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Hierarchical Bayesian model updating for structural identification

Iman Behmanesh [a], Babak Moaveni [a,*], Geert Lombaert [b], Costas Papadimitriou [c]

[a] Department of Civil and Environmental Engineering, Tufts University, MA, USA
[b] Department of Civil Engineering, KU Leuven, Heverlee, Belgium
[c] Department of Mechanical Engineering, University of Thessaly, Volos, Greece

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ABSTRACT

A new probabilistic finite element (FE) model updating technique based on Hierarchical Bayesian modeling is proposed for identification of civil structural systems under changing ambient/environmental conditions. The performance of the proposed technique is investigated for (1) uncertainty quantification of model updating parameters, and (2) probabilistic damage identification of the structural systems. Accurate estimation of the uncertainty in modeling parameters such as mass or stiffness is a challenging task. Several Bayesian model updating frameworks have been proposed in the literature that can successfully provide the “parameter estimation uncertainty” of model parameters with the assumption that there is no underlying inherent variability in the updating parameters. However, this assumption may not be valid for civil structures where structural mass and stiffness have inherent variability due to different sources of uncertainty such as changing ambient temperature, temperature gradient, wind speed, and traffic loads. Hierarchical Bayesian model updating is capable of predicting the overall uncertainty/variability of updating parameters by assuming time-variability of the underlying linear system. A general solution based on Gibbs Sampler is proposed to estimate the joint probability distributions of the updating parameters. The performance of the proposed Hierarchical approach is evaluated numerically for uncertainty quantification and damage identification of a 3-story shear building model. Effects of modeling errors and incomplete modal data are considered in the numerical study.

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1. Introduction

Model updating techniques based on vibration data (e.g., modal parameters) have provided promising results for damage identification of civil structures. Modal parameters such as natural frequencies and mode shapes can be accurately identified from ambient vibration or forced vibration tests. However, the former is more attractive for operational full-scale civil structures than the latter because the forced vibration tests often require suspending the structure's operation. In addition, forced vibration tests are not practical for continuous structural health monitoring applications. The finite element (FE) model updating techniques using the identified modal parameters can potentially predict the existence, location, and severity of damage which is commonly defined as a change in the structures' physical properties [1]. Reviews on vibration-based model updating and damage identification of structural systems have been provided in [2–5]. The FE model updating methods can be divided into

* Corresponding author.

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two broad categories of deterministic and probabilistic approaches. The deterministic FE model updating methods are well established in the literature [6–9], with several successful applications to civil structures [10–16].

The quality of structural identification results obtained from the deterministic FE model updating methods depends on (1) the accuracy and informativeness of measured vibration data (e.g., identified modal parameters), and (2) the accuracy of the initial FE model. In practice, the identified modal parameters of operational structures show significant variations from test to test, especially if the structure is being monitored over a long period of time. These variations can be due to measurement noise, estimation errors, and most importantly changing environmental/ambient conditions [17–24]. Modeling errors also add to the estimation uncertainties of identification results especially for complex civil structures that are usually modeled with many idealizations and simplifications [5,25–27]. These sources of variability motivated researchers to incorporate the underlying structural uncertainties through the probabilistic FE model updating approaches, which can identify the updating model parameters and their estimation uncertainties. For reliable and robust structural health monitoring, it is important to provide a measure of confidence (uncertainty) on the damage identification results. Different probabilistic damage identification methods based on FE model updating have been used in the literature including Bayesian methods [28–31] and perturbation based methods [32–35]. Filtering methods (e.g., Kalman filters) have also been applied for online parameter identification of structural systems based on measured input-output time histories [36,37]. The available Bayesian model updating frameworks can successfully predict the estimation uncertainties of the updating parameters (e.g., structural stiffness or mass), but do not consider the inherent variability of these parameters due to different sources of uncertainties such as changing ambient temperature, temperature gradient, wind speed, and traffic load.

This paper implements the concept of Hierarchical Bayesian modeling [38–40] to develop a new probabilistic FE model updating procedure that can predict the total uncertainty of the updating model parameters, including the parameter estimation uncertainty and more importantly the inherent variability of updating structural parameters. This proposed framework is extended for probabilistic damage identification of civil structures. Section 2 reviews the most commonly used Bayesian model updating framework in the literature, referred to as *classical Bayesian model updating* in this paper. Section 3 introduces the proposed Hierarchical Bayesian model updating procedure. The performance of the proposed method for structural uncertainty quantification and damage identification is evaluated through a numerical application in Section 4. The effects of modeling errors, incompleteness of modal data, error function correlations, and the number of data sets used in the updating process on the identification results are investigated. Finally, Section 5 provides the conclusions of this work.

