DYNAMIC STRAIN MAPPING AND REAL-TIME DAMAGE STATE ESTIMATION UNDER BIAXIAL RANDOM FATIGUE LOADING

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Overview

- Motivation and Objective
- Damage State Estimation
- System Identification Approach
- Experimental Setup
- Results
- Summary and Future Work

Motivation & Objective

Motivation: Automatic and real-time structural health monitoring and condition based life prognosis may reduce life cycle cost and help to avoid catastrophic failure of aerospace, mechanical & civil engineering structural systems.

Objective:
Develop an SHM approach that can use strain gauge measurements to estimate damage condition of a structure under random loading

Online damage state estimator
Based on system identification or machine learning

Current condition updating

Future load

Offline damage state predictor
Based on Bayesian probabilistic model

RUL

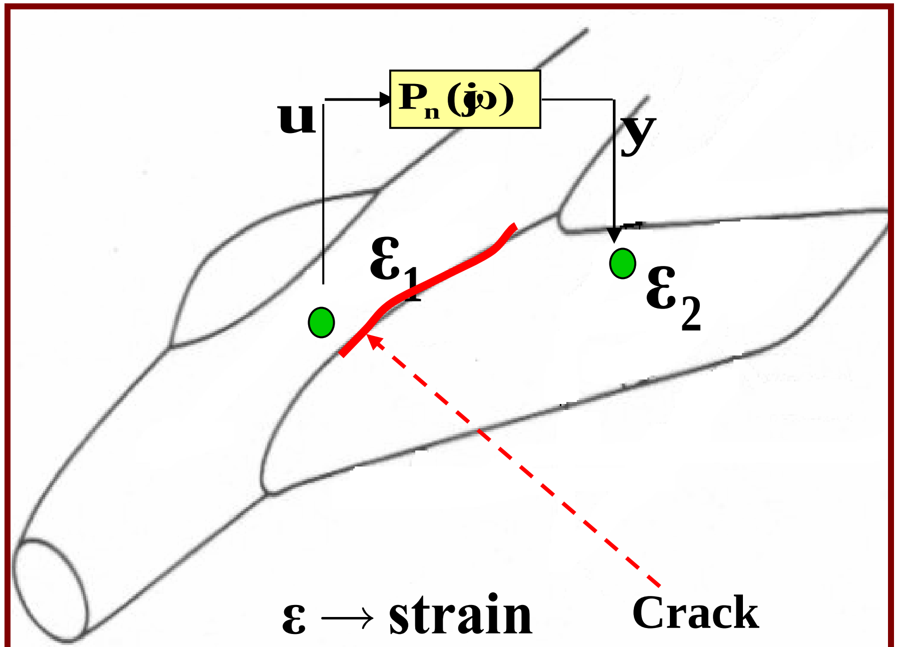
Damage State Estimation

Motivation for passive sensing

- Estimate local damage (Not limited to structural hot-spots)
- No external power source required
- Can use COTS sensors

Damage state estimation using strain measurements

- Due to damage the correlation between strain at two points changes
- Equivalent change in transfer function (TF) is a measure of change in damage states



Motivation from System Identification

Input output mapping at nth damage level

Unmeasured electrical noise: V

Measured input signal

$\mathbf{u}(\varepsilon)$ 1

Transfer function representing degraded structure at nth damage : $\mathbf{P}_n(\mathbf{z})$

Measured output signal

$\mathbf{y}(\varepsilon)$ 2

Transfer function at nth damage level

$$\boxed{P_n = f(R_{uy}, R_{uu});\quad \text{with } u \text{ constant} \quad P_n = f(R_{uy})}$$

Equivalent time-series damage index (for constant loading)

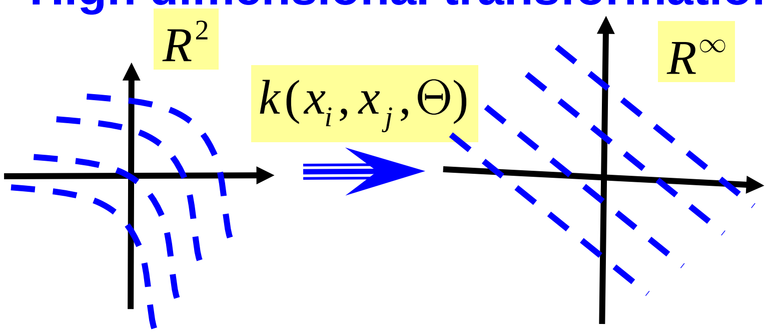
$$\mathbf{a}_n = \sqrt{\frac{\sum_{\mathbf{m=0}}^{\mathbf{m=M}} ((R_{uy})_n(\mathbf{m}) - (R_{uy})_0(\mathbf{m}))^2}{((R_{uy})_0(\mathbf{m}))^2}} \quad ; \mathbf{n} = \mathbf{1}, \mathbf{2}, \cdots$$

$R \rightarrow Correlation \quad coefficients$

Forecasting Using Gaussian Process (GP)

- GP combination of individual distributions (assumed Gaussian)
- Input-output mapped in high dimensional space
- Conjugate gradient optimization used to estimate hyperparameters

