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Title: ON ASSESSING THE ROBUSTNESS OF STRUCTURAL HEATLH MONITORING TECHNOLOGIES

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On Assessing the Robustness of Structural Health Monitoring Technologies

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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 Paradigm[4]

- 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).

$$\mathcal{X}^{\mathrm{u}} = \{x_i^{\mathrm{u}} : \forall i = 1,2,\ldots,R\} \rightarrow \boldsymbol{\Phi}^{\mathrm{u}}(\mathcal{P}) = \{\boldsymbol{\varphi}_i^{\mathrm{u}}(\mathcal{P}) : \forall i = 1,2,\ldots,R\} \rightarrow \boldsymbol{\mu}^{\mathrm{u}}(\mathcal{P}) = \frac{1}{R}\sum_{i=1}^{R} \boldsymbol{\varphi}_i^{\mathrm{u}}(\mathcal{P})$$

$$\mathcal{X}^{\mathrm{d}} = \{x_i^{\mathrm{d}} : \forall i = 1,2,\ldots,S\} \rightarrow \boldsymbol{\Phi}^{\mathrm{d}}(\mathcal{P}) = \{\boldsymbol{\varphi}_i^{\mathrm{d}}(\mathcal{P}) : \forall i = 1,2,\ldots,S\} \rightarrow \boldsymbol{\mu}^{\mathrm{d}}(\mathcal{P}) = \frac{1}{S}\sum_{i=1}^{S} \boldsymbol{\varphi}_i^{\mathrm{d}}(\mathcal{P})$$

Time-history data (vectors) associated w/ undamaged ($\mathcal{X}^{\mathrm{u}}$) and damaged ($\mathcal{X}^{\mathrm{d}}$) systems

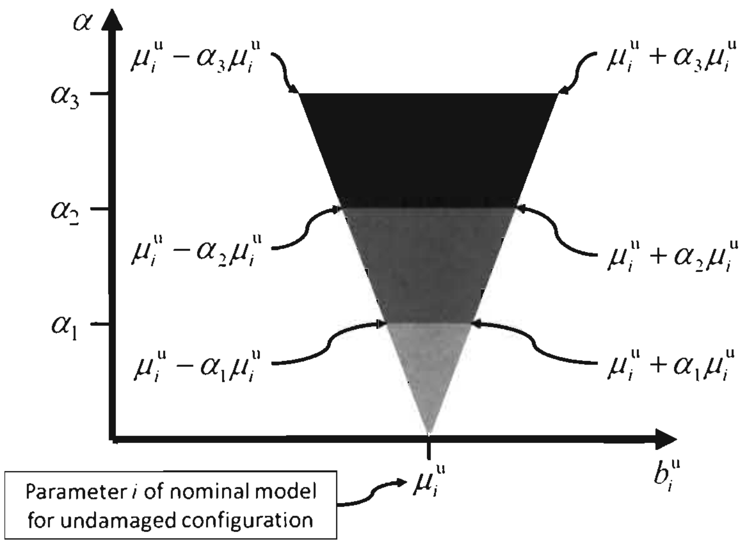
Mean of damage-sensitive features (vectors) for undamaged ($\boldsymbol{\mu}^{\mathrm{u}}$) and damaged ($\boldsymbol{\mu}^{\mathrm{d}}$) systems

Damage-sensitive features (vectors) for undamaged ($\boldsymbol{\Phi}^{\mathrm{u}}$) and damaged ($\boldsymbol{\Phi}^{\mathrm{d}}$) systems

