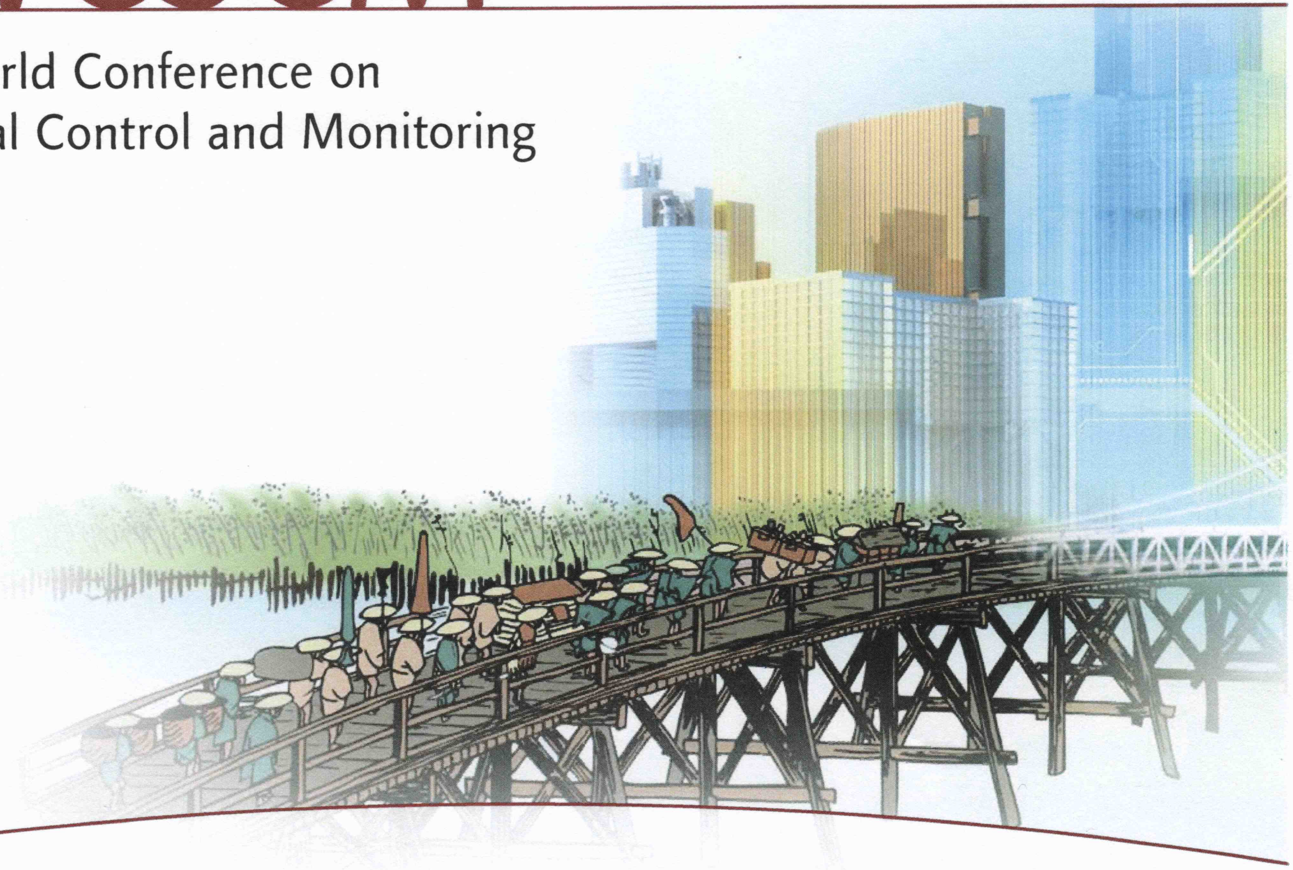
PROGRAM

5WCSCM

Fifth World Conference on
Structural Control and Monitoring



12 - 14 JULY 2010

KEIO PLAZA HOTEL
SHINJUKU, TOKYO

B-3: (OS) Advances in System Identification and SHM

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F. Ubertini, M. Breccolotti

070 ROBUST VIBRATION CONTROL FOR STRUCTURES WITH WIRELESS SENSORS
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DATA-DRIVEN MULTIACTUATOR PIEZOELECTRIC SYSTEM FOR STRUCTURAL DAMAGE LOCALIZATION

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Abstract

In initial studies, it has been shown that the combination of Principal Component Analysis (PCA) and the contribution plots of Q and T^2-*statistics* can be considered an efficient technique to detect, distinguish and localize damages in structures that are equipped with several piezoelectric transducers (PZT's). In those previous works, the specimen (aircraft turbine blade) was excited using just one of the set of PZT's bounded on the surface. This paper studies the advantage of using the whole set of PZT's as actuators as well as sensors. An active piezoelectric system is developed. At each phase of the diagnosis procedure, one PZT is used as actuator (a known electrical signal is applied) and the others are used as sensors (collecting the wave propagated through the structure at different points). A data-driven model for undamaged structure is built applying PCA to the data collected by several experiments. The current structure (damaged or not) is subjected to the same experiments, and the collected data are projected into the baseline PCA model. The indices Q, T^2, φ and I determine whether the structure is healthy or not. In addition, the contribution of each sensor to these indices supplies information about the localization of the damage.

Introduction

Nowadays, the application of Structural Health Monitoring (SHM) in aerospace and aircraft industry has been growing up due to the need for: (i) reducing maintenance costs and, (ii) improving the safety of the components, structures and users. SHM is a multidisciplinary activity that includes different technical knowledge: instrumentation, advanced data processing, strategies for damage identification, prognosis, among others.

