

# Application of Extreme Value Statistics for Structural Health Monitoring

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# Four Goals for Structural Health Monitoring

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- **Step 1: Damage Identification**
- **Step 2: Damage Localization**
- **Step 3: Damage Quantification**
- **Step 4: Damage Prognosis**

# Structural Health Monitoring

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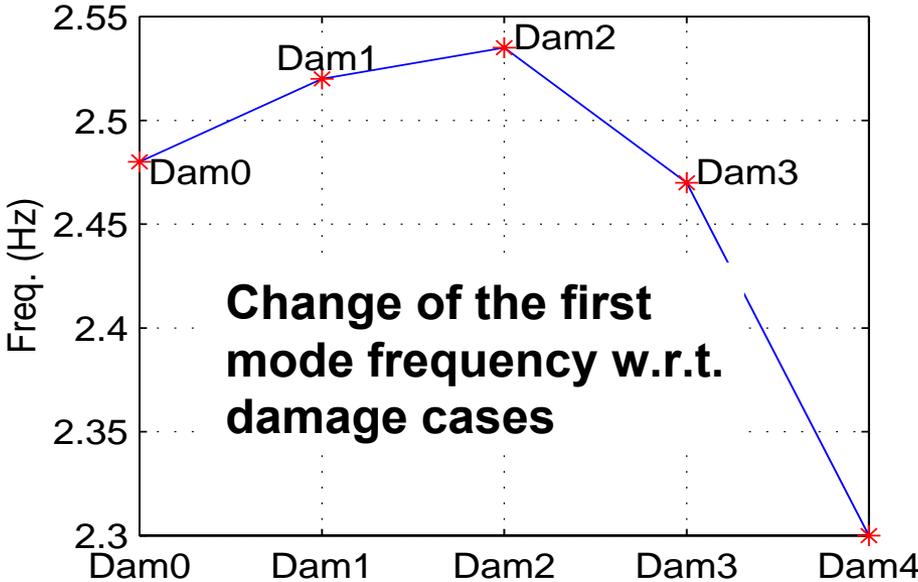
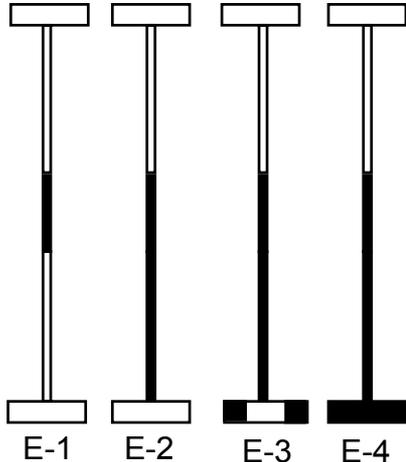
Is this bridge damaged?  Perform pattern comparison.

# Five Steps for Structural Health Monitoring

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- **Step 1: Operational Evaluation**
- **Step 2: Data Acquisition**
- **Step 3: Data Normalization**
- **Step 4: Feature Extraction**
- **Step 5: Statistical Inference**

# Environmental Variation



# Example of Debris in Expansion Joint of the Alamosa Canyon Bridge

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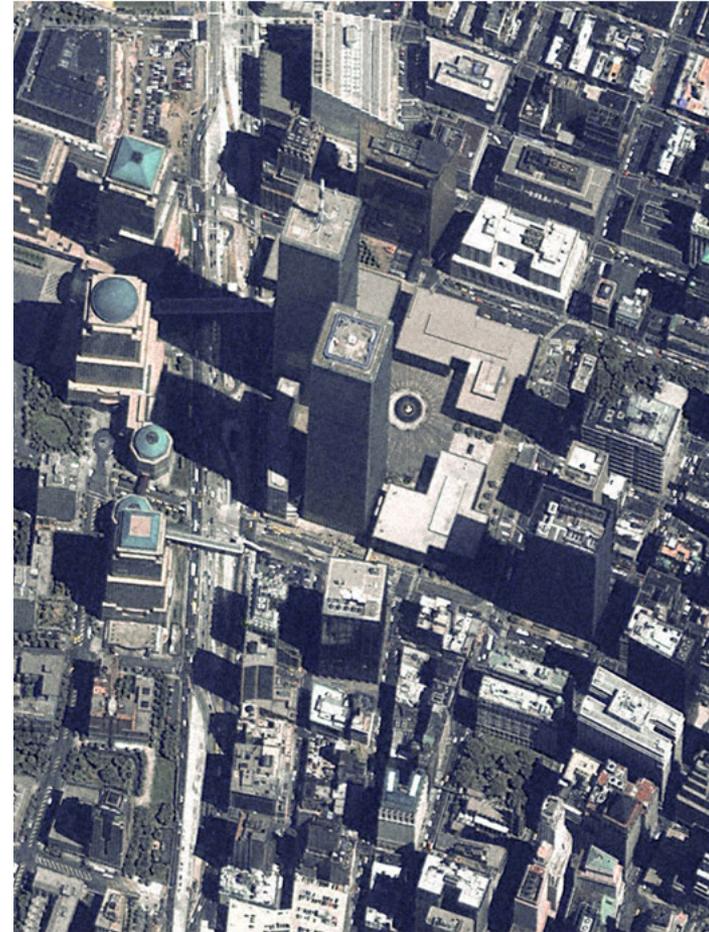
This debris can effect the boundary conditions of the structure and its response to environmental changes

# Statistical Pattern Recognition Paradigm for SHM

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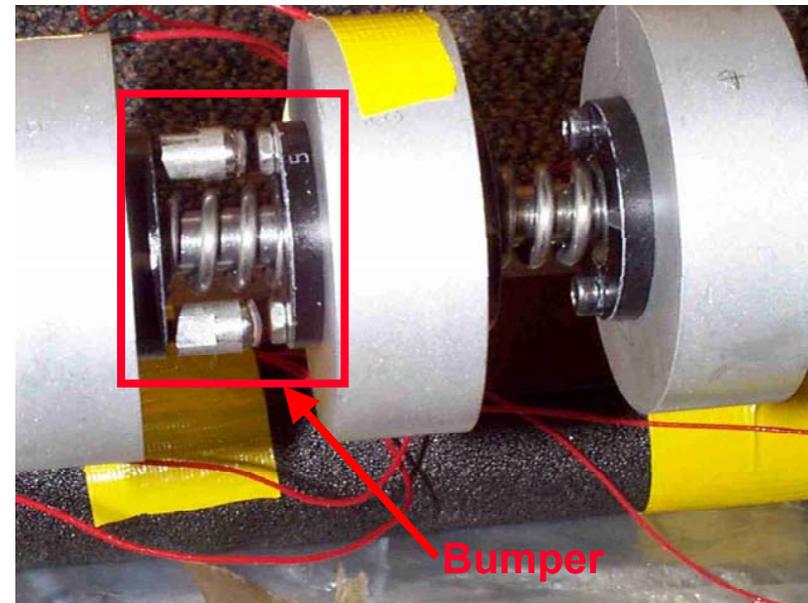
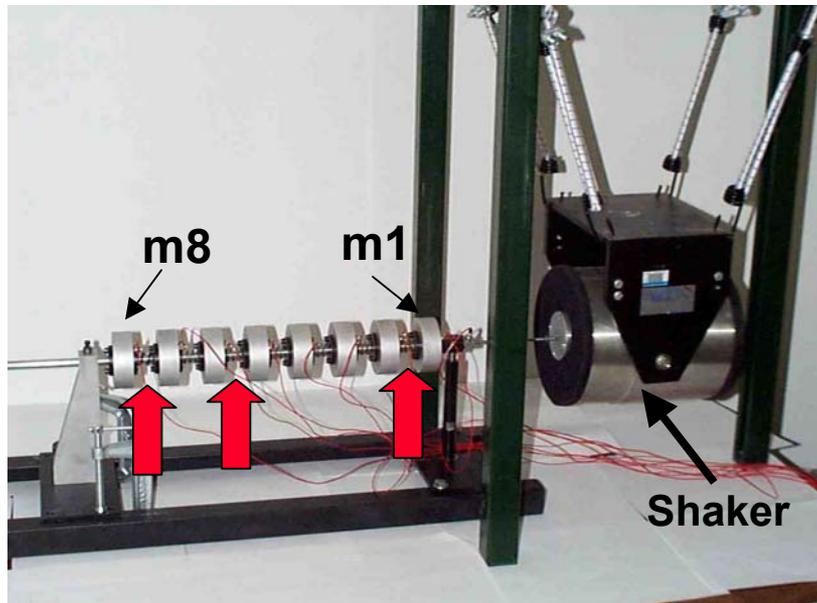


