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## Abstract

This paper presents the main results obtained by using a structural damage detection algorithm based on Principal Component Analysis (PCA) and piezo-actuation principle. A known high frequency piezoactuated signal is applied on an analyzed structure in order to determine the base-line performance for the undamaged state (undamaged PCA model). Q-statistic and hotteling's $T^2$ indexes are computed by projecting time data onto the principal component space, and used to identify deviations of the current dynamical responses respect to the undamaged state. The algorithm was embedded in the Beaglebone Black Hardware (platform based on an ARM cortex A8 processor) and tested by using experimental data supplied by the CODALAB group. The obtained results indicate that it is possible to identify and locate structural faults for this kind of structures. Identification capability of the algorithm for 10 damages is tested by adding masses on the surface of an aircraft turbine blade at different positions.

**Keywords:** *Structural Health Monitoring, Principal Component Analysis, Embedded Code, Statistical Algorithms*.

## Introduction

Principal Component Analysis (PCA) is a statistical technique that has been for the Structural Health Monitoring (SHM) problem. Several reports have demonstrated its ability to detect, locate and classify damages for different structures, for example turbine blades or beam structures [1], [2], [3]. The PCA algorithms used in SHM have been numerically implemented on specialized mathematical software such as MATLAB, where computational demand is typically high.

On other hand, several embedded algorithms used to damage location and classification, have been reported in the literature. For example, in [4] a dual-controller architecture is proposed, by using a FPGA and an 8-bits microcontroller. This system includes signal processing and wireless transmission module, where damages are located by using an energy decay model and iterative optimization methods (gradient descent optimization and Levenberg–Marquardt (LM) method) while a wave is propagated along a plate. The FPGA used is co-controller to improve sensing capability and power efficiency. In [5] a proposed embedded unit is capable of employing a spread-spectrum wireless modem in order to communicate peer-to-peer the sensing units and a complex 32-bit computational core and to achieve local data interrogation in real time. A statistical time-series analysis is proposed to obtain structural damage identification, where an 8 bit microcontroller is selected to control the data acquisition from signals coming from nodes over

 

150 m in civil structures. In [6] an embedded system on a FPGA is implemented, where a system on programmable ship (SoPC) is proposed in order to code a damage localization algorithm in C++, based on elastic wave propagation method. The algorithm creates color maps locating elastic waves reflections. The reflections could be caused by several kinds of discontinuities like boundaries, transducers and different damages. In [7] a Real-time Active Pipeline Integrity Detection system for pipelines was built. It is based on smart layers connected to a portable electronic hardware with diagnostic software, which uses statistical algorithms for locating and featuring damages.

Since, the main purpose of this work was to verify computational efficiency and implementation feasibility of PCA based algorithm for detecting mass adding on a plate when its code is embedded. Experimental validation of the algorithm consists of sending vibration signals of structure under analysis for different damage cases, from a PC to an embedded platform (Beaglebone Black, where the algorithm was coded). The embedded code computes scores, Q-statistic and Hotteling's $T^2$ indexes by using a PCA undamaged model previously obtained. Then, the computed indexes are presented graphically on the PC in order to distinguish each case under analysis. Thus the first part of this paper presents a methodology framework, while hardware used is described in second part, third part presents results obtained and last part correspond to the main conclusion of this work.

## 1 METHODOLOGY FRAMEWORK

### 1.1 Experimental data

The experimental data used to validate the algorithm were obtained by CODALAB group research from a turbine blade used in [2] by varying its vibrational properties. A mass was added at different positions of the blade in order to create 10 damage cases: damage D0 to damage D9. For each experiment 7 PZT transducers where installed (one as actuator and the other ones as sensors). Nineteen (19) experiments for undamaged case were achieved by collecting signals from 6 sensors installed, in order to obtain a matrix of 19x24000 corresponding to a signals base for the undamaged structure and then to create the PCA model. The experimental validation data consists of a 100x24000 matrix, obtained by achieving 100 experiments for 10 damage cases (D0 to D9) of the structure with six (6) sensors installed.