There are several potentially useful techniques, and their applicability to a particular situation depends on the size of critical damage admissible in the structure. All of these techniques follow the same general procedure: the structure is excited using actuators and the dynamical response is sensed at different locations throughout the structure. Any damage will change this vibrational response, as well as the transient by a wave that is spreading through the structure. The state of the structure is diagnosed by means of the processing of these data (Worden and Farrar, 2007).

Lately, several researchers from different fields have been using techniques based on Principal Components Analysis -PCA- (Jolliffe, 2002) as diagnosis methods for process monitoring with potentially promising results (B. Mnassri *et al*, 2009; Y. Yinghua *et al*, 2002; J. Qin, 2003). Recently, authors of this work have been applying PCA for SHM in aeronautical structures. This statistical method, some extensions and some damage indices have been used to distinguish different defects and to localize their positions in the structure. In those works an aircraft turbine blade was used to show that the formulation of indices T^2 and Q based on PCA are successful indices to detect and distinguish damages (Mujica *et al*. 2009; Mujica *et al*. 2010). In these experiments, just one Piezoelectric transducer (PZT) was used as actuator and the others as sensors.

Despite that encouraging results were obtained, it was shown that the detectability depends of the distance from the damage to the actuator. To solve this problem, and seizing on the main characteristic of PZT's (actuator/sensor device), authors propose the application of the mentioned methodology adding new indices to assess the same structure but using an active piezoelectric system that can be considered as multiactuator/multisensor system. In this way, each PZT is used as much as actuator as sensors in several phases. In each phase, one of the PZT's is used as actuator and the rest as sensors. By using the indices mentioned before (Q and T^2) and the new ones (φ and I), different damages can be detected and distinguished form the others (depending of its location). Besides, calculating the contribution of each sensor to each index, a region of the localization of the damage could be determined. Finally, when all phases have been accomplished (one per each PZT's), a general diagnosis must be performed in order to localize and identify the damage considering the diagnosis in each phase.

Principal Component Analysis

Introduction

Principal Component Analysis (PCA) (Jolliffe, 2000), or equivalently Proper Orthogonal Decomposition (POD) (Chatterjee, 2000) 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 Principal Component Analysis 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 filtering that noise and redundancies based on the variance–covariance structure of the original data. PCA can be also considered as a simple, non-parametric method for data compression and information extraction, which finds combinations of variables or factors that describe major trends in a confusing data set. Among their objectives it can be mentioned: to generate new variables that could express the information contained in the original set of data, to reduce the dimensionality of the problem that is studied, to eliminate some original variables if its information is not relevant.

Projection on the Principal Components

Analyzing a physical process by measuring several variables (sensors) at a number of time instants (or experimental trials), considering that each measurement is an individual sample in the data set (just one value, e.g. load, voltage, pressure, etc). The collected data are arranged in a matrix as follows:

$$\mathbf{X} = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1j} & \dots & x_{1m} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ x_{i1} & x_{i2} & \dots & x_{ij} & \dots & x_{im} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ x_{n1} & x_{n2} & \dots & x_{nj} & \dots & x_{nm} \end{pmatrix} = \left(\boldsymbol{v_1} \middle| \boldsymbol{v_2} \middle| \cdots \middle| \boldsymbol{v_j} \middle| \cdots \middle| \boldsymbol{v_m} \right) \qquad (1)$$

This $n \times m$ matrix contains information from m sensors and n experimental trials. Each row vector ($\boldsymbol{x}_i$) represents measurements from all the sensors at a specific time instant or experiment trial. In the same way, each column vector ($\boldsymbol{v}_j$) represents measurements from one sensor (one variable) in the whole set of experiment trials.

Since different physical variables and sensors have different magnitudes and scales, the original data set has to be treated before applying any analysis. Several methods are found in the literature for scaling experimental data, the so-called "autoscaling" being the most popular. It is a processing technique in which each variable is re-scaled to have zero mean and unity variance. This is performed by modifying each sensor vector $\boldsymbol{v}_j$ as follows:

$$\mu_{v_j} = \frac{1}{n}\sum_{i=1}^{n} x_{ij} \qquad \sigma_{v_j}^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(x_{ij} - \mu_{v_j}\right)^2 \qquad \bar{x}_{ij} = \frac{x_{ij} - \mu_{v_j}}{\sigma_{v_j}} \tag{2}$$

where μ_{vj} and $\sigma_{v_j}^2$ are the mean and the variance, respectively, of sensor j measurements ($\boldsymbol{v}_j$), and $\bar{x}_{ij}$ is the re-scaled sample. In the remaining of the paper the scaled data are considered without bar notation for simplicity.

Consider a $m \times n$ linear transformation matrix $\mathbf{P}$, which is used to transform the original data matrix $\mathbf{X}$ into the form

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

To achieve the minimal redundancy goal, we seek for a transformation matrix $\mathbf{P}$ such that the covariance of the new data matrix $\mathbf{T}$ is diagonal, that is

$$\mathbf{C_T} = \frac{1}{n-1}\mathbf{T}^{\mathbf{T}}\mathbf{T} = \text{diagonal} \tag{4}$$

Substituting (3) into (4) the following is written:

$$\mathbf{C_T} = \frac{1}{n-1}\mathbf{P}^{\mathbf{T}}\mathbf{X}^{\mathbf{T}}\mathbf{XP} = \mathbf{P}^{\mathbf{T}}\mathbf{C_X}\mathbf{P} \tag{5}$$

Since $\mathbf{C_X}$ is symmetric, it has m real eigenvalues λ_j and m orthonormal eigenvectors $\boldsymbol{p}_j$, which form a basis in the m-dimensional space. Then, the transformation matrix is chosen having the eigenvectors in their columns, that is

$$\mathbf{P} = \left(\boldsymbol{p}_1 \middle| \boldsymbol{p}_2 \middle| \ \dots \ \middle| \boldsymbol{p}_j \middle| \ \dots \ \middle| \boldsymbol{p}_m\right). \tag{6}$$