High dimensional transformation



$\Theta_n^p \rightarrow$ **Process**

$\Theta_n^w \rightarrow$ **Input Width**

$\Theta_n^{scatter} \rightarrow$ **Scatter in crack growth**

Multi layer perceptron (MLP) kernel

$$\mathbf{k}(\mathbf{x_i}, \mathbf{x_j}, \Theta_n^p, \Theta_n^w, \Theta_n^{scatter}) = \Theta_n^p \mathbf{Sin}^{-1} \frac{\mathbf{x_i^T} \Theta_n^w \mathbf{x_j}}{\sqrt{(\mathbf{x_i^T} \Theta_n^w \mathbf{x_i} + 1)(\mathbf{x_j^T} \Theta_n^w \mathbf{x_j} + 1)}} + \Theta_n^{scatter}$$

Negative log-likelihood function

$$\mathrm{L} = -\tfrac{1}{2} \log \det \mathbf{K}_n - \tfrac{1}{2} \mathbf{y}_n^{\,T} \mathbf{K}_n^{-1} \mathbf{y}_n - \tfrac{n}{2} \log 2\pi$$

Probability density

$$f(y_{n+1} \mid D = \{\mathbf{x_i}, y_i\}_{i=1}^{n}, \mathbf{x_{n+1}}, \Theta) = \mathbf{N}(\mu_{n+1}, \sigma_{n+1}^2)$$

Reference: MacKay (1998); Rasmussen and Williams (2006), Gibbs (2006)

Dynamic Strain Based Online Damage State Estimation (Theoretical Scheme)

- Under random load the **change in correlation** between input (u) & output (y) can be **due to random load or due to damage**
- Need to consider loading information in damage index formulation

Step-1: Reference Model Estimation (at n=0) using Gaussian process (GP)

$$U^{n=0}(=U_x^0, U_y^0, \bullet)$$

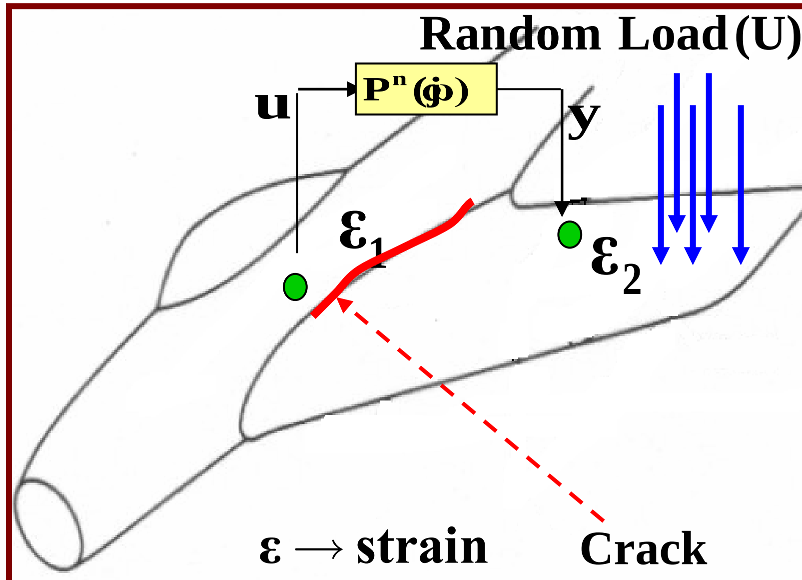
$$P^0_{U\rightarrow u} = ? \quad \rightarrow \quad u^0(\varepsilon_1^0)$$

$$P^0_{U\rightarrow y} = ? \quad \rightarrow \quad y^0(\varepsilon_2^0)$$

U→ External load

u→ input strain

y → Output strain



- GP model parameters estimated using conjugate gradient optimization

Dynamic strain mapping Based Online Damage State Estimation (Theoretical Scheme Contd.)

Step-2: Current stage dynamic strain mapping (Using GP regression)

$$\mathbf{U}^n (= \mathbf{U}_x^n, \mathbf{U}_y^n, \bullet)$$

$$\mathbf{P}^0_{U \to u} \longrightarrow \mathbf{u}_p^n(\varepsilon_{1p}^n) = ?$$

$$\mathbf{P}^0_{U \to y} \longrightarrow \mathbf{y}_p^n(\varepsilon_{2p}^n) = ?$$

Step-3: Current stage error signal estimation

$$\mathbf{e}_u^n(m) = \mathbf{u}_a^n(m) - \mathbf{u}_p^n(m)$$

$$\mathbf{e}_y^n(m) = \mathbf{y}_a^n(m) - \mathbf{y}_p^n(m)$$

Step-4: Current stage damage state

$$\mathbf{a}^n = \sqrt{\frac{\sum_{m=0}^{m=M} (\mathbf{R}^n_{e_u e_y}(\mathbf{m}) - \mathbf{R}^0_{e_u e_y}(\mathbf{m}))^2}{(\mathbf{R}^0_{e_u e_y}(\mathbf{m}))^2}}$$

