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Damage classification in structural health monitoring using principal component analysis and self-organizing maps

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SUMMARY

Damage classification is an important issue within SHM going beyond the purely damage detection. This paper proposes a data-driven statistical approach for damage classification, which is constructed over a distributed piezoelectric active sensor network for excitation and measurement of vibrational structural responses. At different phases, a single piezoelectric transducer is used as actuator, and the others are used as sensors. An initial baseline model for each phase for the healthy structure is built by applying PCA to the data collected in several experiments. In addition, same experiments are performed with the structure in different states (damaged or not), and the dynamic responses are projected into the different baseline PCA models for each actuator. Some of these projections and damage indices are used as input features for a self-organizing map, which is properly trained and validated to build a pattern baseline model. This baseline is further used as a reference for blind diagnosis tests of structures. Both training/validation and diagnosis modes are experimentally assessed using an aluminum plate instrumented with four piezoelectric transducers. Damages are simulated by adding mass at different positions. Results show that all these damages are successfully classified both in the baseline pattern model and in further diagnosis tests. Copyright © 2012 John Wiley & Sons, Ltd.

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KEY WORDS: damage classification; damage indices; principal component analysis (PCA); self-organizing maps (SOM); structural health monitoring (SHM)

1. INTRODUCTION

The main goal of SHM is the continuous assessment of the state or health of structures in order to ensure proper performance by doing non-destructive tests continuously, because sensors, actuators, and all testing equipment are integrated into the structure. The interest in the ability to monitor continuously a structure and detect damage at the earliest possible stage is pervasive throughout the civil, mechanical, and aerospace engineering communities. Among different benefits derived from the implementation of SHM, it is possible to remark the following: knowledge about the behavior of the structure under different loads and different environmental changes and knowledge on the current state in order to verify the integrity of the structure and determine whether a structure can work properly or whether it needs to be repaired or replaced, with the subsequent maintenance cost saving [1].

The paradigm of damage identification (comparison between the data collected from the structure without damages and the current structure in order to determine if any change appears) can be tackled as a pattern recognition application [1]. Some statistical techniques as PCA are very useful for this purpose because they allow obtaining the most relevant information from a large amount of variables. In particular, the authors use the PCA as a tool for data-driven modeling using the data from sensors

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attached to the structure. This paper contributes with a damage classification methodology, which combines PCA, damage detection indices, and self-organizing maps (SOM) for classifying different states of a structure using data collected by a distributed active piezoelectric (PZT) system in different phases. In each phase, a PZT is used as actuator, and the signals from the other PZT transducers are used to build a PCA model using data from the healthy structure. When a structure is in a further inspection stage, some experimental tests are performed and projected onto the PCA model. As a result, the projections on the first component and two indices (T^2-*statistic* and *Q-statistic*) are calculated and used to know the state of the structure in each phase. SOMs are then used as a tool for data fusion by joining and organizing the results of each phase in clusters and representing in a cluster map the final classification.

Most of the theoretical background for the different tools used in the presented approach is known in the available literature. However, the paper supplies a new methodological contribution to the structural damage classification problem through the integration of statistical PCA tools and related damage indices with SOM classifiers, being implemented in a systematic way through an active multiactuator system.

This paper is organized in five sections starting with this Introduction. Section 2 presents a damage classification review focused on artificial neural networks (ANNs) and PCA applications. In the next section, a theoretical background is presented; this includes a description of all the elements used in the methodology such as PCA, damage detection indices, and SOMs. The proposed methodology for damage classification is outlined in Section 4, where a definition of the problem to be solved and the steps to obtain a baseline pattern for classifying different states of the structure are included. In Section 5, experimental results are presented in two parts: First, the training and validation stage includes a review of all the parameters that have to be configured in the SOM and the generation of the final baseline pattern, and second, the diagnosis stage consists in the application of the methodology to new experimental tests and the comparison of its classification with the real damage. Finally, some concluding remarks are summarized in Section 6.

2. DAMAGE CLASSIFICATION REVIEW

2.1. Using ANNs

Damage classification belongs to the SHM level in which damages are grouped according to some characteristics obtained from the structure. To define which damage is present in the structure, a classifier is normally used. A typical classifier is an ANN. Different works have shown the usefulness of neural networks for classification [2]. Some references on the application of neural networks for damage classification in structures are discussed in the following.

Dua *et al*. [3] in 2001 used an ANN with backpropagation algorithm to classify impacts on composite plates. A 503,10,3 ANN was used for training and simulating the data: 503 elements in the input layer, which are excited by strain profiles obtained from finite element analysis, 10 neurons in the hidden layer, and 3 neurons in the output layer. Several impact experiments were performed with different weights falling from different heights in five locations on the composite plate in order to obtain seven classification groups. Sohn *et al*. [4] in 2002 used a combination of time series analysis, neural network, and statistical inference techniques to develop a damage classification system including changes in the environmental and operational conditions. First, an autoregressive (AR) with exogenous inputs model is applied to extract damage sensitive features, after an autoassociative neural network is used for data normalization, which separates the effect of damage on extracted features from those caused by the environmental and vibration variations of the system. A sequential probability ratio test is performed on the normalized features in order to infer the state of the system. The approach is applied in a numerical example of a computer hard disk and an experimental study of an 8 degree-of-freedom spring–mass system. In 2006, Kolakowski *et al*. [5] presented two approaches for damage identification. One of them was based on virtual distortion method. The other methodology involved the use of case-based reasoning applying wavelet transform in order to extract features and reduce the variables to introduce into an SOM for damage identification. These techniques were tested in an aluminum beam. In 2007, Bakhary *et al*. [6] applied a two-stage ANN system for damage location and damage severities. In the first stage, an ANN is used to identify the substructures with damage, and the secondary ANN identifies the damaged elements and its severity. Inputs in the first ANN are modal frequencies and mode shapes of the full structure, and

