Damage Assessment in a Stiffened Composite Panel Using Non-Linear Data-Driven Modelling and Ultrasonic Guided Waves

Miguel Angel TORRES-ARREDONDO*, Diego Alexander TIBADUIZA**,
Luis Eduardo MUJICA**, Jose RODELLAR**,Claus-Peter FRITZEN*
* University of Siegen, Centre for Sensor Systems (ZESS), Institute of Mechanics and Control Engineering-Mechatronics, Paul-Bonatz-Strasse 9-11, 57076 Siegen, Germany
Contact: {torres, fritzen}@imr.mb.uni-siegen.de
** Universitat Politècnica de Catalunya-BARCELONATECH, Department of Applied Mathematics III, Comte d'Urgell 187, 08036 Barcelona, Spain
Contact: {diego.tibaduiza, luis.eduardo.mujica, jose.rodellar}@upc.edu

Abstract. Structural components made of composite materials are being used more often in aerospace and aeronautic structures due to their well-known properties such as high mass specific stiffness and strength. However, their application also increases the analysis complexity of such structures. Structural health monitoring (SHM) systems for these structures aim to determine the status of the system in real time such that a longer safe life and lower operational costs can be guaranteed. On that account, this paper is concerned with the experimental validation of a structural health monitoring methodology where a damage detection and classification scheme based on an acousto-ultrasonic (AU) approach is applied to a composite panel incorporating stiffening elements using a piezoelectric active sensor network in conjunction with time-frequency multiresolution analysis and non-linear feature extraction. Therefore, structural dynamic responses from the simplified aircraft composite skin panel are collected and signal features are then extracted with a signal processing and data fusion methodology in terms of the wavelet transform technique and hierarchical non-linear principal component analysis. A critical comparison with linear feature extraction methods indicates that the proposed method outperforms the traditional linear methods for the purpose of damage classification. Additionally, results show that all the damages were detectable and classifiable, and the selected features proved capable of separating all damage conditions from the undamaged state.

1. Introduction

Many modern structures are constructed with polymer matrix composites which make use of the high stiffness and strength to weight ratio of glass and carbon fibres. These characteristics have made composite materials gain an extensive acceptance within energy, automotive, marine and aerospace industries since extremely lightweight components and structures with excellent mechanical properties could be designed and constructed [1]. Nevertheless, one key shortcoming of composite materials is their susceptibility to damage. For example, it is well-known that low-velocity impact on fibre-reinforced laminated composites can cause significant damage in terms of matrix cracks and delaminations, which are embedded inside the composites, causing a severe degradation of the load-carrying capability of the structures [2-3]. The presence of damage or deterioration in a structure causes changes in the natural frequencies of the structure [4]. Damage occurrence is normally given by an abnormal loss of stiffness when the measured natural frequencies are substantially lower than expected. An alternative way of reducing the frequencies might be to locally increase mass. Following this idea, damage is simulated in the present work by adding masses at localized points. As previously mentioned, the extensive use of composite materials has increased the need for efficient methodologies to inspect their structural condition in a nonintrusive way and on a real-time basis [5]. The objective of this work is to propose a structural health monitoring (SHM) methodology by using a network of piezoelectric transducers to excite and record information on the structural condition and inform the user of the presence of any damage. A combination of time-frequency analysis, auto-associative neural networks for data-driven system modelling, squared prediction errors and self-organizing maps is developed to automate a damage detection and identification problem here. The problem is treated as one of pattern recognition. The paper describes a fundamental study using a laboratory experiment in which the proposed methodology is evaluated. Results show that all damage conditions can be separated from the undamaged state. The layout of this paper is as follows. In Section 2, the methodology for damage detection and classification is introduced. The required background for understanding the proposed algorithms is described in Section 3. Section 4 presents the analysis together with the discussion of the results. Finally, concluding remarks are given in the last section.

2. Description of the Methodology

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 each 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. 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 [6]. 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.