After Sep. 11, 2001



Before Sep. 11, 2001

# Data Normalization Example [Sohn et al. 2002]

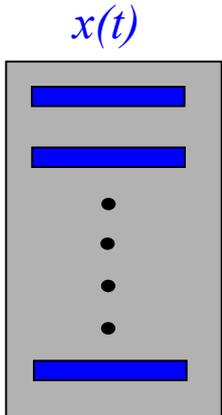


## List of time series employed in this study

| Case | Description          | Input level         | Data # per input | Total data # |
|------|----------------------|---------------------|------------------|--------------|
| 0    | No bumper            | 3, 4, 5, 6, 7 Volts | 15 sets          | 75 sets      |
| 1    | Bumper between m1-m2 | 3, 4, 5, 6, 7 Volts | 5 sets           | 25 sets      |
| 2    | Bumper between m5-m6 | 3, 4, 5, 6, 7 Volts | 5 sets           | 25 sets      |
| 3    | Bumper between m7-m8 | 4, 5, 6, 7 Volts    | 5 sets           | 20 sets      |

# Outline of Damage Diagnosis using AR-ARX, Auto-Associative Network and Hypothesis Test

## 1. COLLECT BASELINE DATA

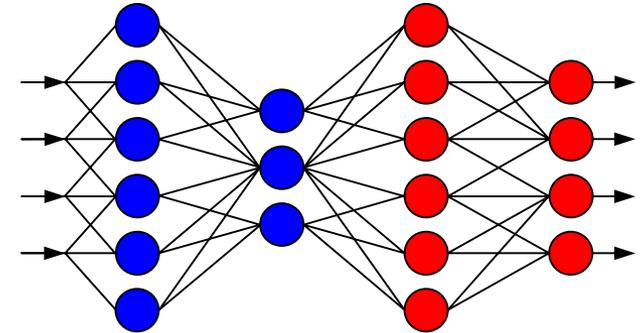


Time series from various operation & environmental conditions

## 2. FEATURE EXTRACTION

$$\varepsilon_x(t) = x(t) - \sum_{i=1}^a \alpha_i x(t-i) - \sum_{j=1}^b \beta_j e_x(t-j)$$

## 3. DATA NORMALIZATION



## 4. FEATURE EXTRACTION

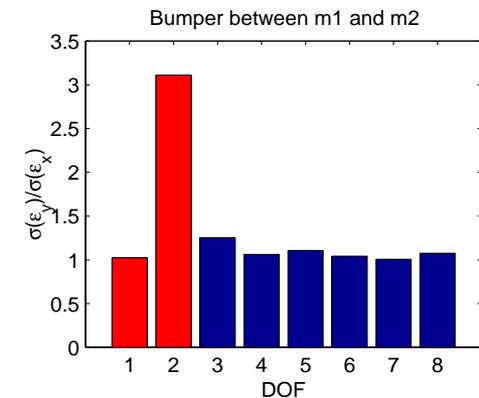
$$\varepsilon_y(t) = x(t) - \sum_{i=1}^a \hat{\alpha}_i x(t-i) - \sum_{j=1}^b \hat{\beta}_j e_x(t-j)$$

## 5. STATISTICAL INFERENCE

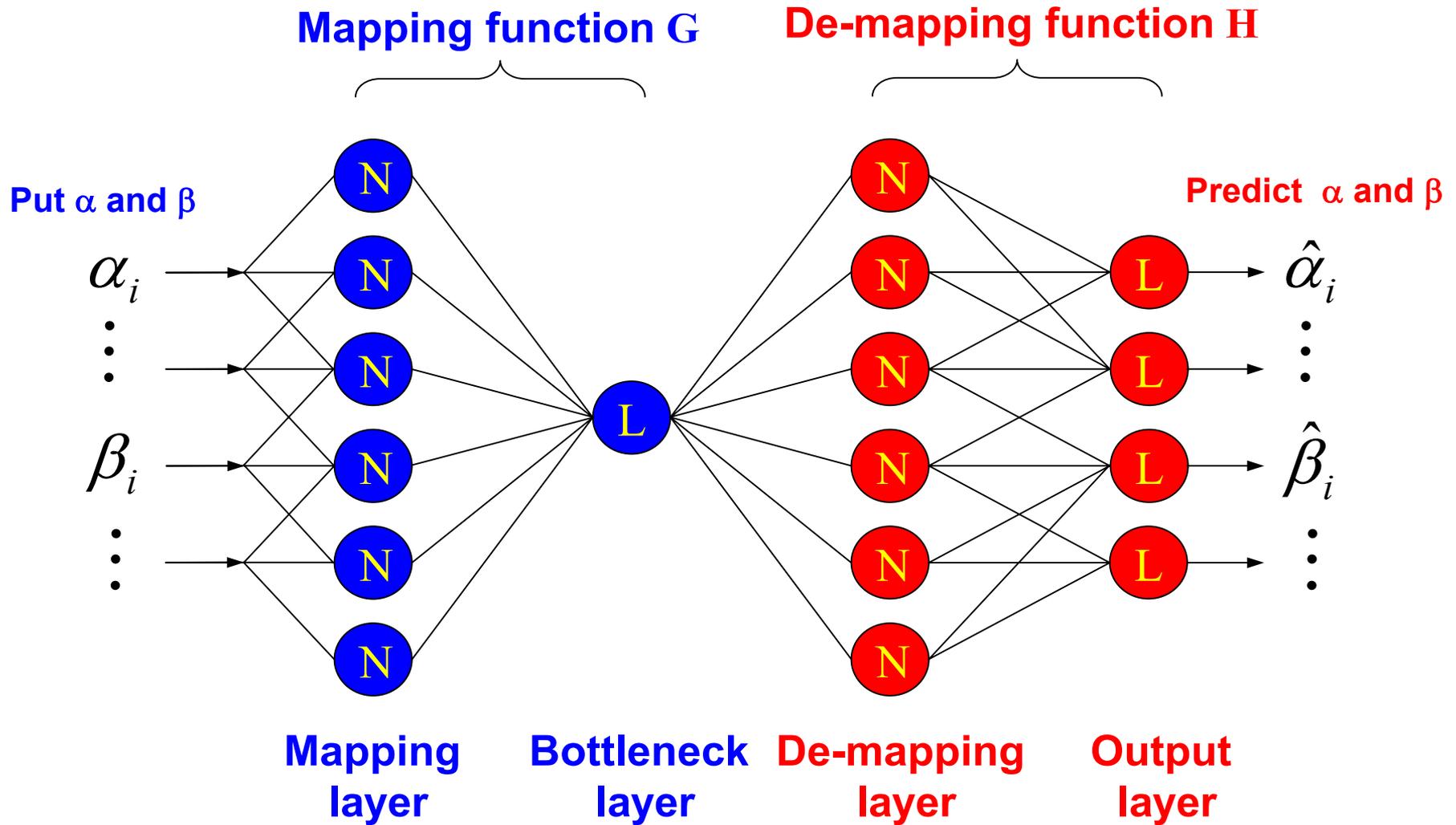
$$H_0 : \sigma(\varepsilon_y) \leq \sigma(\varepsilon_x)$$

