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Finite element model updating using simulated annealing hybridized with unscented Kalman filter

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ABSTRACT

This paper proposes a method for finite element (FE) model updating of civil structures. The method is a hybrid global optimization algorithm combining simulated annealing (SA) with the unscented Kalman filter (UKF). The objective function in the optimization problem can be defined in the modal, time, or frequency domains. The algorithm improves the accuracy, convergence rate, and computational cost of the SA algorithm by local improvements of the accepted candidates though the UKF. The proposed methodology is validated using a mathematical function and numerically simulated response data from linear and nonlinear FE models of realistic three-dimensional structures.

1. Introduction

Finite element model updating (FEMU) can be defined as the process of tuning a finite element (FE) model to minimize the discrepancy between the measured and FE predicted responses of the structure being modeled [18]. The tuning process is usually conducted in an off-line fashion by using batch processing methods and consists of seeking inaccurate or unknown parameters of the FE model assuming that the model structure is fixed.

FEMU has attracted significant attention from the structural engineering community because of its applications in structural dynamics, mainly in damage identification (DID) and response prediction (e.g., [19,47,25,42,15,43]). One of the most popular approaches for DID makes use of a linear FE model which is calibrated using low amplitude vibration data recorded before and after the structure has suffered damage. Then, damage is identified as the reduction of effective stiffness in one or more regions of the structure. Also, approaches for DID based on nonlinear model updating have been proposed (e.g., [13,44,51]), however, all these studies have used simplified nonlinear models with lumped nonlinearities defined phenomenologically. Only in recent years high-fidelity mechanics-based structural nonlinear FE models, which are used for analysis and design, have been employed for DID (e.g., [3,14]). The use of advanced nonlinear structural FE models allows to describe the presence, location, type, and extent of damage in the structure, because these models provide valuable information about history of plastic deformations, residual deformations, loss of strength, and loss of ductility capacity.

Methods for constrained nonlinear optimization are typically used to solve the inverse problem of FEMU considering an objective function describing the discrepancies between the FE predicted and measured responses or quantities derived therefrom (e.g., modal parameters or frequency response functions). Because of the complexity of the relationship between the model parameters to be identified and the objective function, the latter can include many local minima. Gradient-based methods are commonly used for FEMU (e.g., [48,6,37]), however they might be trapped in local minima and their solution highly depends on the starting point (i.e., initial guess of the model parameters). In order to avoid this issue, different global optimization algorithms (GOAs) have been used for FEMU. Teughels et al. [49] and Bakir et al. [7] investigated the use of coupled local minimizers (CLM) for linear FEMU using modal data. Shabbir and Omenzetter [41] combined Particle Swarm Optimization (PSO) with sequential niche technique to improve the finding of global minimum in FEMU and applied the approach to update a linear FE model of a full-scale pedestrian bridge using modal data. PSO was also used by Marwala [33] to update linear FE models of a suspended aluminum beam

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and an unsymmetrical structure tested on a laboratory environment. Perera et al. [40] used PSO and modal data to update a linear FE model of a one-story one-bay reinforced concrete (RC) frame experimentally tested and compared the results with those obtained using Genetic Algorithms (GAs). Hasançebi and Dumlupinar [21] used artificial neural networks (ANNs) to updated FE models of a real RC bridge using the identified natural frequencies and measured static deflections. They employed linear and nonlinear FE models to generate datasets for network training and concluded that nonlinear models provide a better agreement between the updated FE model and the experimental data, especially for static deflection measurements. Betti et al. [9] combined ANNs and GAs to update a linear FE model of a reduced scaled three-story one-by-one bay steel frame at different damage levels using modal data. Other researchers have employed ANNs for FEMU and DID purposes (e.g., [4,16,52,33]). Hao and Xia [20] used modal data and GAs to identify damage in a cantilever beam and a two-dimensional steel frame tested in laboratory conditions. Meruane and Heylen [35] used parallel GAs to identify damage in a RC beam and a simple and small aircraft prototype using model updating based on modal data. Chisari et al. [12] utilized GAs to update a linear FE model of an isolated bridge using experimentally collected static and dynamic data. Kang et al. [28] combined artificial bee colony algorithm with Nelder-Mead simplex method and applied the hybrid approach to identify the model parameters of concrete dam-foundation systems using numerically simulated data. A comprehensive review on system identification and model updating of civil structures using biologically-inspired (e.g., ANNs and GAs) methods can be found in Sirca and Adeli [43]. Methodologies based on modeling to generate alternative (MGA) have also been employed to provide multiple alternative solutions in linear FEMU (e.g., [53,10]). Simulated Annealing (SA) [29] has also been used to update FE models. Levin and Lieven [30] introduced the use of SA in FEMU and compared its performance with GAs using experimental data of a flat plate wing structure. They employed various perturbation schemes to minimize the objective function constructed based on experimental and FE simulated frequency response functions.