$\mathbf{R} \longrightarrow$ *Correlation coefficient*

Experimental Setup

Fatigue testing & data collection

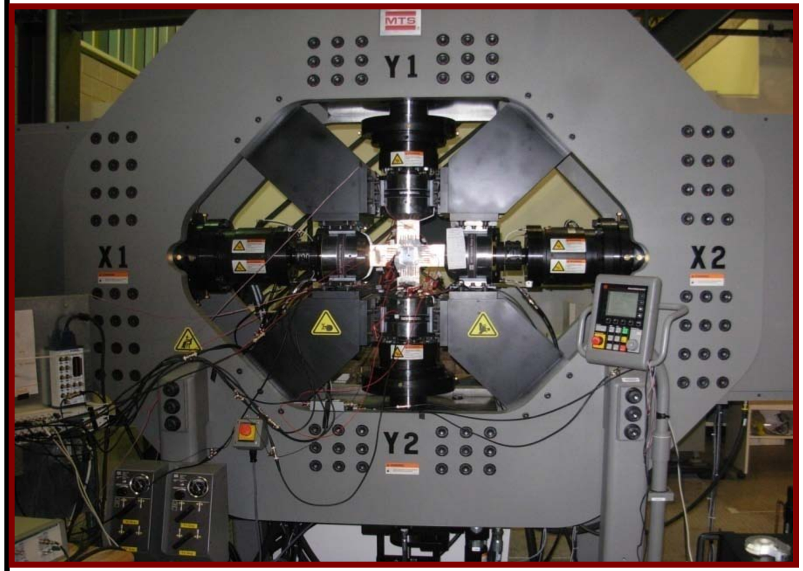
Material: Al-2024

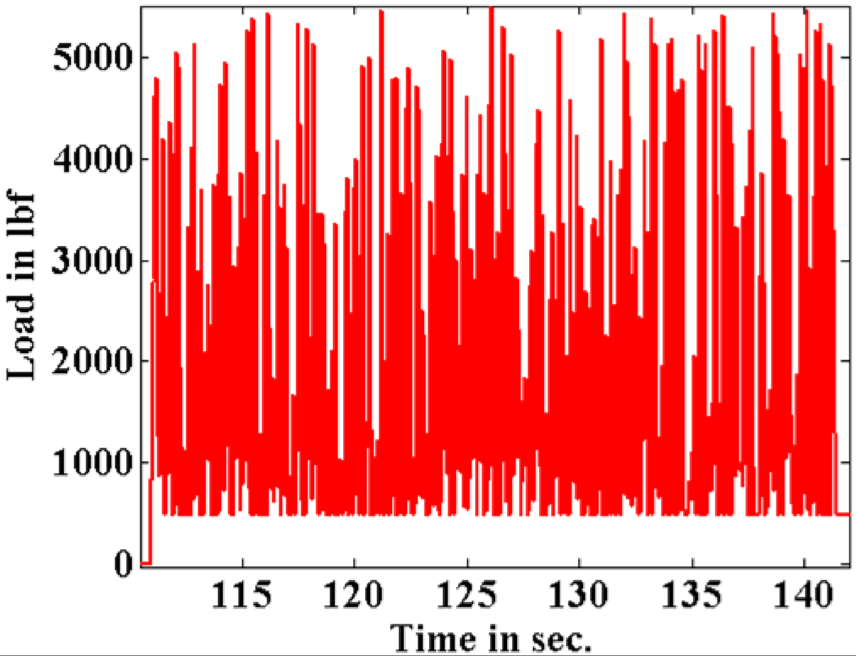
Loading: Random

Loading Frequency = 10Hz

Sampling frequency of data collection: 1kHz

Data collection interval: 300 fatigue cycles

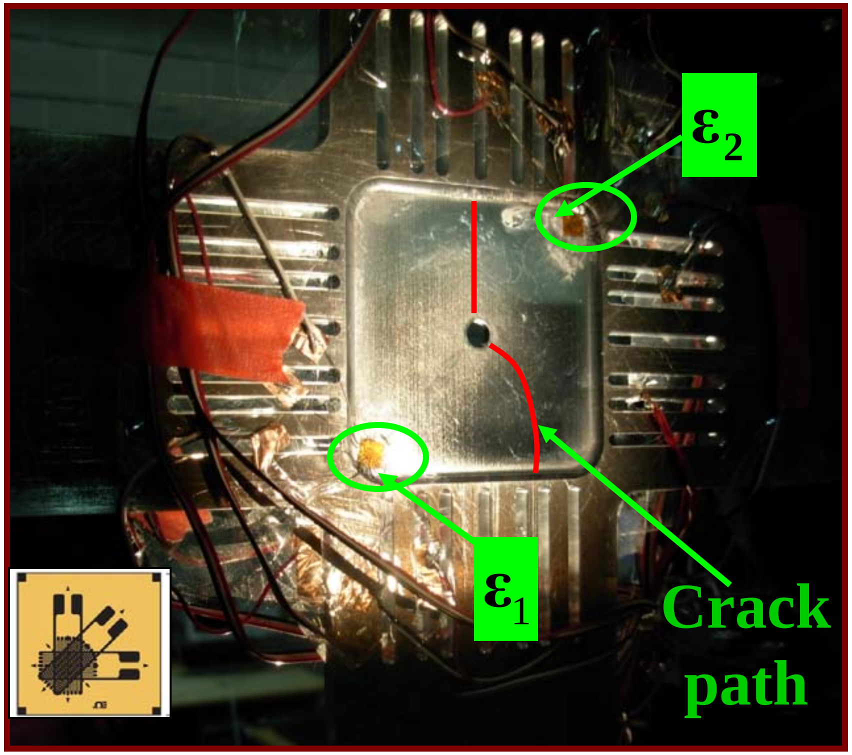