$$H_1 : \sigma(\varepsilon_y) \geq \sigma(\varepsilon_x)$$

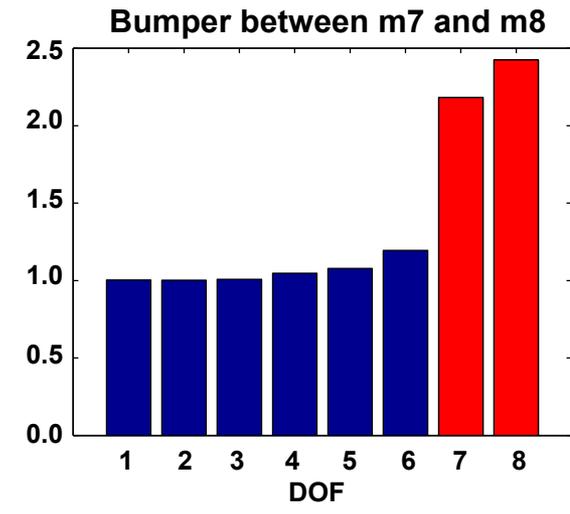
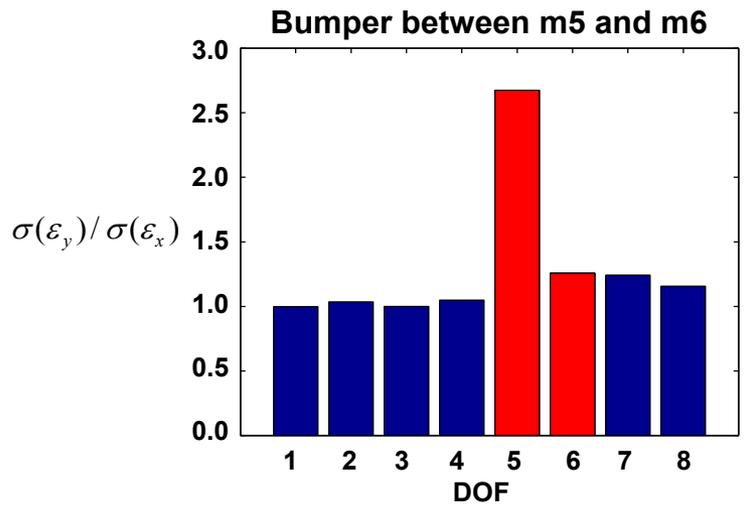
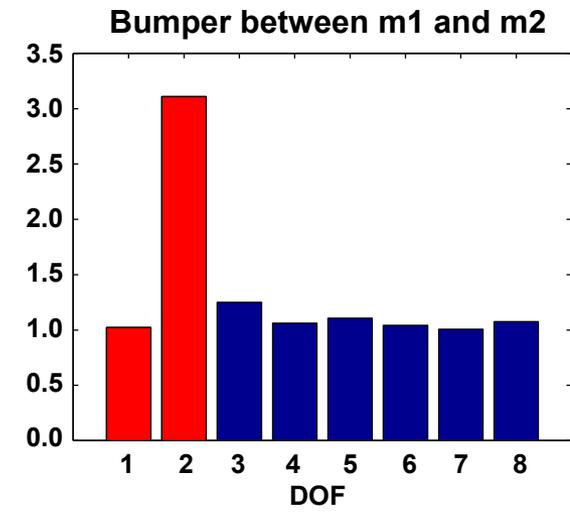
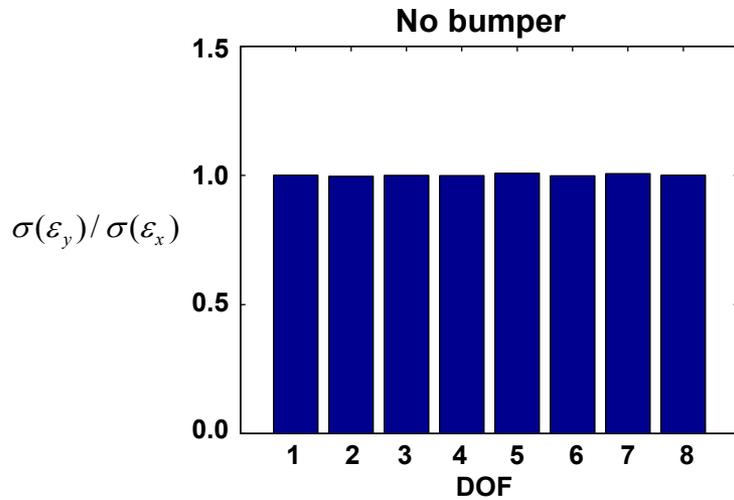
## 6. DECISION MAKING



# Auto-Associative Neural Network for Data Normalization



# Damage Localization

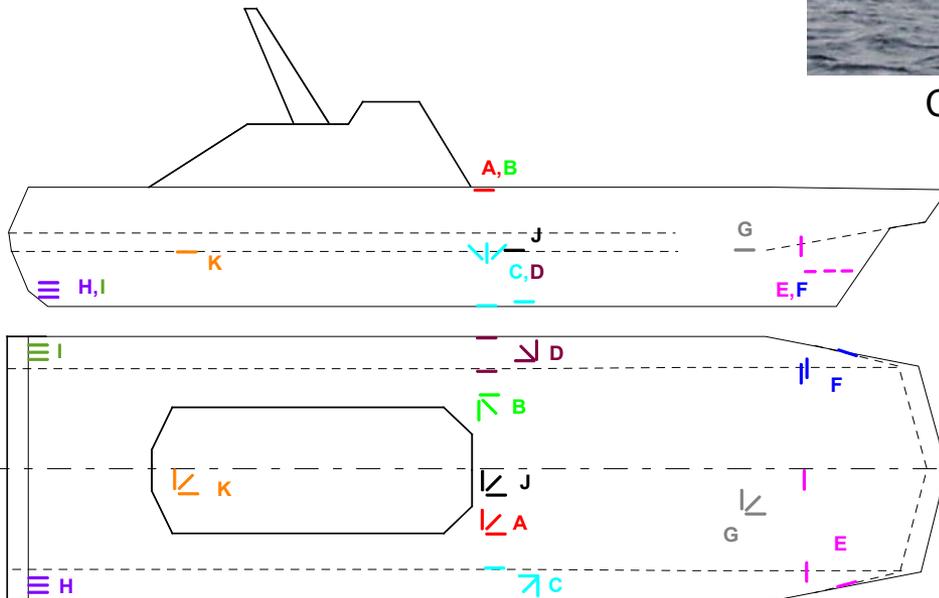


# Real World Application [Sohn et al. 2001]

(a) Surface-Effect Fast Patrol Boat



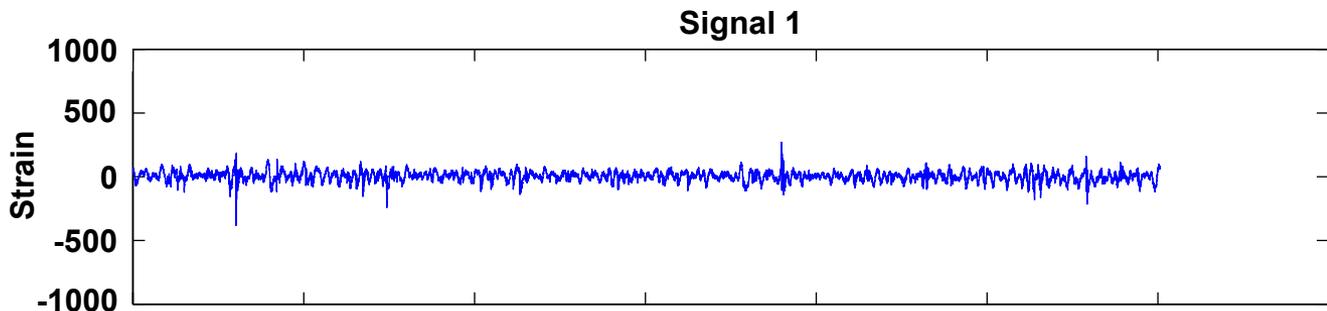
Courtesy of Naval Research Laboratory



(b) Fiber optic strain gauges

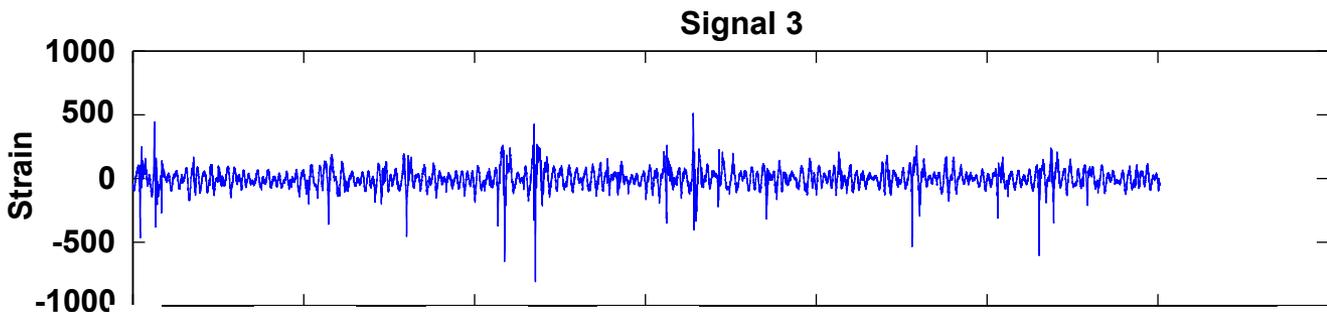
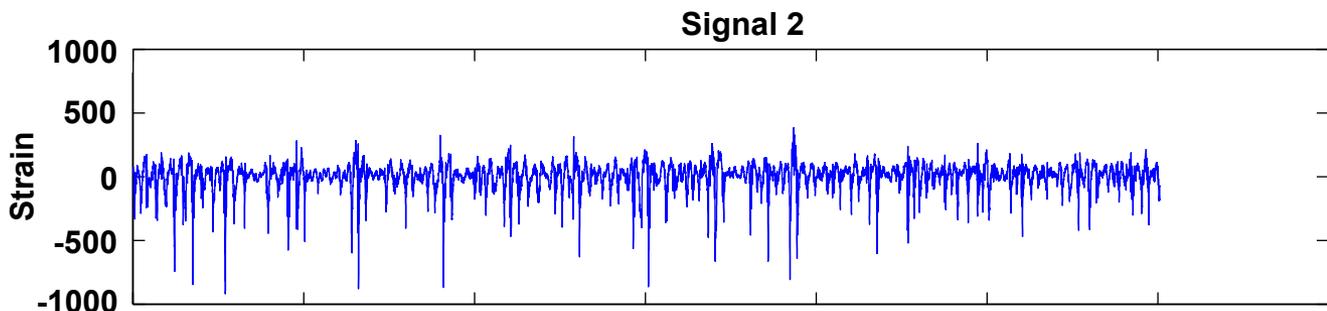
# Raw Dynamic Strain Time Series Data