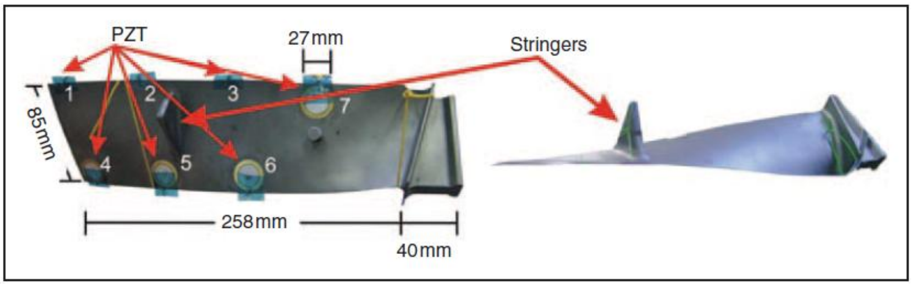


Figure 1: specimen used for getting the experimental data: aircraft turbine blade

### 1.2 PCA based algorithm description

The PCA based algorithm used to detect damages in the structure, consists of exploiting the capabilities of PCA technique for creating statistic models and extracting features. A statistic model is obtained by computing the PCA transformation and normalization matrices, and the principal component's variances vector for vibrational responses of undamaged cases. Then, scores, Hotelling T2 and Q statistics features are computed respect to the base-line performance for the undamaged state by using the undamaged PCA model, which allow separating different mass adding cases. These two stages are explained in the next subsections.

### 1.2.1 Training Stage: PCA model building

In order to process each dynamical response case, it is necessary to obtain a PCA model from an undamaged structural responses case matrix, corresponding to the base-line performance. The matrix is organized such that each column contains vibrational response time samples, collected during a defined time period, obtained from different sensors installed at different points of structure, while each row is a new vibrational response for the same undamaged structure. This undamaged case matrix is represented by first block of figure 2.

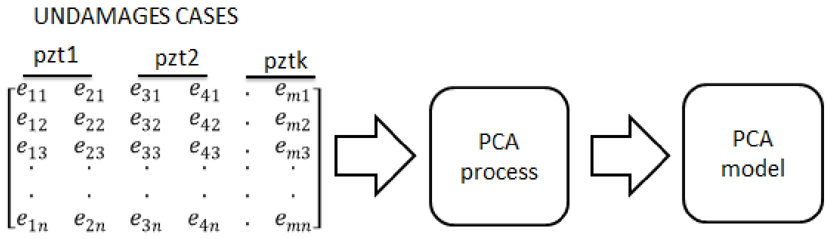


Figure 2: PCA training diagram

Once undamaged case matrix is built, PCA model used by the algorithm is obtained following next steps [2]:

- Normalize the undamaged cases matrix by using the group scaling method
- Find the covariance matrix from the normalized matrix.
- Use the same quantity of principal components than the number of experiments
- Estimate the reduced principal component vector by obtaining the eigenvectors and eigenvalues of the covariance matrix using an iterative method.

The PCA model to be obtained contains the next three elements:

- The normalization matrix represented by mean and deviation values of undamaged cases matrix.
- The transformation matrix represented by the eigenvectors
- The principal components variances represented by the eigenvalues

In order to compute on line the features for each vibrational response under analysis, PCA model is coded on the embedded system.

### 1.2.2 Validation Stage: PCA features extraction

At this stage three PCA statistical features are calculated by using the PCA statistical model: Scores, Hotelling $T^2$ and Q statistics.

- **Scores**: They are a projection of the Normalized Vibrational Case under analysis, onto the undamaged PCA reduced space. Score vector is computed by using equation (1).

$$Z_{damage} = \varphi_i]^{Und} * \left(\frac{X_{Damage} - \hat{\mu}_i}{\hat{\sigma}_i}\right) \quad (1)$$

- **Hotelling $T^2$ and Q statistics indexes:** By means of these indexes, deviations of vibrational case under analysis with respect to the undamaged PCA model can be measured. They are obtained by using equations (2) and (3).

$$T^2 = X^T \varphi]^{Und} \left(\Sigma^T \Sigma\right)^{-1} \left(\varphi]^{Und}\right)^T X \quad (2)$$

$$Q = r^T r, \quad r = \left[I - \varphi]^{Und} * \left(\varphi]^{Und}\right)^T\right] X \tag{3}$$

Where $\Sigma$ is a diagonal matrix comprising $\lambda_i$ values and r is the projection onto the residual left components. Hotelling $T^2$ is a variation measurement respect to the PCA model while Q statistic is a squared 2-norm that measures a deviation of the observation respect to the lower-dimensional PCA representation, avoiding overly sensitive to inaccuracies in the PCA space corresponding to the smaller singular values.

