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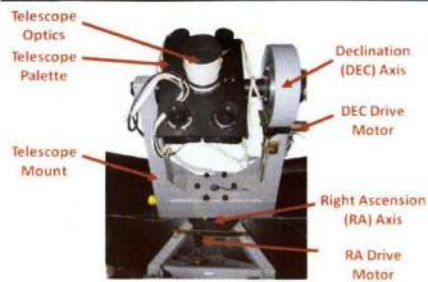
Title: Embedded sensor node deployment to monitor telescope drive system components

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Embedded sensor node deployment to monitor telescope drive system components

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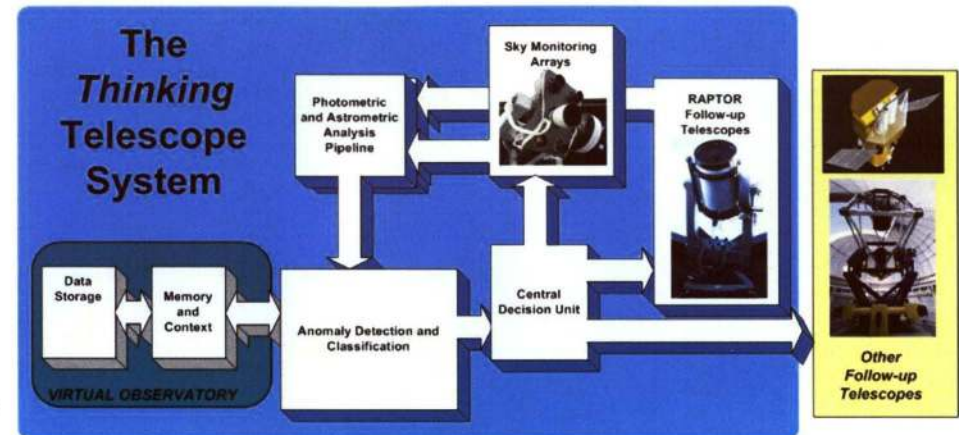
SPIE Smart Structures/NDE
March 11-15, 2012, San Diego, CA

Abstract

- This paper presents the deployment of an embedded active sensing platform for real-time condition monitoring of telescopes in the RAPid Telescopes for Optical Response (RAPTOR) observatory network. The RAPTOR network consists of several ground-based autonomous astronomical observatories primarily designed to search for astrophysical transients such as gamma-ray bursts. In order to capture astrophysical transients of interest, the telescopes must remain in peak operating condition to move swiftly from one potential transient to the next throughout the night. However, certain components of these telescopes have until recently been maintained in an ad hoc manner, often being permitted to run to failure, resulting in the inability to drive the telescope. In a recent study, a damage classifier was developed using the statistical pattern recognition paradigm of structural health monitoring (SHM) to identify the onset of damage in critical telescope drive components.
- In this work, that damage classifier is implemented using data collected with a prototype embedded active sensing platform, which is deployed to the telescope structure in order to detect the onset of telescope drive component damage and alert system administrators prior to system failure.

Project Background

- The LANL Thinking Telescope Project aims at real-time detection / characterization of astrophysical transients (e.g. gamma-ray bursts).
- The RAPid Telescopes for Optical Response (RAPTOR) network of ground-based observatories serves as the primary hardware component of the LANL Thinking Telescope Project.



