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Title: ON ASSESSING THE ROBUSTNESS OF STRUCTURAL
HEALTH MONITORING TECHNOLOGIES

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On Assessing the Robustness of Structural Health Monitoring Technologies

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The 30th International Modal Analysis Conference

Jacksonville, Florida

January 30 – February 2, 2012

Abstract

As *Structural Health Monitoring* (SHM) continues to gain popularity, both as an area of research and as a tool for use in industrial applications, the number of technologies associated with SHM will also continue to grow. As a result, the engineer tasked with developing a SHM system is faced with myriad hardware and software technologies from which to choose, often adopting an *ad hoc* qualitative approach based on physical intuition or past experience to making such decisions, and offering little in the way of justification for a particular decision. The present paper offers a framework that aims to provide the engineer with a qualitative approach for choosing from among a suite of candidate SHM technologies. The framework is outlined for the general case, where a supervised learning approach to SHM is adopted, and is then demonstrated on a problem commonly encountered when developing SHM systems: selection of a damage classifier, where the engineer must select from among a suite of candidate classifiers, the one most appropriate for the task at hand. The data employed for these problems are taken from a preliminary study that examined the feasibility of applying SHM technologies to the RAPid Telescopes for Optical Response observatory network. ***(Approved for unlimited public release on January XX, 2012, LA-UR 12-0XXXX, Unclassified)***

Outline

- **Damage Assessment Methodology**
 - Statistical Pattern Recognition Paradigm
 - Why Info-gap?
- **Problem Formulation**
 - Uncertain Features
 - Info-gap Models of Uncertainty
 - Robustness Function
- **Demonstration Problem**
 - Problem Description
 - Damage Model Selection
 - Damage Classifier Selection
 - Flow of Info-gap Analysis
- **Summary and Conclusion**

Statistical Pattern Recognition Paradigm⁴

- Operational Evaluation
- Data Acquisition, Normalization, and Cleansing
- Feature Selection and Information Condensation
- Statistical Model Development for Feature Discrimination

Sources of Uncertainty?

- Environmental factors (*e.g.* temperature fluctuations, ambient vibrations)
- System factors (*e.g.* subtle differences between systems)
- Instrumentation factors (*e.g.* sensitivities, placement)

➤ *laboratory settings != real-world settings*

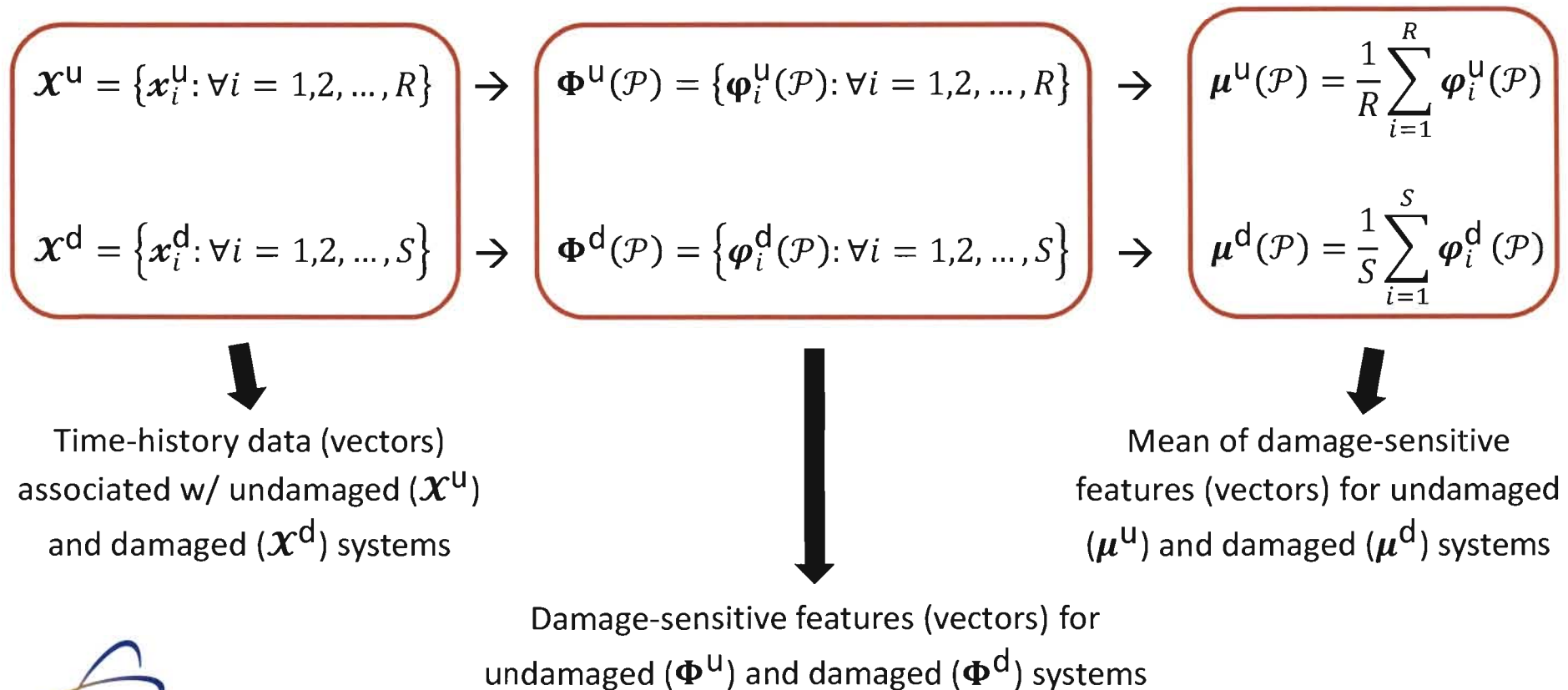
➤ **For our purposes, we will incorporate these sources of uncertainty into the simulated time-history data.**

