Damage Detection and Classification in Pipework Using Acousto-Ultrasonics and Probabilistic Non-Linear Modelling

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Abstract. Structural Health Monitoring (SHM) comprises several procedures such as data fusion, information condensation, feature extraction and probabilistic modelling for the detection, localization, assessment of defects and prediction of remaining life time in civil, aeronautic and aerospace structures. The monitoring system should decide autonomously whether the host structure is damaged or not. On that account, this work proposes a novel approach based on time-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 pipework. The formalism is based on a distributed piezoelectric sensor network for the detection of structural dynamic responses where each sensor acts in turn as an actuator. In a first step, the discrete wavelet transform (DWT) is used for feature selection and extraction from the structural dynamic responses at different frequency scales. Neural Networks are then used to build a probabilistic model from these features for each actuator with the data from the healthy structure by means of sensor data fusion. Next, the features extracted from the structural dynamic responses in different states (damaged or not) are projected into the probabilistic models by each actuator in order to obtain the non-linear principal components, and then the SPE metrics are calculated. Finally, these metrics together with the non-linear principal components are used as input feature vectors to a SOM. 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

Millions of pipelines are used today in residential, commercial and industrial environments for the transportation of water, gas, chemicals and petroleum derivatives. The ageing of such physical infrastructure and well-known problems such as corrosion, cracking and pitting defects require special monitoring and management measures for cost-saving and environmental reasons. Therefore, direct and reliable condition assessment of pipework is indispensable. The monitoring of these pipes may then provide valuable information if a pipeline must be repaired or rehabilitated, or if the pipeline truly needs to be replaced. While non-destructive evaluation (NDE) methods are state of the art for pipe inspection and

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monitoring, pipeline owners are recently moving towards structural health monitoring (SHM) technologies. One possibility in order to tackle the problem of damage detection is the use of ultrasonic guided wave propagation. The use of guided elastic waves for evaluating the structural integrity has been developed extensively for several decades leading to increased efficiency and sensitivity in comparison to other technologies [1-3]. Sensors are permanently attached to the structure, allowing the recording of baseline measurements to track changes in the structural dynamic time-traces that can potentially be related to structural damage. For example, Rizzo et al. used ultrasonic guided waves in a feature extraction and automatic classification framework. They built a six-dimensional damage index and fed it to an artificial neural network classifying the size and the location of a progressively increasing notch cut [4]. Brunner and Barbezat evaluated acoustic emission monitoring for leak detection in pipes for transport of liquid and gaseous media [5]. Demma et al. studied the reflection of guided waves from notches in pipes for interpreting corrosion measurements [6]. Lowe et al. studied the mode conversion of a guided wave by a part-circumferential notch in a pipe [7].

In this paper, a unique 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. 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 required background for understanding wave propagation in hollow cylinders is presented. The methodology and proposed algorithms are 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. Background for Guided Wave Propagation in Hollow Cylinders

The solutions of the equations of motion for hollow cylinders lead to three different classes of propagating modes [8]. These tube modes are designated as longitudinal, torsional and flexural modes. The modes are labelled L(0,m), T(0,m) and F(n,m), where n is the circumferential order and m the number of the mode [9]. These waves can then travel for long distances and their attenuation rate is much lower than that for bulk waves. Figure 1(a) shows the group velocity dispersion curves for a stainless steel pipe with an outer radius of 20mm and 2.15mm wall thickness. They represent the velocity of propagation of the wave energy. The normalized amplitude spectrum is also shown in order to depict the frequency bandwidth of the pulse excitation signal used in this study, i.e. toneburst with 5 cycles and carrier frequency of 180kHz. There are 40 modes in the frequency range up to 300 kHz. These are: L(0,1), L(0,2), T(0,1), F(n,1) for n ≤18, F(m,2) for m ≤12 and F(k,3) for k ≤7.

