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Statistical updating of finite element model with Lamb wave sensing data for damage detection problems

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ABSTRACT

Health monitoring of large structures with embedded, distributed sensor systems is gaining importance. This study proposes a new probabilistic model updating method in order to improve the damage prediction capability of a finite element analysis (FEA) model with experimental observations from a Lamb-wave sensing system. The approach statistically calibrates unknown parameters of the FEA model and estimates a bias-correcting function to achieve a good match between the model predictions and sensor observations. An experimental validation study is presented in which a set of controlled damages are generated on a composite panel. Time-series signals are collected with the damage condition using a Lamb-wave sensing system and a one dimensional FEA model of the panel is constructed to quantify the damages. The damage indices from both the experiments and the computational model are used to calibrate assumed parameters of the FEA model and to estimate a bias-correction function. The updated model is used to predict the size (extent) and location of damage. It is shown that the proposed model updating approach achieves a prediction accuracy that is superior to a purely statistical approach or a deterministic model calibration approach.

1. Introduction

Structural health monitoring (SHM) that utilizes a distributed sensor network embedded within the structure has proven a successful and cost effective method for condition monitoring of structures by detecting existence, extent and location of damage [1]. Accurate prediction of size (extent) and location of structural damage is of crucial importance in SHM application of large structures including dams, bridges, pipes and aircraft. SHM consists of observation of dynamic response of the structure at periodical intervals from an array of sensors, extraction of damage-sensitive features from measurements and statistical analysis of these features to determine current health of the structure. SHM can result in significant cost reduction by eliminating unnecessary maintenance and by preventing catastrophic failures.

SHM methods may be classified as unsupervised learning and supervised learning [15,16]. Unsupervised learning does not use data from the damaged structure, and it can detect the existence of the damage only. By contrast, supervised learning uses data from both damaged and undamaged structures. Many supervised learning methods also use numerical

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simulations to supplement limited data from experiments. This paper deals with the last category, i.e., supervised learning that uses both numerical simulations and experimental data. The literature in this subject is extensive, and the reader is referred to [17,15] for some extensive reviews. Some of the recent developments include the wireless sensor network [18] and guided-wave SHM [19].

This paper proposes a probabilistic model updating method to improve damage size and location prediction of a structural health monitoring system with the aid of finite element analysis (FEA) model. The FEA model is used to calculate a damage index from the nodal displacements of a damaged structure and a maximum likelihood estimation (MLE) is used to statistically calibrate and adjust the model from the measurements of a Lamb-wave sensor system. The error in the damage index prediction is adjusted by estimating a bias function and calibrating the material properties assumed in the model. The bias correction and calibration is collectively referred to as model updating.

Model updating has been utilized for SHM and damage detection by several authors. Rutherford et al. [11] used a polynomial response surface model to identify the stiffness and damping parameters of a five degree of freedom system. Fritzen et al. [12] studied the problem of detecting the location and extent of structural damage from vibration test data and a FEA model of the cracked beam. Zimmerman and Lynch [10] proposed a simulated annealing method for distributed model updating with data from wireless sensor networks.

The main contributions of the proposed model updating compared to existing work are as follows. First, the method can account for the parameter uncertainty in the predictions of the updated model. Traditional calibration approaches treat model parameters to be fixed; however, parameters may vary from experiment to experiment. The proposed approach treats unknown parameters as random variables to account for parameter uncertainty in the predictions. The probability distributional properties of these random variables are estimated to provide the best agreement between physical experiments and computer model predictions. Second, the method allows integrating data from a sensor system with predictions from a simplified FEA model to improve detection accuracy of the sensor system. Many conventional model updating procedures involve development of relatively sophisticated numerical models therefore their applicability is often limited. The proposed approach needs a simple one dimensional FEA model because it is used to predict the size or the location of damage in one dimension rather than a complex model predicting all aspects of the damage. The proposed approach can generally be applied to any type of structure but an illustrative example will be provided for a three-ply composite laminate plate under one-dimensional damage cases.

The remainder of the paper is organized as follows. Section 2 reviews existing work from statistical model updating literature. Section 3 presents the proposed MLE model updating methodology. Section 4 discusses the experimental study conducted for damage detection in composite panels using Lamb-wave sensors and the FEA computational model of the damaged panels. Section 5 illustrates the application of the model updating approach for predicting the size (extent) of damages and Section 6 demonstrates results for localization of damages. Section 7 gives the concluding remarks.

2. Existing approaches

The idea of improving computer models with experimental data has been investigated extensively in the engineering statistics literature under the name of model calibration problem [5]. However, most traditional calibration approaches are deterministic, that is they treat calibration parameters as fixed over the physical experiments, and therefore cannot account for uncertainties due to experimental error, lack of data or variation in material properties. In order to address model updating under uncertainty a probabilistic model updating approach is used in which calibration parameters are treated as varying randomly over the experiments. Chen et al. [22] used an additive bias correction model

$$y^e(x) = y^m(x) + \delta(x) + \epsilon$$

in which $y^e(x)$ is the response measured in the experiment, $y^m(x)$ is the model prediction of the response, x is the input variable that is observable both in the experiment and the model and ϵ is the random experimental error. The authors assumed a Gaussian process to represent the bias correction function $\delta(x)$. Suppose we have N measurements of the response (sensor data of damage index) given by the vector $\boldsymbol{y}^e = (y^e(x_1), \ldots, y^e(x_N))$ under a given set of input (damage conditions) $\boldsymbol{x} = (x_1, x_2, \ldots, x_N)$. The computer model predictions of the response under the same set of input are given by the vector $\boldsymbol{y}^m = (y^m(x_1), \ldots, y^m(x_N))$. The objective of model updating is then to find the parameters of the bias correction function that provides the best agreement between $\boldsymbol{y}^m$ and $\boldsymbol{y}^e$. Chen et al. [22] obtained closed-form Bayesian posterior distributions of the updated model prediction. Gaussian process modeling has been popular in the computer experiments literature for describing input-output behavior of complex nonlinear computer codes with easy to evaluate and simple functions to save from computational time [14]. Reese et al. [8] considered the same model form but used a polynomial regression model in the bias-correction term $\delta(x)$.

When some of the model inputs are not observable in the physical experiment but only exist in the computational model, a common approach is to treat these inputs as calibration parameters [2,3]

$$y^e(x) = y^m(x, \theta) + \delta(x) + \epsilon \quad (1)$$

where θ is the set of calibration parameters that can only be observed or controlled in the computer model $y^m(x, \theta)$. The model updating procedure consists in simultaneously estimating the calibration parameters θ and the bias-correction model