

Methodologies of Damage Identification Using Non-Linear Data-Driven Modelling

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INTRODUCTION

Manufacturers are required to design and construct safe, ecological and reliable structures, which are still cost effective. In order to guarantee these requirements, especially in industries where the component reliability is crucial, regular inspection intervals must be defined. Common techniques are visual inspections, magnetic particle testing, dye penetrant testing, eddy current inspection, radiography, infrared/thermal testing and standard ultrasonics.

As traditional inspection techniques can be very expensive in terms of both man hours and structure down-time, the development of suitable automatic and reliable monitoring methods, which can be used on demand, would be very valuable. This requires techniques which can monitor the given structure either continuously or in fixed intervals and can provide suitable early warning before a propagating damage reaches the limits of criticality. Here is the place where structural health monitoring systems enter into play.

To perform these tasks, a monitoring system should decide autonomously whether the host structure is damaged or not. On that account, this article describes the theoretical background and methodology of a novel data driven approach based on scale-frequency analysis, multiway hierarchical nonlinear principal component analysis (h-NLPCA), squared prediction error statistic (SPE) and self-organizing maps (SOM) for the detection and classification of damage in structures. The application of this approach is described in detail in chapter “Damage Identification using Non-linear Data-Driven Modelling – Application.”

This article contains the theory of the proposed method and is organized as follows. First, the theoretical background introducing the basic concepts of structural health monitoring and the evaluated signal processing techniques are presented. Afterwards the proposed methodology is described in detail including the application of the introduced signal processing techniques. Finally, concluding remarks are given in the last section.

THEORETICAL BACKGROUND

Structural health monitoring (SHM) can be defined as the process of implementing a damage identification strategy for a variety of infrastructures (Farrar & Worden, 2007). The main difference between SHM and non-destructive testing (NDT) techniques is that sensors are permanently installed on the structure providing continuous or on-demand measurements. According to (Rytter, 1993), SHM can be considered as a four-levels process which are defined in hierarchical order as follows:

- **Detection:** Provides a qualitative indication of the presence of damage.
- **Localisation:** Provides information about the position of the damage.
- **Assessment:** Provides a quantitative indication of the extent of the damage.
- **Prediction:** Provides an estimate of the residual life of the structure.

The advantages of using an SHM system are clearly an improved safety, reduction of inspection time, maintenance costs and structural down-time. There exist a number of techniques used for the identification of damage.

Vibration-based damage detection relies on the fact that changes in the physical properties due to damage will cause changes in the measured dynamic response of the structure (Fritzen, 2005), causing a shift of the dynamic characteristics like eigen-frequencies, damping coefficients and mode shapes (Fritzen, Mengelkamp, & Guemes, 2003). The advantage of these methods is that bigger changes in the structures can be detected very precisely with only a small number of sensors (Kraemer, 2011). Nevertheless, these changes are very small and often embedded in the background noise. For these reasons, approaches based solely on signal analysis are very attractive for the development of an automated health monitoring system (Worden, Staszewski, & Hensman, 2011). In damage detection based on the electro-mechanical impedance method, changes in impedance indicate possible damage (Peairs, Park, & Inman, 2004). Methods based on guided waves are used either as passive or active sensing techniques. These approaches are very interesting since guided waves

can propagate over long distances making it possible to detect flaws over a considerable area (Moll, 2011). However, more than one propagating mode is usually contained in the recorded ultrasonic signals which are additionally frequency and angular dispersive, i.e. characteristics such as velocities, attenuation and energy concentration vary according to these parameters. These effects make the analysis of guided waves a non-trivial task. Nevertheless, these techniques have emerged as prominent options in order to estimate the presence, location, and in a more sophisticated level estimate the severity and type of damage. The advantages and potentials from guided wave-based methods mentioned in the previous paragraphs have motivated the selection of the guided waves solely based on acousto-ultrasonic wave signal analysis for the purpose of damage identification presented in this article.

The acousto-ultrasonics (AU) technique was originally developed in the late seventies as a non-destructive tool for the evaluation of the mechanical properties of composite materials (Vary & Bowles, 1979). Once the ultrasonic wave is introduced into the structure, the characteristics of the wave after it has propagated through the structure may be related to a discontinuity of the structure. The structural discontinuity could come from the interaction of the guided waves either with damage in the structure or with a structural component or boundary. To be able to distinguish between damage and other structural features such as rivets, ribs, stiffeners, etc. a baseline signal obtained for the healthy state is stored so that it can be used as reference for comparison with the future test cases. Finally, damage sensitive features are extracted from the recorded signals using specialised signal processing algorithms, before pattern recognition techniques are used to detect and possibly classify and estimate the severity of damage.

The recorded signals are taken from the transducer network, as it is depicted exemplarily in Figure 1. A whole time series is recorded for all receiving transducers. In the approach three techniques are employed for signal processing: discrete wavelet transform to perform the extraction of a first set of features from the signal collected from the sensors, hierarchical Nonlinear Principal Component Analysis to build the statistical model and self-organizing maps to perform the detection and classification of the damages; all these methods are explained in the following subsections.

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