The main reason by using scores and PCA indexes in this algorithm is because visualization on 2D plots of different damage types can be achieved, what facilitates classification tasks. Thus, equations (1) to (3) are coded into the embedded system

### 1.2.3 Experimental Validation of the Embedded Code

By using vibrational responses of the test structure presented in figure 1 and supplied by CODALAB group, the embedded algorithm was validated. Because the embedded algorithm should be evaluated on line, the first part of the validation process consisted on emulating sensors acquisition by sending experimental data of sense signals from a PC to the embedded system through a communication protocol.

The experimental validation was achieved by following next steps (see Figure 3):

- An undamaged case matrix is built by using an experimental vibrational responses case base obtained from the trial experiment for undamaged cases.
- PCA model is obtained and coded in the embedded system.
- Equations (1) to (3) are coded in the embedded system.
- Vibrational data collected in an experimental trial are sent from the computer to the embedded system through a communication protocol. The time samples vector is organized such as presented in Figure 3.
- The time samples vector is normalized by using the media and deviation of the model, according to the group scaling method
- The Score vector and Hotelling's $T^2$ and Q indexes are computed by using the eigenvalues and the eigenvectors and returned to the PC, in order to be graphically presented.

## 2 HARDWARE DESCRIPTION

The hardware platform selected to test the feasibility and performance of the PCA algorithm by being coded on an embedded system Beaglebone Black Board. This includes a Texas Instruments processor, where can be installed a real time operating system with most of functionalities of whatever general-purpose computer. Thus, algorithm code lines can be charged into the board and executed on real time. This board has also a peripherals package that allows to make several improvements using Ethernet communication, USB, SD, HDMI ports, video out, on board memory.

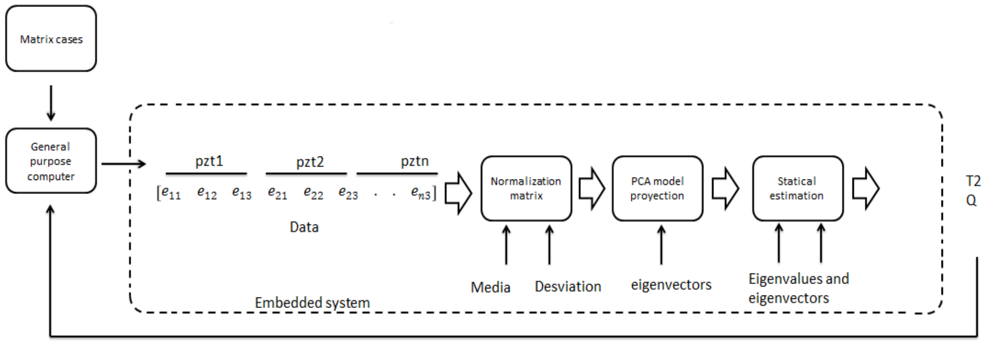


Figure 3: PCA validation diagram

The programming language selected to code the damage detection algorithm is Python. This is a general purpose and high level programming language that allows using fewer lines of code, such as C. By using this language the algorithm was coded in a few lines and indexes were adequately computed during the validation process. The Table 1 compares some features of Beaglebone Board respect to a general-purpose computer.

Figure 4: beaglebone black board.

Table 1: Some comparative features of the Beaglebone board front to a general-purpose computer.

| **Feature** | **Beaglebone Board** | **Toshiba satellite L645 Personal computer** |
|---|---|---|
| Operating system | Linux, android, windows embedded CE, QNX, ThreadX 32 bits | Linux 64 bits |
| CPU | ARM-cortex-A8 | Intel core I5 |
| ARM speed (max) | 2000 MIPs, 1GHz | 2.67GHz |
| Graphics acceleration | 1 3D | - |
| On chip l1 cache | 64 KB (ARM Cortex-A8) | - |
| On chip L2 cache | 256 KB (ARM Cortex-A8) | - |
| SDRAM Memory | 512MB | (RAM) 3.8GB |
| On board Memory Flash | 2G 8 bits MMC | - |

## 3 RESULTS

The structural damage detection algorithm was coded on the embedded platform Beaglobone by using Phyton language. Once a vibrational response time samples vector was read, steps presented in Figure 3 were correctly achieved and Hotelling's $T^2$ and Q indexes were store in the computer.

A validation cases matrix, representing 100 experimental trials, was used. Thus, 100 $T^2$-statistic and 100 Q-statistic values were computed, one for each experiment. Figures 5 and 6 present Q-statistic and $T^2$-statistic indexes obtained with the code embedded in the Beaglebone board by using python language. The same values were obtained by programming the algorithm in MATLAB and running it on a general-purpose computer, what demonstrates consistency of the embedded algorithm.