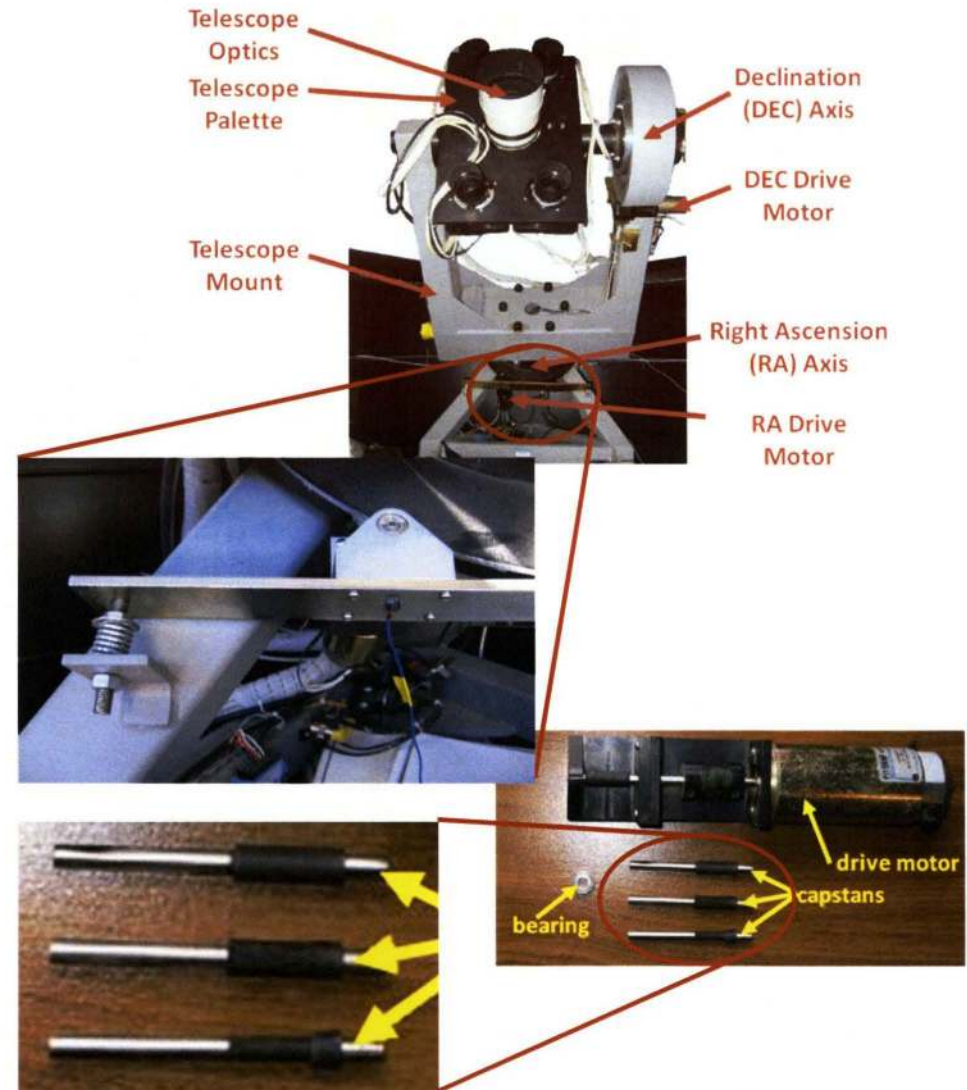
<http://www.thinkingtelescopes.lanl.gov/Concepts.htm>



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

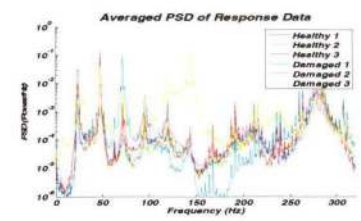
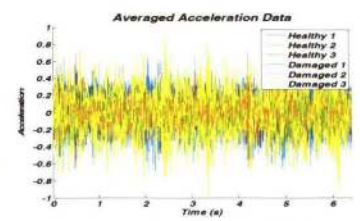
Project Background

- **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



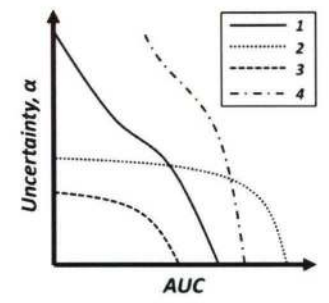
Damage Assessment – Preliminary

Data Collection / Analysis

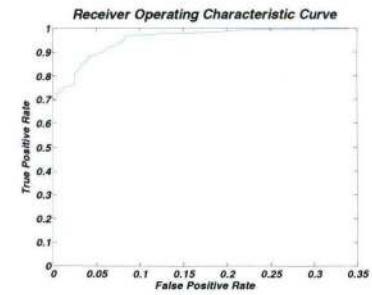
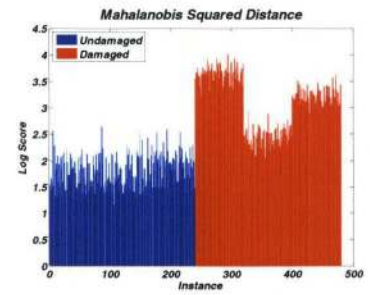