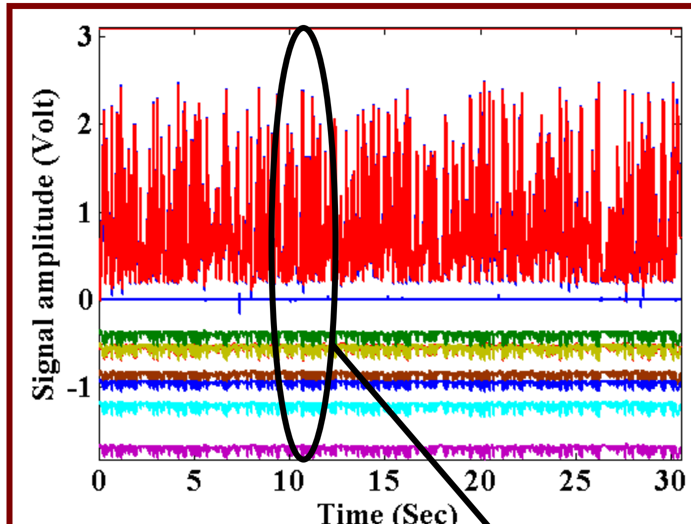
1-block (=300 cycle) of random load

Data Collection

Instrumented cruciform specimen



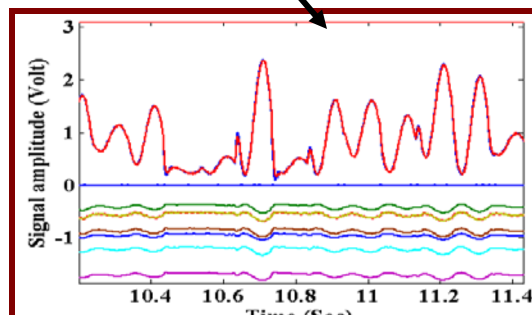
Original signal from DAQ



Load cell

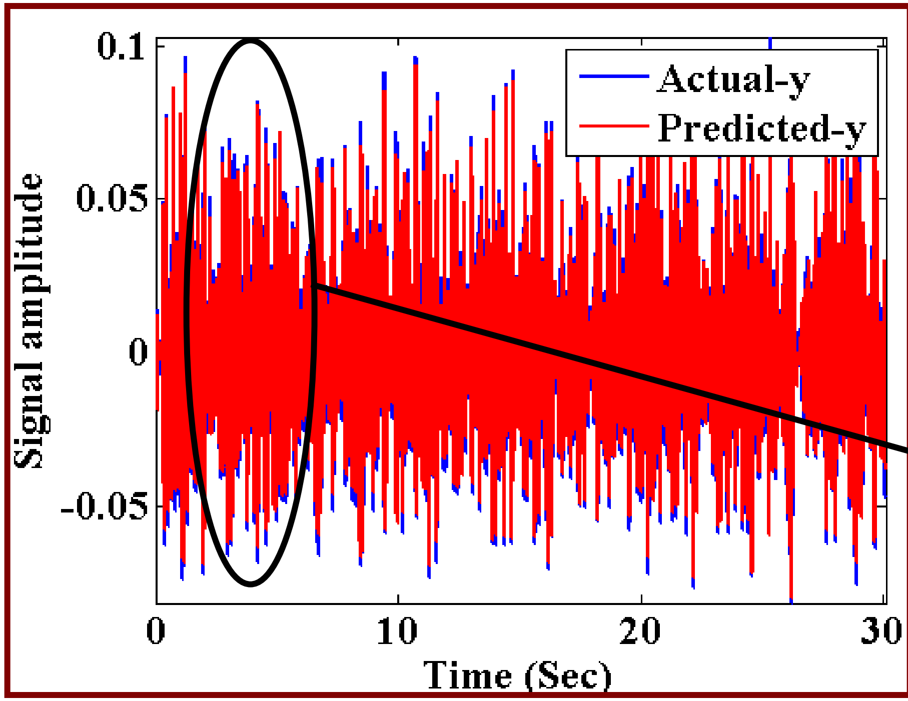
PZT

Strain gauge



Step-1: Reference Model Estimation ($P^0_{U\rightarrow u}$ or $P^0_{U\rightarrow y}$) Using Gaussian process

