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SURFACE SENSING-BASED TECHNIQUE FOR NONDESTRUCTIVE EVALUATION

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ABSTRACT

The use of sensor networks for structural health monitoring purposes has gained popularity due to advances in electronics enabling the deployment of cost-effective solutions. However, linking signal to condition evaluation is still a difficult task, and metrics must be developed to validate the performance of a given sensor network at conducting its as-designed structural health monitoring task. In this paper, we present a model-assisted sensor network validation strategy. The strategy consists of constructing a physical surrogate model to perform numerical investigations of sensor network performance under uncertainty. The update of the physical surrogate provides spatiotemporal data enabling condition evaluation. A metric inspired by probability of detection theory is developed to quantify performance. We demonstrate the methodology to validate the performance of a novel strain-based sensor network.

Keywords: structural health monitoring, dense sensor network, strain sensing, surrogate modeling, damage detection, probability of detection

1. INTRODUCTION

Structural health monitoring (SHM) is the automation of the structural integrity assessment task. Of interest to this paper are SHM strategies based on dense sensor networks (DSNs), which have recently been empowered through advances in smart materials and signal processing. However, linking monitoring data to decisions is not an easy task. The condition assessment capabilities highly depends on the quality of the integrated design of the SHM solution, which is hard to evaluate.

Physical surrogate is a simplified representation of the monitored system that is constructed based on a given DSN configuration. The performance of the DSN is quantified using the probability of detection (POD) metric [1], which allows assessing the capability of a DSN to quantify damage in an uncertain environment. Originally developed for nondestructive evaluation applications, the concept of POD has been extended to SHM applications [2]. For instance, Kabban et al. [3] proposed a statistical method for analyzing dependent measurements and demonstrated the method on a representative aircraft structural component. Forsyth et al. [4] investigated how POD could be generated from multiple sets of repeated measurements.

Work presented in this paper use the physical surrogate model to compute POD (or Model Assisted POD - MAPOD) based on user-defined detection requirements and algorithms. The application of interest is a strain-based DSN previously developed by the authors.

2. METHODS

In this section, we describe the DSN assessment framework, including the DSN of interest, the construction of the reference model and its adaptation, and the MAPOD process.

2.1 Strain-based Dense Sensor Network

In this work, the DSN of interest consists of a network of flexible electronics, termed soft elastomeric capacitors (SECs), proposed by the authors [5]. The SEC technology is a low-cost large area electronics suitable for strain sensing over large-scale surfaces. The sensing principle is:

$$\frac{\Delta C}{C_0} = \lambda(\varepsilon_x + \varepsilon_y) \tag{1}$$

where $\lambda \approx 2$ is the gauge factor, and ε_x and ε_y are the strains along the x and y planes, respectively.

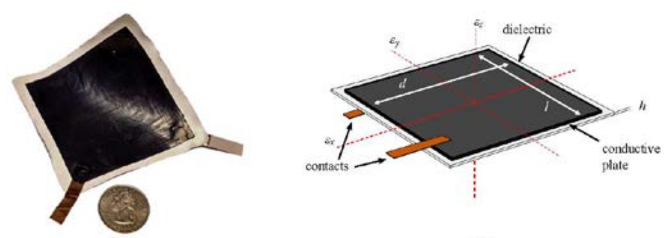

FIGURE 1: (a) picture of an SEC; and (b) SEC schematic with key components annotated.

2.2 Model Adaptation

The reference model is sequentially updated from measurement inputs using sliding mode theory. Assume that the elements of the system's stiffness matrix K are the only adjustable parameters, and consider respectively the real system and estimated systems:

$$\begin{aligned}\dot{\mathbf{X}}&=\mathbf{A}\mathbf{X}+\mathbf{B}\mathbf{f}\\ \dot{\hat{\mathbf{X}}}&=\hat{\mathbf{A}}\hat{\mathbf{X}}+\mathbf{B}\mathbf{f}\end{aligned} \tag{2}$$

with $\mathbf{A}=\begin{bmatrix}\mathbf{0} & \mathbf{I}\\ -\mathbf{M}^{-1}\mathbf{K} & -\mathbf{M}^{-1}\mathbf{D}\end{bmatrix},\hat{\mathbf{A}}=\begin{bmatrix}\mathbf{0} & \mathbf{I}\\ -\mathbf{M}^{-1}\hat{\mathbf{K}} & -\mathbf{M}^{-1}\mathbf{D}\end{bmatrix},\mathbf{B}=\begin{bmatrix}\mathbf{0}\\ -\mathbf{M}^{-1}\end{bmatrix}$