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the outputs are modal frequencies of substructures; these are the inputs to the second ANN where the final analysis to locate the damage is performed. For testing the approach, a numerical example is used; this consists of a two-span concrete slab. Dobrzanski *et al.* [7] used a multilayer perceptron 9-6-5 for the classification of internal damages in steel during creep services using metallographic images. Also in 2008, Mujica *et al.* [8] presented a methodology to detect, quantify, and localize damages and impacts in several structures; among them are a wing aircraft section and an aluminum beam. This methodology used wavelet transforms to extract different characteristics from the collected signal and an SOM to classify them. In 2008, Kabir *et al.* [9] presented an algorithm for damage classification using a multilayer perceptron. The methodology included the use of analysis of texture of surface deterioration using optical imagery in concrete structures. The perceptron has three different data sets: spatial, spectral, and a spatial–spectral combination. Iskandarani [10] in 2010 applied neural networks to classify composite structure conditions. The evaluation of resin injection molded samples' response to impact damage was carried out using low frequency tapping, visual imaging, low temperature thermoimaging, and measurement of tensile strength. One algorithm for classification on each data file using one and two hidden layers with backpropagation algorithm was performed.

2.2. *Using PCA*

This review aims to discus some applications of PCA method in SHM. Some references related to POD, which is another way to call the PCA, are also included.

Trendafilova *et al.* [11] in 2000 used POD and parameter identification to identify nonlinear parameters of a structure, minimizing the difference between the bi-orthogonal decomposition of the measured and the simulated data. Zang and Imregun [12] used frequency responses and ANN for detecting damages. To include the analysis of the frequency responses, they used PCA to reduce the data size. In 2003, Boe *et al.* [13] applied PCA for damage diagnosis using vibrational responses. With the data from PZT sensors distributed in the structure, it is possible to define the localization of the damage. Authors also claimed that this methodology can be used with other kinds of sensors such as accelerometers. The same year, Sophian [14] *et al.* used PCA for feature extraction in the response obtained from the application of Eddy current in two aluminum samples. In 2004, Nitta *et al.* [15] presented a two-stage-based methodology for detecting the reduction in story stiffness of damaged building. In the first step, POD was used to estimate the modal vector of a structure in order to detect and locate damages. In the second step, a methodology for quantifying the damage was performed by means of system identification of subsystems. Golinval *et al.* [16] used PCA and vibration-based signals for damage detection and localization in structures. The excitation was generated by an electro-dynamic shaker, and accelerometers were used as sensors. The approach included the use of the angle between subspaces in the PCA model. In 2005, Yan *et al.* [17,18] proposed a methodology for structural damage diagnosis that included a two-step procedure: first, a clustering of the data space into several regions was performed, and second, PCA was applied in each region for damage detection.

In 2008, Mujica *et al.* [19] explored the use of PCA with T^2-statistic and Q-statistic in order to detect and distinguish damages in structures. In this case, a PCA model was built for each actuator, and the analysis of each model was performed in an individual form. This methodology was tested in an aircraft turbine blade using PZT transducers. It includes also the use of case-based reasoning, and 16 approaches were developed combining those techniques. Also in 2008, Wang *et al.* [20] used an AR model based on vibrational responses. The coefficients of these AR models were extracted to make a set of multivariate data known as vibration response data characteristics, and then Hotelling's T^2 control chart was applied to monitor these characteristics. The methodology was demonstrated by numerically simulated acceleration time histories based on a progressively damaged reinforced concrete frame, either with or without addressing the autocorrelation in the characteristics data. In 2009, Gryllias *et al.* [21] presented a two-step approach for crack detection in beam structures, which includes in a first step the extraction of proper orthogonal modes (POMs) of a beam using POD, and later, morphological processing using four operators (dilation, erosion, opening, and closing) are applied for processing the POMs. In the same year, Leao *et al.* [22] compared different techniques to monitor the health state of aircraft flap and slat systems. T^2-statistic and ranger U^2-statistic based on measurements of motor command current and operational conditions are used.

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The next year, Lautour and Omenzetter [23] used the AR coefficients obtained from the time series as damage sensitive features to classify damages. The approach considered the use of PCA and Sammon mapping to obtain a 2D projection in order to define a quick visualization of the clusters among the AR coefficients and for data reduction in the final classification.

Recently, in 2011, Li *et al.* [24] used damage pattern changes in frequency response functions (FRF) and ANNs to estimate the locations and severities of structural damages. The inputs to the ANN are obtained by calculating the principal components from the residual FRFs, which are obtained using data from the healthy structure and the structure with damage. The same year, Tibaduiza *et al.* [25,26] used four indices for damage localization based on PCA applying five contribution methods; the approach was tested in an aluminum plate. Salehi *et al.* [27] proposed two damage detection techniques based on POD. The first approach uses time responses, and POD is applied for reducing data. The second method is based on FRFs where spatio-spectral FRF shape data are decomposed by POD.

According to the reviewed literature, it can be highlighted that there are no references that integrate the use of PCA, SOM, and damage indices in a joint classification method. On the basis of previous works by the authors, a new approach for classifying states in structures is contributed in this paper.

