A Pattern Recognition Approach for Damage Detection and Temperature Compensation in Acousto-Ultrasonics

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ABSTRACT

The global trends in the construction of modern structures require the integration of sensors together with data recording and analysis modules so that their integrity can be continuously monitored for safe-life, economic and ecological reasons. This process of measuring and analysing the data from a distributed sensor network all over a structural system in order to quantify its condition is known as structural health monitoring (SHM). Guided ultrasonic wave-based techniques are increasingly being adapted and used in several SHM systems which benefit from built-in transduction, large inspection ranges, and high sensitivity to small flaws. However, for reliable health monitoring, much information regarding the innate characteristics of the sources and their propagation is essential. Moreover, any SHM system which is expected to transition to field operation must take into account the influence of environmental and operational changes which cause modifications in the stiffness and damping of the structure and consequently modify its dynamic behaviour. On that account, special attention is paid in this paper to the development of an efficient SHM methodology where robust signal processing and pattern recognition techniques are integrated for the correct interpretation of complex ultrasonic waves within the context of damage detection and identification. The methodology is based on an acousto-ultrasonics technique where the discrete wavelet transform is evaluated for feature extraction and selection, linear principal component analysis for data-driven modelling and self-organizing maps for a two-level clustering under the principle of local density. At the end, the methodology is experimentally demonstrated and results show that all the damages were detectable and identifiable.

KEYWORDS : *Damage Detection, Acousto-Ultrasonics, Signal Processing, Pattern Recognition, Wavelet Transform, Principal Component Analysis, Self-Organizing Maps, Temperature Compensation.*

INTRODUCTION

The well-known properties of guided ultrasonic waves have led to a burst of studies using Lamb waves for the detection and analysis of defects in structures. Nevertheless, in reality, structures are susceptible to varying environmental and operational conditions which affect the measured signals. It is well known that temperature as well as damage can have similar effects on the dynamic behaviour of a structure [1]. These environmental and operational changes of the system can often mask slight changes in the structural dynamic responses caused by damage and covert the damage detection step into a very complex process. Therefore, it is very important to understand the impact of these changing conditions and take them into account. For example, Fritzen et al. [2] modified an existing subspace-based identification method with temperature compensation for damage diagnosis. Moll et al. [3] studied the compensation of environmental influences using a simulation model and a laboratory structure. Buethe et al. [4] evaluated self-organizing maps in order to distinguish between environmental changes and damage of within a structure so that false alarm minimization could be accomplished under changing environmental conditions. Torres and Fritzen [5] presented theoretical developments, numerical and experimental results in order to analyze the effects of all the aforementioned sources of variability on wave propagation velocities, directionality and attenuation. This contribution extends previous works from the authors in the field of damage detection and classification [6-7]. On that account, this paper is concerned with the experimental validation of a data-driven structural health monitoring methodology where a damage detection and classification scheme based on an acousto-ultrasonic (AU) approach is followed. The layout of this paper is as follows. In the first part, an analysis of the effects of variable temperature and operation conditions on wave propagation is shown. The second part introduces the required background for understanding the proposed algorithms and methodology for damage detection. The third part presents the analysis together with the discussion of the results. Finally, concluding remarks are given in the last part.

1 GUIDED WAVE SENSITIVITY ANALYSIS

Several studies regarding the effects of temperature variability on the measured dynamic responses of structures have shown that temperature variation may change the material properties of a structure [8]. Additionally, factors such as material age effect, moisture content and structure operation affect significantly the wave propagation characteristics in the material. In order to depict the changes introduced by these effects, a CFRP plate made of 4 equal layers with a total thickness of 1.7*mm* and stacking of [0° 90° 90° 0°] was studied. Temperature tests were conducted in a temperature-controlled oven. During the test runs the temperature was raised stepwise up to T=60 ± 2°*C*. Figure 1(a) shows the structure with dimensions 200*mm*×250*mm*. Nine piezoelectric transducers PIC151 from PI Ceramics were attached to the surface of the structure. The excitation voltage signal (at P_5) was a 12*V* Hann-windowed toneburst with a carrier frequency of 30*kHz* with 5 cycles. Figure 1(b) shows that the shape of the signal changes significantly due to the wet surface influence. The influence of the variation in temperature also causes a change of structural dynamics. The dynamic response signal of sensor number two and three decreased monotonically in peak-to-peak magnitude with increasing temperature (Figure 1(c)). Interestingly, the inverse effect was seen in sensor number one. The reason of these time-shifts is both thermal expansion and changes in wave velocities with temperature. The attenuation of Lamb wave can be regarded to both wave dispersion as a result of frequency dependent phase velocities and attenuation loss due to frequency/temperature dependent material damping.

