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A numerically-enhanced machine learning approach to damage diagnosis using a Lamb wave sensing network

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ABSTRACT

This paper describes a methodology for the design of a model-based diagnostic unit. The objective of the work is to define a suitable procedure for the design and verification of diagnostic performance in a simulated environment, trying to maximise the generalisation capability of pattern recognition algorithms when tested with real experimental signals. The system is designed and experimentally verified to solve the fatigue crack damage localisation and assessment problems in a realistic, though rather idealised, Structural Health Monitoring (SHM) framework. The study is applied to a piezoelectric Lamb wave sensor network and is validated experimentally on a simple aluminium skin. The analytically-derived dispersion curves for Lamb wave propagation in aluminium are used in order to determine the wave velocities and thus their arrival time at given sensors. The Local Interaction Simulation Approach (LISA) is used to simulate the entire waveform propagation. Once the agreement between analytical, numerical and experimental data is verified on a baseline undamaged condition, the parametric LISA model has been iteratively run, varying the position and the length of a crack on an aluminium skin panel, generating the virtual experience necessary to train a supervised learning regressor based on Artificial Neural Networks (ANNs). After the algorithm structure has been statistically optimised, the network sensitivity to input variations has been evaluated on simulated signals through a technique inspired by information gap theory. Real Lamb wave signals are then processed into the algorithm, providing feasible real-time indication of damage characteristics.

1. Introduction

Structural Health Monitoring (SHM) as a technology offers the promise of reduced cost-of-ownership and increased safety of operation for a wide range of engineering structures. The main advantage of implementing SHM is that it allows a move towards condition-based maintenance. More fundamentally, SHM will facilitate a move from safe-life design principles to damage tolerant ones; the potential result being a reduction in conservative reserve factors, allowing the design and build of lighter greener structures. However, the widespread practical implementation of SHM is still some way away. One of the reasons for this situation is that SHM cannot currently deliver the level of diagnostic information desired by industry with confidence. In the specific case of data-based SHM, one of the main problems is the lack of availability of

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data from damaged structures. Pure data-based SHM makes use of pattern recognition or machine learning methods in the attempt to diagnose structural condition from measured data without recourse to physics-based structural models [1].

Machine learning algorithms fall broadly into two classes: *unsupervised learning* and *supervised learning* approaches. Supervised learning approaches develop a classifier based on the availability of training data that can assign a class label to unseen data; in the context of SHM, this class label could indicate the location or severity of damage or could simply indicate whether the structure is damaged or not. The issue with supervised learning is that the training data must include examples from all classes of interest. In the SHM context, the training data would need to include data from structures with all conceivable damage locations and severities for example. For very high-value structures like aircraft or bridges, such data could not be collected by experiment; the cost would be inconceivable. This leaves the possibility that the training data be collected from a programme of numerical simulation; this also has problems in that models of high enough fidelity for complex structures are impossible to build or could be very expensive. In the absence of damage data, one can pursue *unsupervised learning*. In this approach one uses only data from the undamaged structure in order to build a statistical model of normal condition data; one subsequently tests new data in order to see if it is consistent with the model and any significant deviation is taken as an indication of damage. This approach has problems also (see [1]; Chapter 12), but the main issue is that it really only allows detection of damage, it does not usually deliver higher level diagnostic information like location or severity of damage. If one needs higher level diagnostics, one is forced to adopt supervised learning or abandon the machine learning approach.

As collection of training data for supervised learning by experimental methods is generally impossible, one must address the issue by building physical law-based models, or where possible by referring to surrogate damage such as the application of lumped masses acting as a perturbation of the nominal baseline condition [2–4]. Supervised learning approaches have been used for many years for diagnostic purposes and the possibility to learn from models has a long history too [5,6]. Nevertheless, there has been very little success reported in the literature in developing diagnostic systems trained on simulated data that could generalise well to the real situation. A model-based diagnostic system based on strain field monitoring was presented in [7], providing satisfactory results for anomaly detection, localisation and quantification when used in real time to diagnose a real crack propagating on an aluminium stiffened skin structure. Further noteworthy work is reported in [8,9], where the authors tested a model-based diagnostic system based on Lamb wave scattering for the quantitative diagnosis of through-hole-type defects in a composite quasi-isotropic laminate.

In a model-based SHM framework it is important to stress the attention on the numerical verification and validation with experimental signals in order to provide reliable network outputs. Additionally, as numerical information is generally free from noise and environmental influences (sometimes included if training patterns are experimentally generated) it is also important to verify the system sensitivity to input variations through propagation of artificial uncertainties. Finally, during SHM system design, one has to guarantee sufficient generalisation performance, which is a non-trivial aspect to be considered when pure numerical data are provided as training examples. The modest aim of the current paper is to extend knowledge on how a combination of model-based and data-based SHM can be accomplished in a realistic, but rather idealised, experimental context.

The structure considered in this paper is a simple plate and the objective of the SHM system designed is to locate and quantify the extent of a crack in the plate. A machine learning approach is adopted based on artificial neural networks. The basic data used for diagnostic purposes are Lamb wave time histories for waves transmitted across the plate and thus scattered by any damage. Simulated Lamb wave signals have been used to extract scalar damage indices thus generating a database of numerical experience, describing the sensitivity of the selected feature to crack damage in different positions and with various extents. After verification and validation of numerical experience, damage indices from different paths across the plate are assembled into a feature vector which is used as the basis for two neural network regressors (one for localisation, the other for quantification). The optimisation of the algorithm structure is a crucial aspect, especially when a model which is trained on simulated experience has to generalise on real data. The strategy for network training adopted here is that many networks are trained for both the location and severity assessment and they are then assembled into a *committee* structure. A statistical procedure for the selection of the best performing network structure has been used, based on *Analysis of Variance*. Then, a method inspired by *Information Gap Theory* and based on *interval arithmetic* has been used to propagate uncertainties through the network, with the aim of appreciating the sensitivity to input variations. The system performance has finally been validated with real experimental Lamb wave signals. The main objective of the paper is to show a realistic case study where the data-based approach is enhanced by the availability of a physics-based model that can be used to generate training data. The main outcome of this study is the definition of a methodology for the robust design, verification and validation of a hybrid data/model-based SHM system.

The layout of the paper is as follows: a brief introduction to Lamb wave signal modelling and a summary of the proposed diagnostic methodology steps are reported in Sections 2 and 3 respectively. The experimental setup is described in Section 4. Lamb wave modelling and validation are explained in detail in Section 5, while the diagnostic algorithm structure definition and training are described in Section 6, where a method for the evaluation of network robustness in the simulated environment is also adopted. Finally, a description of the test results when real experimental data are processed into the diagnostic algorithms is presented in Section 7, which is followed by a conclusions section.

2. Elastic Lamb wave propagation modelling

Some basic principles necessary to understand the theory behind the analytical and numerical models for Lamb wave propagation are reported in this section. It is not the purpose of the present paper to explain in detail the mathematics