3. THEORETICAL BACKGROUND

3.1. PCA and damage detection indices

PCA is a technique of multivariable and megavariate analysis [28] that may provide arguments for how to reduce a complex data set to a lower dimension and reveal some hidden and simplified structure/patterns that often underlie it. The goal of PCA is to discern which dynamics are more important in the system, which are redundant, and which are just noise. This goal is essentially achieved by determining a new space (coordinates) to re-express the original data by filtering noise and redundancies on the basis of the variance–covariance structure of the original data. PCA can be also considered as a simple, nonparametric method for data compression and information extraction, which finds combinations of variables or factors that describe major trends in a confusing data set. To develop a PCA model, it is necessary to arrange the collected data in a matrix X. This $n \times m$ matrix contains information from m sensors and n experimental trials [29]. Because physical variables and sensors have different magnitudes and scales, each data point is scaled using the mean of all measurements of the sensor at the same time and the standard deviation of all measurements of the sensor. Once the variables are normalized, the covariance matrix C_x is calculated as follows:

$$C_x = \frac{1}{n-1} X^{\mathrm{T}} X \tag{1}$$

It is a square symmetric $m \times m$ matrix that measures the degree of linear relationship within the data set between all possible pairs of variables (sensors). The subspaces in PCA are defined by the eigenvectors and eigenvalues of the covariance matrix as follows:

$$C_x \tilde{P} = \tilde{P} \Lambda \tag{2}$$

where the eigenvectors of C_x are the columns of $\tilde{\mathrm{P}}$ and the eigenvalues are the diagonal terms of Λ (the off-diagonal terms are zero). Columns of matrix $\tilde{\mathrm{P}}$ are sorted according to the eigenvalues by descending order, and they are called *principal components* of the data set or loading vectors. The eigenvectors with the highest eigenvalue represent the most important pattern in the data with the largest quantity of information. Choosing only a reduced number $r < m$ of principal components, those corresponding to the first eigenvalues, we could imagine the reduced transformation matrix as a model for the structure. In this way, the new matrix P ($\tilde{P}$ sorted and reduced) can be called as PCA model. Geometrically, the transformed data matrix T (score matrix) represents the projection of the original data over the direction of the principal components P:

$$T = XP \tag{3}$$

In the full dimension case (using $\tilde{P}$), this projection is invertible (because $\tilde{P}\tilde{P}^T = I$), and the original data can be recovered as $X = T\tilde{P}^T$. In the reduced case (using P), with the given T, it is not possible to

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fully recover X, but T can be projected back onto the original m-dimensional space and obtain another data matrix as follows:

$$\hat{X} = TP^{\mathrm{T}} = (XP)P^{\mathrm{T}} \tag{4}$$

Therefore, the residual data matrix (the error for not using all the principal components) can be defined as the difference between the original data and that projected back:

$$E = X - \hat{X} = X\left(I - PP^{\mathrm{T}}\right) \tag{5}$$

There are several kinds of indices that can give information about the accuracy of the model and/or the adjustment of each experiment to the model. Two well-known indices are commonly used to this aim: the Q-statistic (*SPE-index*) and the Hotelling's T^2-statistic (*D-index*) [29–31]. The former is based on analyzing the residual data matrix to represent the variability of the data projection within the residual subspace. Denoting e_i as the ith row of the matrix E, the Q-statistic for each experiment can be defined as its squared norm as follows:

$$Q_i = e_i e_i^{\mathrm{T}} = x_i\left(\mathrm{I} - \mathrm{PP}^{\mathrm{T}}\right)x_i^{\mathrm{T}} \tag{6}$$

The latter is based on the analysis of the score matrix T to check the variability of the projected data in the new space of the principal components. It can be obtained from the concept of Euclidean distance normalized using the covariance matrix C_x as normalization factor. The T^2-statistic for the ith sample (or experiment) is defined as follows:

$$T_i^2 = \sum_{j=1}^{r} \frac{t_{sij}^2}{\lambda_j} = {}_{tsi}\Lambda^{-1} t_{si}^{\mathrm{T}} = x_i P \Lambda^{-1} P^{\mathrm{T}} x_i^{\mathrm{T}} \tag{7}$$

where $\boldsymbol{t}_{si}$ is the i row vector of the matrix T, which is the projection of the experiment $\boldsymbol{x}_i$ into the new space. Both are related as $t_{si} = x_i P$.

Previously, Mujica *et al*. [19,29] proposed to use a decomposition of these indices as a tool for damage localization. In these works, one PCA model was built for each actuator, and the contribution of each sensor to T^2- and Q-statistics was calculated to obtain the localization of the damage. The authors of this paper have also used these indices for damage localization using a combined data analysis from each actuator [25,26]. This paper gives a step forward by using PCA model and damage indices as input data sets for an SOM to classify different structural states.

3.2. Self-organizing map

The SOM is a kind of unsupervised neural network also known as Kohonen network [32]. It is specialized in visualization and data analysis of high-dimensional data. This network has the special property of generating one organized map in the output on the basis of the inputs, grouping input data with similar characteristics in clusters. To do that, the SOM internally organizes the data on the basis of features and their abstractions from input data. In particular, these maps have been used in practical speech recognitions, robotics, process control, and telecommunications, among others [33].