2. Classical Bayesian FE model updating framework

2.1. Review of the framework

Detailed and in-depth reviews on the framework can be found in [41–43]. The papers by Beck [28], Beck and Katafygiotis [29], and Sohn and Law [30] are the pioneering efforts in the probabilistic FE model updating using the Bayesian inference scheme. In the past decade, this method has been implemented for identification of several structural systems [27,31,44–50]. There are also a few studies that applied this Bayesian model updating procedure on full-scale civil structures [51–53].

Based on the Bayes theorem the posterior (updated) probability distribution function (PDF) of the updating structural parameters $\boldsymbol{\theta}$, and the model error parameters $\boldsymbol{\sigma}^2$, given a single data set $\mathbf{D}$ can be expressed as:

$$p(\boldsymbol{\theta},\boldsymbol{\sigma}^2|\mathbf{D}) \propto p(\mathbf{D}|\boldsymbol{\theta},\boldsymbol{\sigma}^2)p(\boldsymbol{\theta},\boldsymbol{\sigma}^2) \tag{1}$$

where $p(\mathbf{D}|\boldsymbol{\theta},\boldsymbol{\sigma}^2)$ is the so-called likelihood function and $p(\boldsymbol{\theta},\boldsymbol{\sigma}^2)$ is the prior probability. A common type of measured data $\mathbf{D}$ in structural identification applications includes the identified system eigenvalues (squares of circular natural frequencies) and mode shapes. To formulate the likelihood function, the error functions for a mode m are defined in Eqs. (2) and (3), and they are assumed to have zero-mean Gaussian distributions:

$$\tilde{\lambda}_m - \lambda_m(\boldsymbol{\theta}) = e_{\lambda_m} \sim N\left(0,\sigma^2_{\lambda_m}\right) \tag{2}$$

$$\tilde{\boldsymbol{\Phi}}_m - a_m\boldsymbol{\Phi}_m(\boldsymbol{\theta}) = \mathbf{e}_{\boldsymbol{\Phi}_m} \sim N(\mathbf{0},\boldsymbol{\Sigma}_{\boldsymbol{\Phi}_m}) \tag{3}$$

The identified eigenvalues and mode shapes are shown as $\tilde{\boldsymbol{\lambda}}$ and $\tilde{\boldsymbol{\Phi}}$, respectively. Model calculated eigenvalues and mode shapes are shown by $\boldsymbol{\lambda}(\boldsymbol{\theta})$ and $\boldsymbol{\Phi}(\boldsymbol{\theta})$. Please note that the identified mode shapes and the model-calculated mode shapes at the measured DOFs are normalized to their unit length (i.e., unit L2 norm). In all equations of this paper, the model calculated mode shapes $\boldsymbol{\Phi}(\boldsymbol{\theta})$ contain only the components at the measured DOFs. a_m is the scaling factor of mode m and is set to be the dot product of the two unit-normalized mode shapes $\tilde{\boldsymbol{\Phi}}^T_m.\boldsymbol{\Phi}_m(\boldsymbol{\theta})$. The likelihood function can be written as Eq. (4) by assuming that the identified modal parameters are statistically independent, i.e., knowing the value of any observed modal parameter does not provide any information regarding the probability of observing other modal parameters.

$$p\left(\tilde{\boldsymbol{\lambda}},\tilde{\boldsymbol{\Phi}}|\boldsymbol{\theta},\boldsymbol{\sigma}\right) = \prod_{m=1}^{N_m} p\left(\tilde{\lambda}_m|\boldsymbol{\theta},\sigma^2_{\lambda_m}\right)p\left(\tilde{\boldsymbol{\Phi}}_m|\boldsymbol{\theta},\boldsymbol{\Sigma}_{\boldsymbol{\Phi}_m}\right) = \prod_{m=1}^{N_m} N\left(\tilde{\lambda}_m|\lambda_m(\boldsymbol{\theta}),\sigma^2_{\lambda_m}\right)N\left(\tilde{\boldsymbol{\Phi}}_m|\boldsymbol{\Phi}_m(\boldsymbol{\theta}),\boldsymbol{\Sigma}_{\boldsymbol{\Phi}_m}\right) \tag{4}$$

In this equation, N_m is the total number of identified modes, $N\left(\tilde{\lambda}|\lambda(\boldsymbol{\theta}),\sigma^2_{\lambda}\right)$ is the value of a Gaussian PDF with the mean $\lambda(\boldsymbol{\theta})$ and the standard deviation σ_λ at $\tilde{\lambda}$, and similarly $N\left(\tilde{\boldsymbol{\Phi}}|\boldsymbol{\Phi}(\boldsymbol{\theta}),\boldsymbol{\Sigma}_{\boldsymbol{\Phi}}\right)$ is the vector of a multidimensional Gaussian PDF with the

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