For the current specific application of interest, auto-associative neural networks (h-NLPCA) will be trained independently using the calculated DWT approximation coefficients extracted from the healthy system in order to build the models. However, before training the network, the data gathered in each actuation step are fused following unfolding procedures (multiway) as it is done in multivariate statistical procedures for monitoring the progress of batch processes [7-8]. Finally, the fused data are presented as inputs/outputs to the networks for training. Ultimately, when new structural responses are available (from an unknown structural state), the DWT coefficients are extracted and then projected into the respective models to obtain the model scores. As a first step, an outlier analysis is performed for every actuation phase after collecting all the structural dynamic responses from the healthy and damaged states by evaluating both the principal component analysis (PCA) and hierarchical non-linear principal component analysis (h-NLPCA) from the DWT approximation coefficients as feature selection procedures. The outlier analysis allows to identify observations that appear inconsistent with the rest of the data. Therefore, it is possible to identify data being generated by an alternate mechanism rather than that of the baseline data, i.e. the damaged states. In our case, the novel index measure is taken as the squared prediction error (SPE). It measures the variability that breaks the normal process correlation, which often indicates an abnormal situation [9]. If the new data are characteristic of the healthy structural state, then these data are reproduced accurately at the output of the network and the SPE will be very close to zero. Otherwise, a non-zero value will indicate an abnormality which could be related to a damage condition. Nevertheless, a threshold on the index must be defined in order to provide a statistical analysis. In the absence of damage, the outlier statistics values for the current data should thus remain at the same level as for the baseline data. On the other hand, structural damages should cause an increase in the outlier statistics of the damaged state. In a second step, the calculated Scores together with squared prediction error measures for all actuation steps are presented as input feature vectors to a Self-Organizing Map (SOM) for the detection and classification tasks. This is again accomplished for the PCA and h-NLPCA analysis. For completeness, a brief theoretical background of the proposed algorithms is presented in the following subsections.

3. Description of the Proposed Algorithms

The following two subsections will introduce a brief theoretical background for the understanding of the processing algorithms used and evaluated in this study.

3.1 Hierarchical Non-Linear Principal Component Analysis

This technique is based on a multilayered perceptron (MLP) architecture with an auto-associative topology. As with the traditional non-linear principal component analysis (NLPCA), the network is performing an identity mapping where the output is forced to equal the input with high accuracy. In order to compress the data, there is a bottleneck layer in the middle with fewer units than the input and output layers forcing the data to be projected into a lower dimensional representation (see Figure 1). Note that the nodes in the mapping and de-mapping layers must have nonlinear transfer functions; nonlinear transfer functions are not necessary in the bottleneck layer. With the purpose of guaranteeing that the calculated nonlinear components have the same hierarchical order as the linear components in standard principal component analysis (PCA), and in contrast to standard NLPCA, the reconstruction error is controlled by searching a k dimensional subspace of minimal mean square error (MSE) under the constraint that the (k-1) dimensional subspace is also of minimal MSE [10]. This procedure is repeated for any k-dimensional subspace where all subspaces must be of minimal MSE. It is expected that h-NLPCA will describe the data with greater accuracy and/or by fewer factors than PCA, provided that there are sufficient data to support the formulation of more complex mapping functions [11].

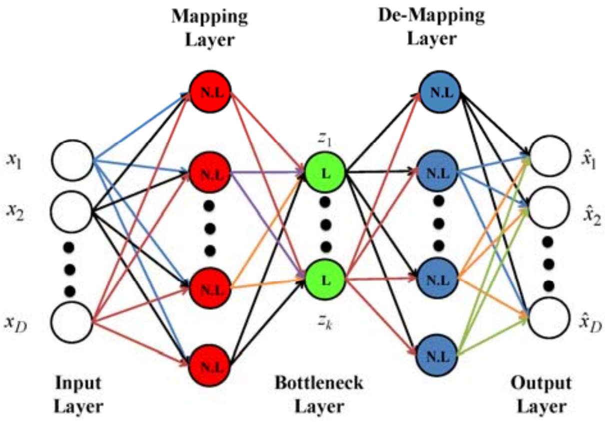

Figure 1. Network Architecture for h-NLPCA.