Feature Selection

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

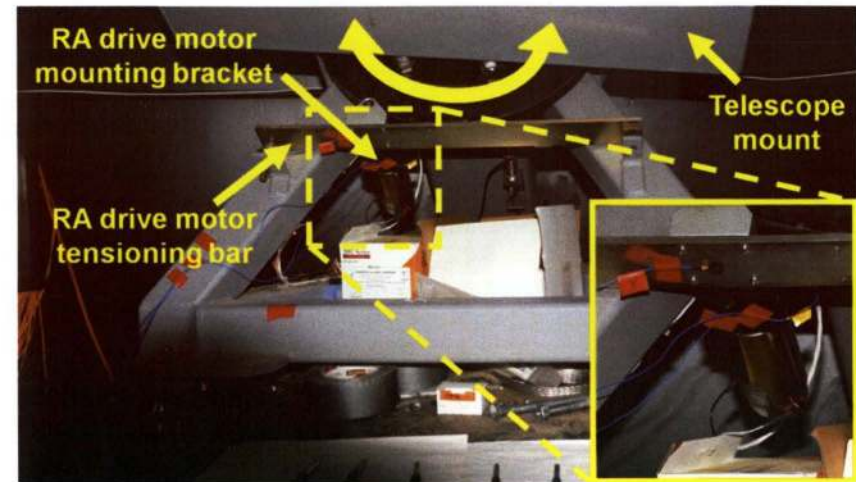


Damage Classifier Development / Validation



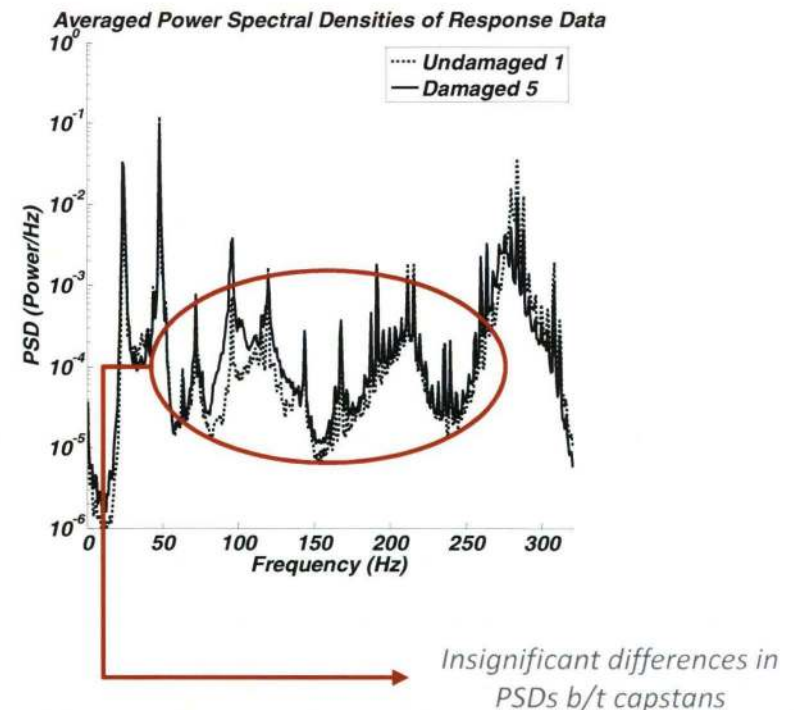
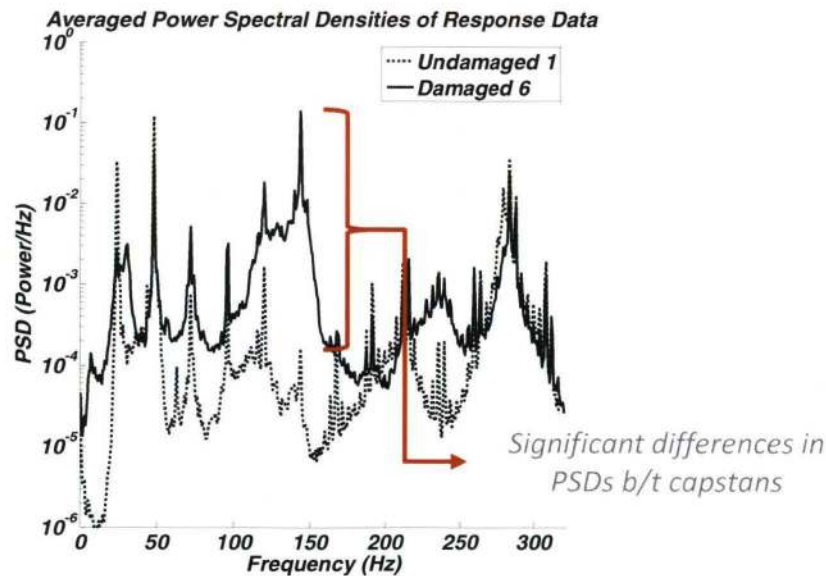
Preliminary Study: Data Collection