Info-gap Models of Uncertainty

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

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

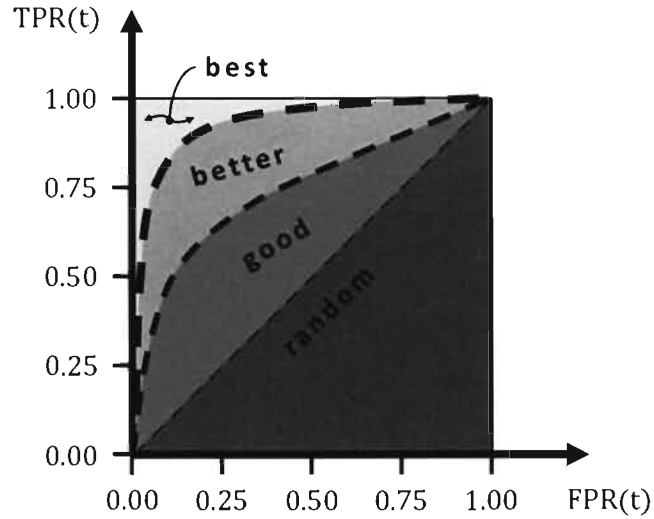


Robustness Function

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

- 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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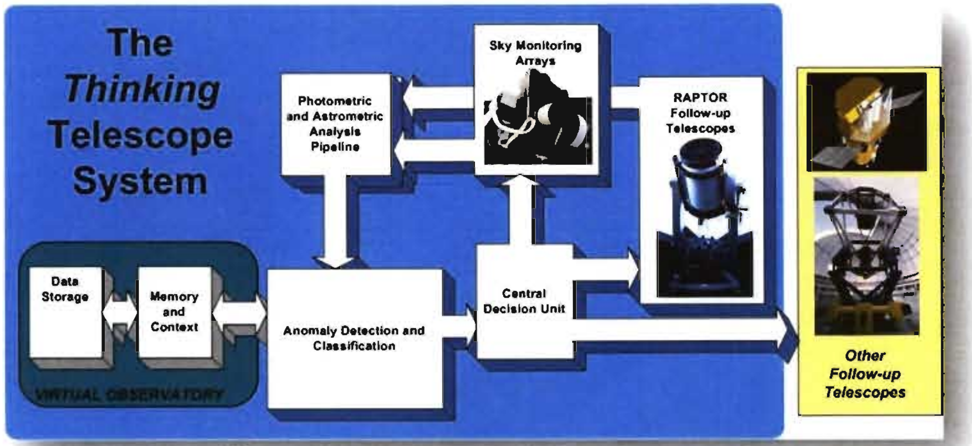
Problem Background

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



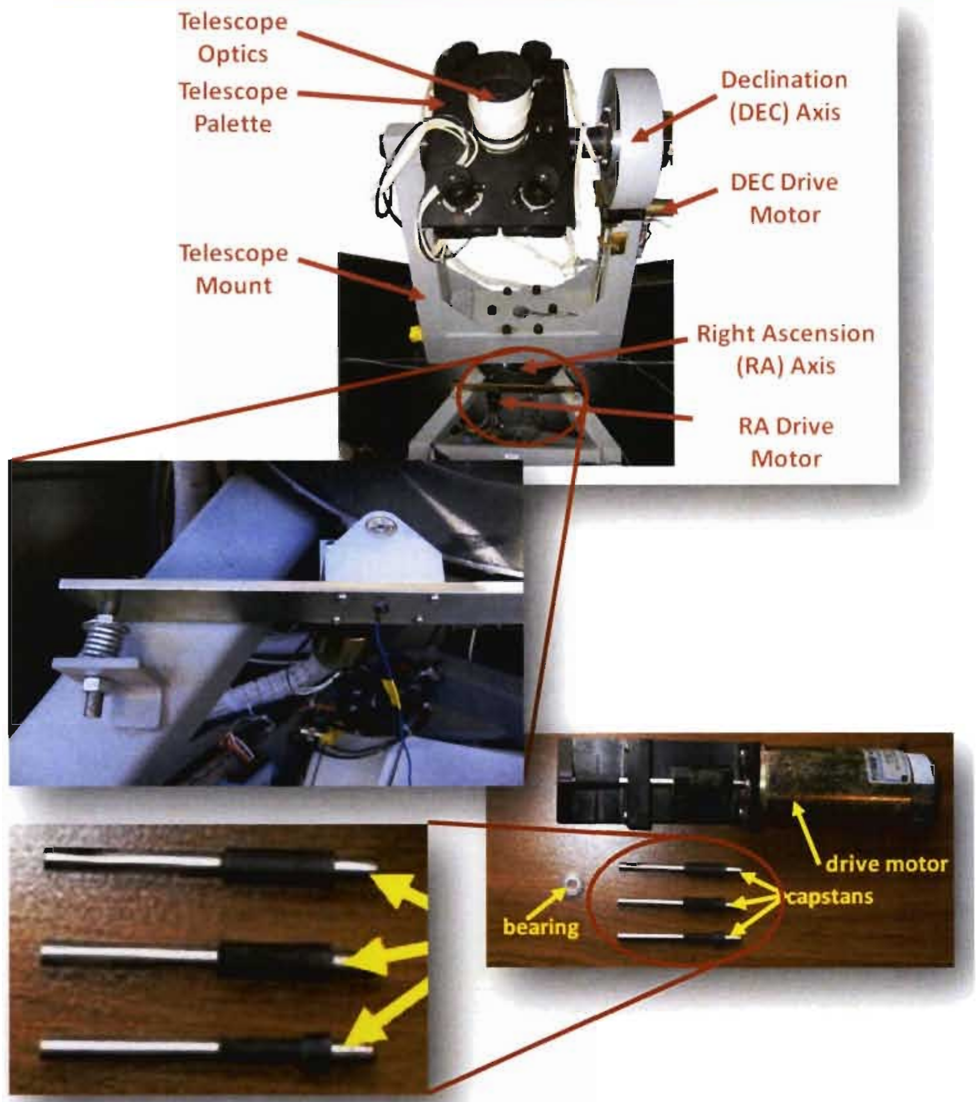
http://www.thinkingtelescopes.lanl.gov/Concepts.htm

- The ***RAP****id* ***T****elescopes for* ***O****ptical* ***R****esponse* (***RAPTOR***) network of ground-based observatories serves as the primary hardware component of the LANL Thinking Telescope Project.