3.2 Self-Organizing Maps

A Self-Organizing Map (SOM) is a special form of un-supervised Artificial Neural Network (ANN) converting the relationships between high-dimensional data into simple geometric relationships of their image points on a low dimensional display [12]. This type of network has the special property of generating one organized map in the output layer based on the inputs allowing the grouping of the input data with similar characteristics into clusters. In order to aid the user in understanding the cluster structure, additional visualization techniques such as the U-Matrix, cluster connections, or local factors have been developed. The U-Matrix, showing the average distance of a cell to its neighbouring cells, will be used in this study in order to depict the difference between the different formed clusters.

4. 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. To ensure a good signal to noise ratio each signal was averaged 100 times. The structure is a simplified aircraft composite skin panel made of carbon fibre reinforced plastic (CFRP). 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. The structure is depicted in Figure 2. Damage on the multilayered composite plate was simulated by placing magnets with different masses at random orientations on the structure as artificial damage. Table 1 outlines the coordinates for the simulated damage on the structure. The excitation voltage signal is a 12V Hanning windowed cosine train signal with 5 cycles and carrier frequency of 50kHz. As previously mentioned, an outlier analysis is performed first using standard PCA and h-NLPCA. A review of the variances retained in the components was performed in order to define the optimal number of components required for building the models from the pristine structure condition. For this purpose, standard PCA was performed first. It was found that the three first components included around 80% of the variance into the model. This previous analysis is important in order to ensure that enough variance is retained in the model that allows performing an optimal reduction.

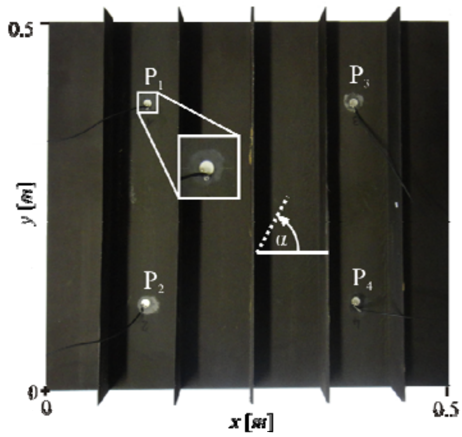

Figure 2. Simplified Aircraft Composite Skin Panel.

Table 1. Damage Locations in the Simplified Aircraft Composite Skin Panel.

Damage Number	Located between the PZTs number	Structure: CFRP Composite plate	
		x position (mm)	*y* position (mm)
1	1-3	208.25	400
2	1-3	291.55	400
3	3-4	374.55	250
4	2-4	291.55	100
5	2-4	208.25	100
6	1-2	124.95	250

A similar analysis was performed for each actuation step and finally, three components were selected as a good representation of the input data for the h-NLPCA as well. This a reasonable option since it is expected that h-NLPCA will describe the data with greater accuracy and/or by fewer factors than standard PCA. In this work, the threshold is calculated from the baseline data. It is adjusted to $\mu+\alpha\sigma$, where μ is the mean value and σ is the standard deviation value of the novelty index over the baseline, i.e. the undamaged structure. The factor α controls the degree of confidence. The confidence level is defined to be 99.99% in this study. It is good to bear in mind that there is an implicit assumption here that the statistics of the novelty index are Gaussian or near-Gaussian distributions. The results by applying PCA and outlier analysis as explained before show that damage can be separated from the pristine state using only the first three linear components for all the actuation steps (see Figure 3(a)-(d)). Nevertheless, it can also be observed that the different simulated damages cannot be clearly distinguished by just using the novelty index. Additionally, one can notice how the first two actuation steps (actuation for transducer one and two) provide a more compact representation of the novelty index in which this value is concentrated in a well-defined cloud around the value of one. This is not case for the last two actuation steps (actuation for transducer three and four) where a clear higher deviation of the novelty index around the value of one is present. The explanation for this effect is