Comparison between regenerated (predicted) and actual strain measurement

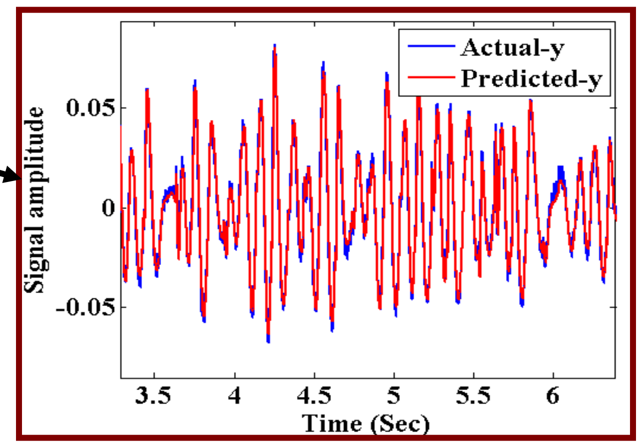


GP Input - Output

Known input $= U^0_x, U^0_y$

Known output $= y^0(\varepsilon^0_2)$

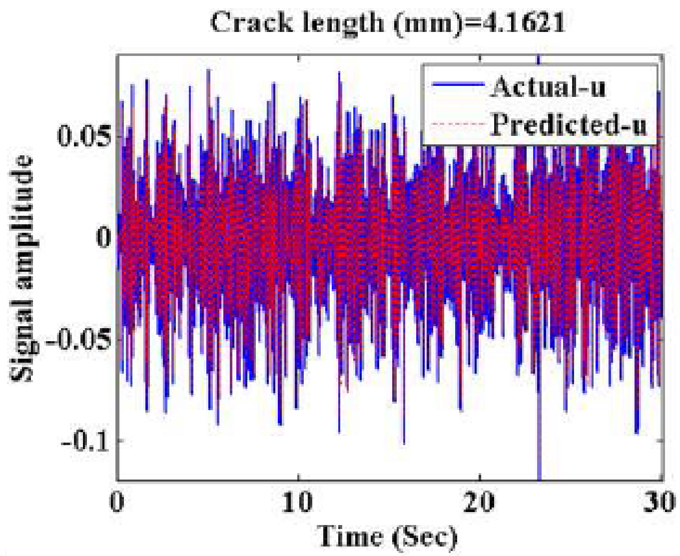
Magnified view



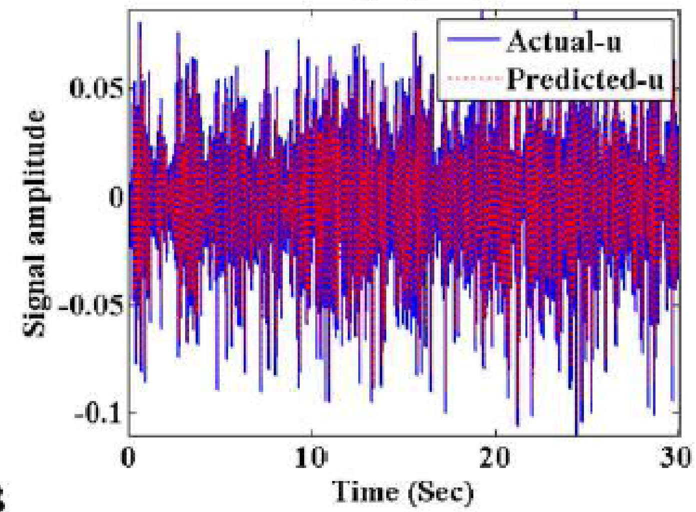
Step 2: Predicted versus actual input (u) dynamic strain at different damage levels

$$\text{Given} = L_x^n, L_y^n;\ \text{Known} = P^0_{L\to u}, P^0_{L\to y}$$

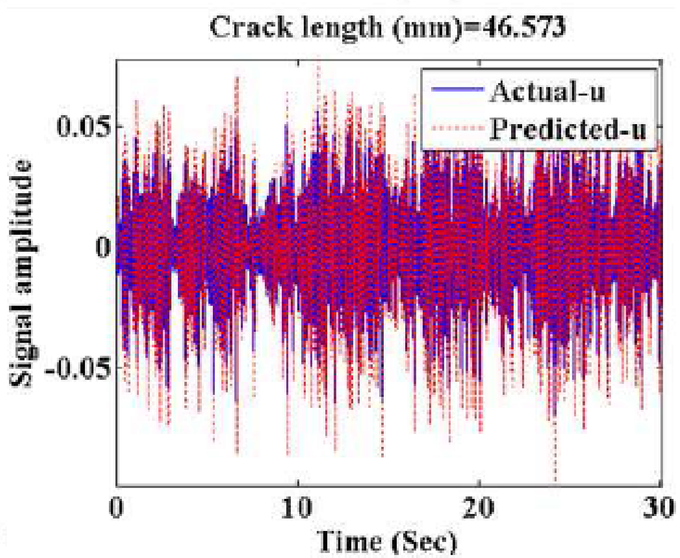
$$\text{Unknown} = u^n (=\varepsilon_1^n) \ \&\ y^n (=\varepsilon_2^n)$$