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

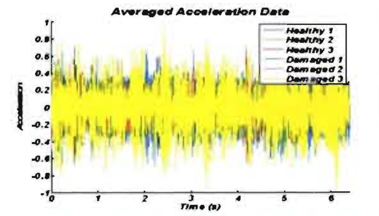
Problem Background

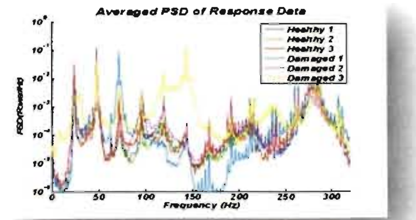
- Damage?
  - Urethane coating on capstan components (part of friction drive mechanism) wears with use
- Why SHM?
  - Expense of observatory components
  - Remote locations of observatories
  - Variable wear of urethane coating
- Advantages?
  - ***No*** life-safety concerns
  - Availability of power,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



Damage Assessment Methodology

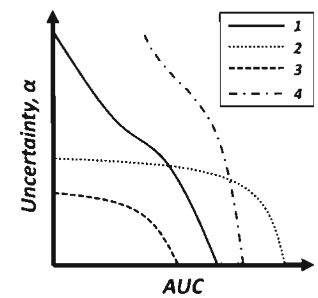
Data Collection / Analysis



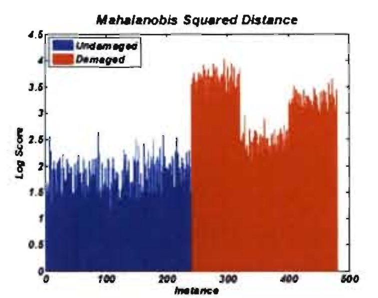


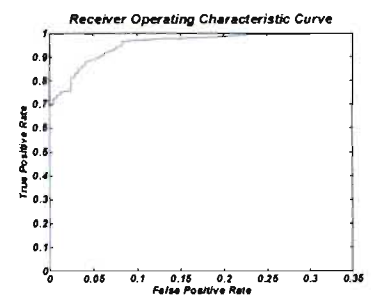
Feature Selection

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



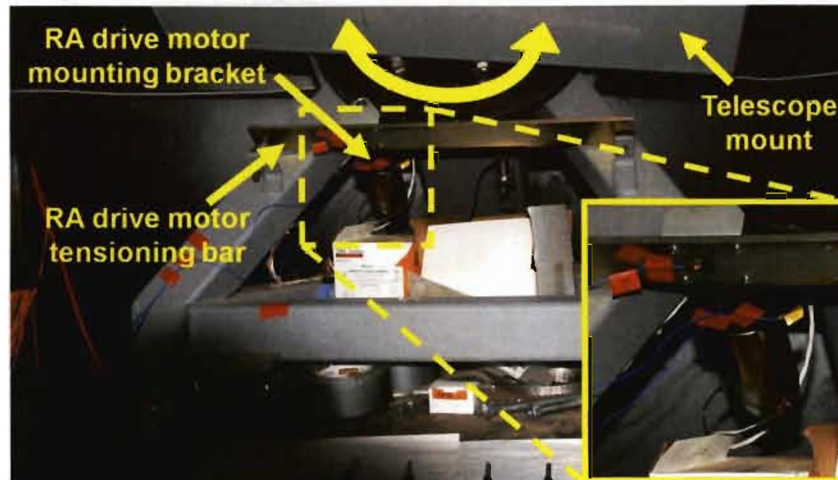
Damage Classifier Development / Validation