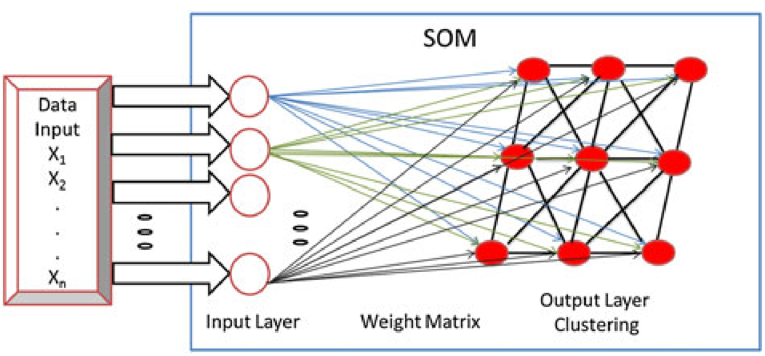

Figure 1. Self-organizing map description.

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Figure 1 illustrates the way it works. The inputs to the network are defined in the input layer, and a weighting matrix relates each input with each cluster in the output layer.

4. PROPOSED METHODOLOGY FOR DAMAGE CLASSIFICATION

4.1. Problem statement

Consider a structure and several possible damage scenarios. The structure can be experimentally tested by means of an active multiactuator system, which consists of a set of sensors and actuators operated in the following way: Every single experimental test consists of exciting the structure with a specific single actuator and recording the responses with the whole set of sensors at different locations. This system is the tool to implement a methodology in two different stages, which are referred to as follows: (1) baseline pattern model building (training and validation) and (2) diagnosis.

In the first stage, four steps are sequentially followed:

1. The structure is considered in an undamaged state, and several experimental phases are performed. For each phase, a single actuator is excited, and the time history responses for the whole set of sensors are recorded and used to build a PCA reference model. This is repeated for each single actuator.
2. The structure is tested under different known damage states. For each state, the previous experimental phases are performed. Two results are obtained for each phase: (i) the projections of the data with the reference PCA models and (ii) the damage indices.
3. The results obtained for each phase are combined and contrasted using an SOM. It produces an organized map by grouping in clusters data with similar characteristics. It is relevant to remark that the information of the structural state is not used at this step because it is an unsupervised algorithm; the SOM groups the clusters according to relative similarities.
4. Once the 'training' has been finished, the known damaged states under consideration are used a posteriori to validate the effectiveness of the classification and to obtain the final baseline pattern.

In the diagnosis stage, any structure is blindly tested. The different phases are performed for each single actuator as in the step 2 of the model building. The results are entered into the trained SOM, and the new pattern is obtained. Comparison with the baseline pattern allows the damage detection and classification. Details on the development of this classification scheme are given in the next section.

4.2. Methodology

In this paper, a specific vibration-based experimental setup is used as a case study to explain, validate, and test the methodology. The multiactuator system here is a set of PZT transducer disks, which can be used reversibly as sensors and actuators. The work presented is divided into five parts: experimental setup, data acquisition, data preprocessing, PCA modeling, and SOM training. It is worth to remark that this methodology can be applied to any structure equipped with a multiactuator system.

4.2.1. Experimental setup. An aluminum plate (250 mm $\times$ 250 mm $\times$ 20 mm) is used in this paper. It is instrumented with four PZT transducers bounded on the surface, as seen in Figure 2a, and suspended by two elastic ropes in a metallic frame in order to isolate the environmental noise and remove boundary conditions. Seven different states including the healthy structure are analyzed. Six damages are simulated adding a mass as shown in Figure 2a, b (attached to the surface of the plate) in six different locations as can be seen in Figure 2c.

4.2.2. Data acquisition. In every data acquisition system, one important previous requirement is to ensure that the measurements are reproducible [34]. This allows defining the reliability of the algorithms and to ensure that the results defined as damages really correspond to a damage and not to a bad data acquisition or faults in the sensor network.

The methodology uses a multisensory architecture in several phases; in every phase, a single PZT is used as actuator, and the others are sensors that receive the wave propagated across the structure at

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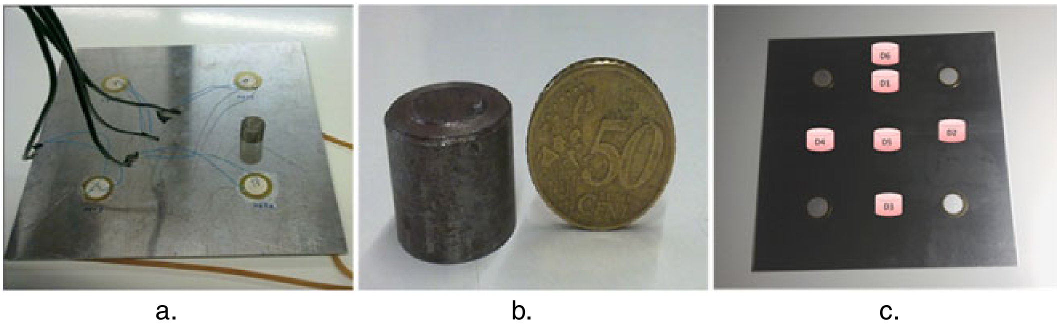

Figure 2. Damage description and locations.

different points. A burst signal with three peaks and 50 KHz frequency is used as excitation (Figure 3). This signal is selected once a sweep frequency is performed in order to obtain the resonance frequency of the structure. Before applying the signal to the structure, it is amplified to 50 V peak-to-peak using a wideband power amplifier. A set of 750 experiments is performed and recorded: 150 with the undamaged structure and 100 per damage. All data are averaged to obtain one signal for each 10 experiments in order to eliminate the noise in the experiments.

