Computers and Structures 192 (2017) 210–232

Contents lists available at ScienceDirect

Computers and Structures

journal homepage: www.elsevier.com/locate/compstruc

Computational framework for model updating of large scale linear and nonlinear finite element models using state of the art evolution strategy

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A R T I C L E I N F O

Article history:
Received 9 April 2017
Accepted 5 July 2017

Keywords:
System identification
Nonlinear dynamics
Substructuring
Large scale models

A B S T R A C T

In this work, a computational framework applying-finite element model updating techniques is presented for identifying the linear and nonlinear parts of large scale dynamic systems using vibration measurements of their components. The measurements are taken to be, response time histories and frequency response functions of nonlinear and linear components of the system. Covariance Matrix Adaptation – Evolution Strategy (CMA-ES) a state of the art optimization algorithm was coupled with robust and accurate finite element analysis software in order to effectively produce optimal computational results. The developed framework is applied to a geometrically complex and lightweight experimental bicycle frame with nonlinear suspension fork components. The identification of modal characteristics of the frame (linear part) is based on an experimental investigation of its dynamic response. The modal characteristics are then used to update the finite element model. The nonlinear suspension components are identified using the experimentally obtained response spectra for each of the components tested separately. Single objective structural identification methods without the need of substructuring methods, are used for estimating the parameters (material properties, shell thickness properties and nonlinear properties) of the finite element models, based on minimizing the deviations between the experimental and analytical dynamic characteristics. Finally, the numerical results of the complete system assembly were compared to the experimental results of the equivalent physical structure of the bike.

1. Introduction

Nowadays, current industrial demands, tend to have the need of improving, modifying and developing new and optimized versions of various parts of mechanical systems or structures and mechanical assemblies as a whole, in order to evolve and keep up with growing competition. In most such cases, there is no available information not only about their geometric and designing details, but also about their material properties and mechanical treatment and procedures carried out during the construction process. In order to address this issue, a reverse engineering strategy is necessary to be applied [1–5]. During this process, many issues are taken into account, related to the development of the CAD and FE model of the examined structure, the experimental modal analysis procedures and the application of robust and effective computational model updating techniques.

Over the recent decade or so, although contemporary finite-element (FE) procedures for structural analysis have been highly sophisticated and modernized, practical problems and applications, reveal notable deviations between analytical and experimental models. In order to diminish the discrepancies between analytical predictions and experimental results, maintaining important practical requirements and the physical meaning of the results, a *model updating* process is necessary to be applied. In model updating, effective computational procedures are applied in order to finely tune and adjust the parameters of analytical finite-element models using experimental test data [6]. Response time histories, frequency response functions or modal parameters (natural frequencies, mode shapes and modal damping ratios) are used, to quantify the discrepancy between analytical and experimental models, defining a modal or a response residual. These residuals are minimized in order to acquire a best match consistency between the analytical quantities and those identified from the experiments. The type of this inverse problem falls within the discipline of *system identification* [7–9] and as usually practiced, produces analytical models with more accurate dynamic response predictions to prescribed dynamic loading.

However, the accuracy of the response predictions will be uncertain, on the one hand, because of the uncertainty of all future structural excitations and on the other hand, because the structural model will always involve approximations of the real dynamic

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http://dx.doi.org/10.1016/j.compstruc.2017.07.004
0045-7949/

behavior that affects in an uncertain manner the predicted responses. In addition, the structural model will usually involve parameters whose values are naturally uncertain [7]. Uncertainties related to model-structure errors, arise from the assumptions made to parameterize and describe the behavior of the physical structure. Such uncertainties include simplifications and erroneous assumptions, inexact modeling of the material constitutive behavior, inexact modeling of boundary conditions (e.g. pinned and fixed joints), errors because of the spatial discretization of the distributed structural system, unmodeled features, such as neglected nonstructural components, as well as errors introduced by numerical methods. In this work, such uncertainties are treated meticulously and are minimized to the most plausible extent according to each problem, as cannot be regarded and tuned by model updating methodologies. Model updating basically regards, erroneous assumptions of model parameters such as material parameters (Young's modulus and mass density), cross section properties (moments of inertia), shell or plate thickness, spring stiffnesses and non-structural mass [6]. For a model updating method to be useful in practice, it should handle distinct difficulties. The incompleteness of experimental test data needed to produce physically meaningful models as a small subset of DOFs are observed due to limited number of sensors and noise contaminated test results, are known and hardly dealt problems. Furthermore, the lack of actual structural parameters among the chosen class as the upper and lower boundaries of updated parameters are limited as well as modal parameters controlling the dynamic response which are insensitive to changes in the stiffness and mass distributions are also problems arising from the introduced methods. Finally, the selected residuals passed to the optimization methodology that need to be globally minimized, avoiding encirclement in local minima, without sacrificing speed of convergence is a difficulty to be carefully overpassed [8].