2 ALGORITHMS AND METHODOLOGY FOR DAMAGE DETECTION

The system is based on a distributed array of permanently attached piezoelectric transducers where pairs of transducers are used in pitch–catch configuration. The dynamic responses collected from an actuation step are stored and then pre-processed by the discrete wavelet transform (DWT), as a feature extraction technique, in order to calculate coefficients representing valuable time and frequency information from these responses. This procedure is repeated for all actuation steps and for all environmental conditions over a temperature range of these changing conditions. The DWT analysis is performed by means of a fast, pyramidal algorithm related to a two-channel subband coding scheme using a special class of filters called quadrature mirror filters as proposed by Mallat (see Figure 2) [9]. The optimum number of level decompositions is determined based on a minimum-entropy decomposition algorithm. The family of Daubechies wavelets ('db8') was chosen for this study. The approximations coefficients are taken here since they represent the interesting dynamics of the recorded waveforms and the detail coefficients will be considered as high-frequency noise.

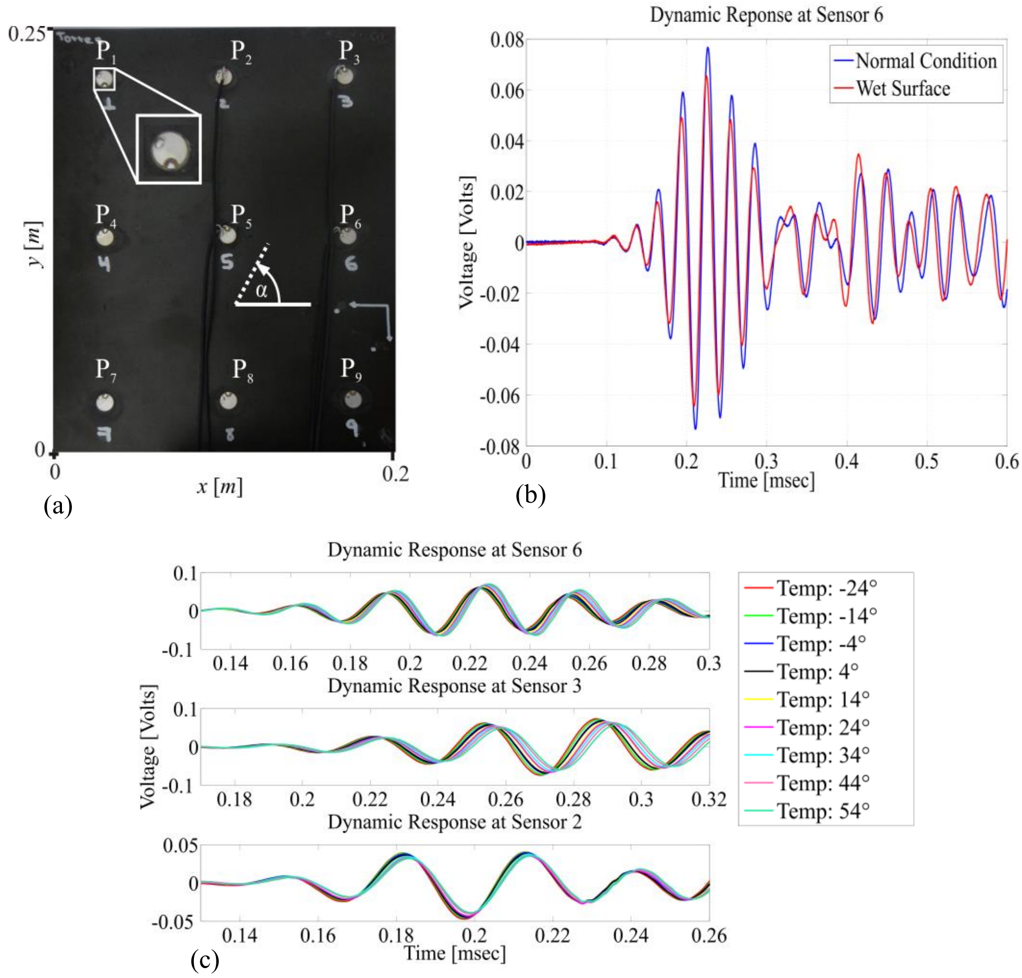

Figure 1. EOC Influences: (a) Experimental Setup, (b) Wet Surface Effect, (c) Temperature Effects on Wave Directionality.