For each experiment, the time histories recorded by each sensor at each sampling time are stored by the data acquisition system into a matrix with dimensions $I \times K$, where I represents the number of experiments and K the number of sampling times [35]. Denoting J as the number of PZT sensors at each experiment, there is a number J of such matrices. Therefore, the whole set of the data collected in each phase can be organized in a 3D matrix ($I \times K \times J$) or in a 2D matrix ($I \times JK$) where data from each sensor are located sequentially as illustrated in Figure 4.

4.2.3. Preprocessing. As a preliminary step to implement the PCA methodology, a preprocessing should be performed to the data collected at each phase. For this kind of data sets (unfolded matrix) [29], several scaling forms have been presented in the literature: continuous scaling, group scaling, and autoscaling [36].

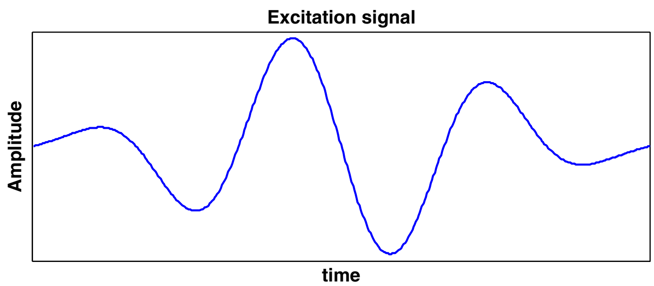

Figure 3. Excitation signal.

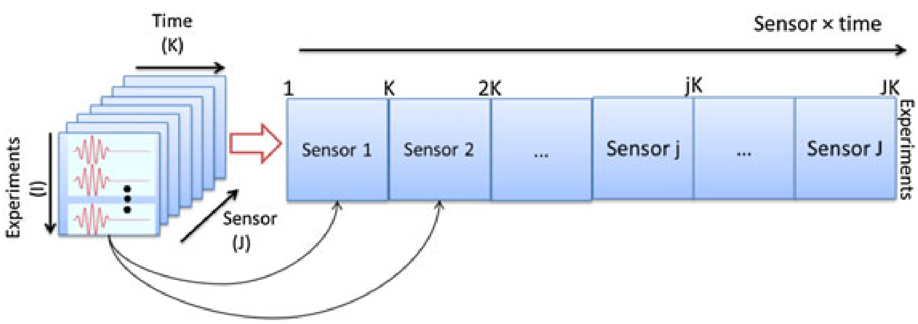

Figure 4. Unfolding the collected data in 3D to bidimensional matrix $(I \times JK)$.

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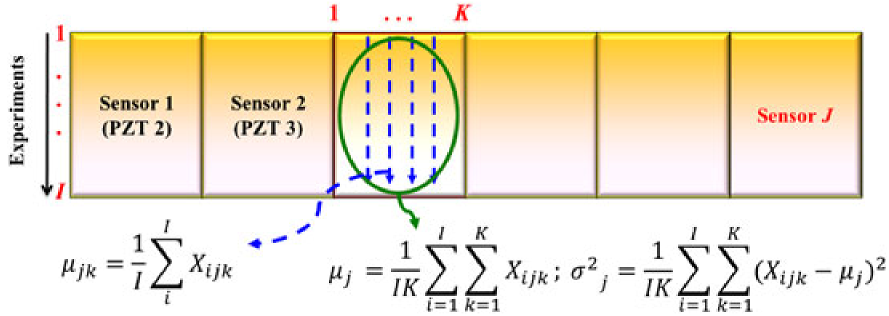

Figure 5. Group scaling preprocessing.

According to these studies, group scaling is selected for this work because it considers changes between sensors and does not process them independently. With this normalization, each data point is scaled as defined in the form

$$\bar{x}_{ij} = \frac{x_{ij} - \mu_{jk}}{\sigma_j} \tag{8}$$

by using the mean of all measurements of the sensor at the same time and the standard deviation of all measurements of the sensor, as can be seen in Figure 5, where x_{ijk} is the kth sample of the jth sensor in the ith experiment, μ_{jk} is the mean of the all kth samples of the jth sensor, μ_j is the mean of all measurements of the jth sensor, μ_j is the standard deviation of all measurements of the jth sensor, and $\bar{x}_{ij}$ is the scaled sample.

Once the normalization is applied, the mean trajectories (by sensor) are removed, and all sensors have equal variance. As a consequence, the experimental trajectories of the sensors and their standard deviations, often nonlinear in nature, are removed from the data.

4.2.4. Model building and calculation of damage indices using PCA. A PCA model is built for each phase (PZT1 as actuator, PZT2 as actuator, and so on) using the signals recorded by sensors during the experiments with the undamaged structure [37]. PCA modeling essentially consists of calculating the matrix P for each phase (Equation (2)). Figure 6 illustrates (from top to bottom) this step and the subsequent step, in which the experiments are performed using the structure in the

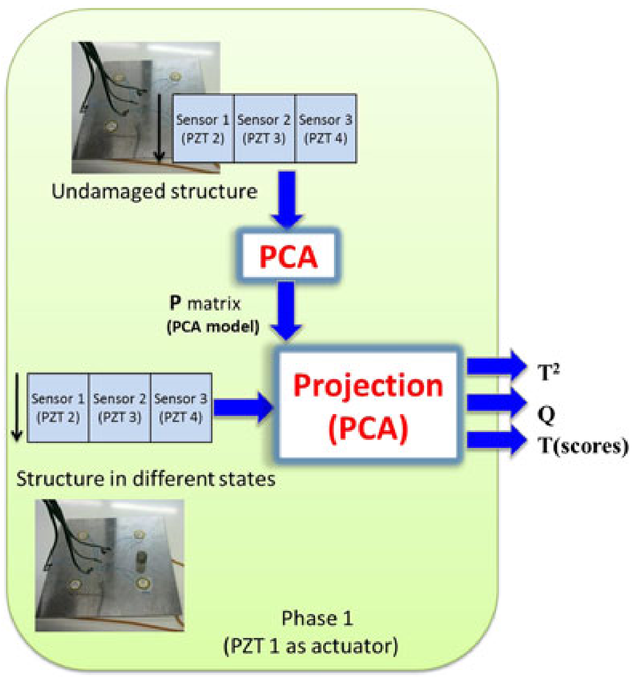

Figure 6. Damage detection methodology in the model building stage.