Structural model parameter estimation based on measured modal data [10–15] are often formulated as weighted least-squares estimation problems in which metrics, measuring the residuals between measured and model predicted modal characteristics, are build up into a single weighted residual metric formed as a weighted average of the multiple individual metrics, using weighting factors. Standard gradient-based optimization techniques are then used to find the optimal values of the structural parameters that minimize the single weighted residuals, representing an overall measure of fit, between measured and model predicted modal characteristics. Due to model error and measurement noise, the results of the optimization are affected by the values assumed for the weighting factors. Conventional gradient-based optimization algorithms do not guarantee convergence to a global optimum. Alternatively, evolutionary strategies [16–19] are more effective in avoiding entrapment in local optima, at the disadvantage of slower convergence rates to the optimum. Evolutionary strategies are highly parallel, so the time to solution of the optimization problem in massively parallel computer architectures, may be comparable to conventional gradient-based optimization methods. Moreover, evolutionary strategies will have a better chance of finding the global optimum and are model non-intrusive.

Randomized search algorithms are regarded to be robust in a rugged search landscape, can comprise discontinuities, (sharp) ridges, or local optima. The covariance matrix adaptation (CMA) in particular is designed to tackle, additionally, ill-conditioned and non- separable problems [20]. Among several classes of evolutionary algorithms, the Covariance Matrix Adaptation – Evolution Strategy (CMA-ES) [18,21–23] has been shown to converge fast in particular when searching for a single global optimum. CMA-ES stochastic optimization algorithm, is a general purpose method, which has not been widely applied to FE updating problems, involving large and complex models and cases, but has been widely tested on mathematical functions and numerical lumped FE models successfully [24]. As CMA-ES is fully parallelizable, in this work a free distribution of the CMA-ES algorithm is applied in parallel computing, to solve the single-objective optimization problem, arising from combining modal and response residuals. Robust and accurate FE Analysis software is employed, in combination to the parallelized strategy, in order to produce results of the proposed objective function residual simultaneously and populate the algorithm's offsprings. Such a computation is performed, using the non-intrusive adaptive Parallel Numerical Differentiation Library (PNDL) [25]. The above optimization algorithm is implemented within Π4U framework [18] based on a state-of-the-art task-parallel library for clusters, called TORC [26], which is designed to provide unified programming and runtime support for computing platforms that range from single-core systems to hybrid multicore-GPU clusters and heterogeneous grid-based supercomputers.

In this work, the applicability and effectiveness of a reverse engineering strategy focusing on the updating methodology, coupled with robust, accurate and efficient finite element analysis software, are applied on linear and non-linear components of a whole structure assembly, using experimentally identified modal and response data. The proposed framework is applied on a bicycle with its nonlinear front suspension component. More specifically, the examined structure is a lightweight and geometrically complex bicycle frame as well as its suspension-fork subassembly, comprising the linear and nonlinear subsystems of the whole bike assembly. Furthermore, the suspension-fork subassembly is consisted of two linear parts (upper and lower fork part) connected with two linear springs and two seals that impose strong nonlinearity in the system. Issues related to estimating unidentifiable solutions [27–30] arising in FE model updating formulations are also addressed. The effect of model error, finite element model parameterization, number of measured modes and number of mode shape components on the optimal models along with and their variability, are examined.

The presentation in this work is organized as follows. The theoretical formulation of finite element model updating based on modal characteristics, frequency response functions is briefly presented in Section 2, summarizing structuring of the objective function. Section 3 presents the adopted objective function for the nonlinear systems. Formulation of the CMA-ES stochastic algorithm is described in Section 4. Section 5 introduces the proposed computational framework, as applied in this work. In Section 6 the experimental arrangements and applications are introduced. At first a quick presentation of the digitization of the bicycle components leading to the final parametric CAD model is shown with the corresponding detailed FE models. Next the applied experimental modal analysis procedure is presented, in order to identify the modal characteristics and the FRF's. The parametric studies on updating the linear and nonlinear FE models of the bicycle components, using predictions of frequency response functions, time histories and transmissibility functions, based on the optimal models, are presented in Sections 7 and 7.3, along with the experimental arrangement and application both of the non-linear subsets and the whole structure. Section 9 presents the correlation of the dynamic response between the finite element and experimental model. Conclusions are summarized in Section 10.

2. Linear finite element model updating strategies

2.1. Modal residuals

Let $D = \{\hat{\omega}_r, \underline{\hat{\phi}_r} \in R^{N_o}, r = 1, \ldots, m\}$ be the measured modal data from a structure, consisting of modal frequencies $\hat{\omega}_r$ and mode