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Assumptions and Definitions

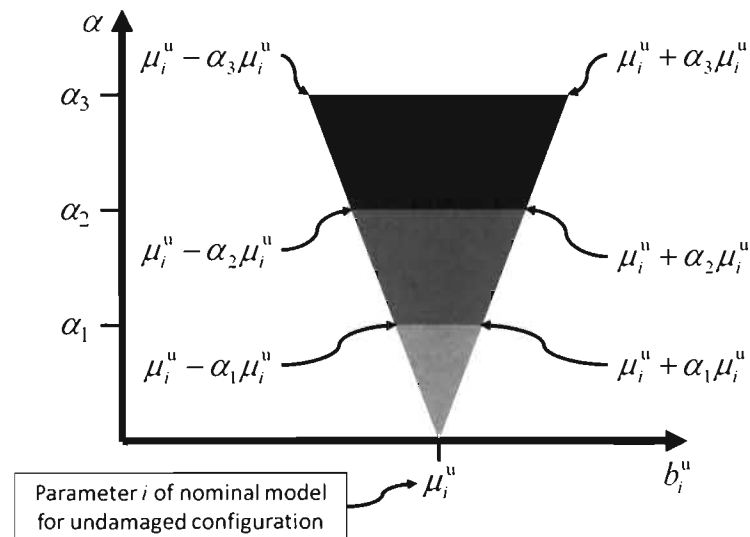
- Assume that we can collect time-histories of response (e.g. acceleration, displacement) for a system of known condition (i.e. undamaged and damaged).



Info-gap Models of Uncertainty

$$\mu^u(\mathcal{P}) = \frac{1}{R} \sum_{i=1}^R \varphi_i^u(\mathcal{P}) \quad \rightarrow \quad \mathcal{B}^u(\alpha, \mu^u) = \left\{ b^u : \left| \frac{b_i^u - \mu_i^u}{\mu_i^u} \right| \leq \alpha, \forall i \right\}, \alpha \geq 0$$

$$\mu^d(\mathcal{P}) = \frac{1}{S} \sum_{i=1}^S \varphi_i^d(\mathcal{P}) \quad \rightarrow \quad \mathcal{B}^d(\alpha, \mu^d) = \left\{ b^d : \left| \frac{b_i^d - \mu_i^d}{\mu_i^d} \right| \leq \alpha, \forall i \right\}, \alpha \geq 0$$

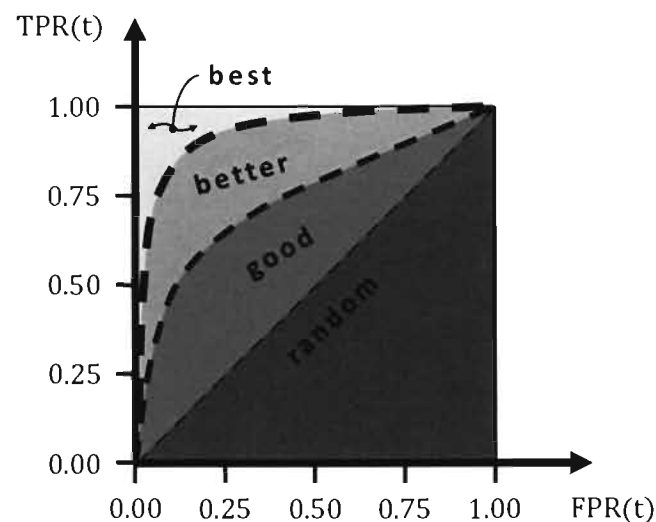


Robustness Function

$$\hat{\alpha}(C, \mathcal{P}) = \max_{\alpha} \left\{ \min_{B^u \subseteq \mathcal{B}^u(\alpha, \mu^u), B^d \subseteq \mathcal{B}^d(\alpha, \mu^d)} AUC > AUC_{\text{critical}} \right\}$$



- Sampling of info-gap models produces sets of feature vectors from which we construct a Receiver-Operator Characteristic (ROC) curve.
- The Area Under the ROC Curve (AUC) provides a global measure of performance for diagnostic tests^{3,6}.

