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# Structural Damage detection and classification based on Machine learning algorithms

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**Abstract**

Structural Health Monitoring is a growing area of interest given the benefits obtained from its use. This area includes different tasks in the damage identification process, among them, the most important is the damage detection at an early stage which enables to increase the security in mechanisms and systems, reducing risks and avoiding accidents. As a contribution in this topic, this work presents a data-driven methodology for the detection and classification of damages by using multivariate data driven approaches and machine learning algorithms which are validated and compared by using data from real structures in order to determine its behavior. In the methodology, PCA (Principal component analysis) and some pre-processing steps are used as the mechanisms to reduce data and build the features vector with relevant information about the different states of the structures under test. This methodology is validated by using some aluminum plates which are instrumented and inspected by means of PZT transducers attached to them and working in in several actuation phases. Results show a properly damage detection and classification of different simulated and real-damages.

## 1 INTRODUCTION

For several decades the need for structural monitoring systems (SHM) have been increasing, stimulated by the multiple possibilities of application of these systems. Several approaches have been proposed, but in most of the cases has started from strategies which seeks only the damage detection in order to monitor constantly seeking the structures in both civilian and militaries applications. The goal in a SHM systems is to provide information sufficient and appropriate in the decision making, this include for example, those designed to perform preventive maintenance or corrective if it is the case, which allow to reduce the possibility of accidents and the reduction in the maintaining cost.

One of the most accepted definition of a damage defines it as: "the change in geometrical or material properties or material properties, including boundary conditions and system connectivity that adversely affects system performance" [1]. In this sense, SHM systems need analyze information in order to go beyond of the merely damage detection task. The structural health Monitoring systems have been used to estimate the state of the structure at different levels of abstraction. According to Rytter's [2], four levels are considered in the damage identification process:

Level 1: Detection level where only the presence or absence of the damage is determined.
Level 2: Location, in which not only the presence of the damage is determined, but is also considered its location within the structure.
Level 3: Size of damage and its severity.
Level 4: Determination of the remaining life time.

Many elements have contributed to the development of SHM systems, first, the obvious progress of the techniques involved that has been producing since some time ago, second, the development of digital [1] systems, the cost reduction, and the increased computing capacity which allows to increase the computational load giving a new perspective to the SHM systems. Many of these systems have been implemented in a wide variety of devices such as embedded circuits [3], micro-controlled [4][5], micro processers [6] and programmable logic devices [7]. In addition, the performance can be increased using strategies such as parallel processing, with GPUs (Graphics Processing Units) [8]. Next to this, the important development of the DSPs (Digital Signal Processors) [9], also the advance of programmable logic devices especially FPGAs (Field Programmable Gate Array) with features such as speed, parallel processing and high performance, provide high-performance platforms for structural health monitoring [10]. Similarly, with the advancement of communications and elements of low consumption, the new technologies have added support for other features like the monitoring through wireless sensor networks (Wireless Sensor Network - WSN) [11][12][13], and other portable devices which enable high-performance processing information on the site and remote monitoring as is the case of SoCs (System On a Chip - System On Chip) [7]. From this point of view, electronic technologies give total support for the development of approaches in the evaluation of the structural state by the analysis of many sensors attached to the structures in order to ensure the proper performance of the inspection process. In this sense, this paper proposes a damage detection and classification methodology based on the use of a piezoelectric sensor network attached to the structure and working as sensor or as actuators in several phases, multivariate analysis and machine learning algorithms. This work is organized as follows: section 2 includes a brief theoretical background, section 3 includes the description of the used methodology, after that the experimental setup is described in section 4 and finally the results are included in section 5.

## 2 THEORETICAL BACKGROUND

This section presents some basic concepts about the methods used in the methodology.

### 2.1 SHM AS PATTERN RECOGNITION

Pattern recognition is a science that deals with extracting features of physical or intangible elements in such a way that can add to a classification, show additional information and make decisions. It's used in speech recognition, image recognition, in bioinformatics and in many other applications [14]. There are different approaches or tools for pattern recognition, some of the most important are: Template Matching, Statistical Classification, Syntactic or structural Matching, Neural Networks [15].

According to Farrar and Worden [1], there are four steps which are fundamental to the process of recognition of statistical patterns: First step is the operational evaluation, which among other things should determine the scope of system, what is its purpose and justification, as well as its environmental and operating conditions. The second is the acquisition, normalization and cleaning information, where it is selected based on the results obtained in the above process, as appropriate with the sensor system, as its type, location and Variable or variables under observation. Similarly efforts should be made to environmental conditions and operation do not affect the measurements or results. It is one of the reasons of processes cleaning and normalization. The third is the extraction of the characteristics. Having the information acquired by the sensors must remove any element that can provide light on the damage, which could well be such magnitude, frequency, phase, or any other element that is characteristic. The last step includes the development of the statistical model to determine the presence or not of a damage, assess its location or determine its magnitude and forecast operating time remaining. It's also important evaluate the operating conditions , specifically the computational load for selection or design of the processing system [16].

## 2.2 MACHINE LEARNING

One of the most widespread definitions about machine learning was given by Arthur Samuel who defines it as a tool to offer the computers the ability to learn without programming explicitly [17]. Machine learning has been widely used to shm. There are two types of learning, supervised and unsupervised. In supervised learning should have info on the structure undamaged and damaged. By Thus, can submit a data set of each type to the algorithm to perform the classification. On the other hand, are the unsupervised learning algorithms, in which case the information of the structure without damage don't have. Therefore there aren't a data set to learning for make the comparison and classification.

