VIBRATION-BASED DAMAGE IDENTIFICATION METHODS FOR CIVIL ENGINEERING STRUCTURES USING ARTIFICIAL NEURAL NETWORKS

By

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CERTIFICATE OF AUTHORSHIP/ORIGINALITY

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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ABSTRACT

This thesis investigates the viability of using dynamic-based 'damage fingerprints' in combination with artificial neural network (ANN) techniques and principal component analysis (PCA) to identify defects in civil engineering structures. Vibration-based damage detection techniques are global methods and are based on the principle that damage alters both the physical properties, such as mass, stiffness and damping, as well as the dynamic properties of a structure. It is therefore feasible to utilise measured dynamic quantities, such as time histories, frequency response functions (FRFs) and modal parameters, from structural vibration to detect damage. Damage identification based on vibrational characteristics is essentially a form of pattern recognition problem, which looks for the discrimination between two or more signal categories, e.g., before and after a structure is damaged, or differences in damage levels or locations. Artificial neural networks are capable of pattern recognition, classification, signal processing and system identification, and are therefore an ideal tool in complementing dynamic-based damage detection techniques. Likewise, PCA has pattern recognition abilities and is capable of data reduction and noise filtering. With these characteristics, both techniques can help overcome limitations associated with previously developed vibration-based methods and assist in delivering more accurate and robust damage identification results.

In this study, two types of dynamic-based damage identification methods are proposed. The first is based on the damage index (DI) method (initially proposed by Stubbs et al.), while the second approach uses changes in FRF data as damage fingerprints. The advantage of using damage patterns from the DI method, which is based on changes in modal strain energies, is that only measured mode shapes are required in the damage identification, without having to know the complete stiffness and mass matrices of the structure. The use of directly measured FRF data, which provide an abundance of information, is further beneficial as the execution of experimental modal analysis is not required, thus greatly reducing human induced errors. Both proposed methods utilise PCA and neural network techniques for damage feature extraction, data reduction and noise filtering. A hierarchical network training scheme based on network ensembles is proposed to take advantage of individual characteristics of damage patterns obtained from different sources (different vibrational modes for the DI-based method and

different sensor locations for the FRF-based method). In the ensemble, a number of individual networks are trained in parallel, which optimises the network training and delivers improved damage identification outcomes. Both methods are first tested on a simple beam structure to assess their feasibility and performance. Then, the FRF-based method is applied to a more complicated structure, a two-storey framed structure, for validation purposes. The two methods are verified by numerical simulations and laboratory testing for both structures. As defects, notch type damage of different severities and locations are investigated for the beam structure. For the two-storey framed structure, three different types of structural change are studied, i.e. boundary damage, added mass changes and section reduction damage. To simulate field-testing conditions, the issue of limited sensor availability is incorporated into the analysis. For the DI-based method, sensor network limitations are compensated for by refining coarse mode shape vectors using cubic spline interpolation techniques. To simulate noise disturbances experienced during experimental testing, for the numerical simulations, measurement data are polluted with different levels of white Gaussian noise.

The damage identifications of both methods are found to be accurate and reliable for all types of damage. For the DI-based method, the results show that the proposed method is capable of overcoming limitations of the original DI method associated with node point singularities and sensitivities to limited number of sensors. For the FRF-based method, excellent results are obtained for damage identification of the beam structure as well as of the two-storey framed structure. A major contribution is the training of the neural networks in a network ensemble scheme, which operates as a filtering mechanism against individual networks with poor performance. The ensemble network, which fuses results of individual networks, gives results that are in general better than the outcomes of any of the individual networks. Further, the noise filtering capabilities of PCA and neural networks demonstrate great performance in the proposed methods, especially for the FRF-based identification scheme.

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