Comparative Study of Two Hardware Development Boards for Implementation of PCA-based Algorithms in Structural Damage Detection

JHONATAN CAMACHO-NAVARRO, MAGDA L. RUIZ, OSCAR PEREZ-GAMBOA, RODOLFO VILLAMIZAR-MEJIA and LUIS E. MUJICA

ABSTRACT

Compact and even portable devices integrated with Structural Health Monitoring systems are a promising solution to overcome issues regarding to practical implementation in real structures. This paper compares the computational capabilities of two Linux based development platforms for implementing structural monitoring algorithms. The Beagle Bone Black and Odroid-U3 single-board computers are studied. Attractive features as open-source software availability, easy configuration, low power requirement and hardware flexibility design, facilitate the use of these hardware platforms as an embedded system to contribute in recent advances obtained in the field of SHM and damage detection. From these devices, in this paper, storage capabilities, memory requirements, computational complexity and time processing consuming are analyzed and compared to evaluate benefits of embedding structural damage detection algorithms. In this work, a Piezo-diagnostics approach based on guided waves methods is embedded. The main components of the proposed damage identification system consist of a piezo actuator active system, a computational core (BBB or Odroid-U3 hardware), and a modelling block based on statistical features estimated by means of principal component analysis. The embedded algorithm was validated by using experimental data gathered from a steel carbon pipe section. Measurements from piezoelectric devices attached to the surface structure are used to distinguish damaged and undamaged conditions. Fifteen damage classes are seeded in the specimen by adding masses at different locations on the surface, where 200 experiments per damage are conducted. The feasibility to implement an automated real time diagnostic system is demonstrated.

Jhonatan Camacho [1-2], Magda Ruiz[1], Oscar Pérez.[2], Rodolfo Villamizar[2], Luis Mujica[1]
[1]{jhonatan.camacho}@estudiant.upc.edu. {magda.ruiz, luis.eduardo.mujica}@upc.edu. Escola Universitària d'Enginyeria Tècnica Industrial de Barcelona. Consorci Escola Industrial de Barcelona. Universitat Politècnica de Catalunya. BARCELONATECH, Departament of Applied Mathematics III.
[2]{rovillam}@uis.edu.co. {oscar.perez.gamboa}@gmail.com. Escuela de Ingenierías Eléctrica, Electrónica y de Telecomunicaciones (E3T), Universidad Industrial de Santander (UIS). Grupo de Control Electrónica Modelado y Simulación (CEMOS). Santander, Colombia.

INTRODUCTION

In recent years, several approaches have been extensively studied in order to develop standalone inspection systems with the capability to detect defects in structures ([1] [2]). The main purpose of these works is the implementation of long-range inspection systems for continuous condition monitoring [3]. Thus, in order to continuously assess the structural integrity, structural health-monitoring methods take advantage of permanently installed transducers, remotely sensing and embedded hardware platforms.

Embedded systems are promising solutions for SHM in real-time condition, since they offer suitable features as low power requirements, easy setup, low cost, small size, expandability, hardware accessibility, and balanced memory/processor performance. These features have motivated the use of embedded systems in SHM applications, for example, Bennouna et. al. [3] implemented on the dSPACE platform a wavelet analysis algorithm to process vibration signals. Siliang et. al. [4] validated the performance of a low-cost, low-power hardware platform to detect incipient faults of the bearings and gearbox based on an embedded sequential algorithm. Other example is described in the work by Kim et.al. [5], where a prototype of a fully self-contained system that performs impedance-based SHM is developed.

In this work, a comparison of the performance of Odroid-U3 and BeagleBoneBlack ARM systems is done, by embedding a damage detection algorithm based on PCA. Since the principle of elastic wave propagation along the structure is exploited, the embedded code process guided waves records, excited and registered by piezoelectric transducers. Changes in the wave patterns are determined by computing statistical indexes with respect to a baseline model of the structure. The performance of the studied platforms is evaluated by processing data recorded from a steel carbon pipe section, where reversible damages by adding masses are induced. The results show the feasibility of embedding SHM-PCA algorithms in the studied technologies for real world structures, with high numerical precision, minor memory requirements and low time consuming.

