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Structural damage assessment using linear approximation with maximum entropy and transmissibility data

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ABSTRACT

Supervised learning algorithms have been proposed as a suitable alternative to model updating methods in structural damage assessment, being Artificial Neural Networks the most frequently used. Notwithstanding, the slow learning speed and the large number of parameters that need to be tuned within the training stage have been a major bottleneck in their application. This article presents a new algorithm for real-time damage assessment that uses a linear approximation method in conjunction with antiresonant frequencies that are identified from transmissibility functions. The linear approximation is handled by a statistical inference model based on the maximum-entropy principle. The merits of this new approach are twofold: training is avoided and data is processed in a period of time that is comparable to the one of Neural Networks. The performance of the proposed methodology is validated by considering three experimental structures: an eight-degree-of-freedom (DOF) mass-spring system, a beam, and an exhaust system of a car. To demonstrate the potential of the proposed algorithm over existing ones, the obtained results are compared with those of a model updating method based on parallel genetic algorithms and a multilayer feedforward neural network approach.

1. Introduction

The purpose of structural damage assessment is to detect and characterize damage at the earliest possible stage, and to estimate how much time remains before maintenance is required, the structure fails or the structure is no longer functional. Damage assessment has a tremendous potential for life-safety and/or economic benefits, this generates a wide interest in the civil, mechanical and aerospace engineering fields.

A global technique called vibration-based damage assessment [1] has been rapidly expanding over the last few years. The basic idea is that vibration characteristics (natural frequencies, mode shapes, damping, frequency response function, etc) are functions of the physical properties of the structure. Thus, changes to the material and/or geometric properties due to damage will cause detectable changes in the vibrations characteristics. Many studies have demonstrated that vibration measurements are sensitive enough to detect damage even if it is located in hidden or internal areas [2].

Vibration-based damage assessment methods are classified as model-based or non-model based. Non-model-based methods detect damage by comparing the measurements from the undamaged and damaged structures, whereas model-based methods locate and quantify damage by correlating an analytical model with test data from the damaged structure.

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Non-model-based methods usually provide the first two levels of damage assessment (detection and location), whereas model-based methods can achieve up to the third level (quantification). Additionally, model-based methods are particularly useful for predicting the system response to new loading conditions and/or new system configurations (damage states), allowing damage prognosis [3].

Model-based damage assessment requires the solution of a nonlinear inverse problem, which can be accomplished using supervised learning algorithms as neural networks or by global optimization algorithms. The most successful applications are model updating methods based on global optimization algorithms [4–8]. Model updating is an inverse method that identifies the uncertain parameters in a numerical model and is commonly formulated as an inverse optimization problem. In model updating-based damage assessment, the algorithm uses the differences between the models of the structure that are updated before and after the presence of damage to localize and determine the extent of damage. The basic assumption is that the damage can be directly related to a decrease of stiffness in the structure. However, these algorithms are exceedingly slow and the damage assessment process is achieved via a costly and time-consuming inverse process, which presents an obstacle for real-time damage assessment applications. Real-time damage assessment allows to continuously monitor the state of a structure, which is critical to avoid catastrophic failures. For example, many catastrophic collapses of wind turbines could have been avoided if the damage had been detected and the turbines had been stopped in time [9].

To reduce the time required to assess damage, supervised learning algorithms have been proposed as an alternative to model updating. The objective of supervised learning is to estimate the structure's health based on current and past samples. Supervised learning can be divided into two classes: parametric and non-parametric. Parametric approaches assumed a statistical model for the data samples. A popular parametric approach is to model each class density as Gaussian [10]. Nonparametric algorithms do not assume a structure for the data. The most frequently nonparametric algorithms used in damage assessment are Artificial Neural Networks [11–14]. A trained neural network can potentially detect, locate and quantify structural damage in a short period of time. Hence, it can be used for real-time damage assessment.

There are different types of network architectures, among which multilayer feedforward networks are the most frequently used. Although once the network is already trained it can process data very quickly, the slow learning speed and the large number of parameters that need to be tuned within the training stage have been a major bottleneck in their application [14]. Gupta et al. [15,16] presented a new nonparametric method, which generalizes linear approximation by using the maximum-entropy (max-ent) principle [17] for statistical inference. A similar approach is adopted by Erkan [18] for semi-supervised learning problems, where a decision rule is to be learned from labeled and unlabeled data. Recently, max-ent methods have become quite popular in the computational mechanics community as a powerful tool for numerical solution of PDEs [19,20], and their applications in the solution of ill-posed inverse problems have also been explored, which includes damage assessment applications [21,22]. By using max-ent linear approximation methods, training is avoided and data is processed in a period of time that is comparable to the one of Neural Networks. In addition, it only requires one parameter to be selected. Hence, max-ent linear approximation methods become very appealing for real-time health monitoring applications. Gupta [15] demonstrated the application of the max-ent linear approximation approach to color management and gas pipeline integrity problems. In the present paper, we demonstrate the applicability in structural damage identification.

An important aspect of structural damage assessment is the selection of an appropriate measure of the system response. The idea of using directly the frequency response functions (FRFs) has attracted many researchers [23]. Among all the dynamic responses, the FRF is one of the easiest to obtain in real-time, as the *in situ* measurement is straightforward. Nevertheless, FRFs have the disadvantage that they cannot be identified from output-only modal analysis; thus the measurement of the excitation force is always required. For structures in real conditions, it often becomes very difficult to measure the excitation force. Thus, a critical issue is to reduce the dependence upon measurable excitation forces. An alternative to FRFs are transmissibility functions. They relate the responses at two sets of co-ordinates. Consequently, they do not involve the measurement of excitation forces. The only condition is that the location of the excitation force must be known.

The majority of the research in transmissibility-based damage identification are data-based approaches for damage detection and localization. Chesné and Deraemaeker [24] presented a review of them, in addition to a study of the feasibility of transmissibility functions for damage detection and localization. The researchers concluded that extreme care should be taken when using transmissibility functions in an unsupervised manner, i.e. without knowing how they will be affected by damage, because damage localization is not always guaranteed. The first study of transmissibility functions as indicators of structural damage was presented by Worden [25]. The researcher showed for a simple lumped-parameter system that transmissibilities are able to detect small stiffness changes. Since then, the research group leaded by Worden and Manson have done extensive research in this topic [26]. In [27], the researchers used a representative aircraft skin panel to investigate the sensitivity of transmissibility features to damage. Damage detection is achieved via a statistical outlier analysis. This algorithm was later compared with the performance of density estimations and auto-associative neural networks in [28]. The feature vector was constructed from transmissibility data, selecting spectral lines centered at a particular peak and then using PCA to reduce the dimension of the data set. Outlier analysis and neural networks prove to be more sensitive to damage. Manson et al. [29,30] tested the performance of the outlier analysis technique to detect damage in an inspection panel of a Gnat aircraft. Damage was introduced as holes and saw-cuts across the panel. To achieve the next step of damage assessment, i.e. localization, Pierce et al. [31] proposed an interval-based classification network. Experimental transmissibility data was collected from a series of undamaged and damaged scenarios. The performance