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Interval model updating using perturbation method and Radial Basis Function neural networks

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ABSTRACT

In recent years, stochastic model updating techniques have been applied to the quantification of uncertainties inherently existing in real-world engineering structures. However in engineering practice, probability density functions of structural parameters are often unavailable due to insufficient information of a structural system. In this circumstance, interval analysis shows a significant advantage of handling uncertain problems since only the upper and lower bounds of inputs and outputs are defined. To this end, a new method for interval identification of structural parameters is proposed using the first-order perturbation method and Radial Basis Function (RBF) neural networks. By the perturbation method, each random variable is denoted as a perturbation around the mean value of the interval of each parameter and that those terms can be used in a two-step deterministic updating sense. Interval model updating equations are then developed on the basis of the perturbation technique. The two-step method is used for updating the mean values of the structural parameters and subsequently estimating the interval radii. The experimental and numerical case studies are given to illustrate and verify the proposed method in the interval identification of structural parameters.

1. Introduction

In the past decades, especially in recent years, there has been an ever-increasing interest in improving the predictive quality of FE models using measurement data as exact reference data, which is referred to as FE model updating [1]. FE model updating is an inverse problem to identify and correct uncertain modeling parameters that leads to better predictions of the response behavior of a target structure [2].

Deterministic FE model updating approaches [3–5] are now well-known and widely used in application to industrial-scale structures where the presence of uncertainties not only in measurement signals due to noise but also in nominally identical test structures is not taken into account. For real-world engineering structures, such simplification is generally impractical and thus it highly limits the application of deterministic FE model updating methods [2,6]. Hence, a model updating procedure involving uncertain analysis is of great importance for the purpose of evaluating the effect of uncertainties in parameters and measurements on model updating results. Uncertainties in model updating can be generally categorized in two groups: (i) model uncertainty and (ii) measurement uncertainty. Model uncertainty contains model parameter uncertainty, model structure uncertainty and model code uncertainty, while measurement uncertainty can arise

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from random measurement noise, or it can arise from a bias or systematic error caused by imperfections in the measurement equipment or during the subsequent signal processing [7].

Statistical methods [2,8–12] have been developed for the treatment of experimental variability caused by random measurement noise in a model updating problem. The minimum variance methods by Collins et al. [8] and more recently by Friswell [9] were first used to handle the reducible uncertainty caused by the measurement noise. Subsequently, Beck and Katafygiotis [10] presented a Bayesian statistical framework for quantitatively analyzing the prediction accuracy of the structural models by utilizing dynamic response data. Steenackers and Guillaume [2] extended the conventional FE updating technique to a statistical one by considering the measurement statistics as an inverse weighting factor in the cost function to be minimized. In addition, random matrix theory of Soize et al. [11] and inverse fuzzy arithmetic of Haag et al. [12] could offer alternative methods when addressing the experimental uncertainty.

On the other hand, researches on parameter uncertainty related to geometric dimensions and material properties are of primary concern of stochastic model updating [6]. To this end, stochastic model updating methods have been found in scientific literature [6,13–21]. Fonseca et al. [14] proposed an updating algorithm based on maximum likelihood function. The Monte Carlo based model updating procedure [6,13,15,16] is relatively easy to implement for identifying the parameter variability but it also requires the huge amount of computational expense. Meanwhile, perturbation methods [18,19] have been successfully applied in stochastic model updating in which structural parameters and measured responses are presented as the summation of a deterministic part and a random variation.

However, an adequate probabilistic estimation always requires sufficient measurement information, which is often impractical in engineering practice [22,23]. In this circumstance, interval methods [24] are introduced as a useful alternative to quantify uncertain parameters. In the field of interval model updating in which the parameter uncertainties are described by interval numbers, some attempts [23,25,26] have been made to establish an interval inverse problem. Nevertheless, from the overall perspective, the research on the interval model updating is still in its preliminary stage and some paramount issues still remain unsolved. For example, the application of interval analysis methods in the field of FE model updating needs to be exploited since direct interval arithmetic operations are difficult to implement during the process of solving inverse solutions [26]. Additionally, Fang et al. [26] proposed an interval response surface model (IRSM) for the interval model updating problem. The application of IRSM can simplify the establishment and implementation of the interval model updating problem, as this model helps to directly perform interval algorithms during the process of interval model updating. It should be noted that IRSM was constructed on the basis of a second-order polynomial model and was unable to consider interaction terms between updating parameters, which can achieve satisfactory updating results for engineering problems with non-obvious interaction effects between different parameters.

For solution of the interval model updating problem, Khodaparast et al. [23] first proposed the parameter vertex method which was valid only for particular parameterization of an FE model and particular output data. Then, they presented another method for a general case based on the sensitivity analysis of the Kriging predictor. However, the updating process of the Kriging model-based method is relatively complex and brings a great deal of calculation burden [25]. In addition, the method in Ref. [26] is subject to a special second-order polynomial model and unable to consider interaction terms between updating parameters. As is discussed above, the purpose of this paper is to present a new method for interval model updating using the first-order perturbation technique and RBF neural networks. Based on the perturbation technique, two deterministic optimization problems are derived and solved for estimating the interval bounds of structural parameters. By this means, the proposed updating method itself is not dependent on types of surrogate models and ones can choose a suitable type of surrogate models (such as the polynomial-based response surface model [15], the Kriging model [23] and so on) according to the need of actual engineering problems, which presents a significant merit over the interval response surface model-based updating method. Meanwhile, RBF neural network-based surrogate models are utilized hereby with the purpose of representing the complex FE models and efficiently performing the interval model updating procedure. Finally, the experimental and numerical case studies are given to illustrate the feasibility of the presented method in the interval identification of structural parameters.

2. Theory

2.1. RBF neural networks

The use of surrogate models in model updating contributes to fast response computation of inverse solution. For example, the second-order interval response surface model (IRSM) has been utilized for interval model updating [26]. Nevertheless, the second-order IRSM is subject to a special second-order polynomial model and could not consider the interaction terms between updating parameters. Due to this reason, this study adopts the neural networks [27,28] establishing a link between the structural parameters (e.g. x) and the corresponding responses (e.g. y) of a target structure. It should be noted that although we employ the RBF neural network to represent a mapping between its inputs and outputs, the proposed method is not dependent on types of surrogate models. Thus, ones can choose a suitable type of surrogate models (such as the polynomial-based response surface model [15], the Kriging model [23] and so on) according to the need of actual engineering problems.