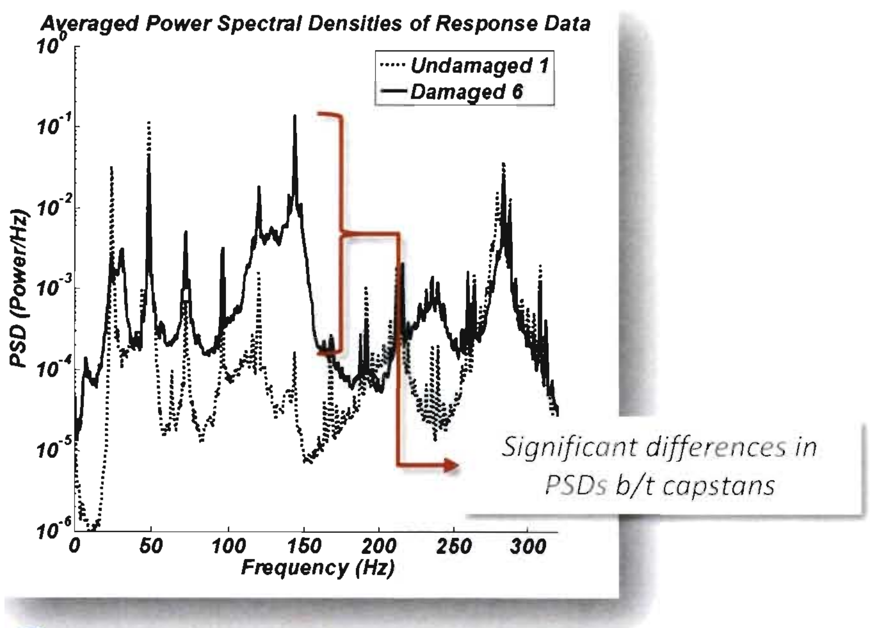
Data Collection

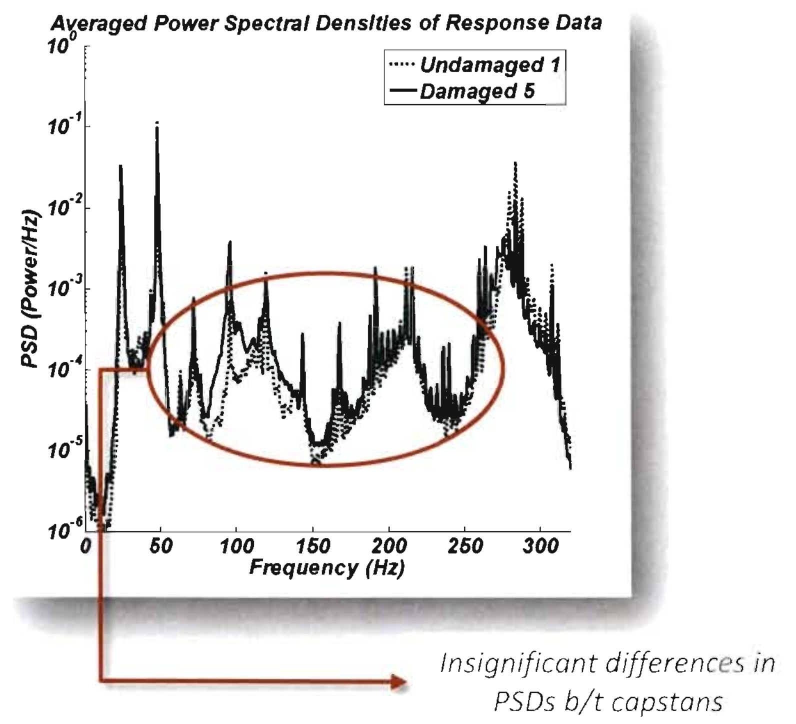
- Study concentrates on drive mechanism associated with *Right Ascension* (RA) axis
- PCB Piezotronics model 352A24 accelerometers adhered to three telescope mount locations
- Six capstans of varying levels of deterioration examined
- Ten cycles similar to "homing sequences" executed for each capstan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