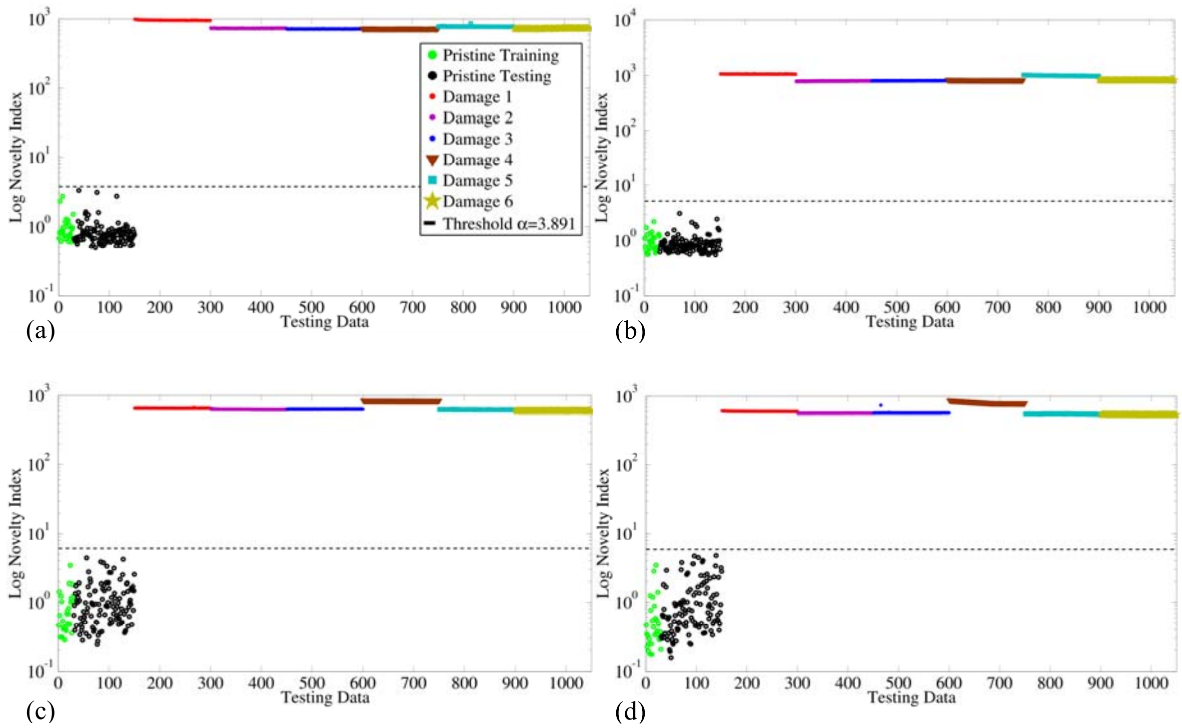

Figure 3. Outlier Analysis by means of PCA : (a) Actuator 1, (b) Actuator 2, (c) Actuator 3, (d) Actuator 4.