Low Speed



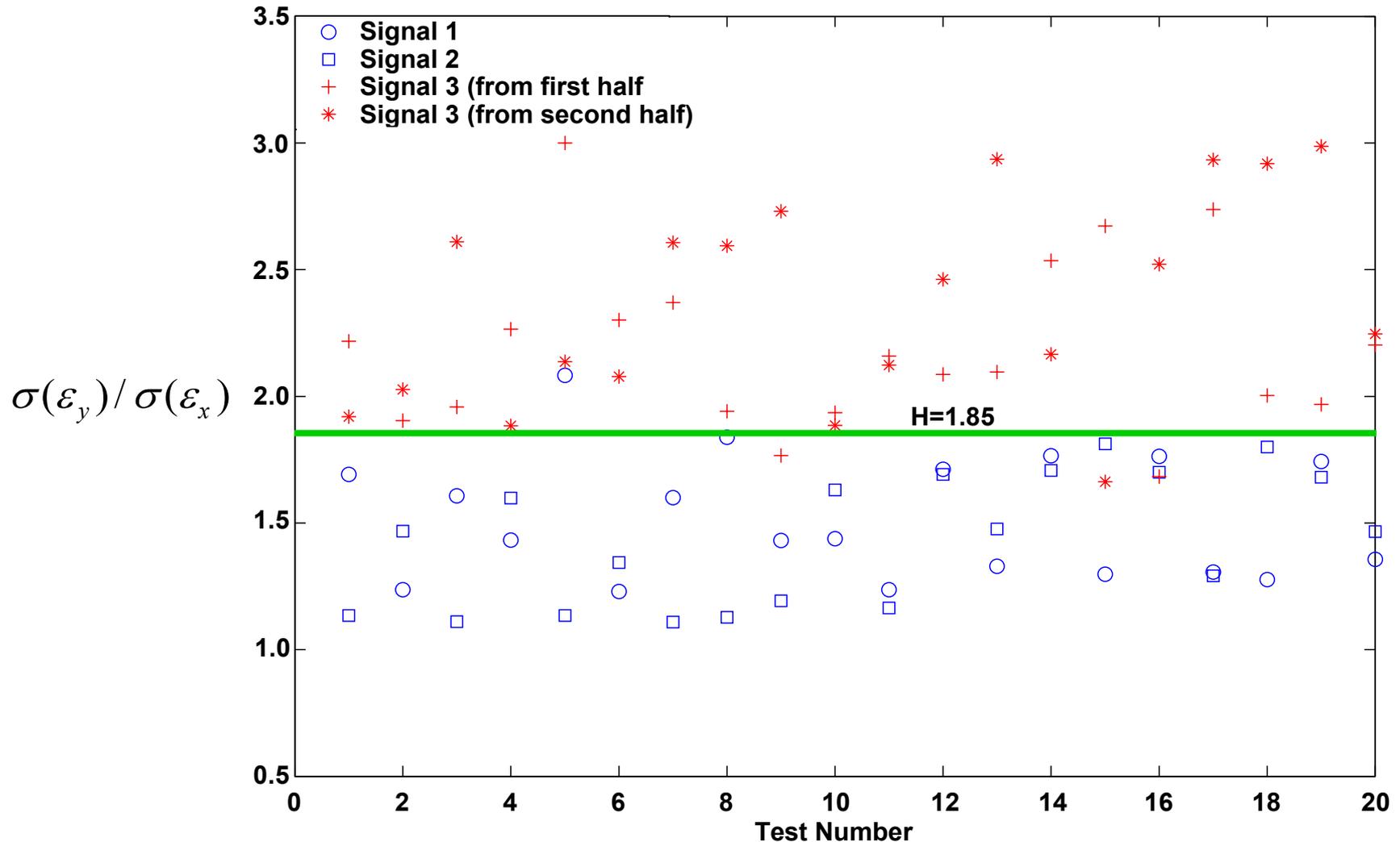
Structural Condition I (undamaged)

High Speed

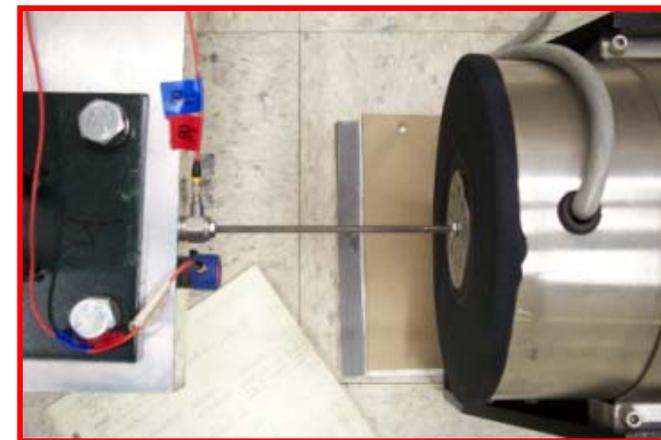


Structural Condition II (damaged)

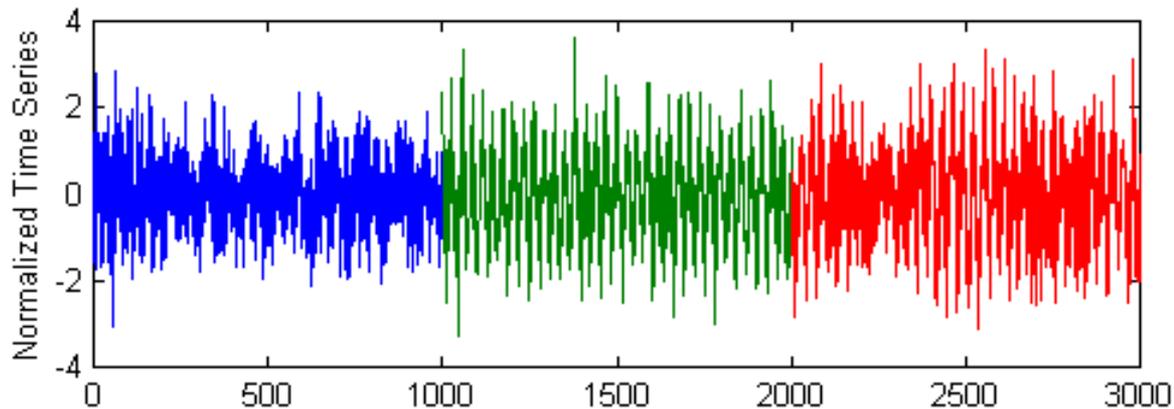
# Damage Classification using $\sigma(\varepsilon_y)/\sigma(\varepsilon_x)$



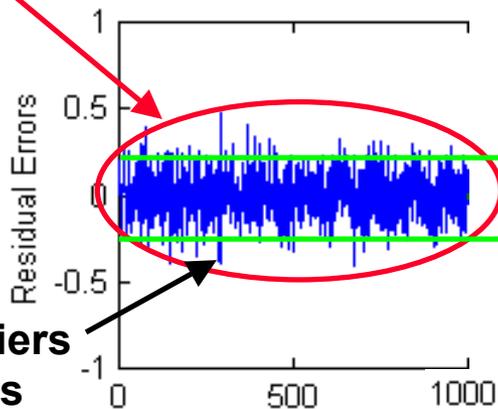
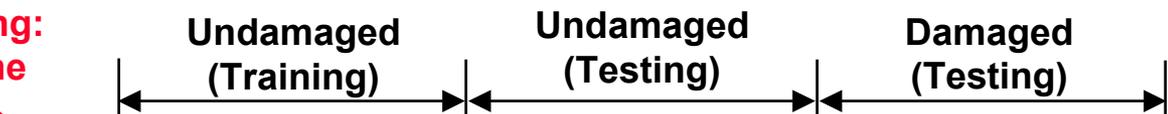
# A Moment Resisting Frame Structure Model