With this matrix the following property is satisfied:

$$\mathbf{C_X P} = \mathbf{P}\Lambda, \tag{7}$$

with $\Lambda = \text{diag}(\lambda_1, \lambda_2, \dots \lambda_m)$. Substituting (7) into (5), the desired condition (4) is satisfied with

$$\mathbf{C_T} = \mathbf{P}^{\mathbf{T}}\mathbf{P}\Lambda = \Lambda. \tag{8}$$

Let us write the transformation (5) in more detail:

$$\left(\boldsymbol{t}_1 \middle| \boldsymbol{t}_2 \middle| \;\dots\; \middle| \boldsymbol{t}_j \middle| \;\dots\; \middle| \boldsymbol{t}_m\right) = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1j} & \dots & x_{1m} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ x_{i1} & x_{i2} & \dots & x_{ij} & \dots & x_{im} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ x_{n1} & x_{n2} & \dots & x_{nj} & \dots & x_{nm} \end{pmatrix} \left(\boldsymbol{p}_1 \middle| \boldsymbol{p}_2 \middle| \;\dots\; \middle| \boldsymbol{p}_j \middle| \;\dots\; \middle| \boldsymbol{p}_m\right) \tag{9}$$

Consequently, the row vectors of the transformed data matrix **T** are uncorrelated and their respective variances are given by the eigenvalues of the covariance matrix $\mathbf{C_X}$ of the original data. Usually the eigenvectors $\boldsymbol{p}_j$ forming the transformation matrix **P** are sorted according to the eigenvalues by descending order and they are called the Principal Components of the data set. The eigenvector with the highest eigenvalue represents the most important pattern in the data with the largest quantity of information.

Geometrically, the j^{th}-column vector $\boldsymbol{t}_j$ of the transformed data matrix **T** is the projection of the original data over the direction of vector $\boldsymbol{p}_j$ (j^{th} principal component). Intuitively speaking, matrix **T** gives a new representation of the data set as "seen" by "virtual sensors" in a non-physical space, where the corresponding "virtual variable vectors" are uncorrelated and have the maximal data variance, thus with best potential to exhibit process features.

Reducing the Dimension

Since eigenvectors are ordered according to the amount of information, it is possible to reduce the dimensionality of the data set **X** by choosing only a reduced number r of principal components, those corresponding to the first eigenvalues. Thus define the following reduced transformation $m \times r$ matrix:

$$\mathbf{P} = \left(\boldsymbol{p}_1 \middle| \boldsymbol{p}_2 \middle| \;\dots\; \middle| \boldsymbol{p}_r\right) \tag{10}$$

Then the original data (1) can be projected onto the space spanned by this matrix as before (5). In the full dimension case, this projection is invertible (since $\mathbf{PP^T=I}$) and the original data can be recovered as $\mathbf{X=TP^T}$. Now, with the given **T**, it is not possible to fully recover **X**, but **T** can be projected back onto the original m-dimensional space and obtain another data matrix as follows:

$$\hat{\mathbf{X}} = \mathbf{TP^T} = \mathbf{X}\left(\mathbf{PP^T}\right) \tag{11}$$

By simple manipulations (adding and subtracting) in expression (11), the following decomposition of the original data matrix **X** can be written:

$$\begin{aligned} \mathbf{X} &= \hat{\mathbf{X}} + \tilde{\mathbf{X}} \\ \hat{\mathbf{X}} &= \mathbf{X}\left(\mathbf{PP^T}\right) \\ \tilde{\mathbf{X}} &= \mathbf{X}\left(\mathbf{I} - \mathbf{PP^T}\right) \end{aligned} \tag{12}$$

where $\hat{\mathbf{X}}$ is the projection of the data matrix **X** onto the selected r principal components and $\tilde{\mathbf{X}}$ is the projection onto the residual left components.

Applying PCA in practice

To perform PCA is simple in practice through the basic steps:

1) Organize the data set as an $n \times m$ matrix, where m is the number of measured variables and n is the number of trials.
2) Normalize the data to have zero mean and unity variance.
3) Calculate the eigenvectors – eigenvalues of the covariance matrix.
4) Select the first eigenvectors as the principal components.
5) Transform the original data by means of the principal components (projection).

The transformed matrix **T** is usually called *score matrix*. Its columns are called *score vectors* $\boldsymbol{t_i}$, each of them associated with the corresponding principal component $\boldsymbol{PC_i}$.

Damage Detection Indices

There are several definitions of fault detection indices (Alcala and Qin, 2009, Mnassri *et al*. 2009, Alawi *et al*. 2006). Two well-known indices are commonly used to this aim: the *Q-index* (*or SPE-index*), the T^2*-index* (*D-index*). The first one is based on analyzing the residual data matrix $\tilde{\mathbf{X}}$ to represent the variability of the data projection in the residual subspace. The second method is based in analyzing the score matrix T to check the variability of the projected data in the new space of the principal components (Mujica *et al*. 2010). There exist another type of indices reported in the literature as φ*-index* (Yue and Qin, 2001) and *I-index* (T. Huedo *et al*. 2006). The first one is a combination of the *Q-index* and T^2*-index* and it is used to monitor the behavior of a process, the second one is used in meta-analysis and it can be interpreted as a percentage of heterogeneity. In a general way, it is possible to define any index as it appears in the equation 6.