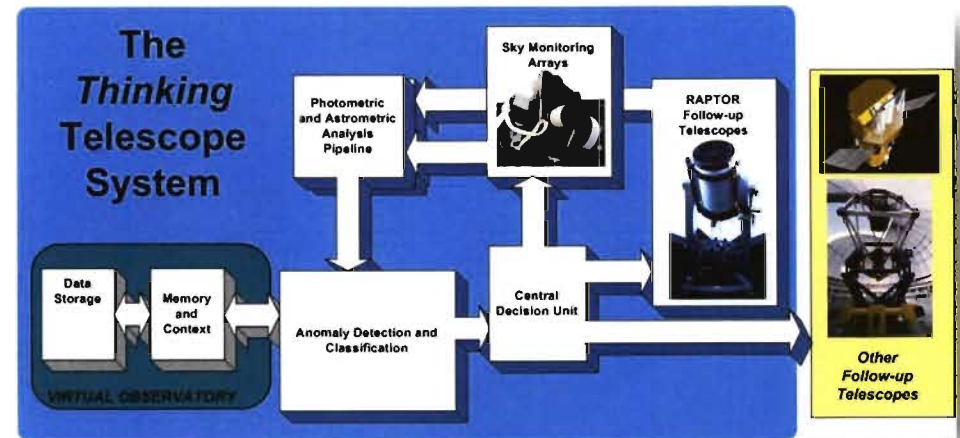


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Problem Background

- The LANL Thinking Telescope Project aims at real-time detection / characterization of astrophysical transients (e.g. gamma-ray bursts).



<http://www.thinkingtelescopes.lanl.gov/Concepts.htm>

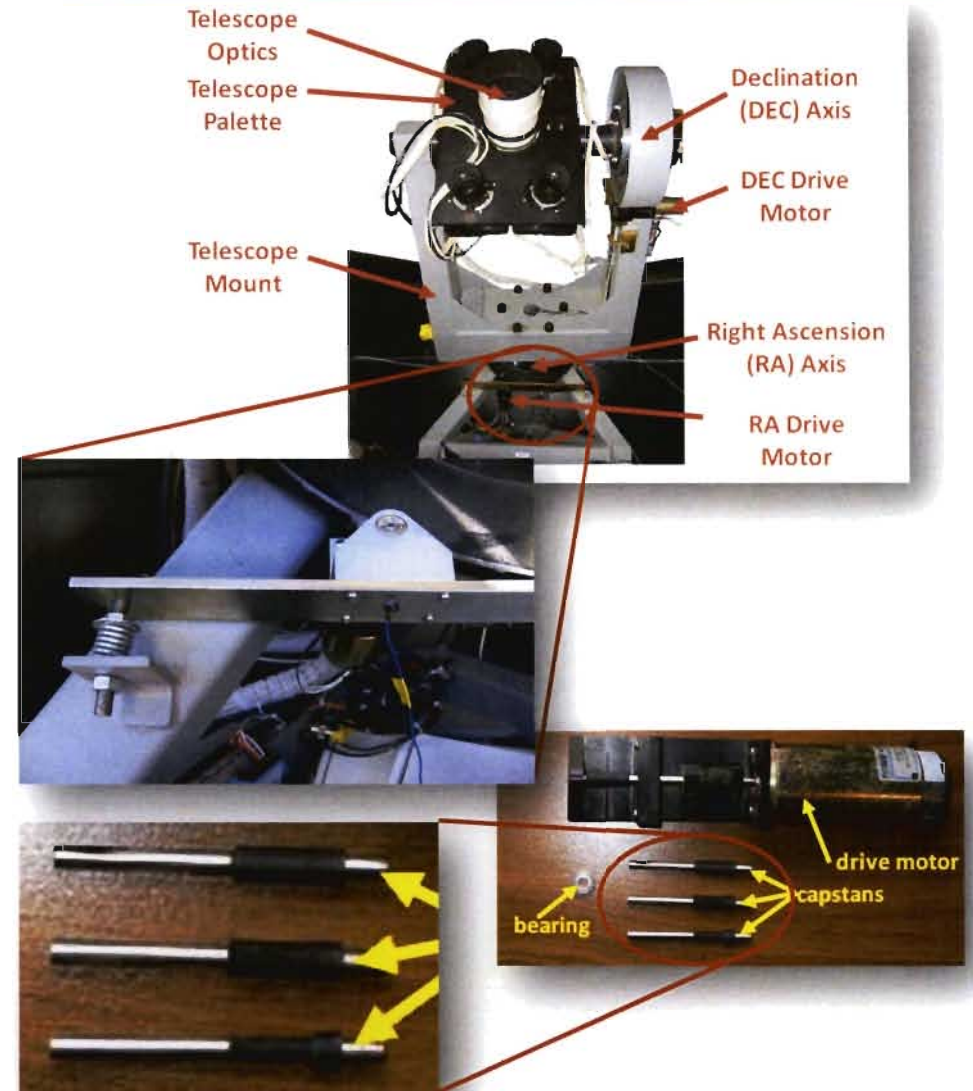
- The **RAP**id Telescopes for **Optical Response (RAPTOR)** network of ground-based observatories serves as the primary hardware component of the LANL Thinking Telescope Project.