STRUCTURAL DAMAGE DETECTION METHODOLOGY

In order to detect structural damages, the methodology consists firstly in obtaining a structural baseline model by means of applying PCA on a set of experiments from pristine condition of the structure. Then, current condition (Damaged or Undamaged) of the structure is evaluated by comparing new measurements respect to the baseline model. PCA has been extensively used for SHM applications, where previous works have demonstrated its effectiveness for damage detection in aircraft sections, composite plates and pipework structures [6-8]. The concept of the methodology for structural damage detection based on PCA, used is this paper, can be visualized as presented in Figure 1, where two stages are followed: Modeling and Monitoring. Several piezoelectric devices are attached to the surface structure, where one of them is used as actuator to generate guided waves along the structure and the remaining ones as sensors.

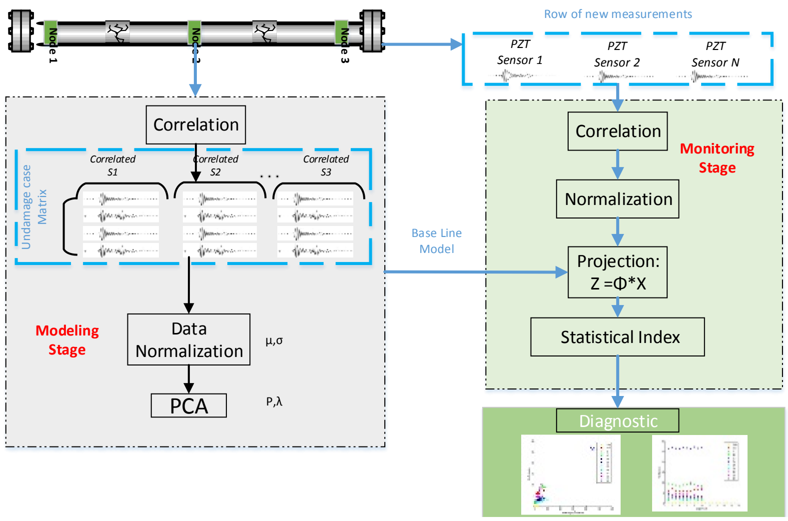

Figure 1: General scheme based on PCA for detecting and distinguishing damages in structures.

Modeling stage: Baseline model building

According to Figure 1, a baseline model is obtained using trial records from the pristine state of the structure. Piezoelectric sensor measurements are arranged in an unfolded matrix (**X**), which contains information about guided wave travelling. $\boldsymbol{n}$ experiment trials are conducted to consider noise and variance due to the stochastic nature of the technique. Next, a preprocessing stage based on cross correlation analysis is implemented in order to exclude external signals common to actuation and sensing elements, and to eliminate noisy data trends. Thus, cross-correlation between actuation and sensing piezo-signals is computed, before applying PCA. The cross-correlation function between two signals X(t) and Y(t) is defined by (1).

$$R_{XY}(t,t+\tau) = \lim_{N\to\infty} \frac{1}{N} \sum_{k=1}^{N} X_k(t) Y_k(t+\tau), \tag{1}$$

Where, N is the number of samples and τ is the lag time interval used to compute the cross-correlation function. After organizing cross-correlated undamaged trials in a new matrix, GroupScaling [9] normalization procedure is applied in order to minimize bias and scale variance effects. The standardization is computed by using the mean of each lag-time sample for every experiment and the standard deviation of each sensor sample vector Eq. (2). Thus, each data-point $\mathbf{x_{pk}}$ of the cross-correlated undamaged matrix is scaled by considering changes between sensors. As a result, from the standardization, $\boldsymbol{k}$ standard deviations and $\boldsymbol{p}$ mean values are obtained.

$$\hat{x}_{pk} = \frac{x_{pk}-\mu_k}{\sigma_{sensor}} \tag{2}$$

Then, the normalized cross-correlated undamaged matrix ($\hat{X}$) is represented in a new reduced space of coordinates with minimal redundancy (Eq. (3)). Thus, a linear transformation (P) is obtained by means of the singular value decomposition of the covariance matrix, as it is described in PCA method [10]. Where, the singular values

(λ) are the respective variances of this new coordinates reduced-space (eigenvectors), known as principal components. In order to obtain a reduced representation, only ***r*** principal components are retained to represent original data with a percentage of the cumulative variance.

$$T = \hat{X}P \tag{3}$$

Validation stage: Monitoring.