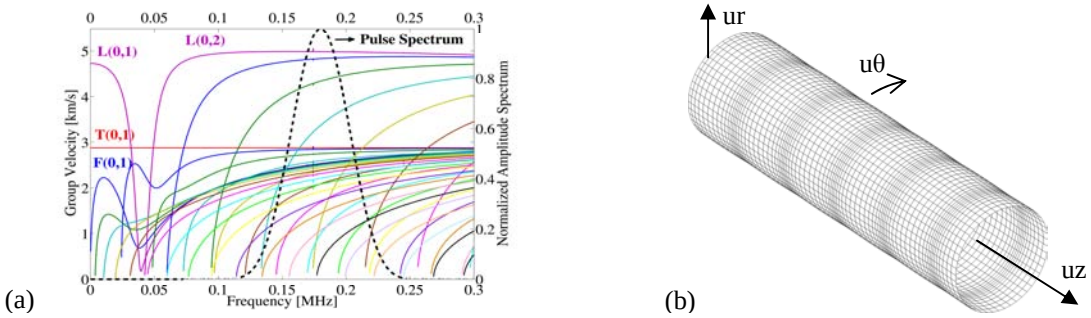

Figure 1. Guided Wave Dispersive Characteristics: (a) Group Velocity Dispersion Curves and Pulse Spectrum and (b) Mode Shape for the Longitudinal L(0,2) Mode at 180kHz.

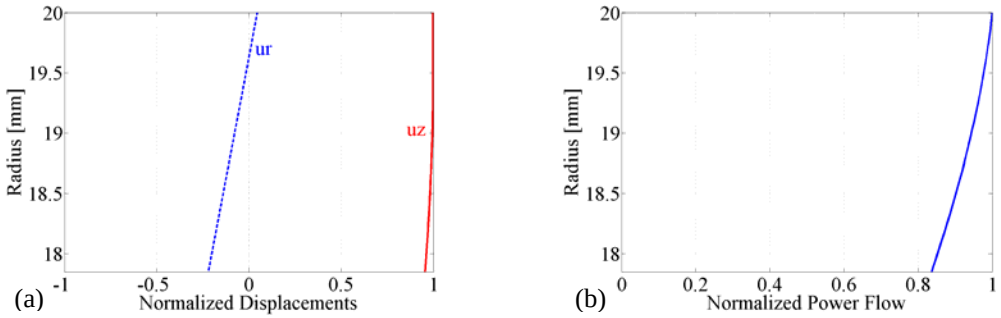

Figure 2. Behaviour of the Longitudinal L(0,2) Mode: (a) Displacement Fields and (b) Power Flow.

It is well-known that each of the possible excited modes will produce different deformation fields along the wall thickness i.e., the particle displacements and velocities as well as the stress and strain fields will all vary for each mode. Therefore, it is desired to select a mode with greater penetration power across the wall thickness in the pipeline. Previous works have shown that the second order longitudinal mode L(0,2) is very attractive to use for long-range testing since it is practically non-dispersive and it is also the fastest mode [10]. Additionally, this mode has more of its energy flow proportionally located across the wall thickness. For this reason, special attention was paid in order to excite this mode. In order to assure the selection of the mode, dispersive characteristics and energy distribution analysis was carried out [11]. As an example, the normalized displacement fields and power flow for the L(0,2) mode at a frequency of 180 kHz are shown in Figure 2 (see also Figure 1(b) for the 3-D Mode Shape).

3. Description of the Methodology and Algorithms

The presented methodology extends ideas presented by the authors in [3, 12]. 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 DWT 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 [13]. In this algorithm, the signal is analyzed at different frequency bands with different resolutions by decomposing the signal into a coarse approximation and detail information. The approximations represent the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components. 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 will be trained independently using both calculated DWT coefficients, i.e. details and approximations, extracted from the healthy baseline 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 [14-15]. 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 just evaluating the