Flow of Info-gap Analysis

2. For all damage classifiers (FA, MSD, PCA, SVD):
    1. For all AR model orders (5,...,30 in increments of 5):

    4. For all α's (0.00,...,1.00 in increments of 0.05):

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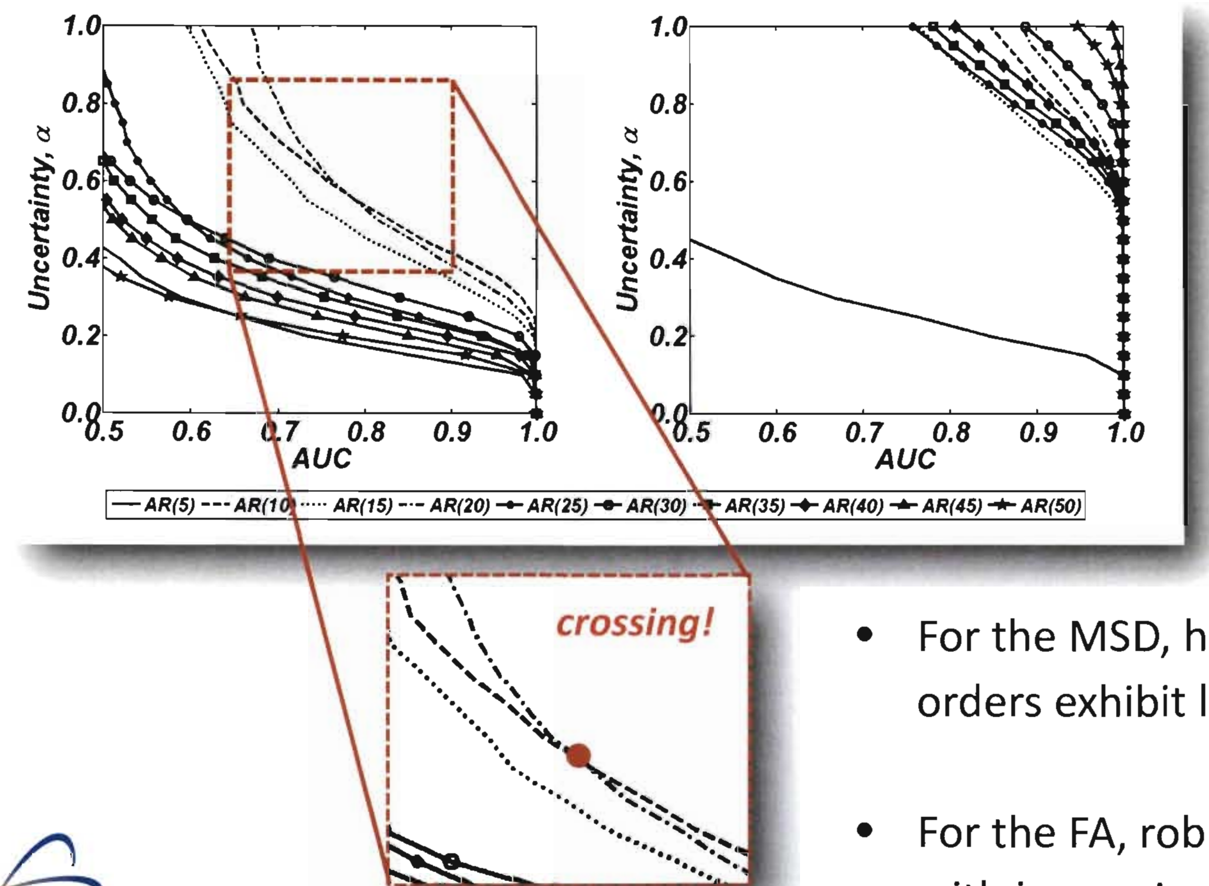
Robust Selection of AR Model Order

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

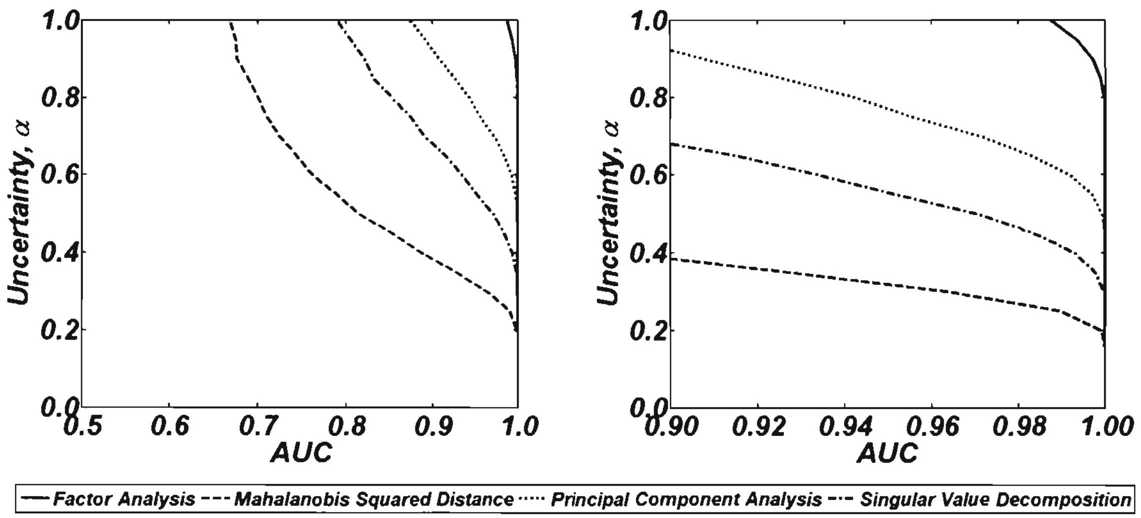


- For the MSD, high and low AR model orders exhibit least robustness.