By observing Figures 5 and 6, distributions of $T^2$ and Q indexes remain in regions or classes separable for each type of damage, similar to results obtained by using MATLAB.

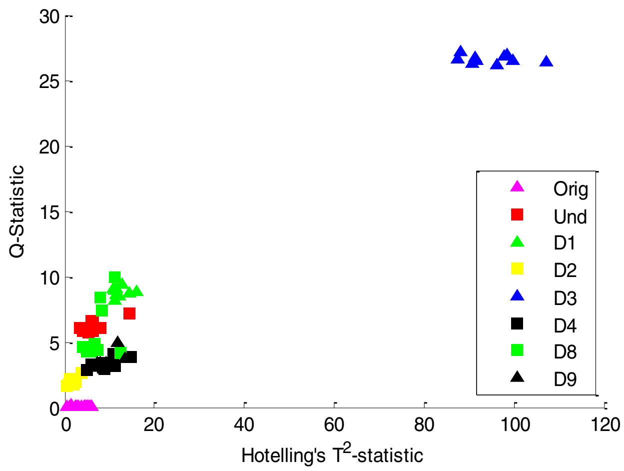


Figure 5: $T^2$-statistic in function of its correspondent Q-statistic

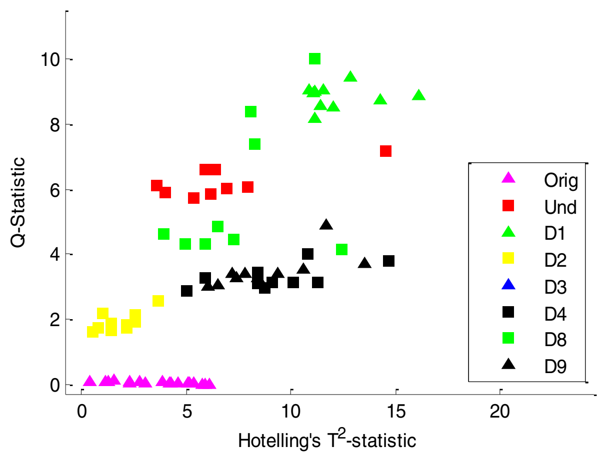


Figure 6: $T^2$-statistic in function of its correspondent Q-statistic with zoom

From Figures 5 and 6 can be observed that:

- 10 principal components were used for computing $T^2$ and Q show because 10 experiments of undamaged cases were used.

- Q indexes for original data (undamaged cases used to obtain the PCA model) are equal to 0 as expected.
- Each color representing a class of damage (a mass added at a located point) is grouped in a particular region of the graph, depending of the damage sensed.
- According to the obtained results it is possible, in most of cases, classifying the damages according to the class where the indexes appear in the graphic.

Table 2 presents some performance features obtained by embedding the algorithm in the Beaglebone board and programming it in MATLAB and tested in a general-purpose computer.

Table 2: comparative results for the beaglebone and a general-purpose computer.

| Algorithm Performance Feature | Beaglebone board | Toshiba satellite L645 |
|---|---|---|
| Time processing for one experimental trial | 5.016966024s | 0.4219993s |
| Time processing for 100 experimental trials | 480.019266s | 45.80999s |
| Number of code lines | 71lines | 46 lines |
| Software | Python | Matlab |

Where the number of code lines is computed by considering every routine needed for processing the information, additional libraries and charging files.

In general, similar results were obtained by using both algorithm implementations, embedded in the Beaglebone Board and programmed in a general-purpose computer. A little difference, of the order of $10^{-3}$ for $T^2$ and $10^{-4}$ for Q, are presented and they are plotted for each experiment in Figures 7 and 8.