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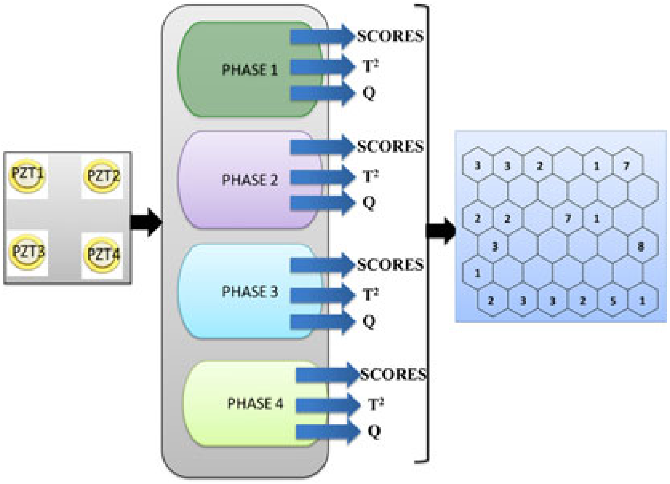

Figure 7. Self-organizing map training.

different possible states (undamaged and six damages). These signals are projected on the PCA model (Equation (3)), thus obtaining a selected number of the first principal components (scores T). In addition, the Q-statistic and T^2-statistic are calculated by using Equations (6) and (7). In this work, each PCA model is created using 66% of the whole data set collected using the undamaged structure. Signals from the remaining 34% plus 80% of the data set of the damaged structure are used in the second step.

4.2.5. SOM training and validation. The results (T, T^2-statistic, and Q-statistic) obtained previously for each experiment at each phase can be used themselves as parameters for damage detection as it was proposed in [29]. The goal of this work is to organize, combine, and contrast the information obtained from all models (all phases) in order to provide a general diagnosis of the structure. To do that, all the aforementioned results are used as inputs to an SOM as illustrated in Figure 7. An SOM was chosen because its characteristics can provide a good support for the classification and graphical representation and grouping input data with similar features in clusters. One important characteristic of this kind of ANN is that it does not need previous knowledge about the state of the structure (healthy or with some damage) to obtain the final clustering. The numbers indicate how many experiments are grouped together in each cluster.

To validate if the classification is acceptable and to obtain the final baseline pattern, the known information from the states of the structure at each experiment is used to label each cluster. This procedure is illustrated in Figure 8. The details on how this is performed in practice are given in the next section.

5. EXPERIMENTAL RESULTS

Results are divided in two parts: the training and validation stage and the diagnosis stage. The SOM Toolbox of MATLAB© [2] is used for the implementations.

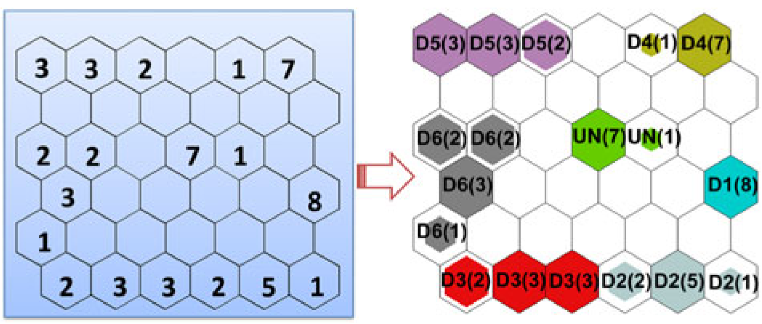

Figure 8. Final baseline damage pattern.

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5.1. Training and validation stage

To define the optimal set of parameters to configure the map, several SOMs are trained and validated. To determine the cluster size, a study is previously performed. Larger map sizes present more detailed patterns. On the contrary, smaller map sizes present more general patterns. Maps smaller than 4×4 show many overlapped clusters; big SOMs generate too many empty clusters that add uncertainty to the classification of the damage. In this work, optimal results are obtained using a map of 6×6 clusters. In addition to the map size, the map lattice and shape must be specified. The SOM lattice gives the local topology of the map, that is, the connectivity of the map units. The lattice can be either rectangular or hexagonal in the SOM toolbox. For the present study, 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 neighborhood function is used.

On the other hand, this study also analyzes in depth how the classification results are affected by three issues: (i) the method used to normalize the input data; (2) the number of scores used in the input vector; and (iii) the specific damage detection indices, which a priori are T^2-statistic and Q-statistic. Six possible normalizations are implemented in the toolbox to preprocess the input data: *range*, *var*, *log*, *logistic*, *histD*, and *histC* [2]. According to Vesanto *et al*. [2], the normalization type *var* performs a linear transformation that scales the value such that their variance is 1. Normalization type *range* scales the variable values between [0,1] using also a linear transformation. *Log* normalization makes a logarithmic transformation of the input variables. The *logistic* normalization is more or less linear in the middle range and has a smooth nonlinearity at both ends, which ensures that all values (even in the future) are within the range [0,1]. Normalization type *histD* is a discrete histogram equalization. It sorts the values and replaces each value by its ordinal number. Finally, it scales the values such that they are between [0,1]. Normalization type *histC* is a continuous histogram equalization. The value range is divided into a number of bins, and the values are linearly transformed in each bin.