- 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



Preliminary Study: 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



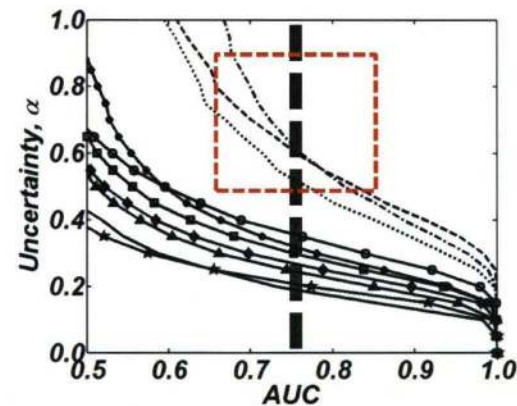
Preliminary Study: Feature Selection

- Time-history data modeled as auto-regressive (AR) process
- AR model coefficients employed as damage-sensitive features
- Choose AR model order based on the robustness of its performance to uncertainty about future data sets
- Info-gap decision theory provides a framework to model and manage this uncertainty

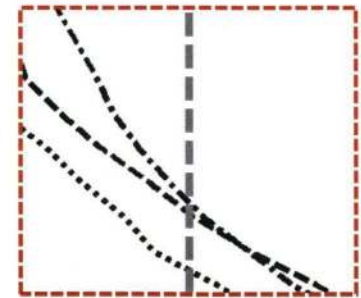
$$x_i = \sum_{j=1}^p \varphi_j x_{i-j} + e_i$$

How to choose AR model order, p ?

Example of robust AR model order selection



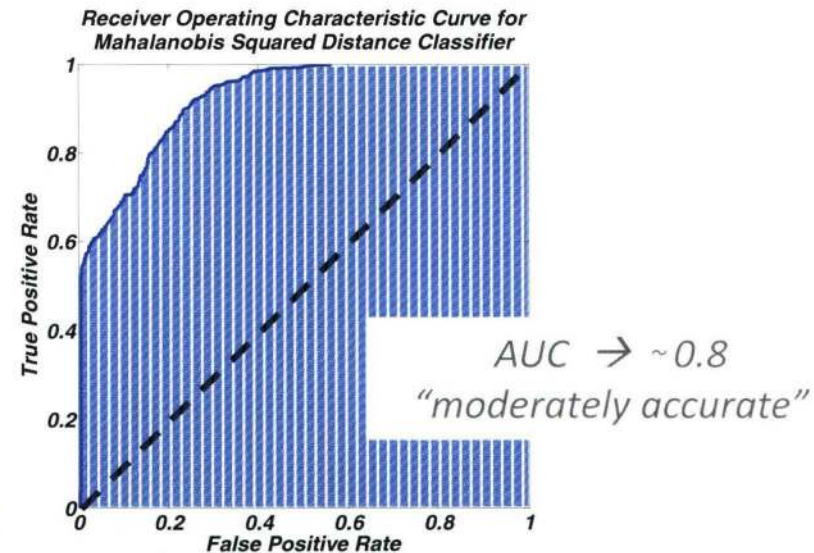
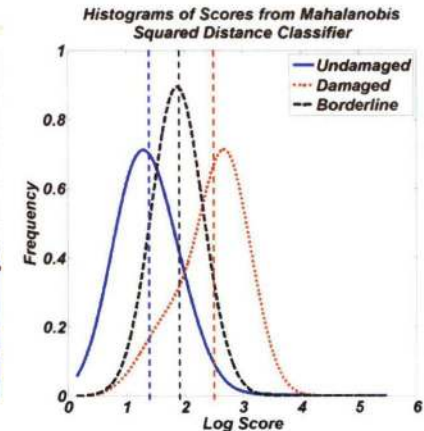
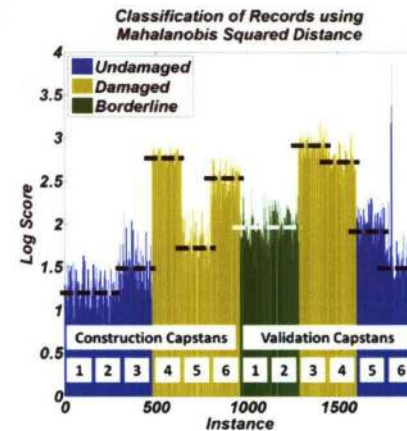
AR(20) most robust for AUC of 0.75