Afterwards, the coefficients for each actuation step are fused following unfolding procedures (multiway) as it is done in multivariate statistical procedures for monitoring the progress of batch processes. This sensor data fusion procedure is depicted in Figure 3. Finally, the fused coefficients are used to build a data-driven model based on Principal Component Analysis (PCA) [10]. When new structural responses are available (from an unknown state), DWT approximation coefficients are extracted and projected into the respective models by each actuation step. Finally, by retaining a certain number of principal components, squared prediction error (SPE) measures for all the actuation steps are calculated and used as input feature vectors for a self-organizing map (SOM) for the detection and identification tasks [11]. In order to calculate the number of clusters inside the data and provide a way for damage classification, a simultaneous two-level clustering approach using SOM is evaluated [12]. Within this approach the structure of the data and its segmentation is learnt at the same time by using both distance and density information. The clustering algorithm assumes that a cluster is a dense region of objects surrounded by a region of low density.

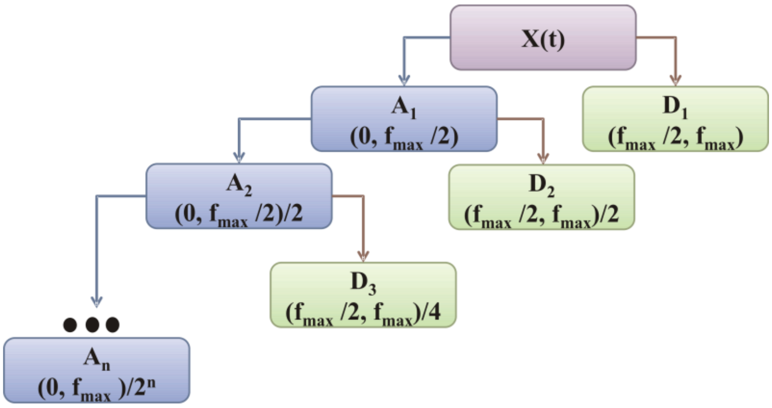

Figure 2. Discrete wavelet transform decomposition tree.

This approach is very effective when the clusters are irregular or intertwined, and when noise and outliers are present. The proposed clustering algorithm, called the DS2L-SOM algorithm (Density-based Simultaneous Two-Level - SOM) divides automatically a given dataset into a collection of subsets (clusters representing the pristine and damaged structural states) and the number of clusters is determined automatically during the learning process, i.e., no a priori hypothesis for the number of clusters is required [13].

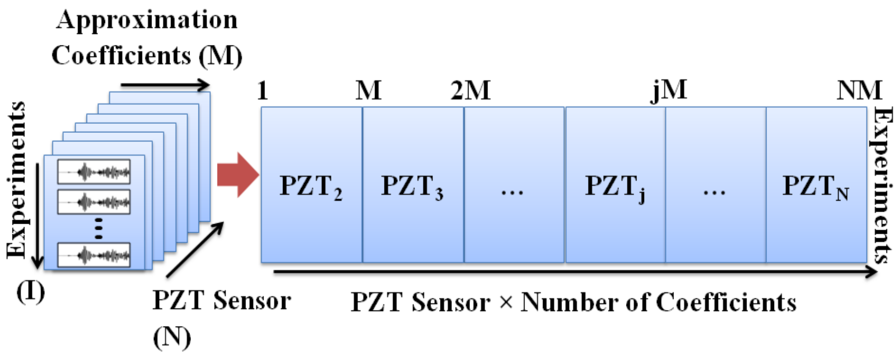

Figure 3. Unfolding procedure for sensor data fusion.

3 EXPERIMENTAL SETUP AND RESULTS

A fully independent experiment was performed in order to evaluate the practical performance of the proposed methodology. The experiment used pairs of transducers operating in pitch-catch mode. The input signal to the actuators was generated using the arbitrary signal generation capability of a combined signal generator and oscilloscope instrument manufactured by TiePie Engineering, Holland. The time histories were digitized at a sampling frequency of 50 MHz and transferred to a portable PC for post-processing. The structure is a simplified aircraft composite skin panel made of carbon fibre reinforced plastic (CFRP) depicted in Figure 4.