The error between both systems can be written $\tilde{\mathbf{A}} = \mathbf{A} - \hat{\mathbf{A}}$, where the tilde denotes the estimation error. The estimation error matrix $\tilde{\mathbf{A}}$ can be written $\tilde{\mathbf{A}}=\tilde{\theta}\mathbf{Q}$, where θ is the vector of adjustable parameters, and Q is the matrix containing the non-adjustable parameters. Consider the sliding surface s :

$$s=\left(\frac{d}{dt}+c\right)\mathbf{e}=\mathbf{P}\mathbf{e} \tag{3}$$

where $\mathbf{e}=\mathbf{X}-\hat{\mathbf{X}}$ is the state error, P = [1, c] is a user-defined vector, and c is a strictly positive constant, and take the following Lyapunov function

$$\mathbf{V}=\frac{1}{2}(s^2+\tilde{\theta}\Gamma_{\theta}^{-1}\dot{\tilde{\theta}})^{\mathrm{T}} \tag{4}$$

where Γ_{θ} is the positive definite diagonal matrix representing learning parameters. Function $\mathbf{V}$ is positive definite and contains all time-varying parameters. Taking its time derivative yields:

$$\begin{aligned}\dot{\mathbf{V}}\ &=s^{\mathrm{T}}\mathbf{P}\dot{e}+\tilde{\theta}\Gamma_{\theta}^{-1}\dot{\tilde{\theta}}^{\mathrm{T}}\\ &=s^{\mathrm{T}}\mathbf{P}\left[\mathbf{A}\mathbf{X}-\hat{\mathbf{A}}\hat{\mathbf{X}}\right]+\tilde{\theta}\Gamma_{\theta}^{-1}\dot{\tilde{\theta}}^{\mathrm{T}}\\ &=s^{\mathrm{T}}\mathbf{P}\left[\mathbf{A}\mathbf{X}-(\mathbf{A}-\tilde{\mathbf{A}})\hat{\mathbf{X}}\right]+\tilde{\theta}\Gamma_{\theta}^{-1}\dot{\tilde{\theta}}^{\mathrm{T}}\\ &=s^{\mathrm{T}}\mathbf{P}\left[\mathbf{A}\mathbf{e}+\tilde{\mathbf{A}}\hat{\mathbf{X}}\right]+\tilde{\theta}\Gamma_{\theta}^{-1}\dot{\tilde{\theta}}^{\mathrm{T}}\\ &=\mathbf{e}^{\mathrm{T}}\mathbf{P}^{\mathrm{T}}\mathbf{P}\mathbf{A}\mathbf{e}+s^{\mathrm{T}}\mathbf{P}\tilde{\mathbf{A}}\hat{\mathbf{X}}+\tilde{\theta}\Gamma_{\theta}^{-1}\dot{\tilde{\theta}}^{\mathrm{T}}\end{aligned} \tag{5}$$

The first term in Equation 5 is negative semi-definite. The adaptation rule is selected such that

$$s^{\mathrm{T}}\mathbf{P}\tilde{\mathbf{A}}\hat{\mathbf{X}}+\tilde{\theta}\Gamma_{\theta}^{-1}\dot{\tilde{\theta}}^{\mathrm{T}}<0 \tag{6}$$

Using Equation 6 and noting that $\dot{\tilde{\theta}}=\dot{\theta}-\dot{\hat{\theta}}=-\dot{\hat{\theta}}$ yields

$$\begin{aligned}\dot{\mathbf{V}}\ &=\mathbf{e}^{\mathrm{T}}\mathbf{P}^{\mathrm{T}}\mathbf{P}\mathbf{A}\mathbf{e}+s^{\mathrm{T}}\mathbf{P}\tilde{\mathbf{A}}\hat{\mathbf{X}}-\tilde{\theta}\Gamma_{\theta}^{-1}(\Gamma_{\theta}s^{\mathrm{T}}\mathbf{P}\mathbf{Q}\hat{\mathbf{X}})\\ &=\mathbf{e}^{\mathrm{T}}\mathbf{P}^{\mathrm{T}}\mathbf{P}\mathbf{A}\mathbf{e}+s^{\mathrm{T}}\mathbf{P}\tilde{\mathbf{A}}\hat{\mathbf{X}}-s^{\mathrm{T}}\mathbf{P}\tilde{\mathbf{A}}\hat{\mathbf{X}}\\ &=\mathbf{e}^{\mathrm{T}}\mathbf{P}^{\mathrm{T}}\mathbf{P}\mathbf{A}\mathbf{e}\end{aligned} \tag{7}$$