According to Figure 1, the monitoring stage is applied to new PZT measurements representing the current state of the structure. These measurements are organized in a row vector. This row vector is then standardized by applying GroupScaling and considering mean values and standard deviations of the undamaged baseline matrix. Then, the normalized row vector of new measurements is projected onto the reduced space by using Eq.(1). Q and T^2 statistics indexes are used to detect abnormal behavior of guided wave signals, traveling along the structure compared with the baseline records, where differences between baseline and current state are attributed to damage.

The Q-statistic is a lack of fit measure between the analyzed experiment and the baseline records (Eq. (4)).

$$Q = \sum_j \left(e_j\right)^2 \tag{4}$$

Where, e_j is the residual error for each $j-th$ principal component used to reconstruct the trial experiment.

The Hotelling T^2 statistic indicates how far each trial is from the center (T = 0) of the reduced space of coordinates (Eq. (5)).

$$T^2 = \sum_{j=1}^{r} \frac{t_{sij}^2}{\lambda_j} = T'\lambda^{-1}T \tag{5}$$

EMBEDDED SYSTEM

The monitoring stage code of the studied methodology (Figure 1) is embedded in a selected hardware as it is shown in Figure 2. For this purpose, python language was used to implement Eq.(1) to Eq.(5), which define the monitoring stage. Hardware-in-the-loop simulation is used in the development and test of the feasibility of PCA algorithm for real-time condition monitoring. Thus, baseline model parameters (P, λ, μ, and σ) are computed off-line in a PC and loaded to the embedded system. Also, piezoelectric measurements with the current condition of the structure are previously recorded through an acquisition system and stored in a PC, which works as an interface for the interaction between the embedded platform and structural dynamic response. Thus, by using the above configuration, it is possible to study simultaneous damage scenarios in a unique test (quickly prototyping).

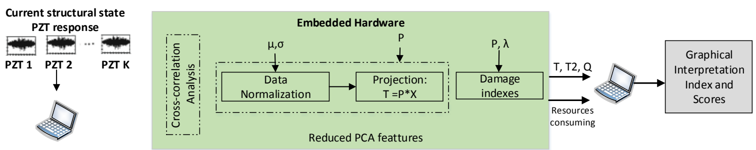

Figure 2: Hardware in the loop test performance of embedded systems.

In this work, two embedded platforms were used to implement the monitoring stage: Beaglebone-Black Board (BBB) and Odroid-U3. Table I summarizes the main features of these Linux based systems.

TABLE I. EMBEDDED HARDWARE SPECIFICATION

	BeagleBone Black	**Odroid-U3**
CORE	CPU: Sitara AM3359AZCZ100 1GHz, 2000 MIPS. RAM: 498 [MB]	CPU: 1.7GHz Exynos4412 Prime Cortex-A9, Quad-core processor with PoP (Package on Package) 2Gbyte LPDDR2 880Mega Data Rate. RAM: 2072 [MB]
Onboard Flash	2GB, 8bit Embedded MMC miniUSB USB or DC Jack. 5VDC External Via Expansion Header.	8Gb, Emmc 5VDC/2[a]
Ports	2 × USB A Host, 1 × ADB/Mass storage (Micro USB). UART0 3.3V TTL Header. Ethernet 10/100, RJ45. 16b HDMI. 69 GPIO	3 x USB 2.0, 1 x Micro USB. UART 1.8 V. Ethernet 10/100, RJ45. HDMI (480p/720p/1080p). 5 GPIO

USB protocol serves as interface to emulate real-time monitoring, by sending online structural dynamic response from the PC to the embedded system. In this sense, Secure Shell (ssh) network protocol was used to establish remote session in a secure way. In addition, the efficiency of embedded hardware was compared respect to a Sony VAIO PC with 64-bit Windows S.O., Intel CoreTM2 Duo Processor T8100, CPU 2.10 GHz, and 2 GB RAM, where a dedicated MATLAB® software is utilized to perform the cross-correlation analysis, normalization procedure, PCA projection, and damage indexes computation.

EXPERIMENTAL SETUP

Experimental data obtained from a carbon-steel pipe section were used to validate the embedded hardware performance. The pipe section (Figure 3) contains bridles at its ends and it is 100x 2.54 x0.3 cm (length, diameter, thickness). Two piezoelectric devices (sensor-actuator) were attached near to the structure bridles.