The overall size of the plate is approximately 500×500×1.9mm and its weight is about 1.125 kg. The stringers are 36mm high and 2.5mm thick. The plate and the stringers consist of 9 plies.

Damage on the multilayered composite plate was simulated by placing magnets with different masses at the same position (see Figure 4) on the structure as artificial damage in four increasing steps of 0.024 kg. Temperature was varied from 35°C to 75°C in steps of 10°C for a total of five temperature levels. The excitation voltage signal is a 12V Hanning windowed cosine train signal with 5 cycles and carrier frequency of 50kHz. In a first step, all the collected baseline signals were processed by means of the DWT (a 8th level was found to be the optimum in all experiments), fused and presented to the DS2L-SOM algorithm in order to depict the changes introduced by the changing temperature.

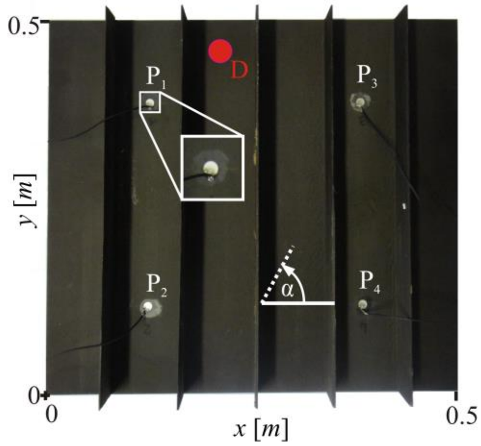

Figure 4. Experimental Setup: Stiffened Composite Panel.

To find the optimal map size, a control run is repeated by hanging the map size for all the experiments here. As it can be seen from Figure 5(a) and 5(b), all the temperature levels were properly separated and distinguished. The U-Matrix, showing the average distance of a cell to its neighboring cells, allowed depicting the difference between the different formed clusters.

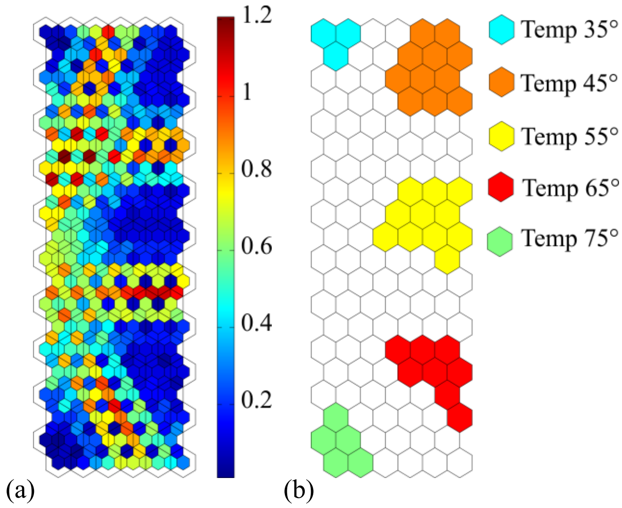

Figure 5. All baselines presented to the DS2L-SOM algorithm: (a) U-Matrix and (b) DS2L-SOM cluster map.

This result is of special attention in baseline-based methods where the detection and characterization of damage is performed normally by means of metric indices by comparison of two dynamic response signatures what can lead to trigger a false alarm for damage detection just because of a change in environmental conditions. For the second experiment, four damage evolution steps were simulated using a local mass increase as it was defined before (all damages at 35°*C*).