In the discrete time form, the varying parameter becomes:

$$\theta_{k+1}=\theta_k-\Gamma_{\theta}\Delta t s^{T}\mathbf{P}\mathbf{Q}\hat{\mathbf{X}}_k \tag{8}$$

2.3 Model Assisted Probability of Detection

MAPOD is used to quantify the performance of a given DSN. The process starts by defining the uncertain model parameters as random variables with specific probability distributions. After, sensor measurements are linked to a damage indicator J through a user-defined damage discovery algorithm. The MAPOD process is conducted by constructing the plot where α is the damage severity by drawing the samples and using linear regression to plot the damage indicator versus the degree of damage

$$\ln\hat{\alpha}=\beta_0+\beta_1\ln\alpha+\epsilon \tag{9}$$

where coefficients β_0 , β_1 can be determined by a least squares estimator, and the ϵ has a Normal distribution $\mathcal{N}(0,\sigma_{\epsilon}^2)$ with zero mean and standard deviation σ_{ϵ} . For a given threshold $\bar{\alpha}$, the POD is computed as follows:

$$\mathrm{POD}(\alpha)=P(\log(\alpha)>\bar{\alpha})=1-\Phi\left(\frac{\log\bar{\alpha}-\beta_0+\beta_1\log\alpha}{\sigma_{\epsilon}}\right) \tag{10}$$

3. RESULTS AND DISCUSSION

The DSN assessment framework is verified through numerical simulations of a cantilevered plate of length 276 mm, width 33 mm, and thickness 1 mm, illustrated in Figure 2, with an assigned Young's modulus193 GPa, density 8027kg/m^3, and Poisson's ratio 0.3.

The study starts with the plate virtually equipped with five SECs, and synthetic data were produced in MATLAB by discretizing the plate into 100 elements and subjecting a point load at the tip taken as the real or true system. A white noise excitation with a bandwidth of 100 Hz and magnitude of 20 N (Figure 2(b)) was used to produce synthetic measurements for the reference model verification stage, and a harmonic excitation of magnitude 10 N at 5 rad/s (Figure 2(c)) was used for the MAPOD-based DSN assessment. An arbitrary 20% Gaussian noise was added to the simulated measurements.

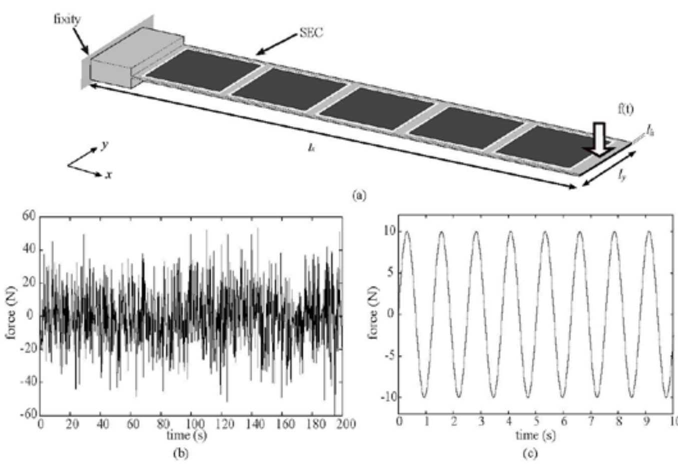

FIGURE 2: (a) Virtual system under investigation; (b) white noise excitation; and (c) harmonic excitation.

The proposed framework was verified by assessing the performance of the DSN configuration using MAPOD and subjecting the plate to a harmonic load at its tip. Two sources of uncertainties were considered including uncertainty on the input, where a Gaussian variation of 10% was added to its magnitude, and an uncertainty on the strain measurements, with the 20% added Gaussian noise. A total of 20 damage patterns were simulated by reducing the bending rigidity of the fixity to represent damage at the cantilever root. Damage cases were generated by reducing the bending rigidity randomly between $\alpha = 0.02$ and $\alpha = 0.4$. Damage is considered “discovered” when the damage indicator J exceeds the threshold value $J = 10^{-5}$. The analysis conducted using 1000 realizations of synthetic data sets for each damage by Latin hypercube sampling.