$$Index = x\mathbf{M}x^{\mathrm{T}} \tag{6}$$

where the vector x represents measurements from all the sensors at a specific experiment trial, besides the matrix M depends of the type of index as follows:

$$Q\text{-}index = x\mathbf{M_Q}x^T = x\,(\,\mathbf{I\text{-}PP}^{\mathrm{T}}\,)\,x^{\mathrm{T}} \tag{7}$$

$$T^2\text{-}index = x\mathbf{M_T}x^T = x\,(\,\mathbf{P\Lambda}^{-1}\mathbf{P}^{\mathrm{T}}\,)\,x^{\mathrm{T}} \tag{8}$$

$$\varphi\text{-}index = Q\text{-}index + T^2\text{-}index = x\mathbf{M_\varphi}x^T = x\,(\,\mathbf{I\text{-}PP}^{\mathrm{T}} + \mathbf{P\Lambda}^{-1}\mathbf{P}^{\mathrm{T}}\,)\,x^{\mathrm{T}} \tag{9}$$

$$I\text{-}index = x\mathbf{M_I}x^T$$

where:

$$M_I = \begin{cases} 0 & \text{for} \quad Q \le (k-1) \\ \dfrac{Q-(k-1)}{Q} * 100\% & \text{for} \quad Q > (k-1) \end{cases} \tag{10}$$

and k is the number of experiments

Contribution Plots

Contribution plots are well known diagnostic tools for fault identification (B. Mnassri *et al*, 2009). Contribution plots (also called Complete Decomposition Contributions -CDC) in each index indicate the significance of the effect of each variable on the index. All the indices can determine if there are damages and distinguish between them, however they do not provide reasons for it. The main idea is to determine which variable or variables are responsible. The variables with the largest contribution are considered major contributors to the damage.

The contribution of the variable (or sensor) *j* to the *index* is defined as:

$$Index = x\mathbf{M}x^{\mathrm{T}} = \left\|\mathbf{M}^{1/2}x\right\|^2 \tag{12}$$

$$Index = \sum_{j=1}^{n}\left(\xi_j^{\mathrm{T}}\mathbf{M}x\right)^2 = \sum_{j=1}^{n} C_j^{Index} \tag{13}$$

$$C_j^{Index} = x\mathbf{M}^{1/2}\xi_i\xi_i^{\mathrm{T}}\mathbf{M}^{1/2}x^{\mathrm{T}} \tag{14}$$

where ξ_i is the i^{th} column of the identity matrix.

Experimental Setup

This work involves experiments with an aircraft turbine blade. This blade was instrumented with seven Piezoelectric transducer discs (PZT's) attached on the surface: three of them were distributed in one face and the others on the other face (see Figure 1). In previous work (Mujica *et al*. 2009; Mujica *et al*. 2010), it was concluded that the farther is the damage from the actuator, the more difficult is its detection. Therefore, to detect damage on a larger area and being useful the fact that PZT's can be used as much as actuators as sensors, the experiment to assess the structure is performed in several phases. In every phase, just one PZT is used as actuator (an electrical excitation signal is applied) and the others are used as sensors. The signal excitation and the dynamic response of the undamaged structure collected in the sensor 2 in the phase 1 are shown in Figure 2.

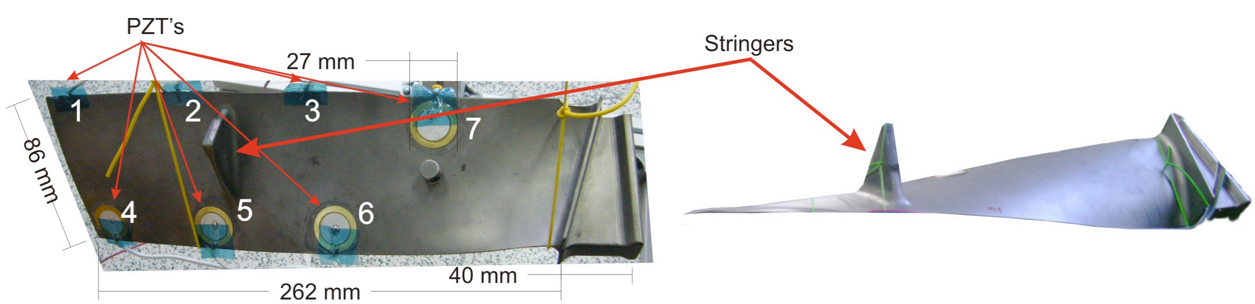

Figure 1. Blade with the PZT's location.

Adding two masses in different locations, nine damages were simulated as shown in the Figure 3. 140 experiments were performed and recorded: 50 with the undamaged structure, and 10 per damage. The PCA model was created using 80% of the whole dataset collected using the undamaged structure. Signals from the other 20% and the whole dataset of the damaged structure were used for testing the approach.

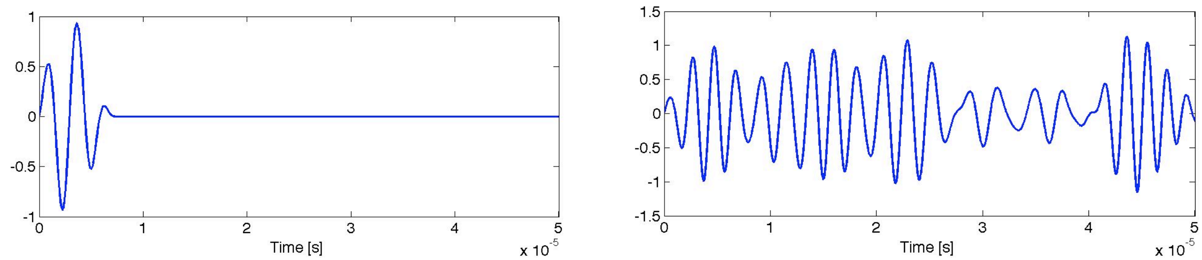

Figure 2. Signal excitation and dynamical response in sensor 2.