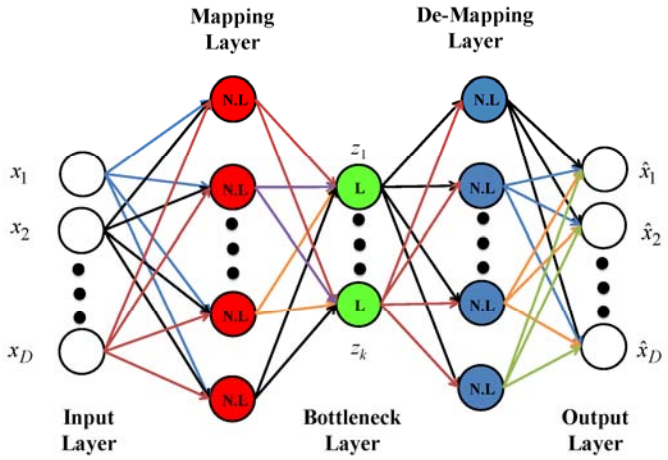

Figure 3. Network Architecture for h-NLPCA.

h-NLPCA from the DWT approximation coefficients. 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 [16]. 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 are presented as input feature vectors to a Self-Organizing Map (SOM) for the detection and classification tasks. For completeness, a brief theoretical background of the proposed algorithms is presented in the following subsections.

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 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 that forces the data to be projected into a lower dimensional representation (see Figure 3). 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 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 [17]. 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 [18].

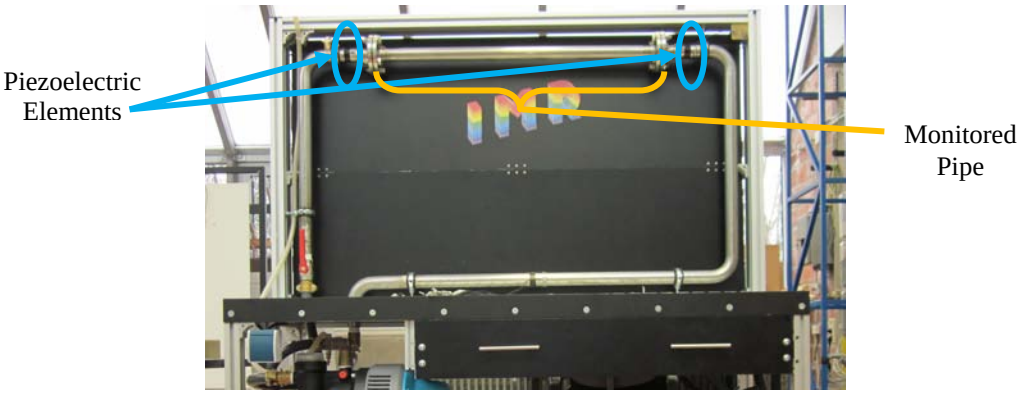

Figure 4. Experimental Setup.

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 [19]. 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 to evaluate the practical performance of the proposed methodology. Figure 4 depicts the experimental setup used for testing. Damage was introduced into the structure in several steps. It was executed as a cut with an angular grinder. The depth and its vertical extension are enlarged in four steps, starting with a cut of 0.75mm depth. This cut is increased in depth in a second step until the wall is almost penetrated, followed by an increase in vertical direction. Finally the pipe's wall is penetrated, increasing the depth in the middle of the former notch. The different states can be found in Figure 5. 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 HandyScope HS3 (a combined signal generator and oscilloscope instrument manufactured by TiePie Engineering, Holland). The receiver sensors are connected to the input channels of an auxiliary HandyScope HS4. The processing engine for transmitting the waveform signal and acquiring the dynamic responses was written in Matlab® 7.9 using the DLLs provided by TiePie Engineering running under Windows operating system.

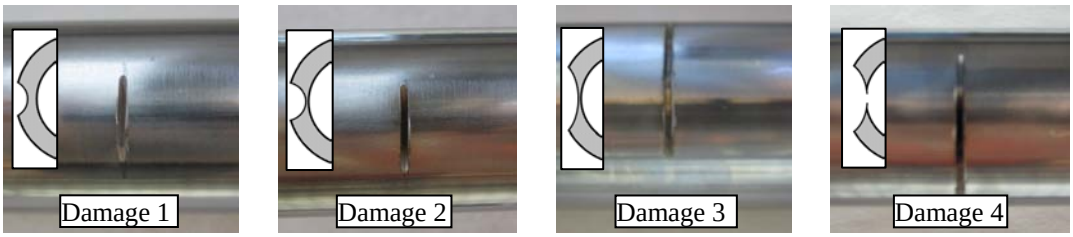

Figure 5. Different damage steps: Damage 1 to Damage 4 and its cross sections.