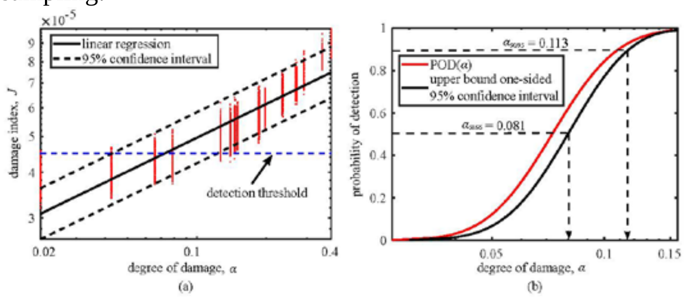

FIGURE 3: (a) J vs. α; and (b) POD plot.

Figure 3(a) is the J-α plots showing the simulated values, linear regression, 95% confidence bounds on the linear regression, and damage detection bound. Figure 3(b) is the resulting POD plot and the black curve represents the upper (conservative) 95% confidence bound of the linear regression. Results show that for the particular DSN configuration and damage detection algorithm, there is a 50% probability with 95% confidence of detecting a change of bending rigidity greater than $\alpha 50/95 = 0.081$ at the cantilever’s root (bottom black dashed arrow), and a 90% probability with 95% confidence of detecting a change greater than $\alpha 90/95 = 0.113$ (upper black dashed arrow).

The DSN assessment procedure is repeated on different DSN configurations (six DSN scenarios: 5, 6, 7, 8, 9 and 10 SECs) to demonstrate how the proposed framework can be leveraged in designing a DSN (Figure 4(a)). POD curves were generated using the same methodology as for the five SECs. Figure 4(b) reports the resulting POD surface plot for damage detection with a 95% confidence. Results in Figure 4(c) shows that, by increasing the resolution of the network, the 90% damage detection with 95% improves substantially from an 11.3% change in bending rigidity using 5 SECs to a 3.1% change in rigidity using 10 SECs.

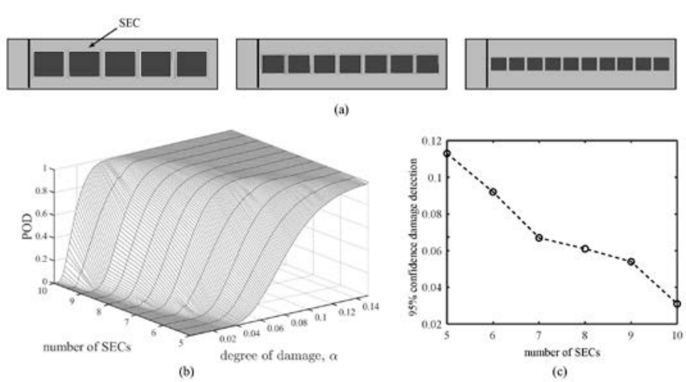

FIGURE 4:(a) Different DSN configurations under investigation (5 SECs (left), 7 SECs (center), and 10 SECs (right)); and (b) 95% POD surface plots; and (c) 90%/95% damage detection under different DSN configurations

4. CONCLUSION

This paper presented a preliminary investigation of a performance assessment framework for structural health monitoring solutions leveraging dense sensor networks (DSNs). The framework consists of constructing a physical surrogate model based on a given DSN configuration, sequentially adapting the model from field data using sliding mode theory, and using a model-assisted probability of detection (MAPOD) to assess the DSN’s capability at detecting user-defined damage cases of varying degrees of severity.

A numerical study was conducted to verify and demonstrate the framework on a simple cantilevered plate equipped with a DSN measuring strain. Uncertainties considered in the model included uncertainties in the applied load and sensor noise. Results showed that MAPOD was capable of assessing the performance of the DSN at detecting damage at the root. Other DSN configurations were considered in the simulations, and the MAPOD-based assessment showed that it was possible to quantify the performance of each DSN configuration. Such results could be used to conduct a cost-benefit analysis of the SHM system to select an optimal DSN resolution.

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