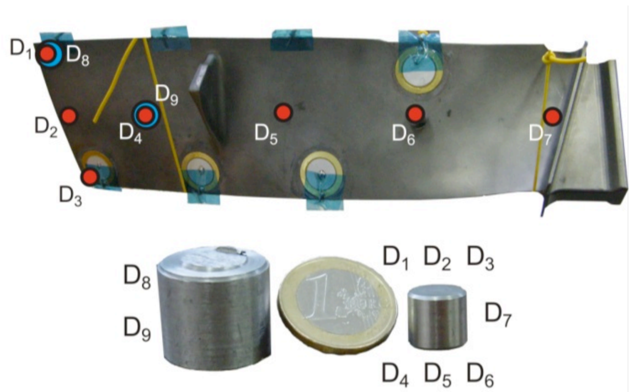

Figure 3. Added masses to the blade

Finally, the set of these signals was arranged in two 3-D matrices (one for building the PCA model, and the other one for testing it) in which *j=1,2,..J* sensors were recorded at *k=1,2,…,K* time instants throughout a particular experiment. Similar data was generated for a number of such experiment runs *i=1,2,…,I*. That generates a three-way data array $\mathbf{X} \in \Re^{IxJxK}$ (as shown in Figure 4a). This multivariable data set is unfolded as shown in Figure 4b. In this way, this new matrix 2D is the matrix **X** to perform PCA analysis.

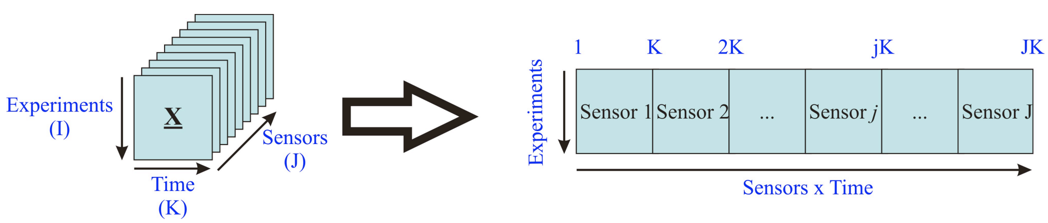

Figure 4. Collected data: (a) 3D-matrix (b) unfolded matrix (Mujica *et al.* 2010).

Damage Localization

The damage localization methodology used in this work has been previously suggested by the authors in (Mujica *et al*. 2009). It is based on the analysis of Principal Components and some measures (Mujica *et al*. 2010). In this work the methodology is extended to the fact that all PZTs can be used as actuators as well as sensors, besides another indices are also applied.

One PCA model is built in each phase (PZT1 as actuator, PZT2 as actuator, and so on) using the signals recorded by sensors during the experiments with the undamaged structure. Data from the experiments using the current structure (damaged or not) are projected on the model (see Figure 5). Projections onto the first principal components (scores), T^2*-index, Q-index, φ-index* and the *I-index* are calculated by each PCA model.

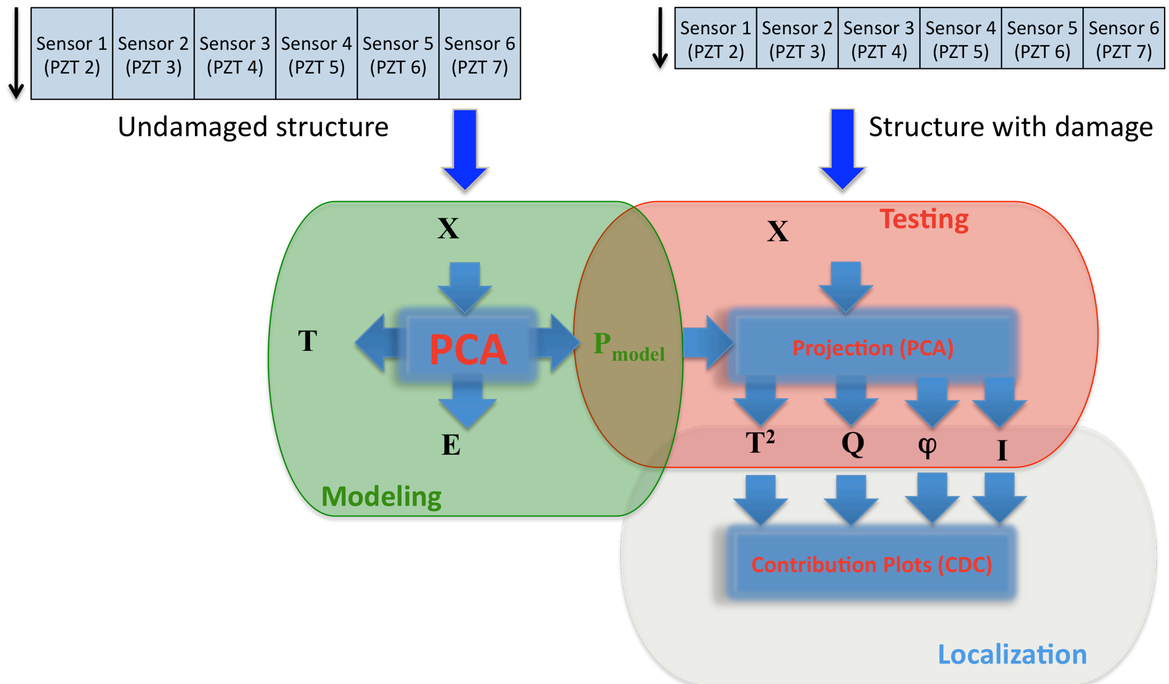

Figure 5. General scheme per phase based on PCA for damage localization in structures.

To find the localization of the damage, the contribution of each sensor to the index is calculated, this contribution is a measure of the level of influence of the damage to the sensor. Therefore, it is expected that the damage is located between the actuator and the most influenced sensor.

In each phase, a region of the structure is selected as the region where the damage is located. Considering all phases, a general diagnosis could be performed (intersection of all the regions).