- For the FA, robustness generally increases with increasing model order.

Robust Selection of Damage Classifier

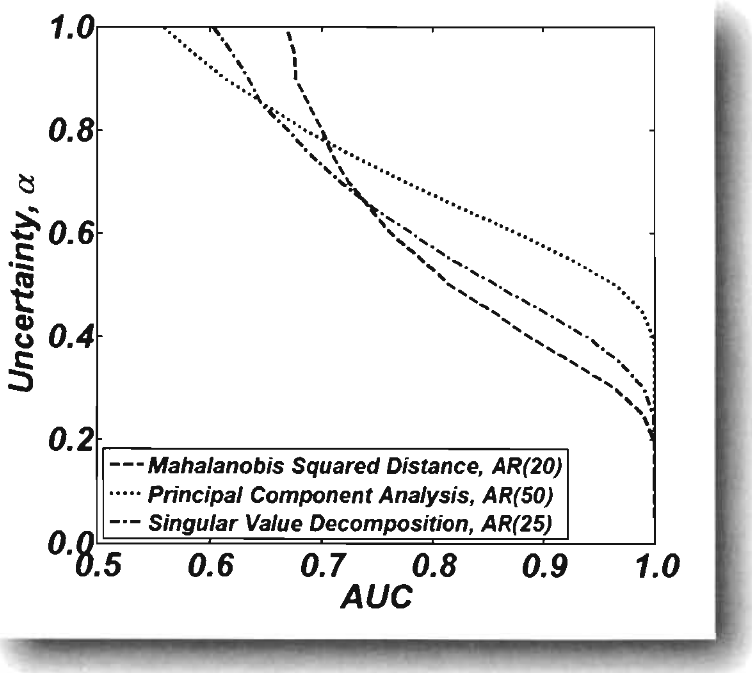
- The "robust-optimal" AR model orders are selected (from previous analysis) for robustness analysis of damage classifiers.
    - same data, alternative analysis
- "robust-optimal" = the AR model order that exhibits the most robust performance (*i.e.* the highest AUC) at the maximum horizon of uncertainty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

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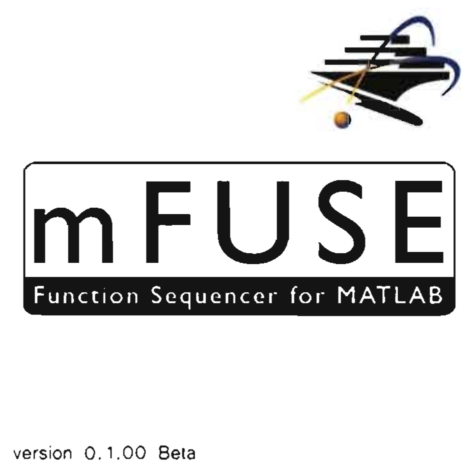
Software Utilized in Info-gap Analyses