<http://www.raptor.lanl.gov/>

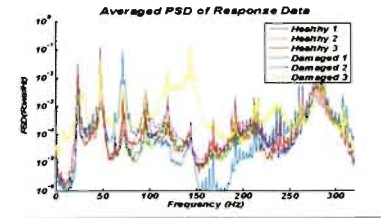
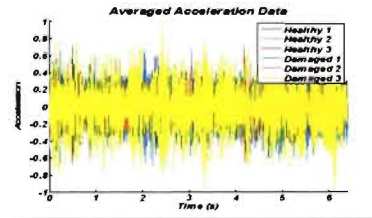
Problem Background

- Damage?
 - Urethane coating on capstan components (part of friction drive mechanism) wears with use
- Why SHM?
 - Expense of observatory components
 - Remote locations of observatories
 - Variable wear of urethane coating
- Advantages?
 - **No** life-safety concerns
 - Availability of power, computing, network connectivity
 - Feasibility of controlled diagnostic tests
 - Availability of damaged capstans



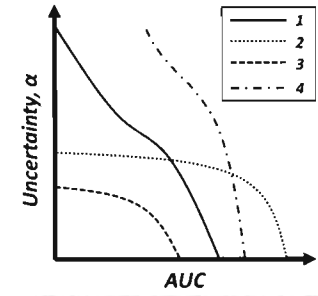
Damage Assessment Methodology

Data Collection / Analysis

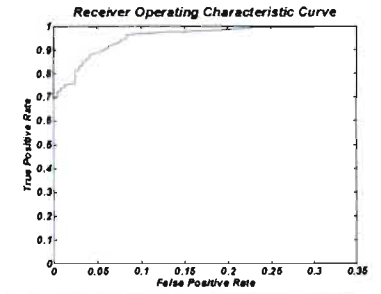
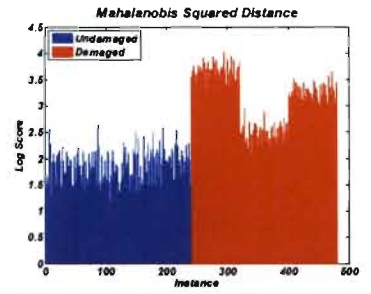