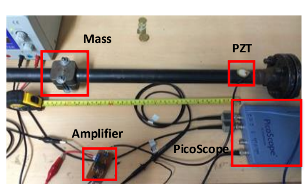

Figure 3: Experiment Mockup.

Fifteen damage classes are recreated in the test specimen by adding masses at different locations of the surface. Each damage scenario, (denominated D1, D2 ⋯ D15), corresponds to a mass located at 5cm, 10cm, and so on, respect to the PZT actuator. Experiments related to pristine structure cases are labeled as 'UND'.

A number of 200 experiments per condition (Damaged/Undamaged) were conducted. The baseline model was obtained by using only 70% of undamaged experiments and the remaining ones (30% - 'Orig') are used for validation purposes. Guided waves are induced with a 5 cycles Burst type pulse, which is then amplified to excite the PZT actuator at 80 [KHz]. The *picoscope 2208A* series is used as DAQ/Generation system by using a sample frequency of T_s=40 ns. All experiments (Damaged/Undamaged) are unfolded in a matrix with dimensions [3200x19235].

EXPERIMENTAL RESULTS

Damage indexes (T2 and Q statistics), computed by means of MATLAB® software and embedded platforms, are shown in Figure 5a and 5b respectively. It can be observed that no meaning visual differences are observed in the scatter plots, thus, both results are similar for visualization purposes. It is remarked that 90% of data variability can be explained by the first 80 principal components.

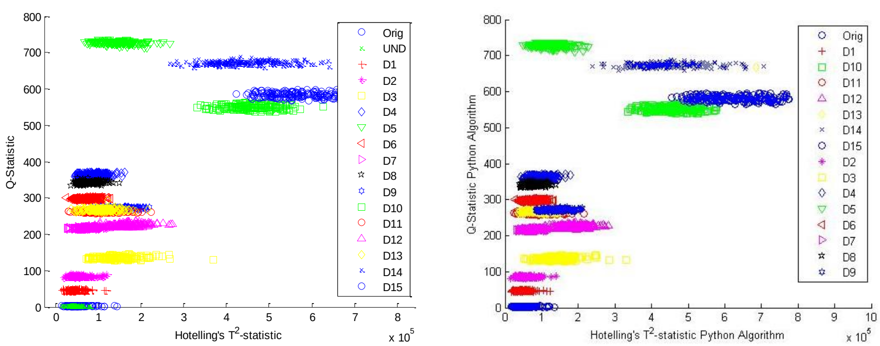

Figure 6: Statistical indexes. a) Matlab® software. b) Odroid-U3 and BBB embedded hardware.

Time and memory resources, required to implement the monitoring stage by using 15 principal components (elbow point in Log eigenvalue plot – Figure 5), are summarized in Table II.

TABLE II. COMPARISSON OF TIME-MEMORY CONSUMING

	Total time processing [s]	**Maximum resource memory**
BBB	12378.85316	62.5%
Odroid-U3	2184.31472	14.9%
Sony VAIO PC	701.11772	6.9 %

According to table II, the VAIO PC requires minimum resources due to its better hardware features. In addition, the two embedded hardware platforms accomplish the monitoring stage, however, it is remarked that BBB platform is limited to process matrices greater than 200x19235. The percentage relative errors between statistical indexes values computed by using the Odroid-U3 hardware and MATLAB® PC software are depicted in Figure 6. It is observed that error values are lower than 0.1%, which is an acceptable threshold for monitoring purposes.

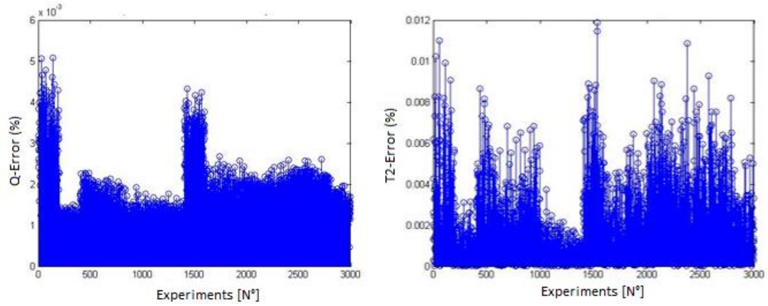

Figure 6: Errors between statistical index values - Matlab® software versus Odroid-U3.