All the normalizations are implemented using, as input vector, 8 scores and both damage indices (T^2-statistic and Q-statistic) by each phase. After the resulting maps are validated (labeling the cluster), it can be seen that the maps with least amount of clusters with different state of the structure (overlapped clusters) are those that are normalized using *histC*, *histD*, and *var* normalization. These maps are depicted in Figure 9; each cluster (or output neuron) of the SOM is represented by a hexagon. The color of the cluster shows the kind of damage (Undamaged, Damage 1, D2, D3, etc), and the portion of the cluster shows the portion of the damage among the total of the experiments grouped in the cluster. Besides, the damage and the number of experiments of this damage are shown (i.e., D3(2) means that two experiments with the damage three are grouped in the cluster).

Because T^2-statistic is a measure calculated from the scores, including this damage index together with the scores in the input vector to the SOM could be redundant. To analyze the influence of T^2-statistic into the SOM, three maps are trained and validated using 8 scores and just Q-statistic as damage index by each phase. These maps have similar configuration, which is presented in Figure 9. After validating (Figure 10) and comparing with the maps from Figure 9, we can see that T^2-statistic does not influence so much in the results but it does increase the number of elements in the input vector since this includes an additional input by each phase.

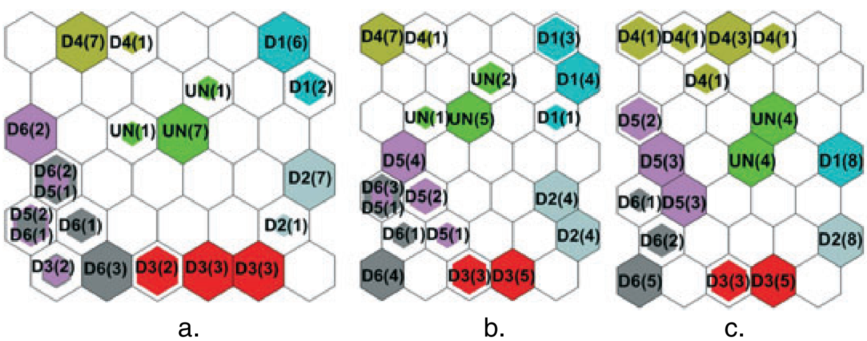

Figure 9. Classification of damages using 8 scores, both damage indices (T^2-statistic and Q-statistic) and normalization types (a) *histC*, (b) *histD*, and (c) *var*.

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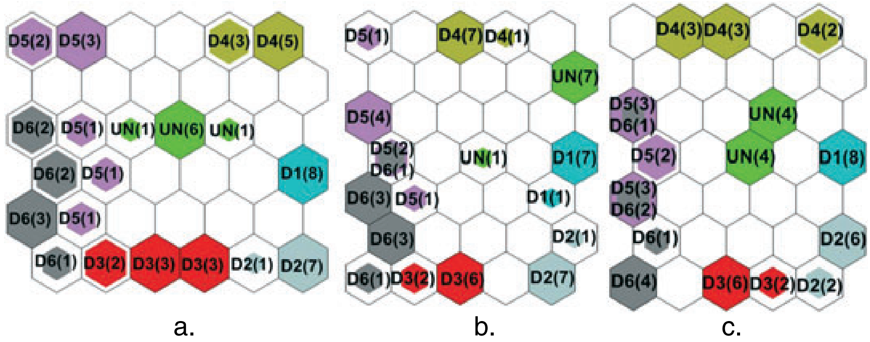

Figure 10. Classification of damages using 8 scores, Q-statistic and normalization types (a) *histC*, (b) *histD*, and (c) *var*.

The size of the input vector is also a parameter to consider when an SOM is being trained. To study the number of scores to be used, several maps are trained and validated. The number of scores is varied between 2 and 10, and the normalization methods are the chosen ones in the previous analysis (*histC*, *histD*, and *var*). In general, results show that the more scores are used, the better classification, although no big differences are found. On the other hand, time consumption is also greater. To see this disparity, the resulting maps after using 2, 7, and 8 scores are depicted in Figures 11–13.

From the figures, it may be observed that, using 7 and 8 scores and any normalization, maps have less overlapped clusters than using just 2 scores. Moreover, comparing the normalization methods, we found that *histC* is the one that classifies better the damages.

In summary, there are certain important results to highlight here. First, it is possible to use a reduced number of inputs in the SOM to obtain a good classification of the different structure states. Furthermore, it is demonstrated that it is not necessary to include the T^2-statistic index. Another important result is concerned with the relationship between the normalization method and the number of inputs in the SOM.