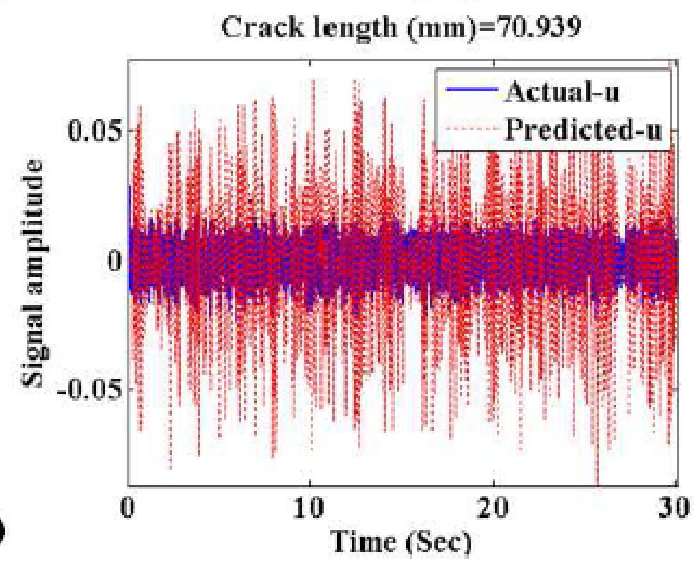
A



B



C

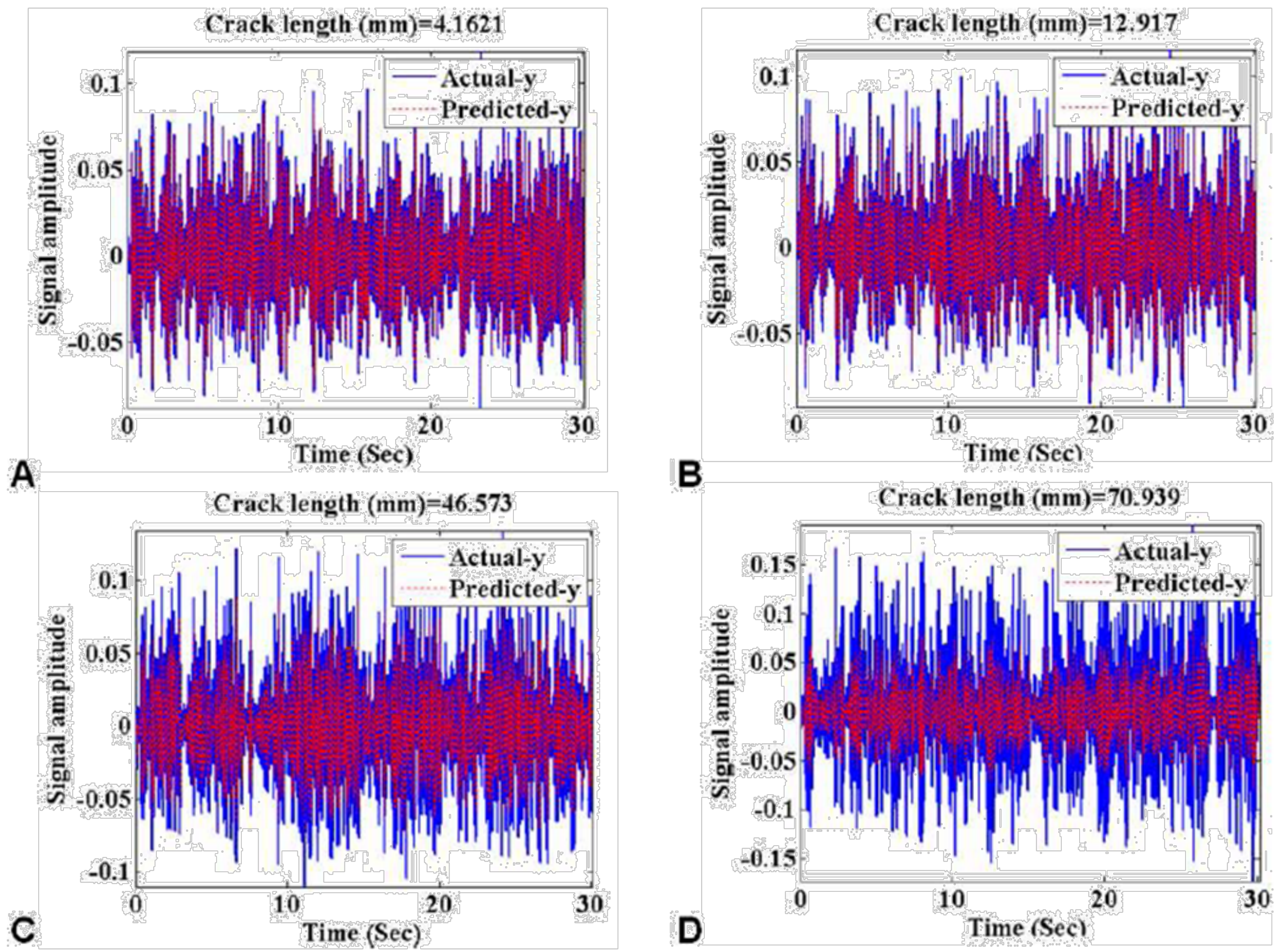


D

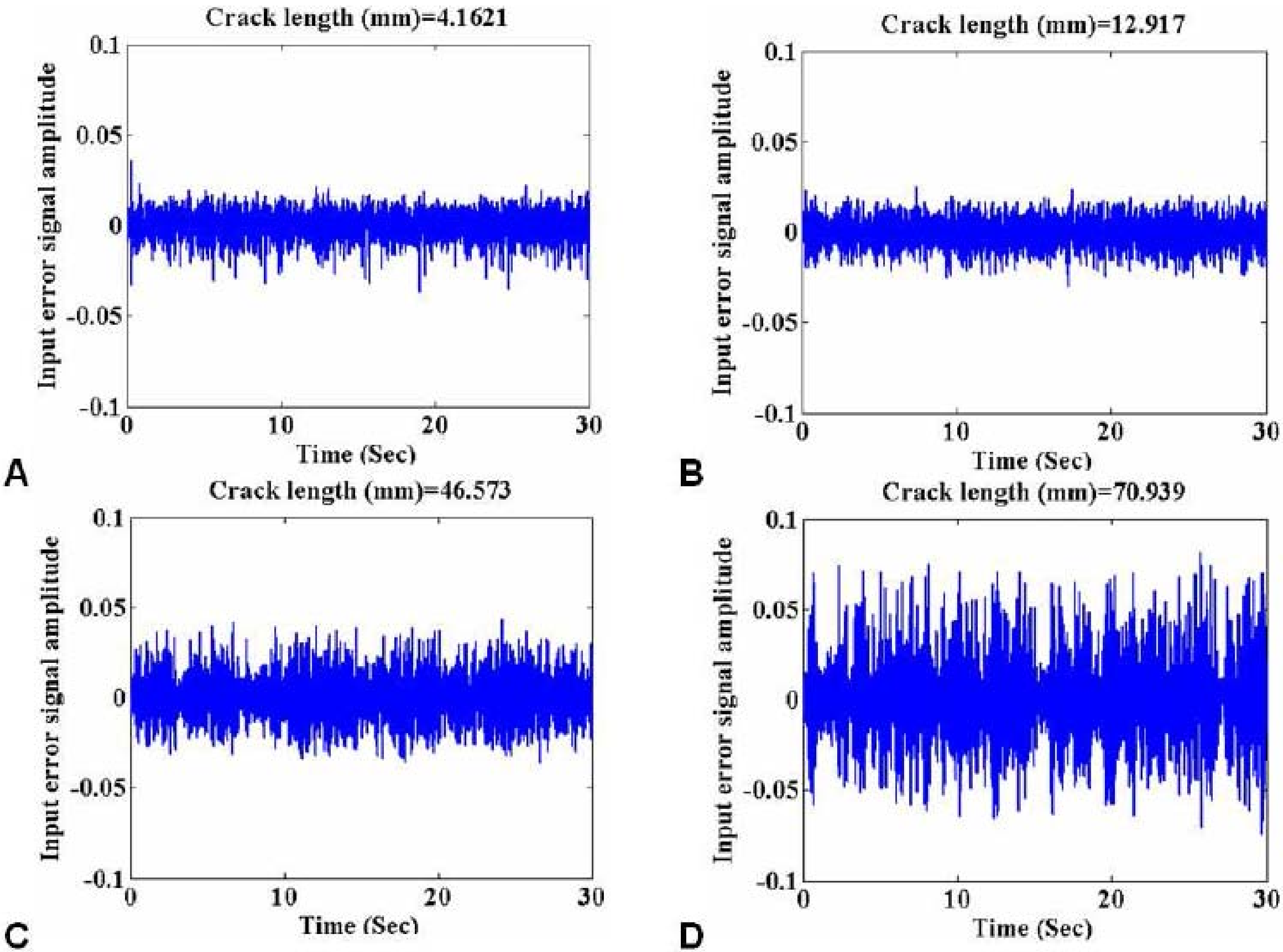
Step 2 (contd.): Predicted versus actual output (y) dynamic strain at different damage levels