Experimental Results

Figures 6,8,9 and 10 show the contribution of each PZT (1 to 7) to each index (T^2, Q, φ and I) at a specific trial (experiment using the structure to diagnose). In this case, the structure has the damage 3 (D3 in Figure 3.

Analyzing Figure 6 (contributions to *Q-index*) it is possible to observe the following: During the phase 1 (PZT1 as actuator), the highest contribution is obtained in the PZT4. Therefore, the damage is located between PZT1 and PZT4. A similar situation is founded in phases 2,3,5,6 and 7; so, the damage is located between PZT2 and PZT4 (phase 2), PZT3 and PZT4 (phase 3), PZT5 and PZT4 (phase 5), PZT6 and PZT4 (phase 6), and PZT7 and PZT4 (phase 7).

In a general way, the region or area of the damage can be defined as the intersection of the different areas found in each phase. In this case, it can be concluded that the damage is nearby to PZT4. Figure 7 shows the areas of the damage in each phase.

From Figure 8 (contributions to T^2*-index*) it can be seen that some contributions are negative. Negative contributions do not have any physical sense and therefore, they are not considered in the analysis. Results are similar to obtained by using *Q-index*. The main difference appears in phase 6, the highest contribution is obtained by PZT7.

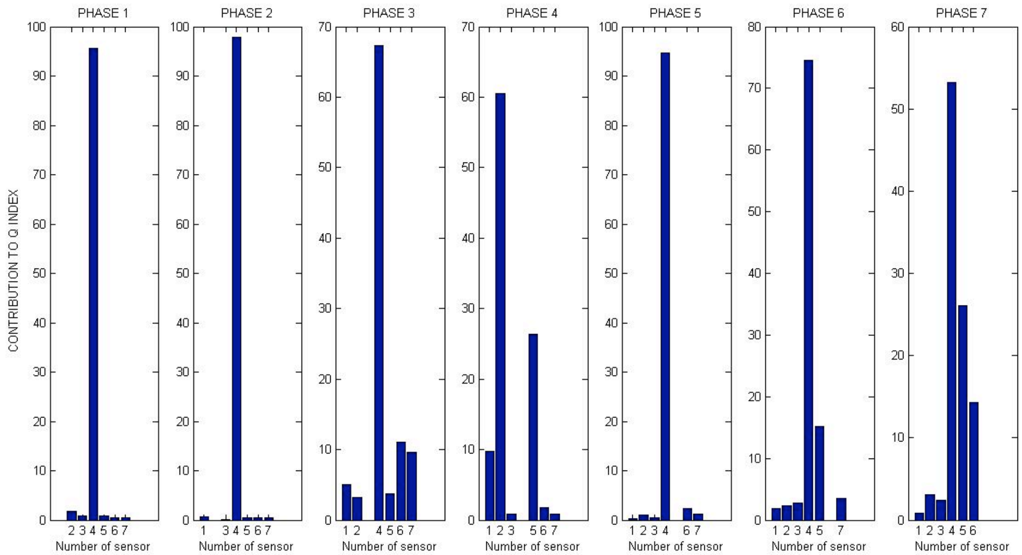

Figure 6. Contributions of each PZT to *Q-index*.

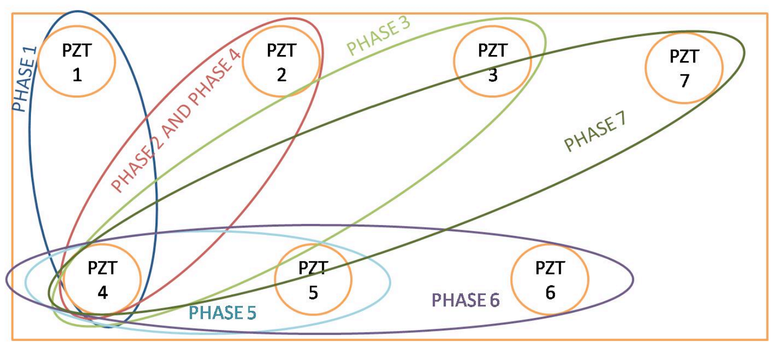

Figure 7. Localization of the damage

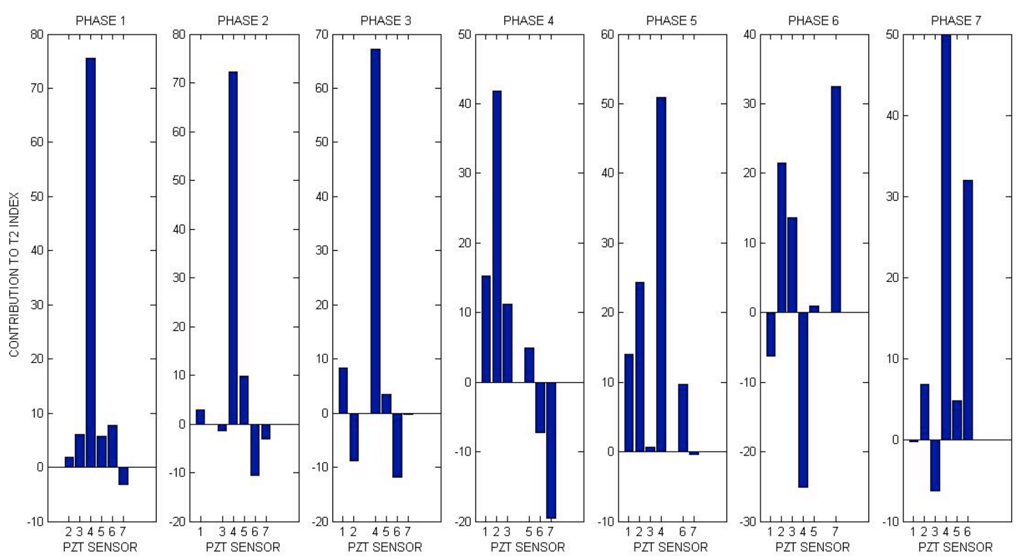

Figure 8. Contributions of each PZT to *T^2-index*.