# Establishment of Decision Boundaries



**Unsupervised Learning:**  
Use only the baseline  
data for training

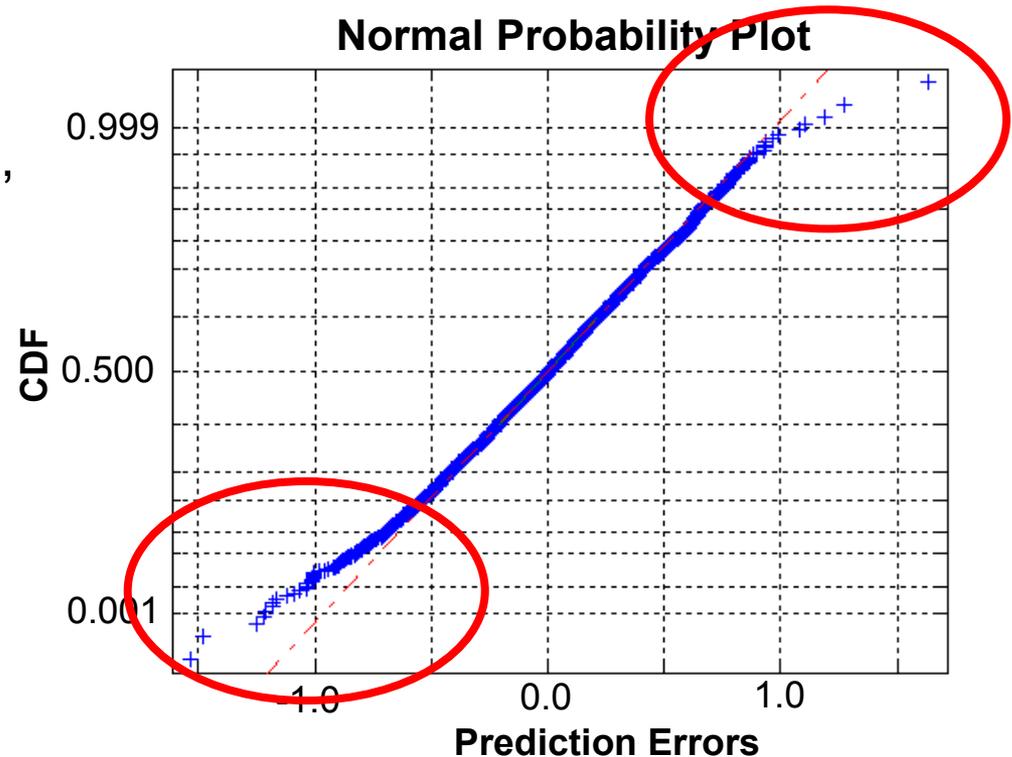


From Normal  
# of outliers: 48

# of Expected outliers  
= 1% of 1000 points  
= 10 outliers

# Normality Assumption of Data

- Let's look at the baseline prediction errors to see whether they have a normal distribution or not.
- A **normal probability plot** graphically assesses whether the data come from a normal distribution.
- If the data are normal, the plot will be linear. Otherwise, there would be curvature in the plot.
- The central population of data seems to fit to the normal distribution well, but the tails do not.



# Why Extreme Value Statistics ?

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- In general, the distribution type of the parent data is unknown, and there are **infinite** numbers of candidate distributions.
- There are only **three types** of distributions for extreme (maximum or minimum) values **regardless the distribution type of the parent data** [Fisher and Tippett, 1928].
- That means, the model selection for the extreme values becomes much **easier**, because there are only three models to choose. (**Gumbel, Weibull, Frechet** distributions)

# Feasible Cumulative Density Functions for Maxima

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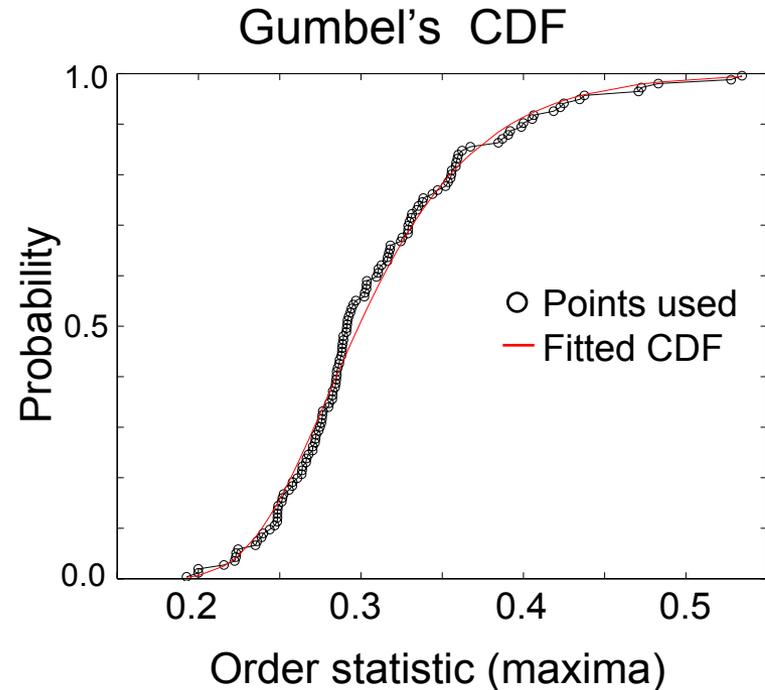
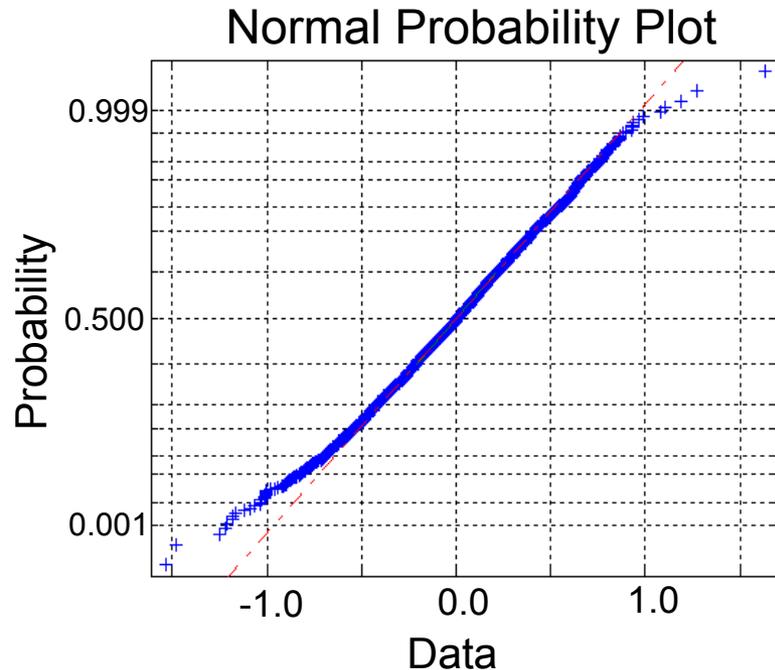
From Castillo [1988]:

▪ Gumbel  $F(x) = \exp\left[-\exp\left(-\frac{x-\lambda}{\delta}\right)\right] \quad -\infty < x < \infty, \delta > 0$

▪ Weibull:  $F(x) = \begin{cases} 1 & \text{if } x \geq \lambda \\ \exp\left[-\left(\frac{\lambda-x}{\delta}\right)^\beta\right] & \text{otherwise} \end{cases}$