Feature Selection

$$x_i = \sum_{j=1}^p \varphi_j x_{i-j} + e_i$$

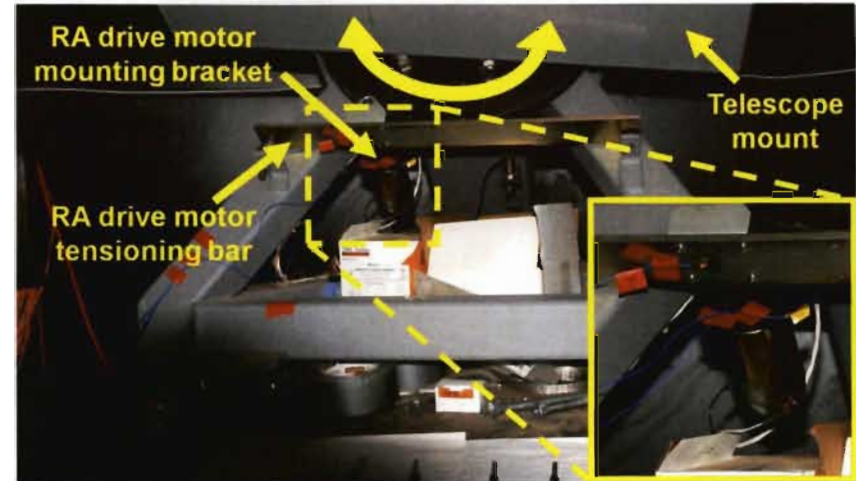


Damage Classifier Development / Validation



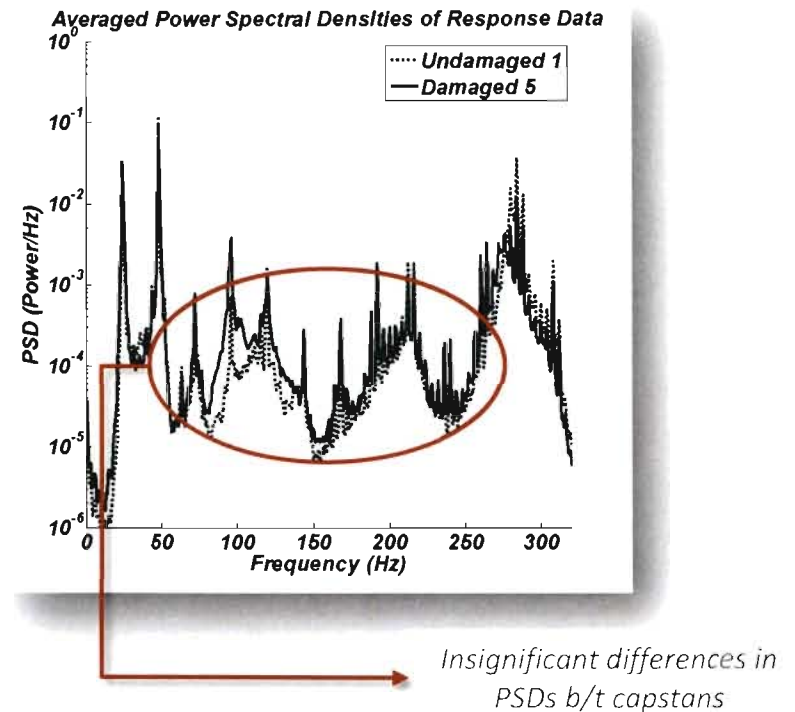
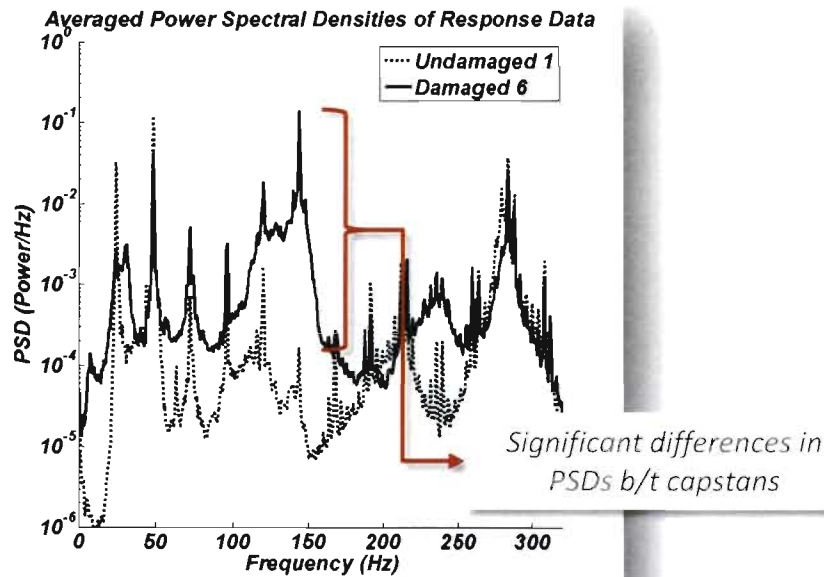
Data Collection

- Study concentrates on drive mechanism associated with *Right Ascension* (RA) axis
- PCB Piezotronics model 352A24 accelerometers adhered to three telescope mount locations
- Six capstans of varying levels of deterioration examined
- Ten cycles similar to “homing sequences” executed for each capstan with a data sampling rate of 640 Hz



Data Analysis

- Individual time-histories divided into equal-sized records in order to simulate data replicates
- Power spectral densities (PSDs) computed from each time history, and averaged across each capstan condition



Feature Selection

- Time-history data modeled as auto-regressive (AR) process
- AR model coefficients employed as damage-sensitive features

$$x_i = \sum_{j=1}^p \varphi_j x_{i-j} + e_i$$

How to choose AR model order, p ?

- Choose AR model order based on the robustness of its performance to uncertain data sets
- Wait, what about choosing a damage classifier?!

Flow of Info-gap Analysis

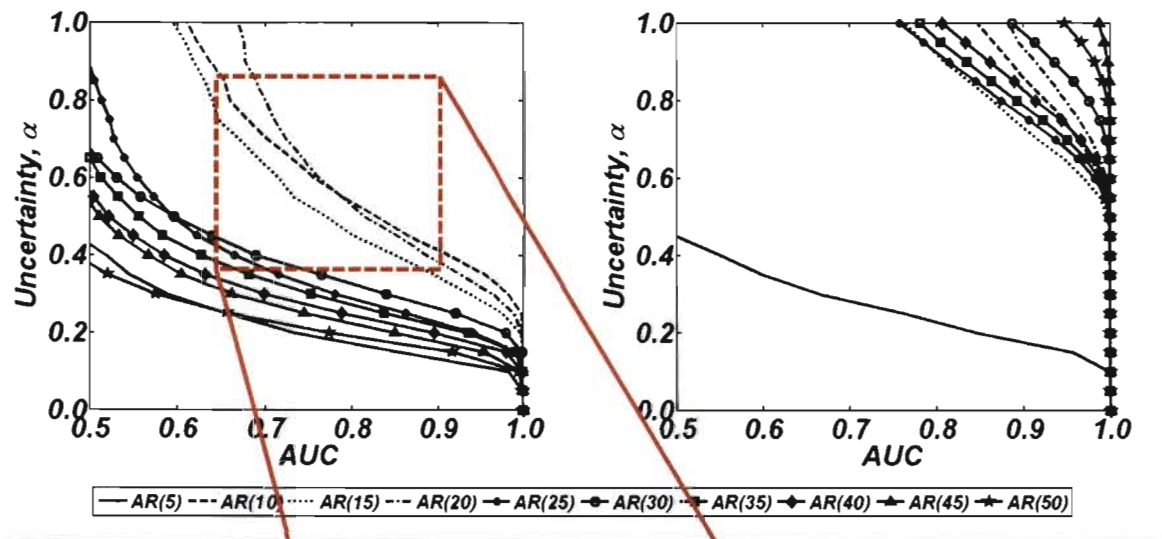
1. Collect time-history data (controlled experiments)
2. For all damage classifiers:
 1. For all AR model orders:
 1. Compute feature vectors
 2. Train damage classifier
 3. Compute mean of feature vectors
 4. For all α 's:
 1. Sample info-gap models
 - yields sets of feature vectors associated with undamaged and damaged systems
 2. Evaluate sets of uncertain feature vectors as undamaged or damaged
 - employs damage classifier from Step 3 (previous loop).
 3. Construct ROC curve
 4. Approximate the AUC
5. Store minimum value of AUC from α -loop