Contributions to *φ-index* (Figure 9) and to *I-index* (Figure 10) show similar results. The highest contribution is carry out by PZT4

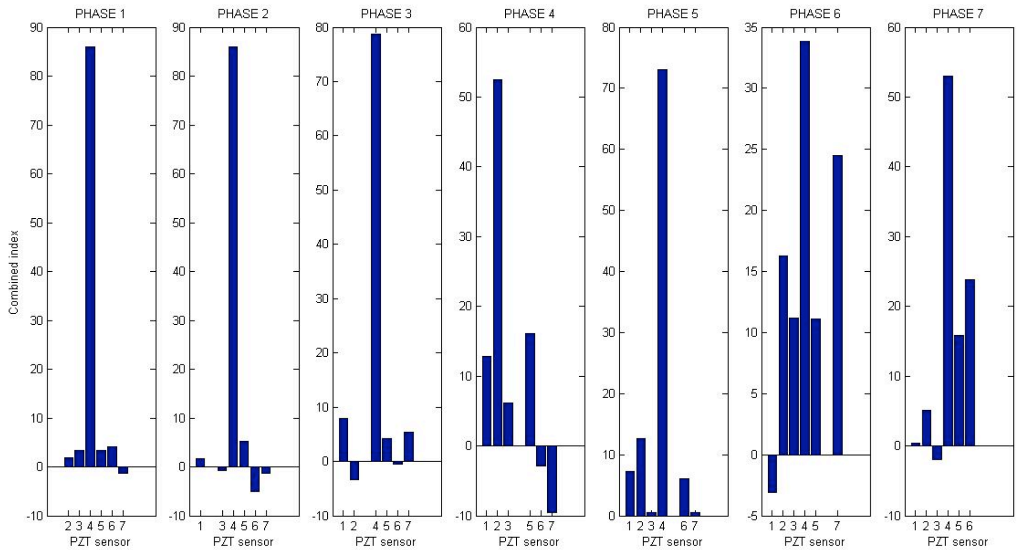

Figure 9. Contributions of each PZT to *φ-index*.

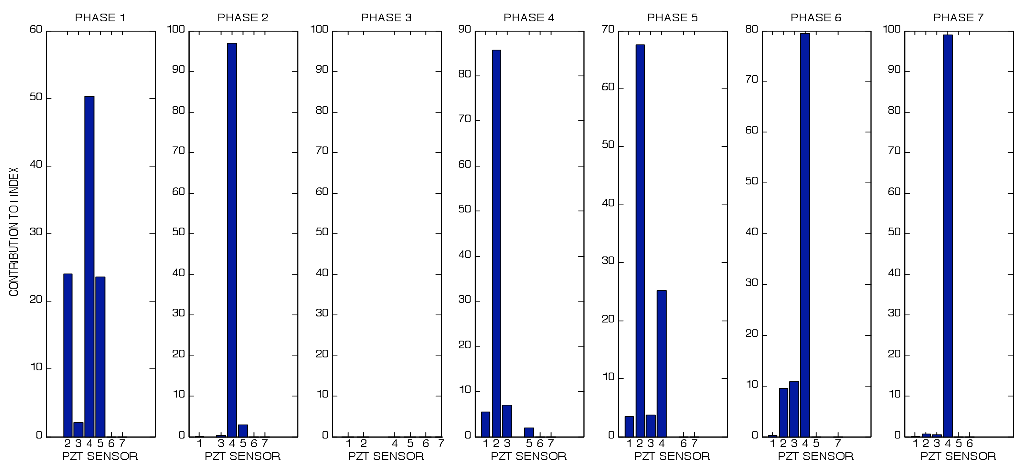

Figure 10. Contributions of each PZT to *I-index*.

In order to show the final diagnosis (considering contributions at all phases) it is necessary to specify areas in the structure that consider paths between actuator and sensors. The contribution of each sensor in each phase defines the weight of the path (region between actuator and sensor). Finally, the sum of all the weighted regions establishes the region where the damage is located.

From Figure 11 it can be seen the software application developed in Matlab. Here, the image of the structure is loaded, and the position of every PZT is manually defined (using the mouse). A typical path-planning algorithm is implemented to define the areas between PZT's.

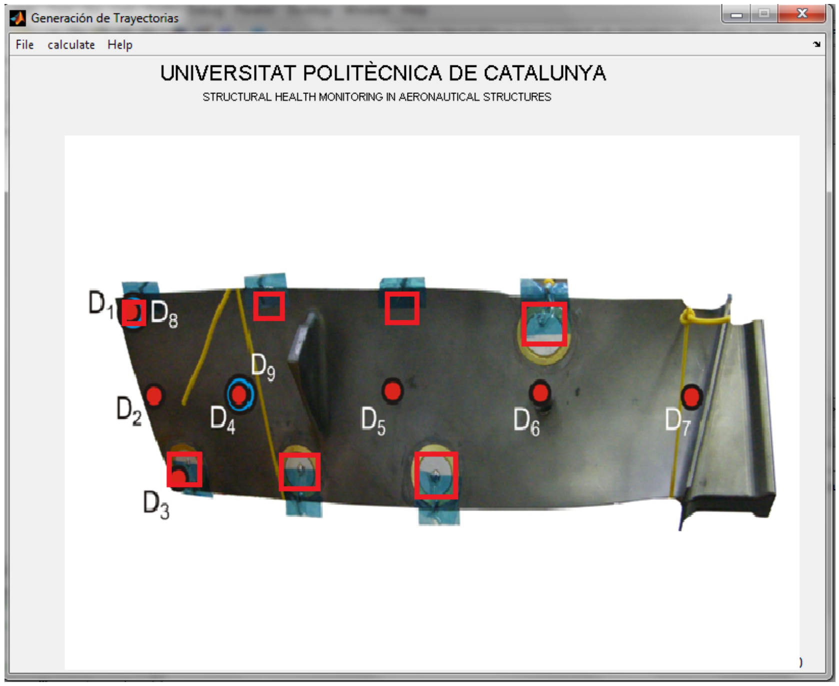

Figure 11. Interface of location of damage

The final diagnostic of the current structure (with damage 3) using contributions to *Q-index* is presented in Figure 12 (the higher the value of the color, the more probability of the localization of the damage). As it is expected, the damage is located near to PZT4