— AR(5) - - - AR(10) ····· AR(15) - - - AR(20) - - - AR(25) - - - AR(30) - - - AR(35) - - - AR(40) - - - AR(45) - - - AR(50)

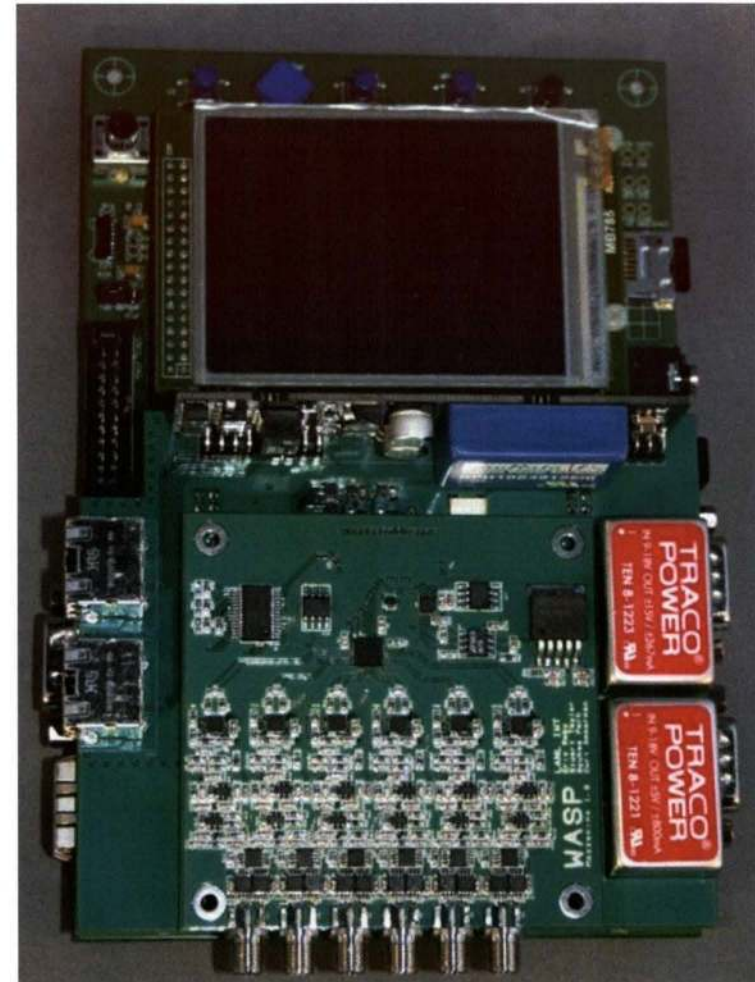
Preliminary Study: Classifier Validation

- Classifier employs *Mahalanobis Squared Distance* as a scalar feature
- *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