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Robust Selection of AR Model Order

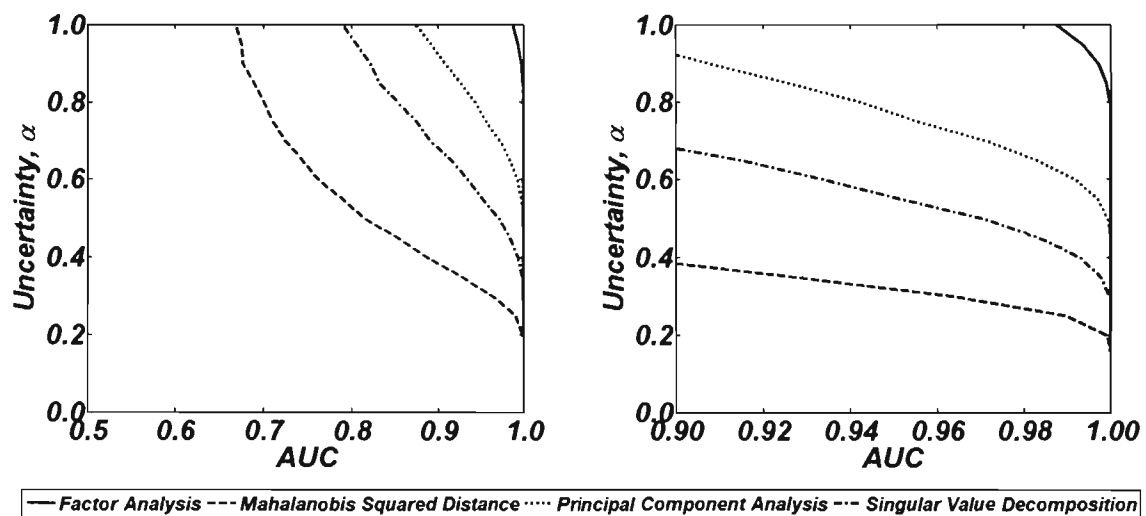
- Showing results of AR model order info-gap analysis for MSD and FA damage classifiers.



- For the MSD, high and low AR model orders exhibit least robustness.
- For the FA, robustness generally increases with increasing model order.

Robust Selection of Damage Classifier

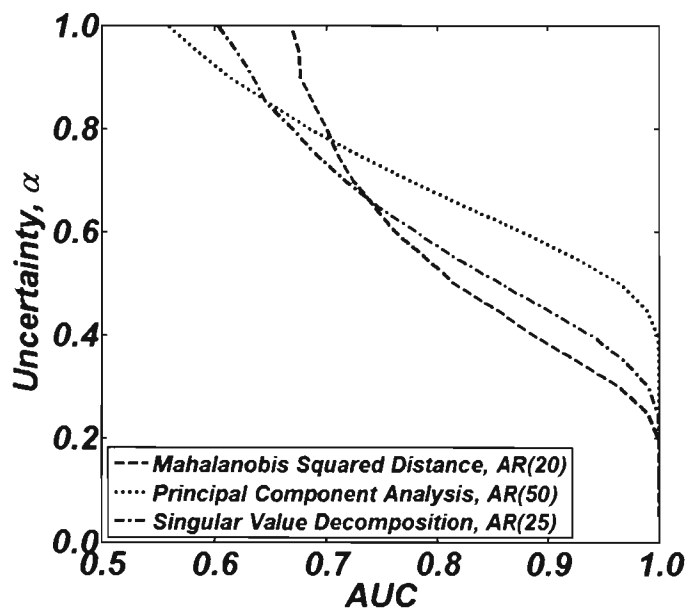
- The “robust-optimal” AR model orders are selected (from previous analysis) for robustness analysis of damage classifiers.
 - same data, alternative analysis
- “robust-optimal” = the AR model order that exhibits the most robust performance (*i.e.* the highest AUC) at the maximum horizon of uncertainty examined (*i.e.* $\alpha = 1.0$)



- FA damage classifier clearly dominates the others, but requires a higher AR model order (45 vs. 20 for the others)
- Other performance metrics? algorithm execution speed, storage considerations, ...

Hypothetical Example

- What if we're less careful about how we select AR model order?
- What if the engineer thinks the first info-gap analysis is too expensive?