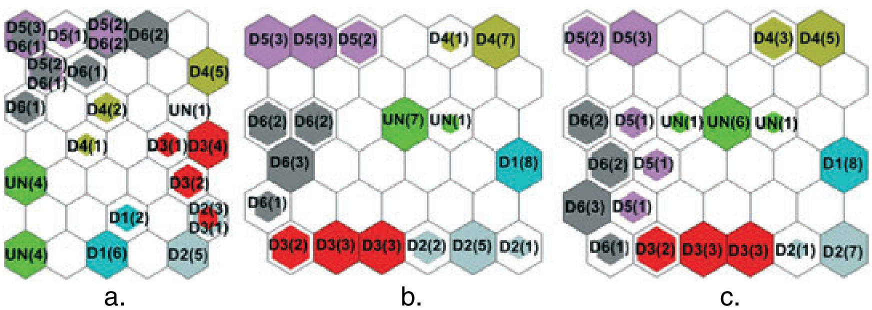

Figure 11. Classification of damages using Q-statistic, normalization type *histC*, and (a) 2, (b) 7, and (c) 8 scores.

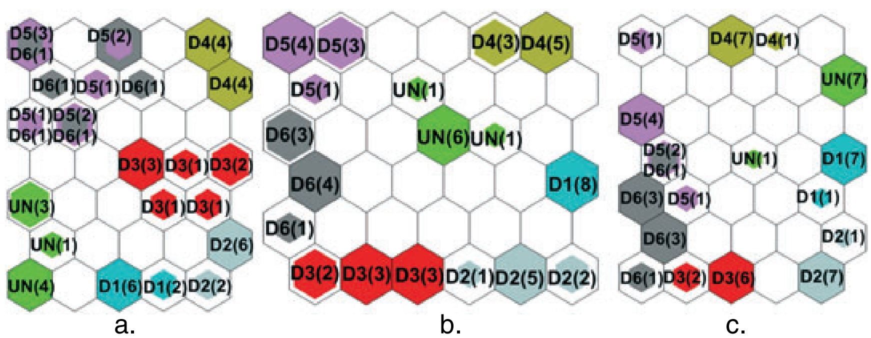

Figure 12. Classification of damages using Q-statistic, normalization type *histD*, and (a) 2, (b) 7, and (c) 8 scores.

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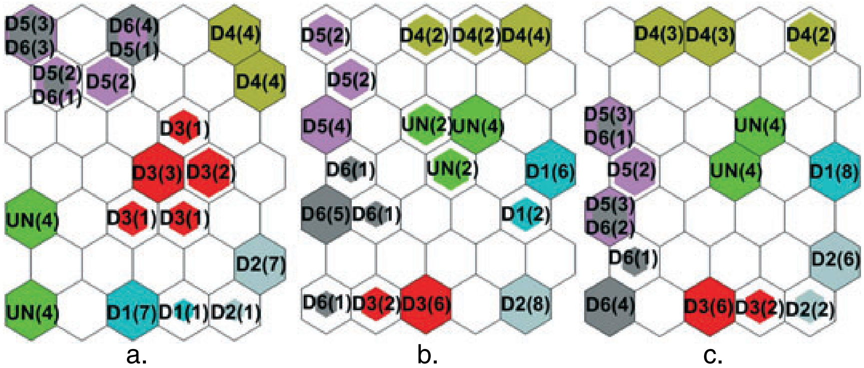

Figure 13. Classification of damages using Q-statistic, normalization type *var*, and (a) 2, (b) 7, and (c) 8 scores.

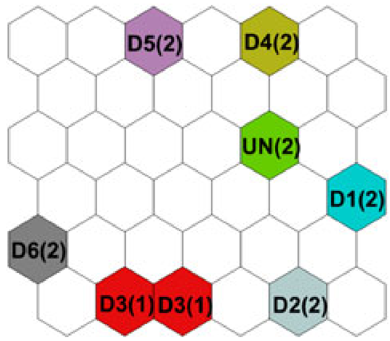

Figure 14. Tested map using *histC* normalization, 7 scores, and Q-index.

5.2. Diagnosis stage

From the results obtained in the training and validation stage, a 6×6 map that uses *histC* method for normalization, 7 scores, and T^2-statistic as input vector (Figure 11b) is selected as the baseline pattern model to be used in future diagnosis of structures. To assess the effectiveness of such diagnosis, two new experiments for each state of the structure are performed, which are not included in the training and validation stages. For each experiment, the data matrix is projected into the reference PCA model as illustrated in Figure 6 for each phase. The first 7 scores and Q-statistic from each model are the inputs to the baseline pattern SOM. Each experiment activates one cluster of this SOM. Because the baseline is labeled, it is possible to identify which damage has occurred if such damage was included in the training/validation stage. Figure 14 shows the clusters activated by each experiment. The comparison with Figure 11b (baseline) clearly shows that each state of the structure is satisfactorily identified.

6. CONCLUSION

This paper has proposed an approach for structural damage classification through the integration of a multiactuator system (several PZT transducers working as actuator and sensors in several phases), a statistical reference model based on PCA, a damage index, and an SOM as classification tool to combine and contrast the information obtained from each phase. The approach has been experimentally analyzed showing good results in classifying different states of the structure: healthy structure and six different damages.

To demonstrate the effectiveness of the approach, two stages have been performed: training and validation stage and testing stage using different data. The first stage has demonstrated how the results are highly influenced by the inputs and the normalization method applied in the SOM. The information from the state of the structure has been used to verify the quality of the classification and the best parameters of the approach: how many scores should be used, how many damage indices are necessary, and the configuration of the SOM (structure, number of output clusters, normalization, etc.). Additionally, it has been shown that the T^2-statistic (although is a good index for damage detection by itself) can be avoided to reduce the number of inputs to the SOM. This result is potentially useful in future applications for working with structures instrumented with a large sensor network in order to optimize the computational cost. The second stage allowed assessing the effectiveness of the proposed approach by using new data from each state of the structure, which are not included in the training and validation stages.

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