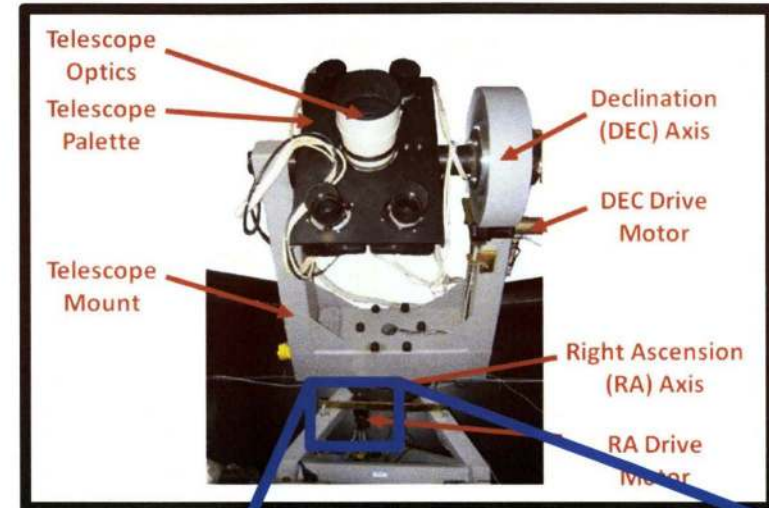
Embedded SHM: Platform Overview

- **Active/Passive sensing with 2-50 kHz bandwidth**
- **Multiple sensing modes**
 - Active
 - Passive
 - Impedance
- **Autonomous or web-driven data acquisition**
- **Power over Ethernet (PoE)**
- **Modular/replaceable analog front-end**
- **Common “smartphone” features implementable**



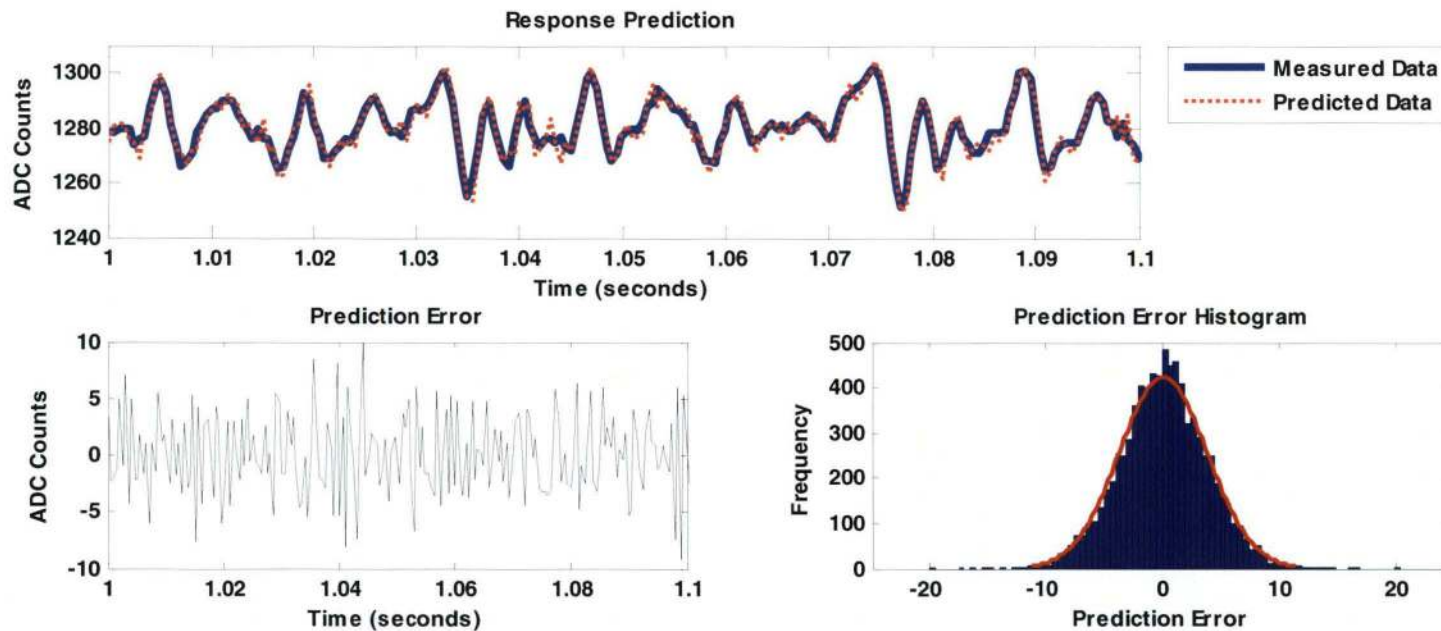
Embedded SHM: Platform Deployment

- **Accelerometers in biaxial configuration**
 - Rieker B1 (100 mV/g)
 - Rieker B2 (30 mV/g)
- **Sensor block bonded to motor mount bar**
 - Location shown in preliminary study to provide most informative data



Embedded SHM: Data Collection

- Data are automatically collected at the start of each night during a controlled “homing” operation
- Data are fed into a training model for outlier detection
- As the statistical significance of the data increases, deviations indicative of component failure will be identifiable



Future Work

- Analyze automated data as it is received
- Update firmware to implement validated classifier
- Provide real-time feedback for adaptive control