Finally, the percentage relative error is estimated when the statistical indexes are computed with different number of principal components. Figure 7 shows a comparison between the statistical indexes values obtained with Odroid-U3 and MATLAB®. It is observed a high numerical difference when a big number (>80) of principal components are considered. Also, the T^2 index is more sensible than Q statistic because its value depends directly from eigenvalues, which have a logarithmic decay and very small values for high principal components.

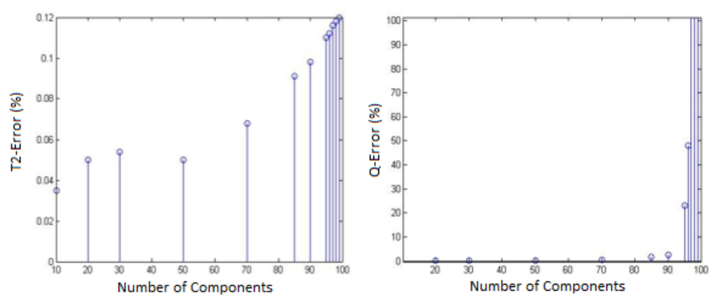

Figure 7: Statistical index error with different number of principal components.

CONCLUSION

In this paper, the feasibility and efficiency of embedding a PCA based algorithm for damage detection in pipeline structures were demonstrated. Two embedded systems were validated without meaning differences related to time and memory consuming as well as numerical precision (< 0.07% of error). Future researching is required to test online performance of embedding PCA based algorithms for real-time condition monitoring of structures.

ACKNOWLEDGEMENTS

This work has been developed as part of the research project: “Monitorización y Detección de Defectos en Estructuras usando Algoritmos Expertos Embebidos”, financed by the Departamento Administrativo de Ciencia y Tecnología Francisco José de Caldas – COLCIENCIAS and Banca Mundial in the Universidad Industrial de Santander, Colombia. Agosto 2012-Junio 2015.

REFERENCES

1. M. Lallart, D. Guyomar y T. Monnier, «Low-power computation methods and self-powered systems for Structural Health Monitoring techniques using Lamb waves for embedded sensing,» Shock and Vibration, vol. 19, pp. 867-877, 2012.
2. G. Dib, R. Lattrelf, L. Udpa y G. Yang, «A wireless sensor node for structural health monitoring using guided wave testing,» Materials Evaluation, vol. 71(10), pp. 1232-1241, 2013.
3. O. Bennouna y J. P. Roux, «Real Time Diagnosis & Fault Detection for the Reliability Improvement of the Embedded Systems,» Journal of Signal Processing Systems, vol. 73, nº 2, pp. 153-160, 2013.
4. S. Lu, Q. He, F. Hu y F. Kong, «Sequential Multiscale Noise Tuning Stochastic Resonance for Train Bearing Fault Diagnosis in an Embedded System,» Instrumentation and Measurement, IEEE Transactions, vol. 63, nº 1, pp. 106 - 116, 2013.
5. Kim, J., Grisso, B. L., Ha, D. S., & Inman, D. J. (2007, April). A system-on-board approach for impedance-based structural health monitoring. In The 14th International Symposium on: Smart Structures and Materials & Nondestructive Evaluation and Health Monitoring (pp. 65290O-65290O). International Society for Optics and Photonics.
6. Mujica, L. E., Rodellar, J., Fernandez, A., & Guemes, A. (2010). Q-statistic and T2-statistic PCA-based measures for damage assessment in structures.Structural Health Monitoring, 1475921710388972.
7. Tibaduiza Burgos, D. A., Mujica Delgado, L. E., Güemes Gordo, A., & Rodellar Benedé, J. (2010). Active piezoelectric system using PCA.
8. Torres-Arredondo, M. A., Buethe, I., Tibaduiza, D. A., Rodellar, J., & Fritzen, C. P. (2013). Damage detection and classification in pipework using acousto-ultrasonics and non-linear data-driven modelling. Journal of Civil Structural Health Monitoring, 3(4), 297-306.
9. Ruiz Ordóñez, M. L. (2008). Multivariate statistical process control and case-based reasoning for situation assessment of sequencing batch reactors.
10. Jolliffe, I. (2002). Principal component analysis. John Wiley & Sons, Ltd.