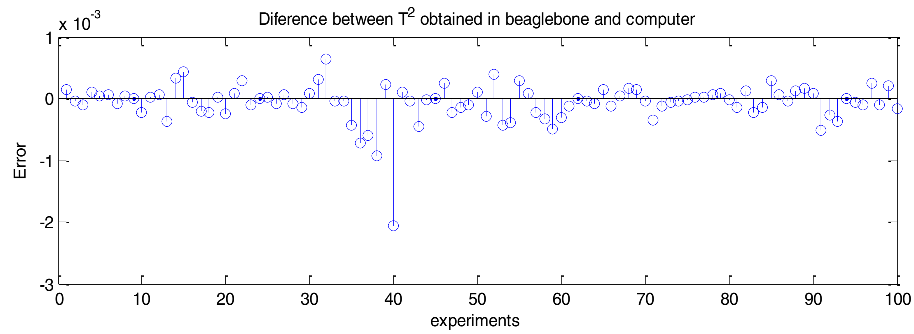


Figure 7: Difference between the $T^2$ given by the Beaglebone and the computer

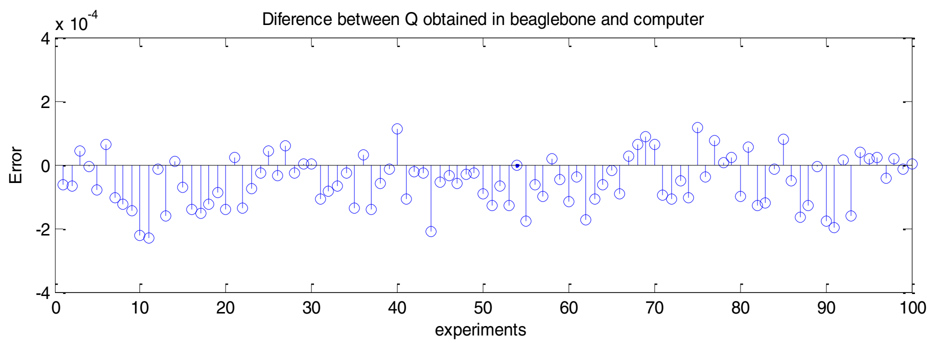


Figure 8: Difference between the Q given by the beaglebone and the computer

## CONCLUSION

The experimental results obtained by embedding a structural damage detection algorithm based on principal component indexes on a Beaglebone real time platform, have demonstrated that the embedded option can be used, since Hotelling's $T^2$ and Q statistics indexes are very similar with a maximum error percentage of 0.1%. Thus, it could be possible to run on line the algorithm on a stand-alone system such as the Beaglebone Board with the option of using pheriperal hardware to present graphically the computed indexes.

## ACKNOWLEDGMENTS

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## REFERENCES

[1] L.E. Mujica, J. Vehí, M. Ruiz, M. Verleysen, W. Staszewski, K. Worden, Multivariate statistics process control for dimensionality reduction in structural assessment. *Mechanical Systems and Signal Processing*, 22:155-171, January 2008, ISSN: 0888-3270, http://www.sciencedirect.com/science/article/pii/S0888327007000751.

[2] L. E. Mujica, J. Rodellar, A. Fernandez, A. Guemez. Q-statistic and T2-statistic PCA-based measures for damage assessment in structures. *Structural Health Monitoring-An International Journal*, 10:539-553, September 2011, ISSN: 1475-9217 doi: 10.1177/1475921710388972. http://shm.sagepub.com/content/early/2010/11/20/1475921710388972.

[3] D.A. Tibaduiza, L.E. Mujica, J. Rodellar. Comparison of several methods for damage localization using indices and contributions based on PCA. *9th International Conference on Damage Assessment of Structures (DAMAS 2011)*, 11–13 July 2011, St Anne's College, University of Oxford. *Journal of Phisycs: Conference Series,* 305:012013 doi:10.1088/1742-6596/305/1/012013.

[4] L. Liu, F.G. Yuan. 2008. Active damage localization for plate-like structures using wireless sensors and a distributed algorithm, *Smart Materials and Structures Journal*, 17: 055022, October 2008, http://iopscience.iop.org/0964-1726/17/5/055022.

[5] L. Si; Z. Chen; X. Yu; Q. Zhang; X. Liu. Embedded real-time damage detection and identification algorithms in wireless health monitoring system for smart structures, *IEEE International Conference on Communications Technology and Applications, 2009. ICCTA '09.* 676-681, October 2009. doi: 10.1109/ICCOMTA.2009.5349114

[6] P. Malinowsi, T. Wandowski, W. Ostachowicz, T.Luba, G. Borowick, M. Rawski, P. Tomaszewski. Signal processing system for guided wave-based SHM technique, *Proceedings of 9th International Workshop on Structural Health Monitoring,* Stanford University, California, USA

[7] X. P. Qing, S. Beard, S. B. Shen, S. Banerjee, I. Bradley, M. M. Salama and F .K. Chang. Development of a real-time active pipeline integrity detection system. *Smart Material and Structures Journal*, 18: 115010, September 2009, doi:10.1088/0964-1726/18/11/115010.