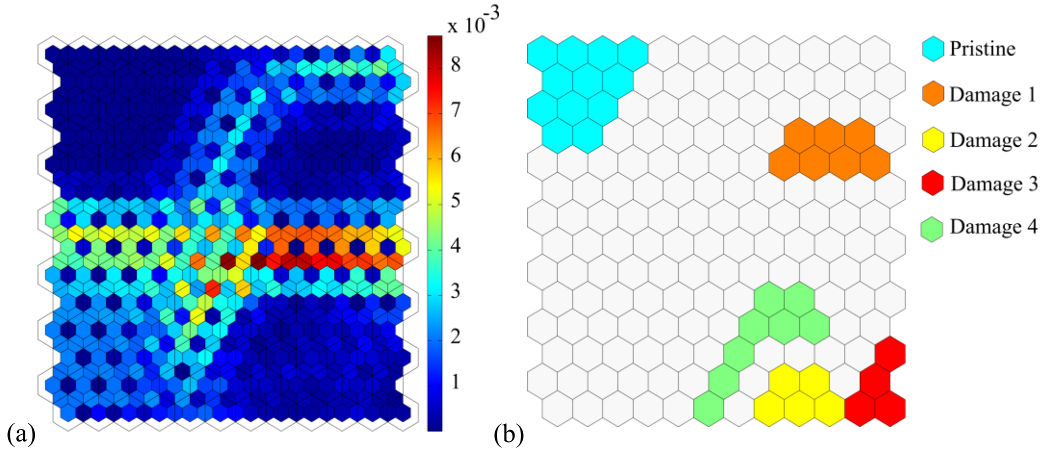

Figure 6. Damage detection with baseline models built with all the temperature range (35°C-75°C): (a) U-Matrix and (b) DS2L-SOM cluster map.

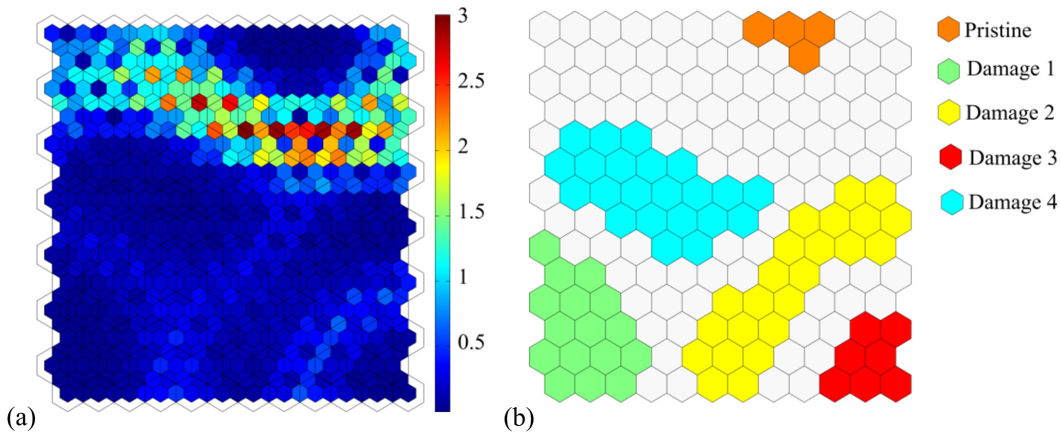

Figure 7. Damage detection with baseline models built with the same temperature level (only 35°C): (a) U-Matrix and (b) DS2L-SOM cluster map.

Additionally, the baseline models are built with all the data coming from the different temperature conditions. A review of the variances retained in the components was performed in order to define the optimal number of components required for building the PCA models from the pristine structural condition. It was found that the first three hundred components included around 95% of the total variance into the reduced models for each actuation step. As it is depicted in Figure 6(a) and (b), all the damaged states were not only separated from the pristine condition but also between them. Nevertheless, due to the big amount of data used for building the baseline models, a huge number of retained components (almost all) are required for obtaining an accurate approximate model. In order to depict how this effect could be mitigated, new models are built just with baseline measurements lying in the range where damage records were taken, i.e. around $35°C$. In this case, it was found that the first thirty components included around 95% of the total variance into the reduced models for each actuation step. Figure 7(a) and (b) show, that here again, the proposed methodology was capable of separating all the damage cases from the pristine condition with the additional advantage of using a much more compact and reduce model in comparison to the previous example. These results pose the requirement of improving the proposed methodology by following an approach for optimal baseline selection and compensation of the recorded signals.

4 CONCLUSIONS

The goal of this study was to illustrate and develop a methodology to counterbalance the effects of environmental sources of variability on the performance of baseline data-driven models within the context of structural health monitoring systems and damage detection algorithms. The proposed methodology proved being effective in the detecting and classifying the different structural states under different temperature conditions. The approach includes the combination of Discrete Wavelet Transform, Multi-Way Principal Component Analysis, Squared Prediction Error measures and Self-Organizing Maps. Future work will involve the improvement of the proposed methodology by including more advanced techniques for temperature compensation.

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