Horizon of Uncertainty Range	Damage Classifier Preference*
$\alpha < 0.2$	No preference
$0.2 < \alpha < 0.67$	PCA, SVD, MSD
$0.67 < \alpha < 0.78$	PCA, MSD, SVD
$0.78 < \alpha < 0.85$	MSD, PCA, SVD
$0.85 < \alpha < 1.0$	MSD, SVD, PCA

* ordered left to right, with the more preferred approach to the left

Summary and Conclusion

- A framework for assessing the info-gap robustness of SHM technologies has been presented.
- The framework was demonstrated using data from a real-world SHM example for guiding the selection of (1) damage-sensitive features and (2) damage classifiers.
 - Sources of uncertainty were simulated by imposing noise on damage sensitive features
 - The area under the receiver operating characteristic curve served as a measure of performance.
- As SHM continues to grow in popularity, the proposed framework offers a mechanism by which scientists and engineers may select models appropriately.

References

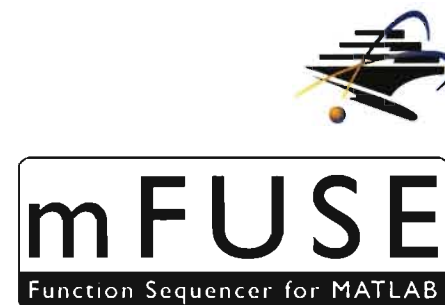
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Software Utilized in Info-gap Analyses

- Software system developed at the LANL/UCSD Engineering Institute
 - SHMTools: a suite of structural health monitoring tools
 - mFUSE: a graphical user interface serving as a MATLAB function sequencer



<http://institute.lanl.gov/ei/>



version 0.1.00 Beta

<http://institute.lanl.gov/ei/software-and-data/SHMTools/>

Backup Slides

Damage Classifier Development

- Damage classifier employs *Mahalanobis Squared Distance* (MSD) metric, expressed as

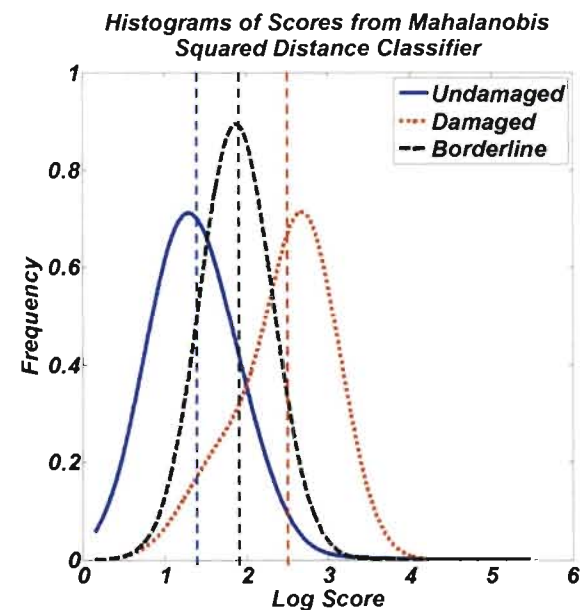
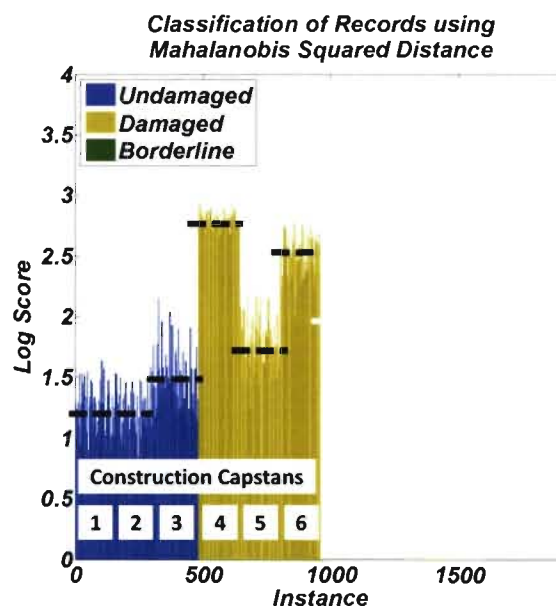
$$- D_M = |x - \mu| / \sigma$$

for scalar features and

$$- D_M = \sqrt{(\boldsymbol{\varphi}^{\text{unknown}} - \boldsymbol{\mu}^u)^T (\boldsymbol{\Sigma}^u)^{-1} (\boldsymbol{\varphi}^{\text{unknown}} - \boldsymbol{\mu}^u)}$$