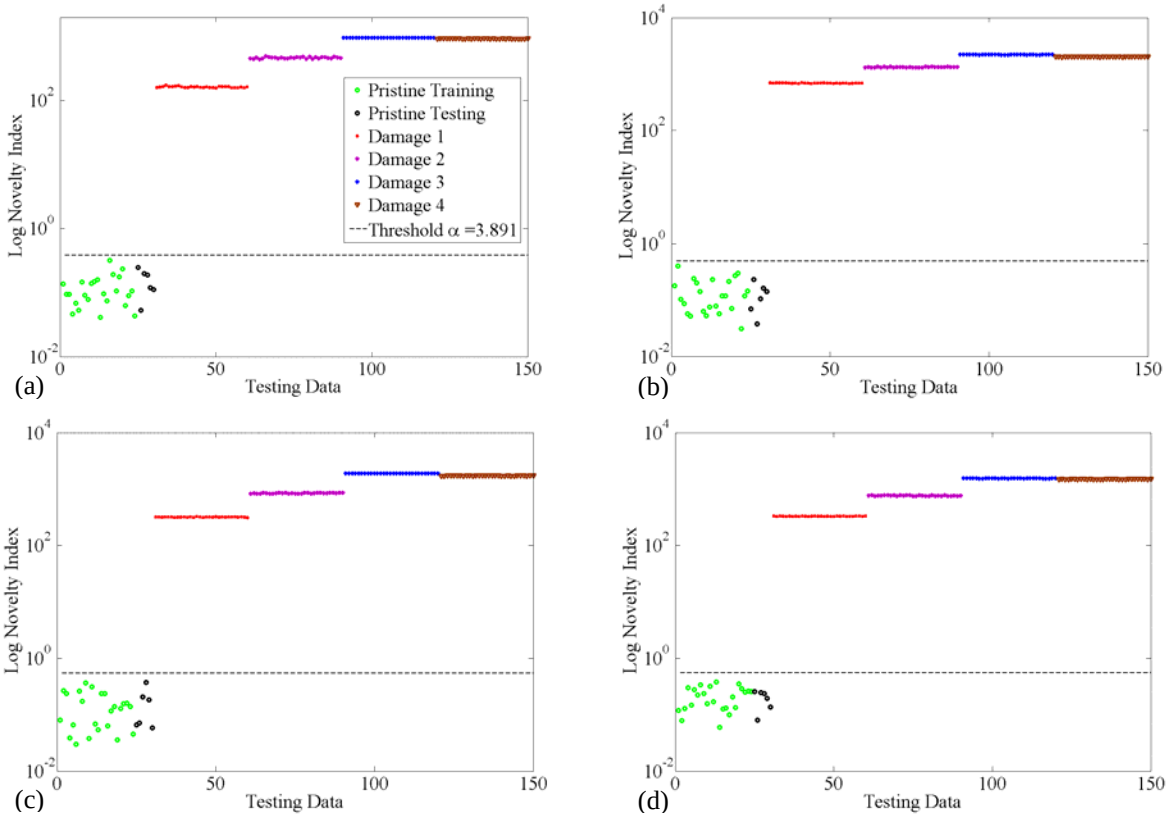

Figure 6. Novelty Index: (a) Actuator 1, (b) Actuator 2, (c) Actuator 3, (d) Actuator 4.