$\textbf{Given} = L_x^n, L_y^n$; $\textbf{Known} = P^0_{L\to u}, P^0_{L\to y}$

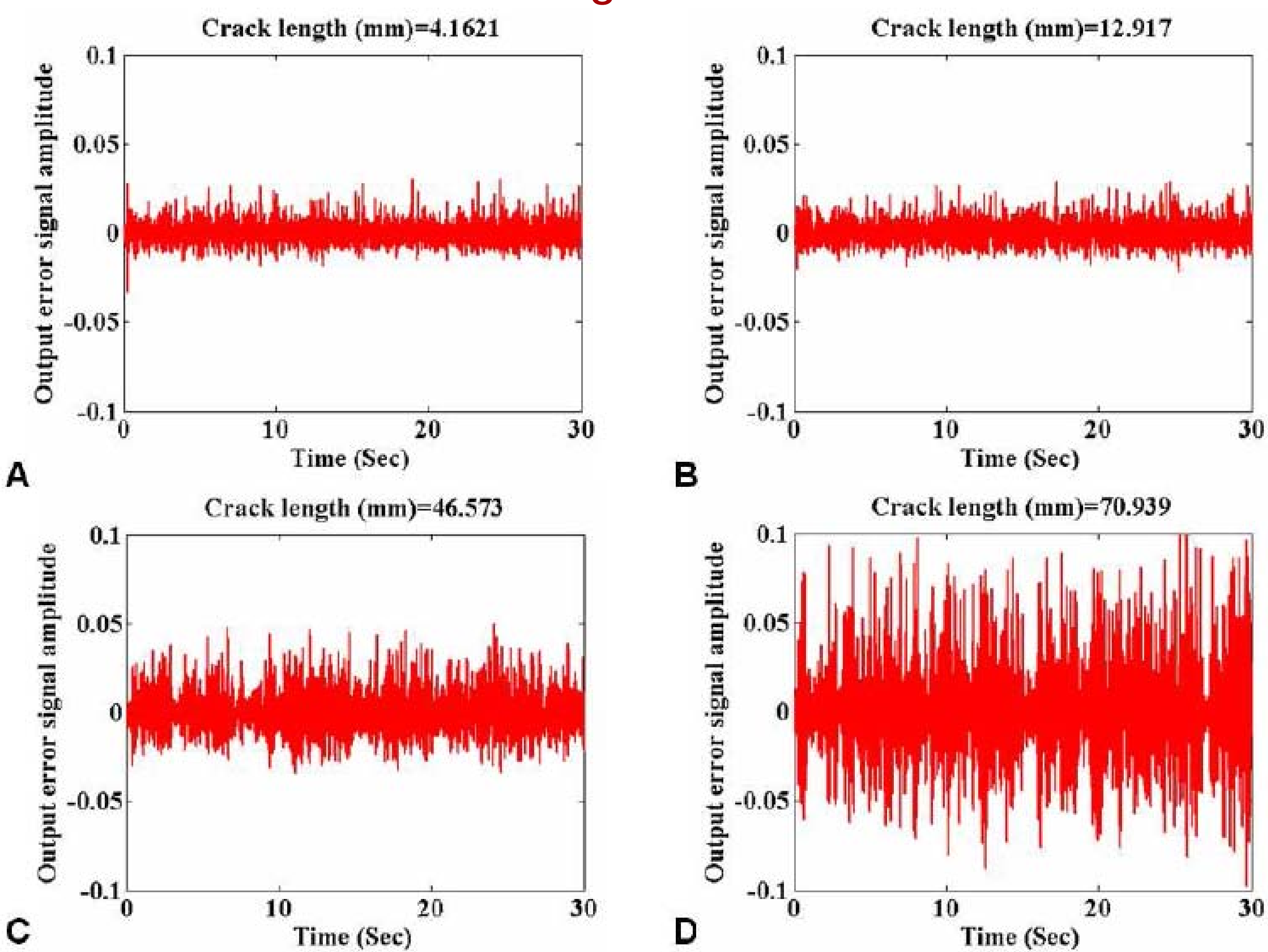
$\textbf{Unknown} = u^n (= \varepsilon_1^n)$ & $y^n (= \varepsilon_2^n)$