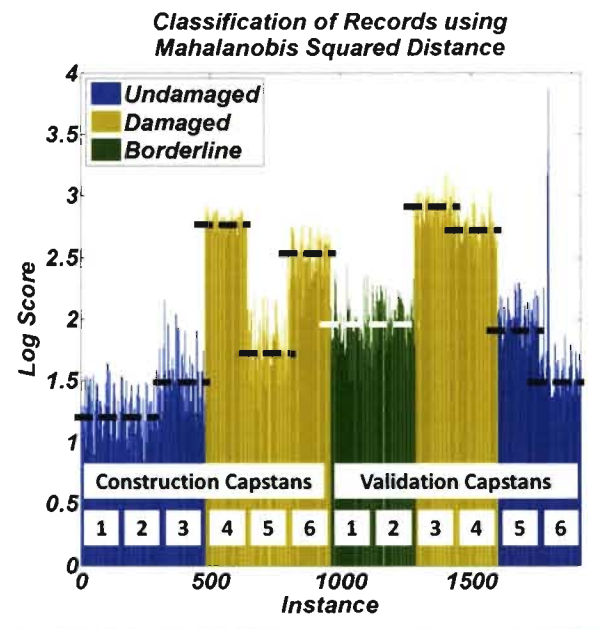
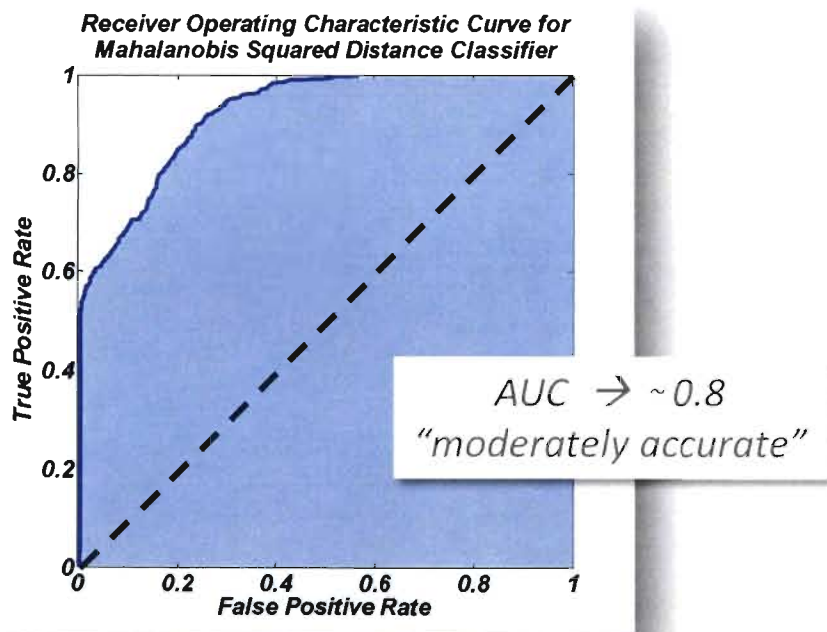
for n -dimensional feature vectors

- $\boldsymbol{\mu}^u$ and $\boldsymbol{\Sigma}^u$ built from data from with undamaged capstans (a.k.a. "Construction Capstans")
- All time-history records are then "scored" against $\boldsymbol{\mu}^u$ and $\boldsymbol{\Sigma}^u$



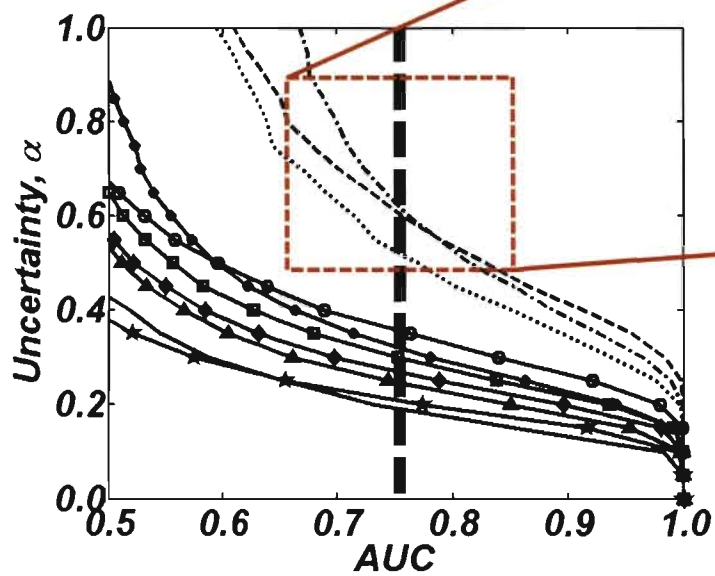
Damage Classifier Validation

- Receiver-Operating Characteristic (ROC) curve and the Area Under the ROC Curve (AUC) computed to assess global MSD damage classifier performance
- After development and initial testing of the MSD damage classifier, six “blind tests” were conducted to validate damage classifier against as yet unseen capstans



Feature Selection

- Example of robust selection of AR model order



AR(20) most robust at minimum AUC performance requirement of 0.75

— AR(5) --- AR(10) AR(15) - - - AR(20) —●— AR(25) —○— AR(30) —■— AR(35) —◆— AR(40) —▲— AR(45) —★— AR(50)

Future Work

- Further development and validation of damage classifiers



Info-gap decision theory for full SHM system development???

- Full life-cycle testing of capstans to facilitate improved characterization of damage



- Implementation of embedded sensing platforms to facilitate autonomous SHM system

