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

**Offline damage state predictor**
Based on Bayesian probabilistic model

Current condition updating

Future load

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 $n^{th}$ damage level

Measured input signal $u(\varepsilon)$

Transfer function representing degraded structure at $n^{th}$ damage: $P_n(z)$

Measured output signal $y(\varepsilon)$

Unmeasured electrical noise: $\nu$

Transfer function at $n^{th}$ damage level

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

Equivalent time-series damage index (for constant loading)

$$a_n = \sqrt{\sum_{m=0}^{m=M} ((R_{uy})_n(m) - (R_{uy})_0(m))^2} / ((R_{uy})_0(m))^2 \quad ; \quad n = 1, 2, \ldots$$

$R \rightarrow$ Correlation 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**

\[ k(x_i, x_j, \Theta) \]

\[ \Theta^p_n \rightarrow \text{Process} \]
\[ \Theta^w_n \rightarrow \text{Input Width} \]
\[ \Theta^{scatter}_n \rightarrow \text{Scatter in crack growth} \]

**Multi layer perceptron (MLP) kernel**

\[ k(x_i, x_j, \Theta^p_n, \Theta^w_n, \Theta^{scatter}_n) = \Theta^p_n \sin^{-1} \frac{x_i^T \Theta^w_n x_j}{\sqrt{(x_i^T \Theta^w_n x_i + 1)(x_j^T \Theta^w_n x_j + 1)}} + \Theta^{scatter}_n \]

**Negative log-likelihood function**

\[ L = -\frac{1}{2} \log \det K_n - \frac{1}{2} y_n^T K_n^{-1} y_n - \frac{n}{2} \log 2\pi \]

**Probability density**

\[ f(y_{n+1} | D = \{x_i, \Theta\}_{i=1}^n, x_{n+1}, \ldots) = \mathcal{N}(\mu_{n+1}, \sigma^2_{n+1}) \]

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)

\[ P^0_{U \rightarrow u} = ? \]
\[ U^{n=0} (= U^0_x, U^0_y, \cdot) \]
\[ P^0_{U \rightarrow y} = ? \]
\[ y^0 (\varepsilon) \]

\[ u^0 (\varepsilon) \]

GP model parameters estimated using conjugate gradient optimization
Step-2: Current stage dynamic strain mapping (Using GP regression)

\[ P_{U \rightarrow u}^0 \]

\[ U^n (= U^n_x, U^n_y, \bullet) \]

\[ P_{U \rightarrow y}^0 \]

\[ Y_p^n (\varepsilon_p) = ? \]

Step-3: Current stage error signal estimation

\[ e_u^n (m) = u_a^n (m) - u_p^n (m) \]

\[ e_y^n (m) = y_a^n (m) - y_p^n (m) \]

Step-4: Current stage damage state

\[ a^n = \sqrt{\sum_{m=0}^{m=M} (R_{e_{uey}}^n (m) - R_{e_{uey}}^0 (m))^2} \]

\[ \frac{(R_{e_{uey}}^0 (m))^2}{(R_{e_{uey}}^0 (m))^2} \]

\[ R \rightarrow Correlation \ coefficient \]
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

![Graph showing load in lbf over time in sec.](image)
Data Collection

Instrumented cruciform specimen

Original signal from DAQ

Signal amplitude (Volt)

Time (Sec)

Load cell

PZT

Strain gauge

Crack path

\( \varepsilon_1 \)

\( \varepsilon_2 \)
Step-1: Reference Model Estimation ($P_{U \rightarrow u}^0$ or $P_{U \rightarrow y}^0$) Using Gaussian process

Comparison between regenerated (predicted) and actual strain measurement

GP Input - Output
Known input = $U_x^0, U_y^0$
Known output = $y^0(\cdot)$

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

Given = $L^x_n, L^y_n$; Known = $P^0_{L→u}, P^0_{L→y}$
Unknown = $u^n (= ε^n)_x & y (= ε^n)_y$
Step 2 (contd.): Predicted versus actual output (y) dynamic strain at different damage levels

Given $= L_x^n, L_y^n$; Known $= P_{L\to u}^0, P_{L\to y}^0$
Unknown $= u^n(\varepsilon), y^2(\varepsilon)^n$
Step 3: Time-series input (u) error signal at different damage levels

A. Crack length (mm) = 4.1621

B. Crack length (mm) = 12.917

C. Crack length (mm) = 46.573

D. Crack length (mm) = 70.939
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)**

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

**CRA based damage index (DI)**

\[ a^n = \sqrt{\sum_{m=0}^{m=M} \frac{(R_{e_y}(m) - R_{e_y}^0(m))^2}{(R_{e_y}^0(m))^2}} \]

- **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