- 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/



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

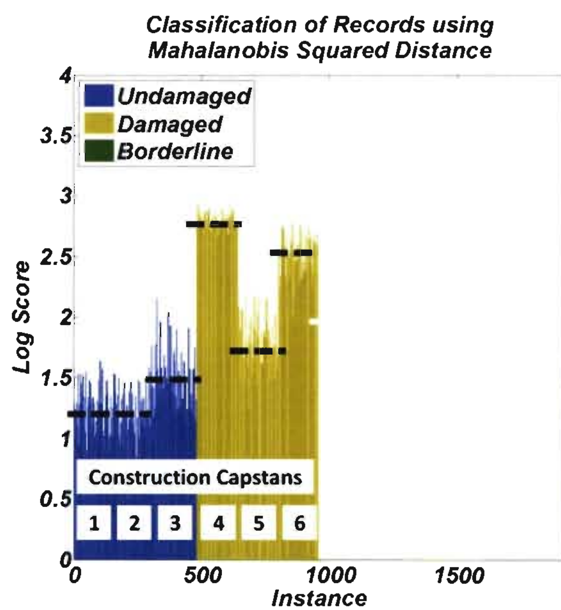
Backup Slides

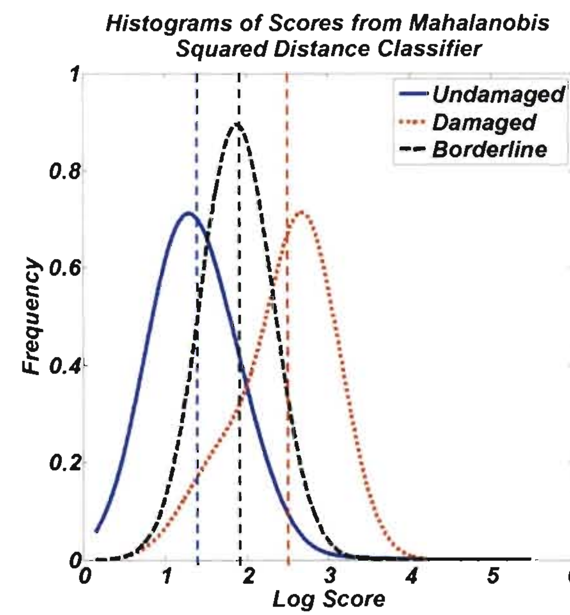
Damage Classifier Development

- Damage classifier employs *Mahalanobis Squared Distance* (MSD) metric, expressed as
  - $D_M = {|x-\mu|}/{\sigma}$ for scalar features and
  - $D_M = \sqrt{(\boldsymbol{\varphi}^{\mathrm{uknown}} - \boldsymbol{\mu}^{\mathrm{u}})^{\mathrm{T}} (\boldsymbol{\Sigma}^{\mathrm{u}})^{-1} (\boldsymbol{\varphi}^{\mathrm{uknown}} - \boldsymbol{\mu}^{\mathrm{u}})}$ for n-dimensional feature vectors

- $\boldsymbol{\mu}^{\mathrm{u}}$ and $\boldsymbol{\Sigma}^{\mathrm{u}}$ built from data from with undamaged capstans (*a.k.a.* "Construction Capstans")

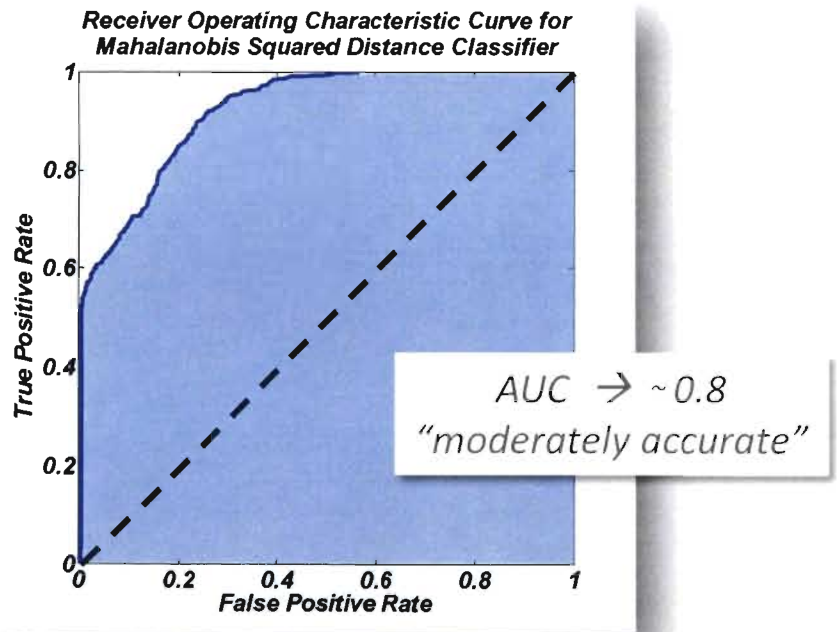
- All time-history records are then "scored" against $\boldsymbol{\mu}^{\mathrm{u}}$ and $\boldsymbol{\Sigma}^{\mathrm{u}}$