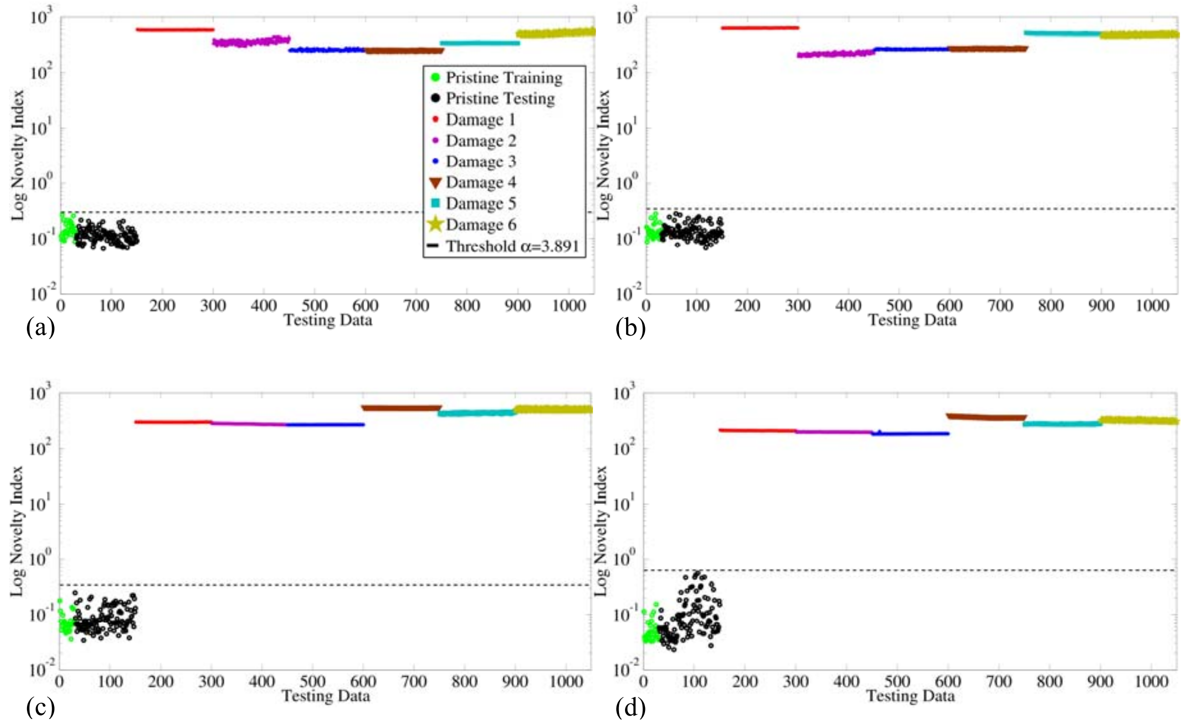

Figure 4. Outlier Analysis with h-NLPCA: (a) Actuator 1, (b) Actuator 2, (c) Actuator 3, (d) Actuator 4.

not clear and require further study. However, theoretically, one would expect to obtain a similar behaviour in all the actuation steps due to the geometrical symmetry of the structure. Following the outlier analysis with the help of h-NLPCA, the results are similar to the ones obtained by applying PCA. In this case again, damage can be separated from the pristine state using only the first three nonlinear components for all the actuation steps (see Figure 4(a)-(d)). However, the distribution of the novelty index value seems to be relatively better concentrated around the value of one in almost of the actuation steps. Nevertheless, there seem to be almost no considerable differences between both algorithms for the outlier analysis results. One disadvantage of using the outlier analysis is that, even when unfolding procedures are taken and the sensor data are fused, the information from all the actuation steps (models) must be analyzed independently. This is not the case for the methodology proposed in the previous section of this paper. The advantage of the proposed methodology is the ability to fuse all the information contained in the different actuation steps for the analysis rather than just analyzing each actuation step one by one. The results obtained applying the proposed methodology with help of PCA, SPE measures and SOM are presented in Figure 5.

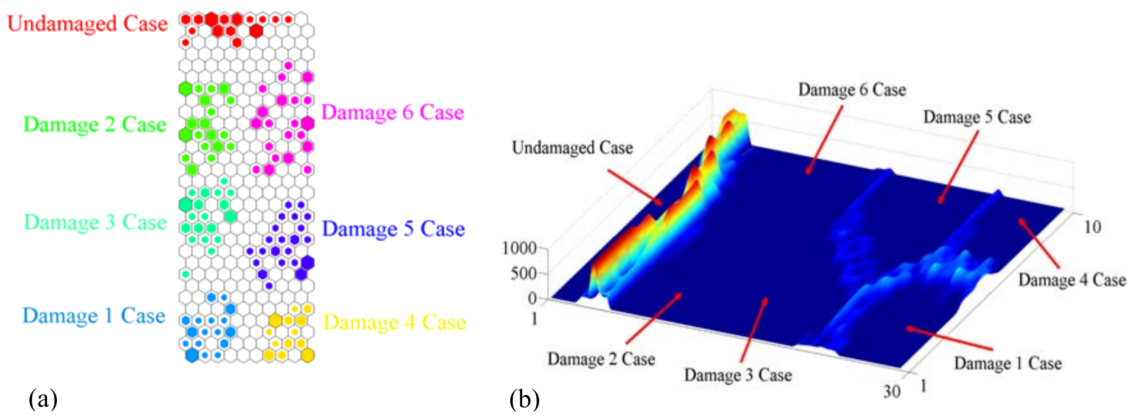

Figure 5. Analysis with fused PCA, SPE and SOM: (a) Cluster Map and (b) U-Matrix Surface.