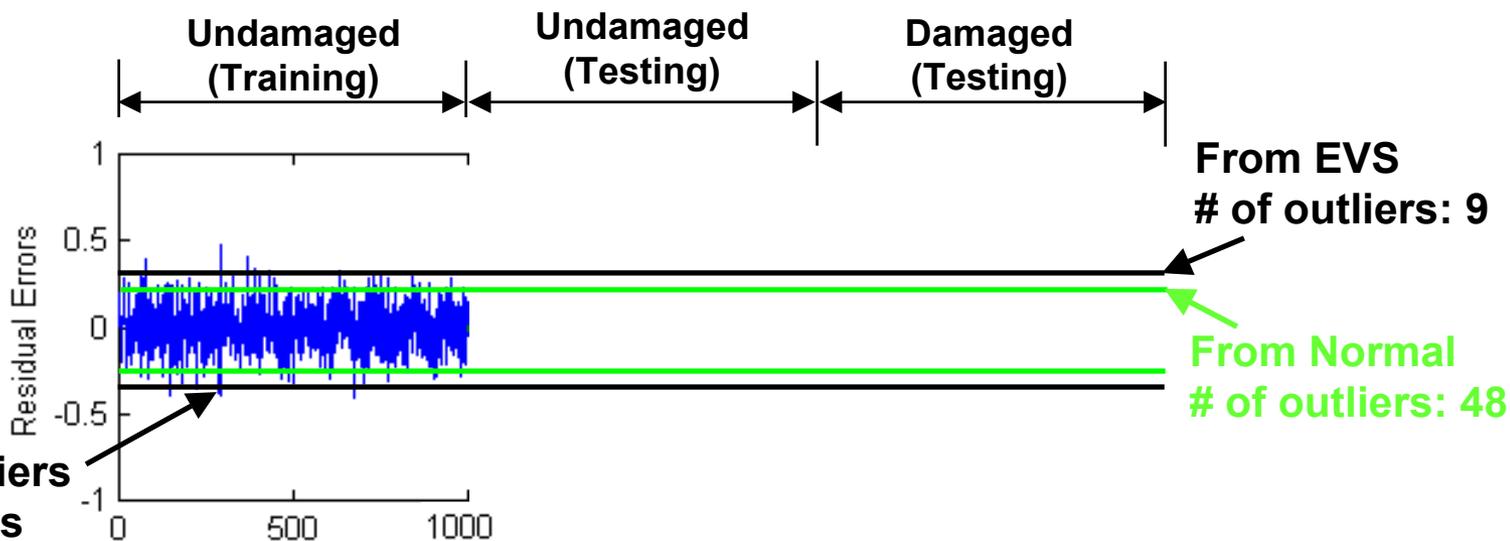
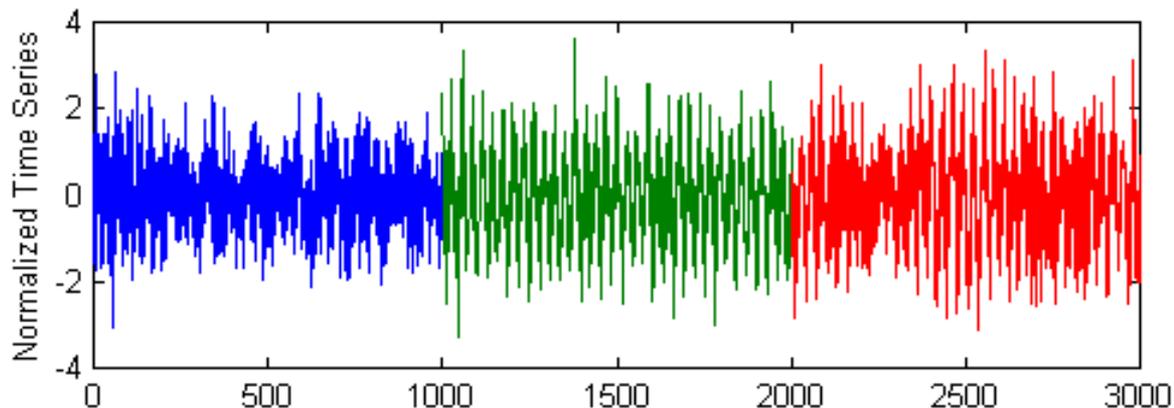
▪ Frechet:  $F(x) = \begin{cases} \exp\left[-\left(\frac{\delta}{x-\lambda}\right)^\beta\right] & \text{if } x \geq \lambda \\ 0 & \text{otherwise} \end{cases}$

# Fitting to Gumbel Distribution



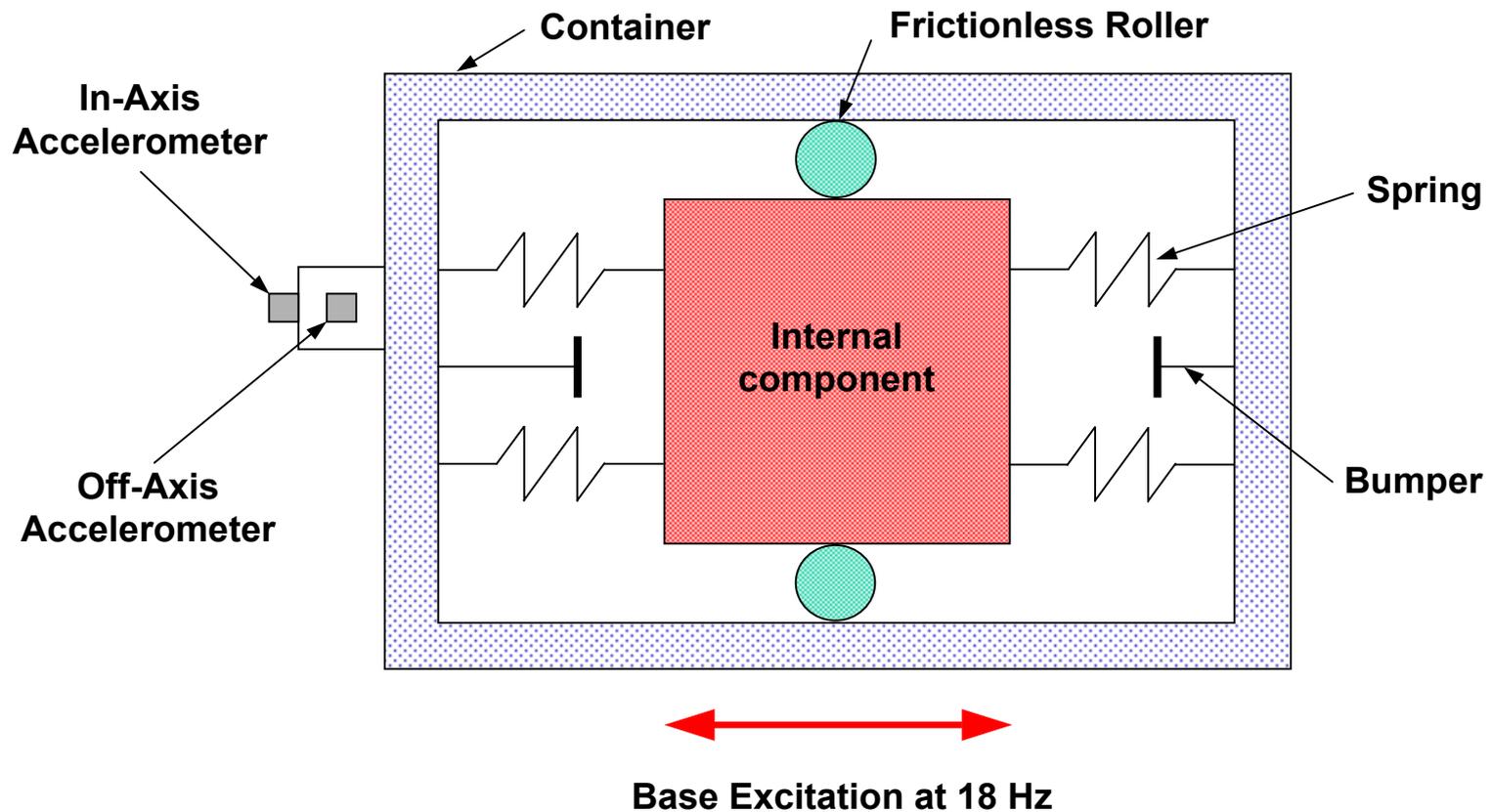
- Divide the original times series with 8192 data points into 128 time series with 64 points.
- Compute the maximum value from each block and fit the 128 maxima to a Gumbel distribution.