The literature on the use of heuristic optimization methods for structural FEMU shows only a few works that have employed SA as an optimization method. The fact that SA has not received as much attention as other metaheuristic optimization methods is because the standard SA requires a large number of annealing cycles to converge to a satisfactory solution. This means that many simulations of the FE model need to be run during the sequential SA process. This issue limits the applicability of SA in large scale and physics-based complex FE models of geo-materials and structures such as tunnels, building, dams, and bridges. Zimmerman and Lynch [54] proposed the parallel SA implemented on a wireless sensor network for structural health monitoring (SHM) that reduces the runtime of the SA algorithm by breaking the annealing into a number of temperature steps, each run on a separate computer node supported with appropriate communication to other wireless nodes. Jeong and Lee [26] as well as He and Hwang [22] combined GAs with SA to create an adaptive SA-GA that can fix the poor hill-climbing capability of the GA for applications in generic system identification and damage detection, respectively.

In this paper, an acceleration scheme recently proposed by some of the authors to reduce annealing steps of the SA by local improvements of the accepted candidates is employed to solve structural FEMU problems. The hybridized scheme has proved effective for a parameter identification problem of waveform inversion of the underground tunnel seismic waves in Nguyen and Nestorović [39]. Similar to the principle in Martin and Otto [32], a method for improving an intermediate candidate locally is coupled to the main SA algorithm. However, in contrast to the idea in Martin and Otto [32], the local improvement method employed in this work is run only if the suggested candidate is accepted following the Metropolis' rule, thus reducing the number of FE model evaluations. The combined global-local optimization method presented in this work couples SA algorithm with the unscented Kalman filter (UKF). The UKF [27], which belongs to the sigma-point Kalman filter family, is a derivative-free estimator for nonlinear state-space models that can be efficiently adapted for solving parameter identification of static and dynamic models [50]. As shown later in the paper, the choice of the UKF as a local minimization method is based on the observation that the UKF can be very efficient to converge to a nearby local minimum. Application examples consisting of a test function (the Styblinski–Tang function) with six parameters and linear and nonlinear FE models are presented to verify the performance of the proposed method. For the FEMU examples, inverse problems involving different number of model parameters are analyzed and modal and time history data simulated numerically from realistic three-dimensional steel frame structures are used in the objective functions. Accurate results are obtained in the different application examples even when a limited number of response quantities (modal properties or time history responses) are used to define the objective function. The hybrid scheme improves the accuracy and reduces the computational cost of the standard SA algorithm, proving that its application to realistic civil structures is feasible. The effects of using modal parameters, acceleration time history responses, and heterogeneous time history response quantities on the estimation results are investigated. Based on the analyses presented in the paper, values for the parameters involved in the hybrid scheme are proposed to solve FEMU problems. It is noted that properly calibrated nonlinear FE models can be used to identify potential damage in the structure, providing an excellent tool for SHM. It is worth nothing that the hybrid scheme also has the capability to be employed with surrogate models.

2. Simulated annealing combined with the unscented Kalman filter

2.1. Forward model and the objective function

The forward model that relates hidden model parameters to responses, for both linear and nonlinear finite element models, can be generally represented as

$$\mathbf{d} = \mathbf{h}(\mathbf{m}) + \mathbf{v}, \tag{1}$$

where vector $\mathbf{m}$ contains n hidden parameters of the model, $\mathbf{d}$ stores the model outputs obtained from the computational model $\mathbf{h}(\cdot)$. Modeling errors $\mathbf{v}$ are caused by assumptions made in building the mathematical model and the numerical approximations involved. Throughout this work, $\mathbf{v}$ is assumed to be a stationary, zero-mean Gaussian white vector process with covariance $\mathbf{R}^m$. Measuring the real life structural responses for the corresponding observed quantities results in a set of measurement data $\mathbf{d}^{obs}$ that are intrinsically contaminated by measurement noise. Measurement noise is often satisfactorily represented as having normal distribution with zero-mean and covariance $\mathbf{R}^{obs}$. Then, the total observation error covariance is formed by the addition rule $\mathbf{R} = \mathbf{R}^{obs} + \mathbf{R}^m$ [45]. In this work the effects of modeling uncertainty are not considered since the same models are employed in the simulation and estimation phases. Thus, the total observation error covariance consists of the measurement noise covariance only, i.e., $\mathbf{R} = \mathbf{R}^{obs}$.

In this work, different definitions to build the objective function that needs to be minimized are used. For the proposed algorithm, it is desired that the L^2 norm of the residual is broken down into r