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Frequency response function-based model updating using Kriging model

J.T. Wang[a,*], C.J. Wang[a,b], J.P. Zhao[a]

[a] School of Mechanical Engineering and Automation, Beihang University, Beijing, China
[b] State Key Laboratory of Virtual Reality Technology and Systems, Beihang University, Beijing, China

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ABSTRACT

An acceleration frequency response function (FRF) based model updating method is presented in this paper, which introduces Kriging model as metamodel into the optimization process instead of iterating the finite element analysis directly. The Kriging model is taken as a fast running model that can reduce solving time and facilitate the application of intelligent algorithms in model updating. The training samples for Kriging model are generated by the design of experiment (DOE), whose response corresponds to the difference between experimental acceleration FRFs and its counterpart of finite element model (FEM) at selected frequency points. The boundary condition is taken into account, and a two-step DOE method is proposed for reducing the number of training samples. The first step is to select the design variables from the boundary condition, and the selected variables will be passed to the second step for generating the training samples. The optimization results of the design variables are taken as the updated values of the design variables to calibrate the FEM, and then the analytical FRFs tend to coincide with the experimental FRFs. The proposed method is performed successfully on a composite structure of honeycomb sandwich beam, after model updating, the analytical acceleration FRFs have a significant improvement to match the experimental data especially when the damping ratios are adjusted.

1. Introduction

Finite element model updating method can be employed as an important tool to calibrate the finite element model (FEM) for mitigating modeling error. It can make the updated FEM have the same behavior to the corresponding real structure as much as possible. There are two main dynamic model updating method: modal parameters based method and frequency response function (FRF) based method. The former has been thoroughly studied, but the FRF based method [1] introduced by Hemez and Brown [2] and other researchers [3,4] has received considerable attention and applications [5–9] in recent years due to its advantage: Firstly, the measured FRF data can be utilized directly without data transformation. In some special software, the calculation of modal parameters is based on the measured FRF data. And the modal analysis is more complex, the error might arise from the modal identification. The identification error might greater than the modeling error. Secondly, the FRF can be measured in more locations of the structure and taken as an objective so it can provide more data.

Model updating process is intrinsically an inverse problem [10] and usually formulated as optimization problem, which aims to minimize the differences between the FEM behavior and the corresponding experimental behavior. However, the conventional

* Corresponding author.
E-mail address: tjwjt@163.com (J.T. Wang).

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sensitivity based optimization algorithms have disadvantages, such as: (1) the sensitivity analysis may be computation expensive, and the sensitivity results might not be obtained easily; (2) huge computational cost may be required to meet the convergence point for optimization algorithm. Although the modern intelligent algorithms (Genetic Algorithm, Particle Swarm Optimization and Simulated Annealing etc.) can avoid calculating the sensitivity. But to the structural dynamic analysis of FEM, its large number function calls of finite element analysis (FEA) is time consuming, this even cause the intelligent algorithms is impractical applied to the complex structure.

Fortunately, the barrier between the practical applications and the intelligent algorithm can be overcome via the metamodel technique which is known as approximate model or surrogate model. This technique considers the relationship between the input and output as a black-box system, and other information of the system such as internal process of dynamic analysis are not required. It can create a fast running surrogate model to replace the exact FEA, and then the solving time of optimization will be reduced significantly. In addition, in-house FEA codes and existing commercial software can be integrated directly, and it is suitable for parallel computing. Thereby the potential of metamodel techniques is indisputable in model updating field.

There are several types of construction method of metamodel are commonly used: response surface methodology (RSM), radial basis function (RBF), Kriging method, polynomial correlated function expansion [11], Polynomial Chaos expansion [12] and Support Vector Regression. Most of them are constructed based on training samples which include input and output information of the interested system. The metamodel technique has been applied in fields such as: structural reliability analysis [13], structural static model updating [14], structural dynamic model updating based on modal parameters [15], and structural damage identification [16,17]. The comparison [18,19] and recommendation [20] of the main metamodels also have been studied.

As one of the main method, Kriging model is constructed based on the correlation function theory. Particularly, it is an exact interpolation of given data and goes through all the sampling points. So the Kriging model usually has a higher approximation accuracy than traditional RSM. Khodaparast et al. [21] solved the problem interval model updating by using the Kriging method, and the good accuracy of Kriging method was illustrated by beam experiment. Liu et al. [22] calibrated the FEM based on the modal parameters of a complex structure, the Kriging model was taken as a surrogate model. But there is few application of Kriging model in FRF based model updating in nowadays.

In this article, the Kriging model is applied to the model updating based on FRF data. The training samples for the Kriging model are obtained via the design of experiment (DOE), whose factors and response are corresponding to design variables and FRF based data respectively. The case study is followed by an impact hammer test of cantilever beam of honeycomb sandwich structure. The acceleration FRF (AFRF) data are measured and used for DOE and optimization. A two-step DOE method is proposed to reduce the design variables and training samples. The model updating result shows the updated damped FEM has significant improvement to match the experimental AFRF data, and demonstrate the effectiveness of the proposed approach. Moreover, the proposed method can be extended to stochastic model updating [23–25] where usually require a huge number function calls of FEA.

2. AFRF based model updating and objective function

Model updating method aims to reduce the modeling error of FEM making the FEM agree better with the real experimental situation. In AFRF based model updating, both FEM data and experimental data corresponding to AFRF amplitude curves, are simulated and measured at the interested degree of freedoms (DOFs) of the structure, respectively. Because of the modeling error, the mass matrix, damping matrix and stiffness matrix of FEM have deviation from the experimental situation, therefore, the two analogous amplitude curves cannot overlap. Then minimizing the difference between the coupled curves is considered as an optimization problem. In which, the design variables appointed by the user are taken as input variables. Optimal results (updated input variables) are obtained via minimizing the objective function. The results can in turn change the matrixes for FEA, and finally lead the AFRF curve of FEM to coincide with the experimental AFRF curve as much as possible.

The optimization problem can be formulated in the following form:

$$\text{Minimize } \mathbf{F},\ s.\ t. \quad x_{iL} \le x_i \le x_{iU}, \quad i = 1, 2, \ldots, n \tag{1}$$

where $\mathbf{F}$ is the objective function, x_i is the design variables of the structure, x_{iL} and x_{iU} are the lower and upper bound of the input variables, respectively.

In this study, the objective function is established based on the differences between the corresponding AFRF curves at each selected frequency point, it can be formulated as follows:

$$F = \sum_{n=1}^{np} \sum_{i=1}^{nf} w_i \left(\frac{A_t^n(\omega_i) - A_a^n(\omega_i)}{A_t^n(\omega_i)} \right)^2 \tag{2}$$

where w_i is the weights, np is the number of measured DOFs, nf is the number of selected frequency points of AFRF, ω_i is the selected frequency points, $A_t^n(\omega_i)$ is the experimental acceleration amplitude at ω_i, $A_a^n(\omega_i)$ is the corresponding amplitude of the FEM.

As mentioned in the previous section, during the optimization process, the FEA process can be replaced by Kriging model, which does not require the internal information of the matrix operation in FEA. The construction method of Kriging model will be introduced in the following section.