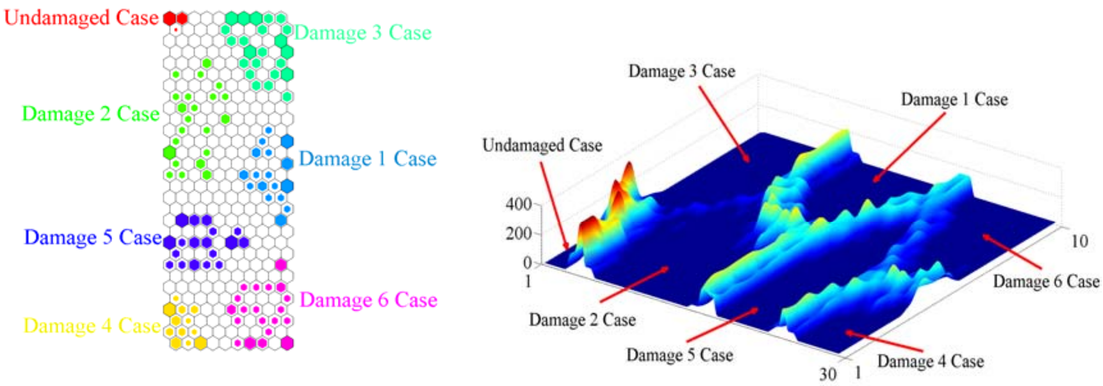

Figure 6. Analysis with fused h-NLPCA, SPE and SOM: (a) Cluster Map and (b) U-Matrix Surface.

The SOM training algorithm used here is implemented in a Matlab®-Toolbox created by [13]. To find the optimal map size, a control run is repeated by changing the map size. In order to accomplish the selection of the optimal map size, two quantitative measures of mapping quality known as the average quantization error (QE) and topographic error (TE) were analyzed. The QE is the average distance between each data vector and the best matching unit (BMU). The TE gives the percentage of the data vectors for which the first BMU and the second BMU are not neighbouring units. Lower QE and TE values indicate better mapping quality. As a result, a map size of 30×10 was defined. For the present study a hexagonal lattice is used. Different shapes such as sheet, cylinder or toroid can be chosen. For ease, a flat sheet shape is considered here. Additionally, a Gaussian neighbourhood function is used. Nonetheless, for a proper understanding of the figures, some properties of the U-Matrix must be discussed. Once the SOM has been trained, weight vectors of neurons with large U-values are very distant from other vectors in the input data space. Conversely, weight vectors of neurons with small U-values are surrounded by other vectors in the data space. The mountain-like surfaces formed on a U-Matrix define the cluster boundaries. Valleys on a U-Matrix point to cluster centres. The cluster maps in Fig. 5(a) can be used as a tool to show the different data set grouped with similar characteristics showing the clustering tendency. However, in this specific case, no clear cluster separation between all the damage scenarios can be identified in the corresponding U-Matrix surface (see Fig. 5(b)). This can be clearly seen since the simulated damages number two, three and six cannot be differentiated in the U-Matrix surface, i.e. mountain-like surfaces were not formed for allowing a separation between the damage types. Nevertheless, the undamaged state can be separated very well from the other simulated damage states. This result is sufficient if the objective is just to identify if the system departs from normal condition. However, if one wishes to address the problem of damage classification (identification), the obtained results cannot provide that much information about the damage type.

In a similar manner as the one discussed before, analysis are carried out by means of h-NLPCA, SPE measures and SOM. Figure 6(a) show the cluster map. In this case, seven clusters seem to have been well identified. This is the case for the U-Matrix surface as well. Additionally, the formed boundaries are more clearly depicted compared with the previous example. It is also visible that a more compact representation of the clusters with a lesser variance around the cluster centre is present for the undamaged scenario. In this case, the proposed methodology and algorithms seem to outperform the results obtained with the previous methodology based on standard principal component analysis. The main advantage of using the processing approach presented here is to provide robustness in the analysis by the use of data fusion using the projections obtained by each model together with the Square Prediction Errors measurements as inputs to a Self-Organizing Map.