# Establishment of Decision Boundaries

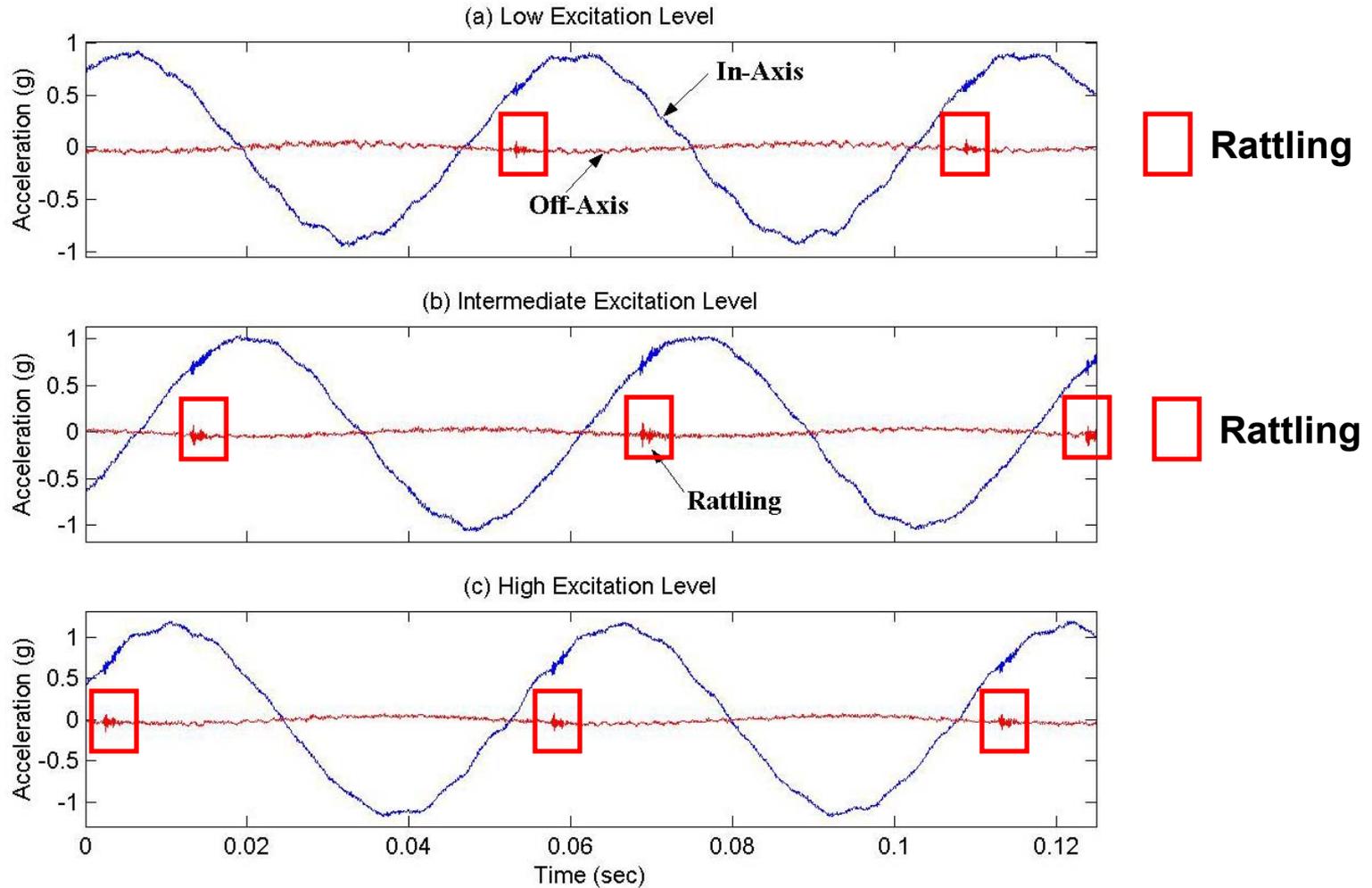


# of Expected outliers  
= 1% of 1000 points  
= 10 outliers

# Detection of Rattling



# Acceleration Response

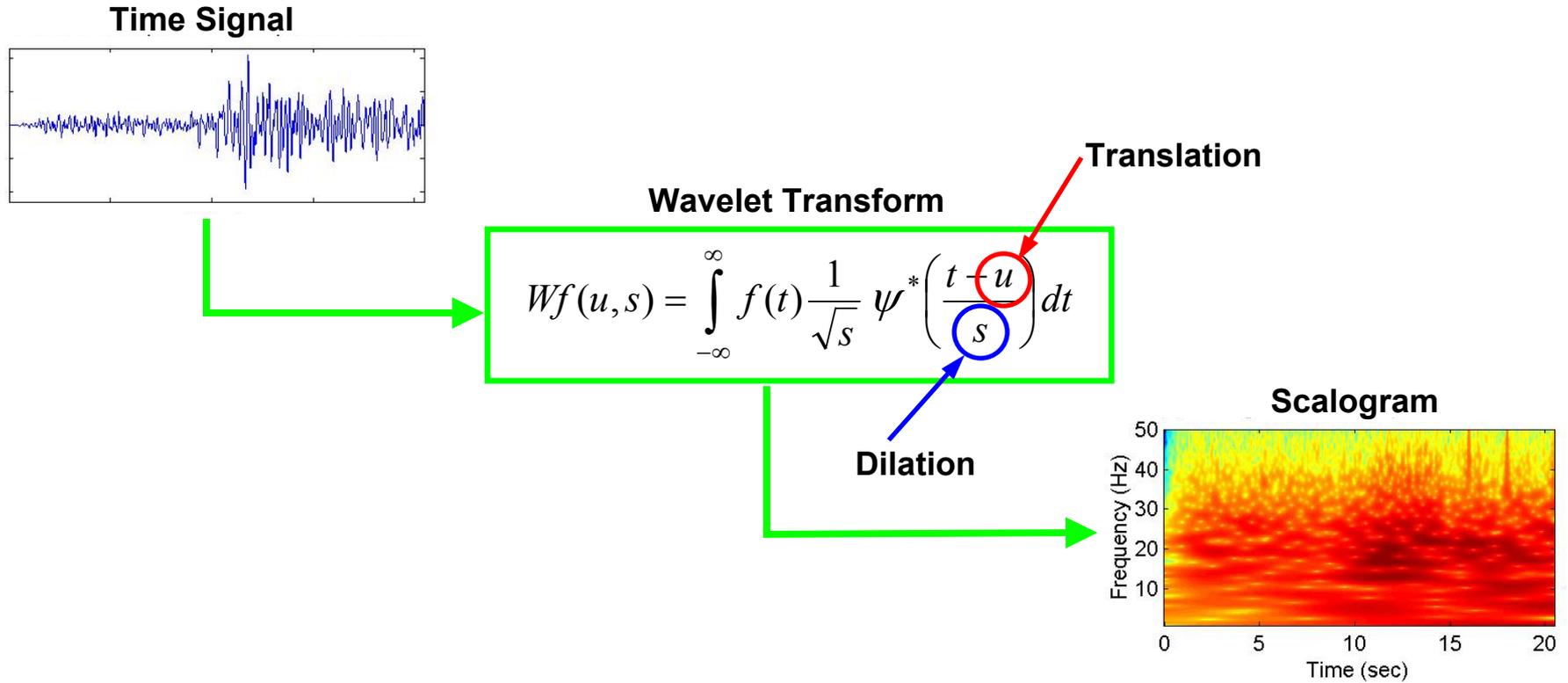


# Discontinuity Detection via Holder Exponent

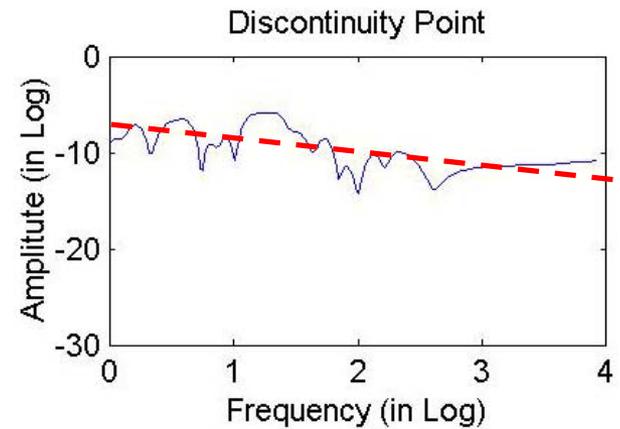
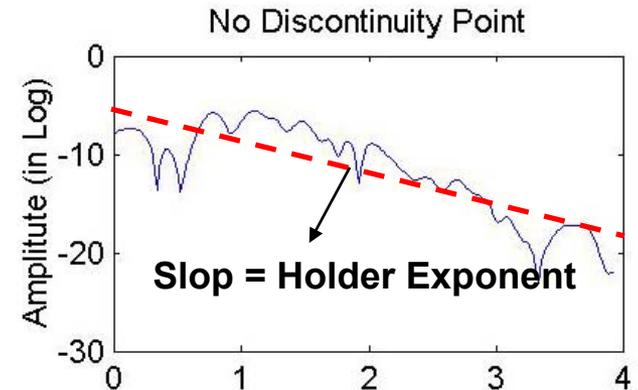
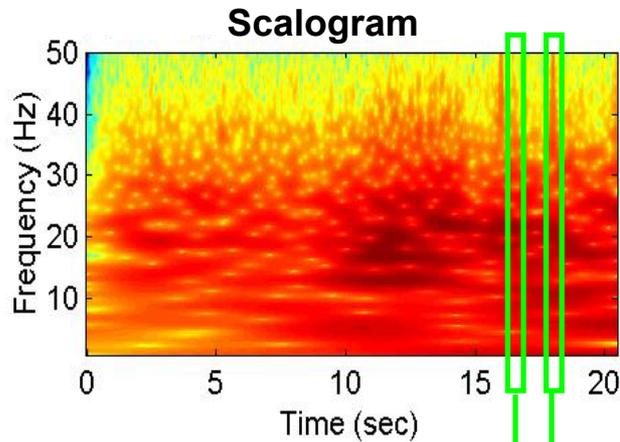
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- **Definition:** The Holder Exponent is a measure of the **regularity** of the signal. The regularity of the signal is the number of continuous derivatives that the signal possesses.
- **Objective:** Identify **discontinuity** in signals that can be caused by certain types of damage.
- **Application:** Examples of damage that might induce discontinuity into the dynamic response signal include:
  - Opening and closing of cracks
  - A loose joint that is allowing contact (rattle) to occur