The excitation voltage signal is a 12V Hanning windowed cosine train signal with 5 cycles and carrier frequency of 180kHz. As previously mentioned, an outlier analysis is performed first. A review of the variances retained in the components was performed in order to define the optimal number of components required for building the model. For this purpose, standard PCA was performed. 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. 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. 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. The factor α controls the degree of confidence. The confidence level is defined to be 99.99% in this study. The analysis shows that damage can be separated from the pristine state using only the first three non-linear components for all the actuation steps (see Figure 6). It can also be observed that the damages could be relatively well distinguished by just using the novelty index. Even when not depicted, due to lack of space, the healthy structural state can be also separated from the damaged states in the case of using the DWT detail coefficients. Nevertheless, no distinction could be made between the different damage states. 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 methodology proposed in the previous section of this paper. As previously mentioned, the whole set of the data collected in each actuation step is stored and pre-processed by the DWT. This is then organized following standard unfolding procedures in the sensor direction, i.e. data from each sensor are located

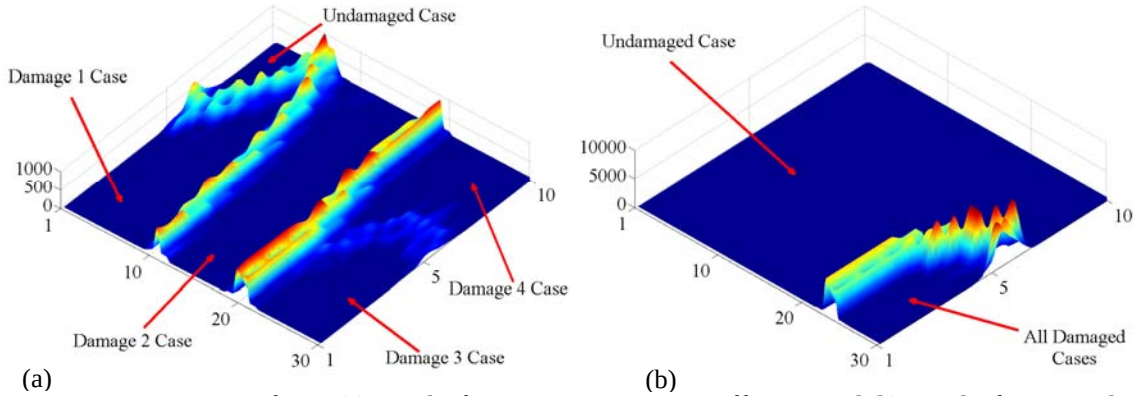

Figure 7. U-Matrix Surfaces: (a) Results from Approximation Coefficients and (b) Results from Detail Coefficients.

besides the other sensors in order to generate a matrix in which each row corresponds to an experiment. After this step, a data-driven model is built for each actuation step using the either the approximation or detail coefficients obtained from the undamaged structure data. After this procedure, h-Nonlinear PCA is performed independently for each actuation step. In the present work, auto-associative neural networks with different dimensions in the mapping and de-mapping layers are applied to this training data to determine the best network architecture. However, the total number of adjustable parameters is restricted to be less than $n \times m$, where n is number of observations and m the number of variables under the assumption that all nodes have biases. The SOM training algorithm used here is implemented in a Matlab®-Toolbox created by [20]. To find the optimal map size, a control run is repeated by changing the map size. 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. Figure 7 shows the U-Matrixes using the proposed methodology. However, 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. As it can be observed in Figure 7(a), five clusters seem to have been well identified. However, the results obtained with the detail coefficients are not satisfactory (see Figure 7(b)). In particular, it can be observed that the undamaged state can be properly separated from the rest of damage states. Nevertheless, a classification between the different damaged states is not possible.

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 advantage of self-organizing maps visualization makes this approach interesting, especially for larger amount of data with high dimensional feature vectors. The U-matrix allows the identification of sparser regions between the maps and clustering data pertaining to different damage states. Two important conclusions can be drawn from the results. First, the multiway extensions 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. Second, the fusion of the actuation steps within the SOM permitted to take into consideration all data avoiding the separate analysis for each

actuation step. The proposed methodology proved being effective in the detecting and classifying the different structural states. Nevertheless, it is good be bear in mind that reliable statistical models for the healthy and damage conditions are required for this aim.

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