5. Conclusions

An efficient way for detecting and classifying damages is presented in this work. The approach includes the combination of Discrete Wavelet Transform, Multi-Way Hierarchical Non-linear Principal Component Analysis, Squared Prediction Error measures and Self-Organizing Maps. The multiway extension of h-NLPCA proved to be very useful in systems involving several sensors since it allows building a model for the whole system instead of one by each sensor. Additionally, the fusion of all the actuation steps within the SOM permitted to take into consideration all the data avoiding the separate analysis for each actuation step. The results show that the proposed methodology outperforms the traditional outlier analysis using standard PCA in securing the separability of the data classes. Using the cluster map, the clustering tendency can be evaluated and the identification of the data set can be performed. However, the U-matrix surface allows to identify the sparser regions inside the map and evaluate the robustness of the clustering. The proposed methodology proved being effective in the detecting and classifying the different structural states. Nevertheless, it is assumed that reliable statistical models for the healthy condition are available. Future work will involve the use of Self Organizing Maps for analysing data under changing environmental and operational conditions. This will allow to provide a more critical comparison of the proposed methodology under more complicated scenarios.

Acknowledgement

The authors would like to express their gratitude to the Research School on Multi Modal Sensor Systems for Environmental Exploration (MOSES) and the Centre for Sensor Systems (ZESS) for sponsoring the research presented herein.

References

[1] Vasiliev, V.V. and E.V. Morozov, *Advanced mechanics of composite materials*. 2nd ed. Oxford: Elsevier, 2007.

[2] Choi, H.Y., R.J. Downs, and F.-K. Chang, *A New Approach toward Understanding Damage Mechanisms and Mechanics of Laminated Composites Due to Low-Velocity Impact: Part I - Experiments.* Journal of Composite Materials, 1991. **25**(8): pp. 993-1011.

[3] Choi, K. and F.-K. Chang, *Identification of Foreign Object Impact in Structures Using Distributed Sensors.* Journal of Intelligent Material Systems and Structures, 1994. **5**(6).

[4] Staszewski, W., C. Boller, and G.R. Tomlinson, *Health Monitoring of Aerospace Structures: Smart Sensor Technologies and Signal Processing*. Munich: Wiley, 2004.

[5] Salas, K.I. and C.E.S. Cesnik, *Guided wave structural health monitoring using CLoVER transducers in composite materials.* Smart Materials and Structures, 2010. **19**(1): pp. 015014.

[6] Mallat, S.G., *A theory for multiresolution signal decomposition: the wavelet representation.* IEEE Transactions on Pattern Analysis and Machine Intelligence, 1989. **11**(7): pp. 674-693.

[7] Nomikos, P. and J.F. MacGregor, *Monitoring batch processes using multiway principal component analysis.* AIChE Journal, 1994. **40**(8): pp. 1361-1375.

[8] Mujica, L.E., J. Rodellar, A. Fernandez, and A. Guemes, *Q-statistic and T2-statistic PCA-based measures for damage assessment in structures.* Structural Health Monitoring, 2010. **10**(5): pp. 539-553.

[9] Joe Qin, S., *Statistical process monitoring: basics and beyond.* Journal of Chemometrics, 2003. **17**(8-9): pp. 480-502.

[10] Scholz, M., *Approaches to analyse and interpret biological profile data.* PhD Thesis. Max Planck Institute of Molecular Plant Physiology, Potsdam University, 2006.

[11] Kramer, M.A., *Nonlinear principal component analysis using autoassociative neural networks.* AIChE Journal, 1991. **37**(2): pp. 233-243.

[12] Kohonen, T., *Self Organizing Maps*: Springer, 2001.

[13] Vesanto, J., J. Himberg, E. Alhoniemi, and J. Parhankangas, *SOM Toolbox for Matlab 5*. 2000, Helsinki University of Technology: Helsinki, Finland.