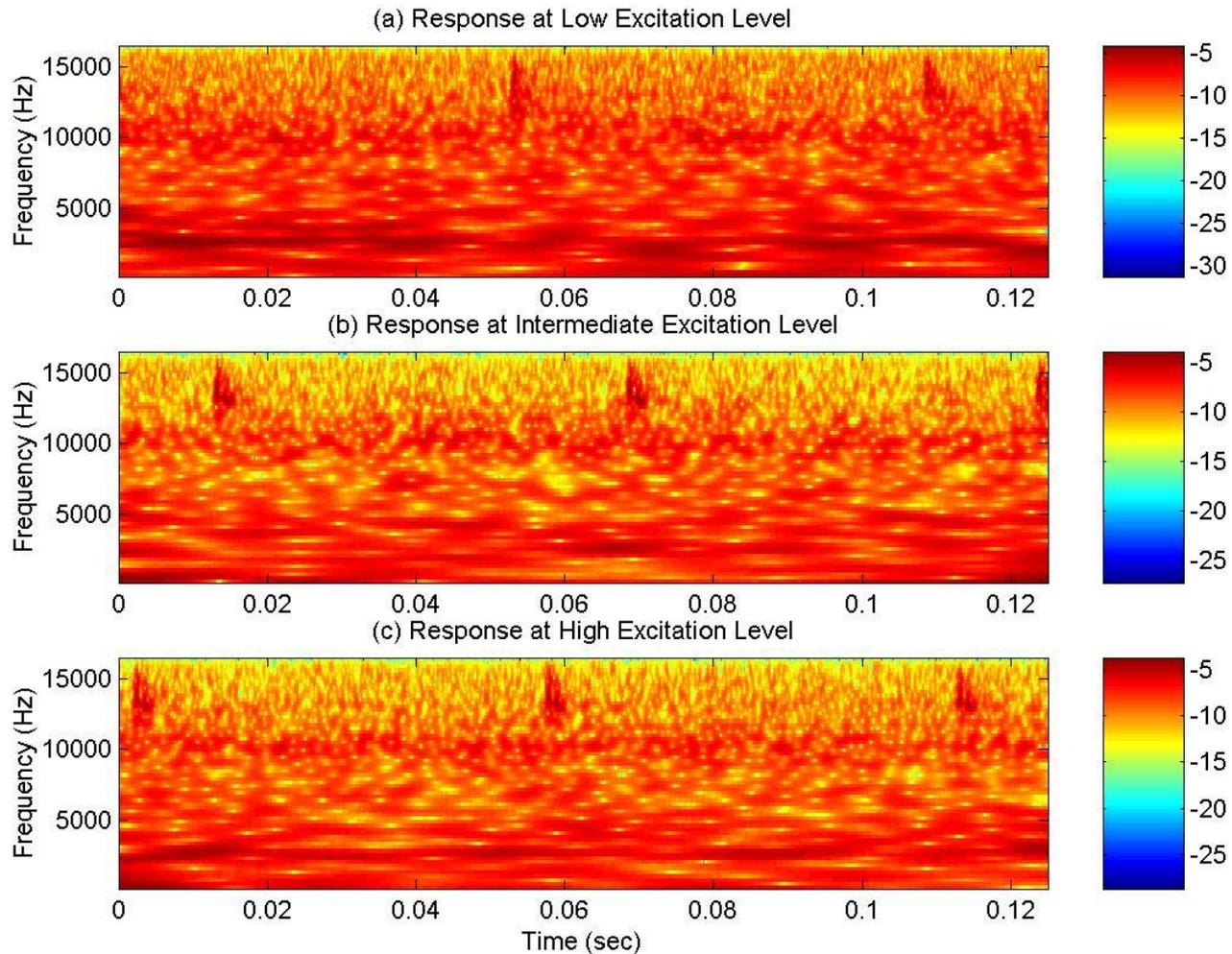
# Holder Exponent Analysis



# Holder Exponent Analysis

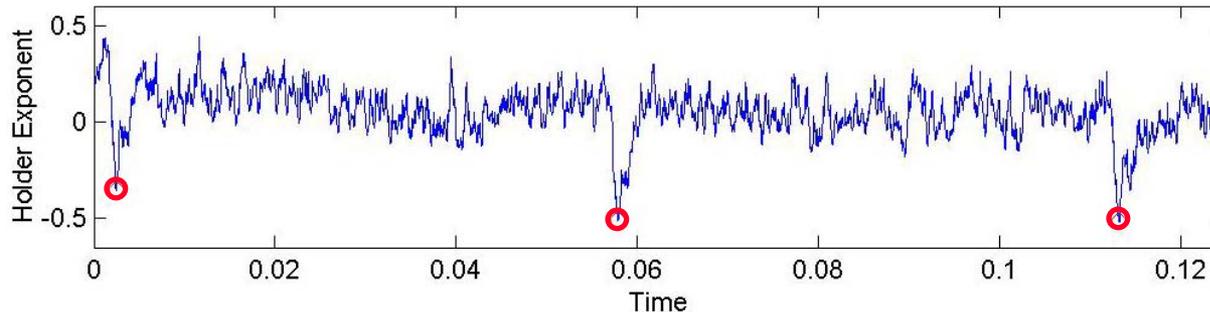
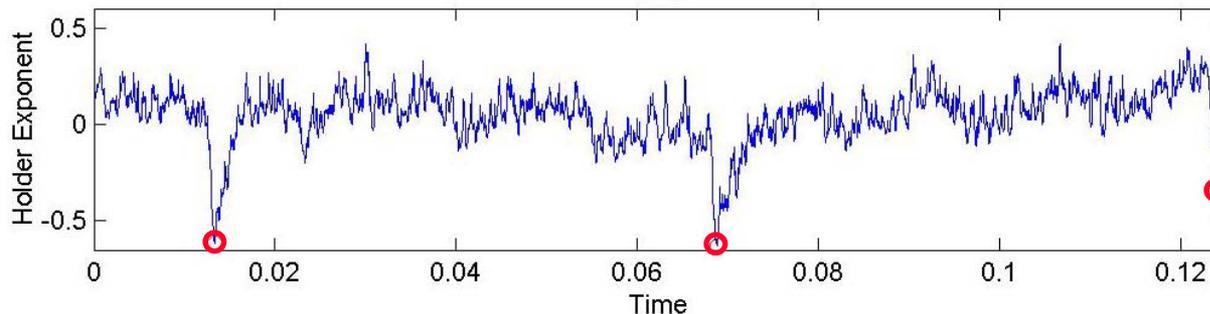
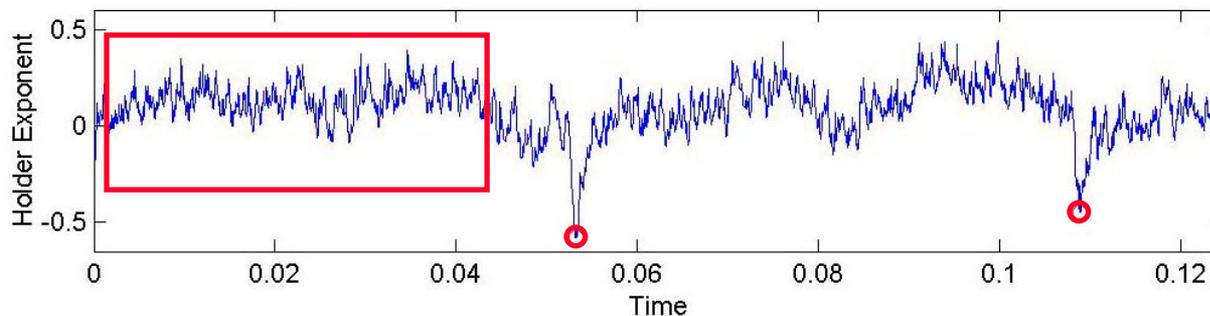


# Scalogram from Wavelet Transform



# Holder Exponent Analysis

(1) Find the max drop (2) Threshold =  $C \times \text{max drop}$  (3) Discontinuity > Threshold



# Summary

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- Cast structural health monitoring problems in the framework of **statistical pattern recognition**.
- Developed various **signal-based** damage detection algorithms.
- Embed damage detection algorithms into on-board **microprocessors**.
- Address **data normalization** issue explicitly.
- Decision making is based on rigorous statistical modeling.
- Provide a suite of data interrogation algorithms for structural health monitoring in the format of **GUI software** called DIAMOND II (**patent pending**).