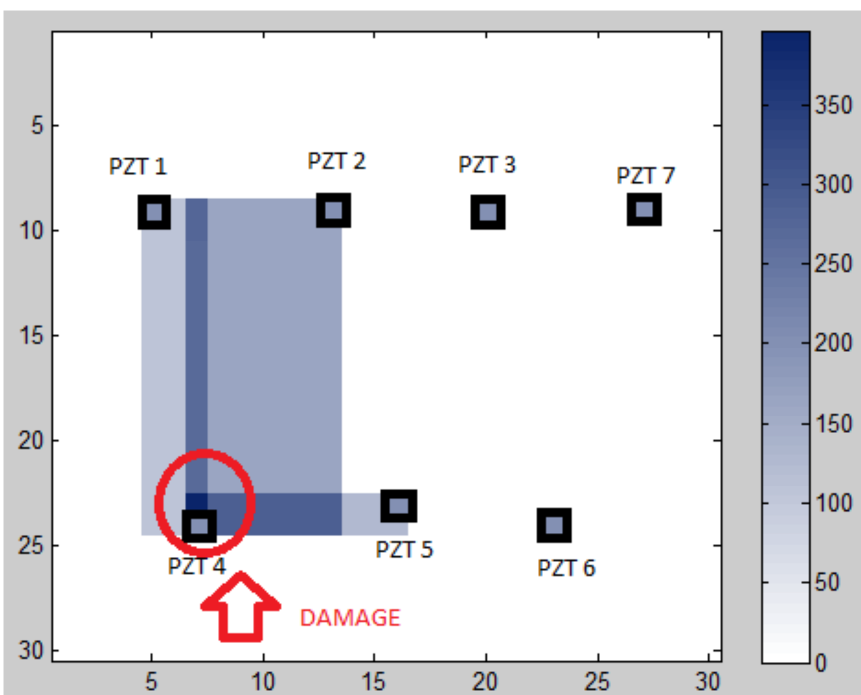

Figure 12. Localization of the damage 3 using contributions to *Q-index*.

Additionally, performing experiments with damage 1 present in the structure, the approach identifies the localization of the damage near to PZT1 as is shown in Figure 13.

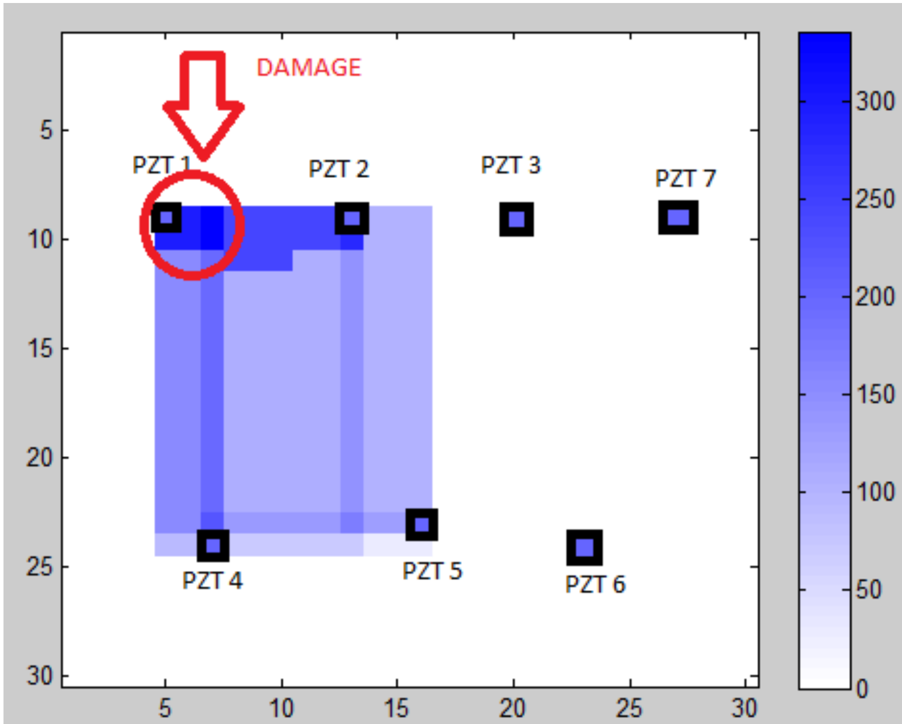

Figure 13. Localization of the damage 1 using contributions to *Q-index*.

Conclusions

A novelty multiactuator piezoelectric system for localization of damages has been developed. The approach combines strategies to study: (i) The dynamic or vibrational response of the structure at different exciting and receiving points. (ii) The correlation of these dynamical responses when some damage is presented in the structure by using PCA and some statistical measures that can be used as indices of damage. (iii) The influence of every sensor in the indices, this contribution can be used to localize the origin of the change in the vibrational characteristic (damage).

This work is still in developing state; a general diagnosis was performed just using contributions to *Q-index*. Despite that few but encouraging results have been obtained, authors expect to get satisfactory and reliable results also by using the rest of the indices.

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