log P(Y | H_k) - \log P(H_k)) \]
  \[ k = \arg \min_k \left( c + w \| y - b^k \|_1 + d \right) \]
  \[ k = \arg \min_k \| y - b^k \|_1 \]
Conclusions

• Basic diagnostics estimation methods
  – Are known for long time
  – Used in on-line systems for less time
  – Can be explained in several ways, e.g., Bayesian

• Engineering of fault diagnostics systems
  – Is new and current
  – Will be discussed in guest lectures
  – Not just diagnostics algorithms
## Guest Lectures: Approaches

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