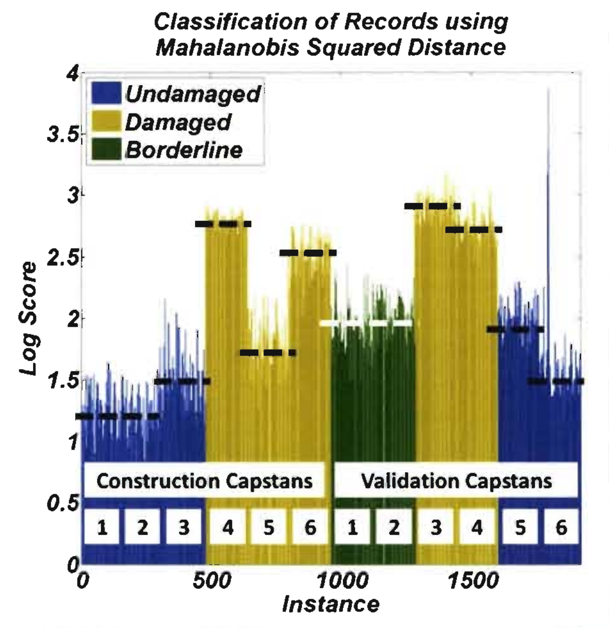




Damage Classifier Validation

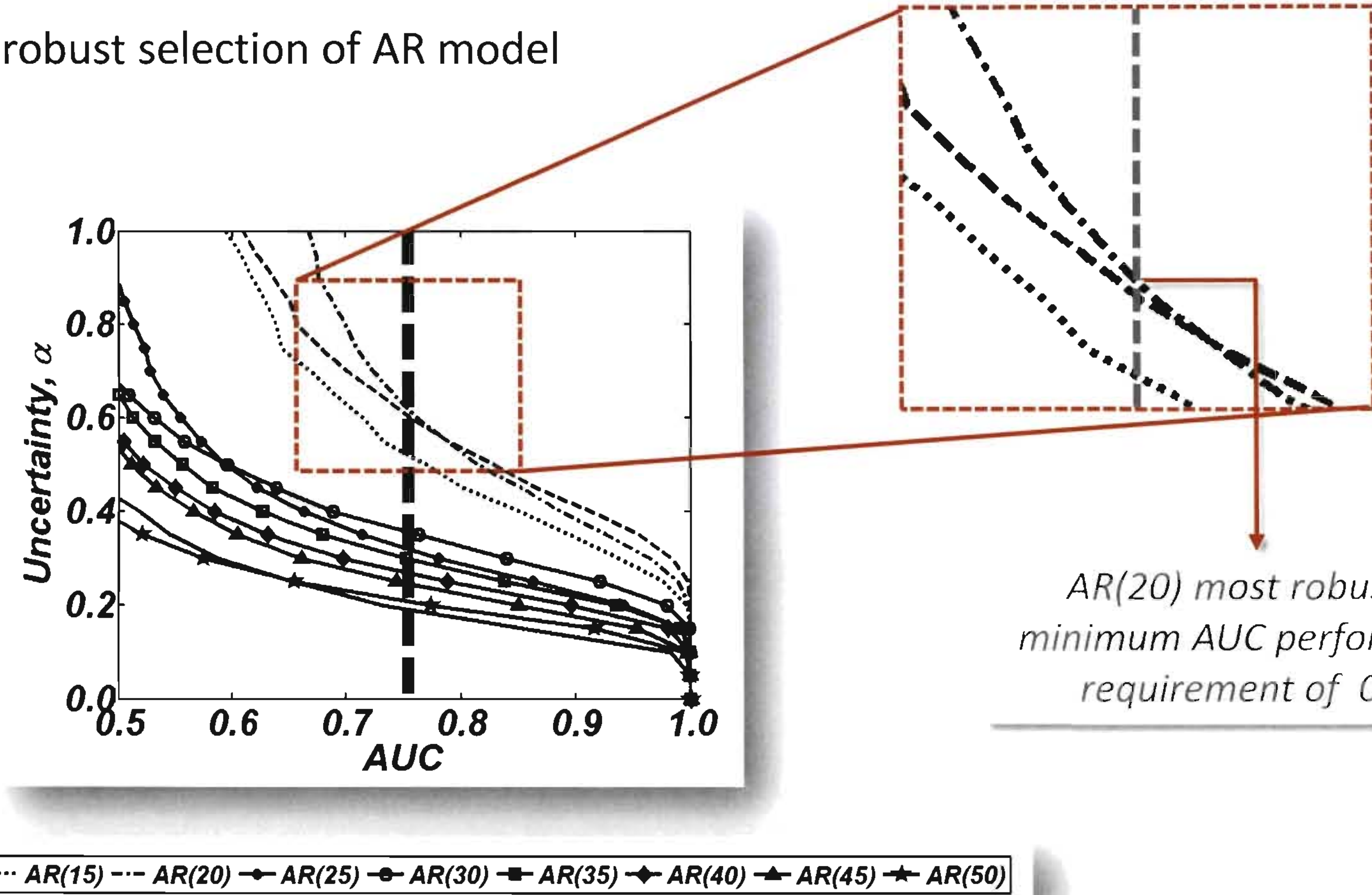
- *Receiver-Operating Characteristic* (ROC) curve and the *Area Under the ROC Curve* (AUC) computed to assess global MSD damage classifier performance
- After development and initial testing of the MSD damage classifier, six "blind tests" were conducted to validate damage classifier against as yet unseen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





Feature Selection

- Example of robust selection of AR model order



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

Future Work

- Further development and validation of damage classifiers
- Full life-cycle testing of capstans to facilitate improved characterization of damage

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

- Implementation of embedded sensing platforms to facilitate autonomous SHM system