Step 3: Time-series input (u) error signal at different damage levels



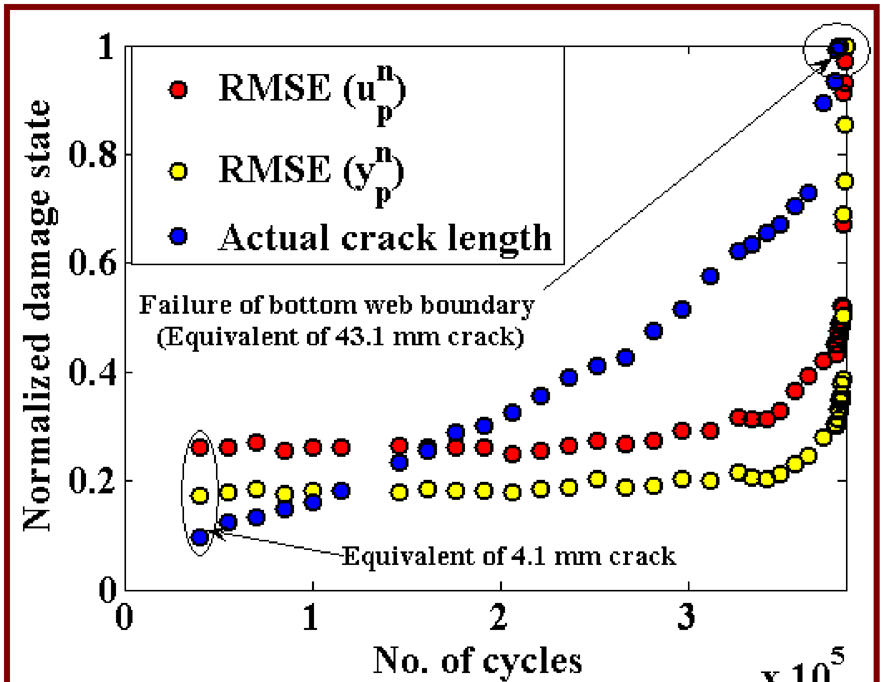
Step 3 (contd) : Time-series output (y) error signal at different damage levels



Step 4 : Time-series Damage State Estimation

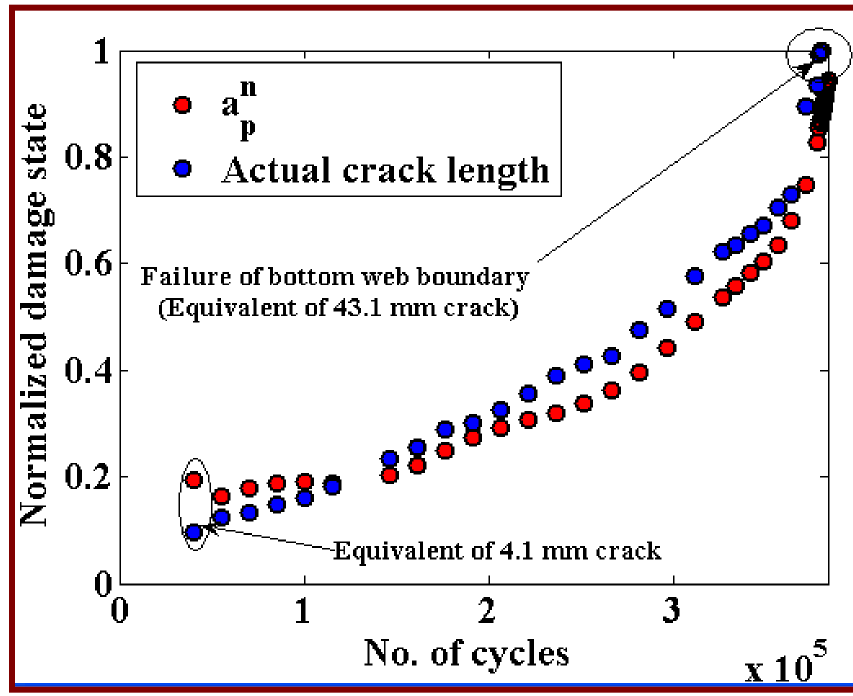
RMSE based damage index (DI)

$$a^n = \sqrt{\frac{1}{M}\sum_{m=1}^{m=M}\left[e^n_{(u\ or\ y)}(m)\right]^2}$$



CRA based damage index (DI)

$$a^n = \sqrt{\frac{\sum_{m=0}^{m=M}\left(R^n_{e_u e_y}(m) - R^0_{e_u e_y}(m)\right)^2}{\left(R^0_{e_u e_y}(m)\right)^2}}$$



- ❑ Good correlation between visual measurements and DI time-series
- ❑ CRA is better than RMSE of predicted error signal

Summary & Future Work

Summary

- Applications of dynamic strain mapping model presented for online damage state estimation using passive sensing
- Gaussian process used to create input-output model
- Approach demonstrates clear trend over the entire stage II and stage III damage regime

Future work

- More testing on different geometries
- Test using out of phase or independent random load on each axis
- Investigate alternative passive sensors to try and detect stage I cracks
- Implementing multisensor information