Different machine learning algorithms are used to address the problem of pattern recognition, particularly in monitoring structures in the research of K. Worden and C. Farrar [18] are used neural networks, genetic algorithms and support vector machines. In a research paper written by Willian Nick and others [19], support vector machines, Gaussian classifiers (Gaussian NBs), random forests and AdaBoost is shown. In the work of H. Hothu shows the behavior of support vector machines for locating damage to structures using only two sensors and the first three natural frequencies [20].

# 3 DAMAGE DETECTION AND CLASSIFICATION BY MACHINE LEARNING

The methodology used in this work includes the use of a piezoelectric active system for the inspection of the structures [21],[22], multivariate analysis for the analysis of the data from different structural states, PCA for reducing data [23] and machine learning algorithms for classifying all the structural states (with damages and without damages). Figure 1 shows the general procedure of the methodology, this is as follows: first a matrix with the information of the data from the sensors is built and pre-processed by group scaling normalization. This process is repeated to all the damage scenarios. After that, PCA is applied in order to extract the first two components which are used for training the machines. Finally, the machines are tested and compared with the goal to make the confusion matrix with all the structural states (damaged or not).

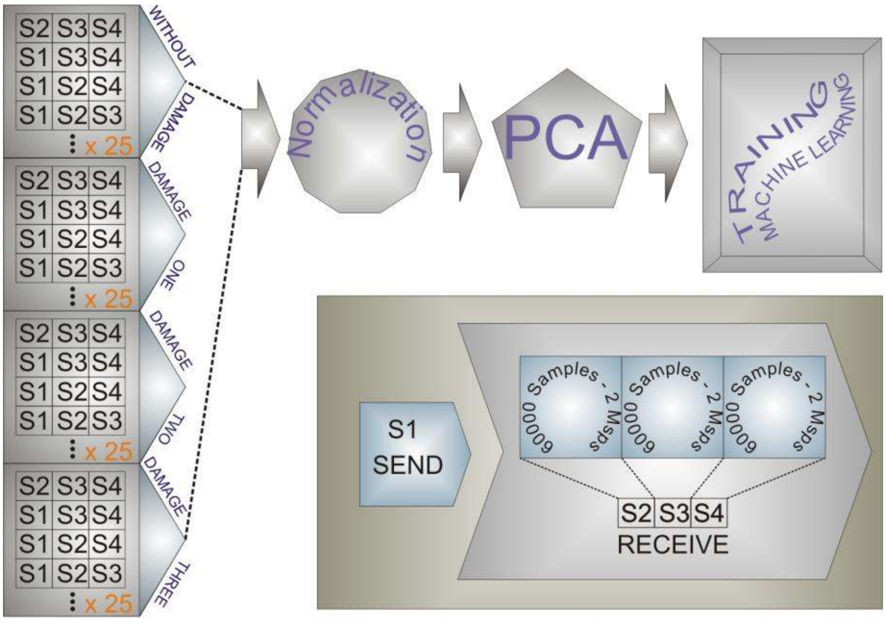



Figure 1: General procedure of the methodology.

## 4 EXPERIMENTAL SETUP

For the experimental test were selected piezoelectric sensors for their benefits, among them: low cost and easy installation although one of the disadvantages is the complexity of the data processing due to the lenght of the captured signals by each sensor. Figure 2 shows a diagram of the system used. For the excitation, an arbitrary waveform generator (Tiepie HS5) was used and for the acquisition, an oscilloscope Tiepie HS4 with four channels and a multiplexing system were used. As structure, an aluminium plate was selected and instrumented with four piezoelectric transducers.

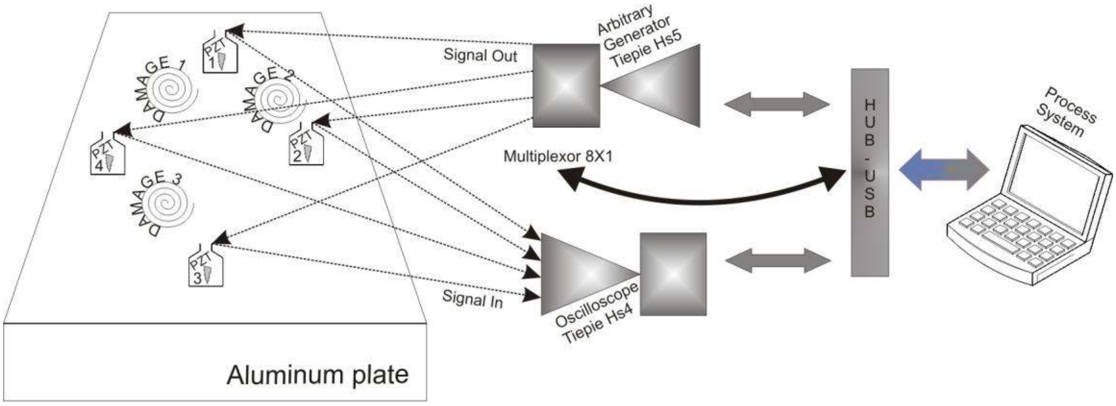



Figure 2: Test system.

The stimulus signal applied to the structure is showed in Figure 3, this signal is a burst signal with 8 volts of amplitude and a frequency is 10 kHz. This frequency was defined after to perform a frequency sweep.

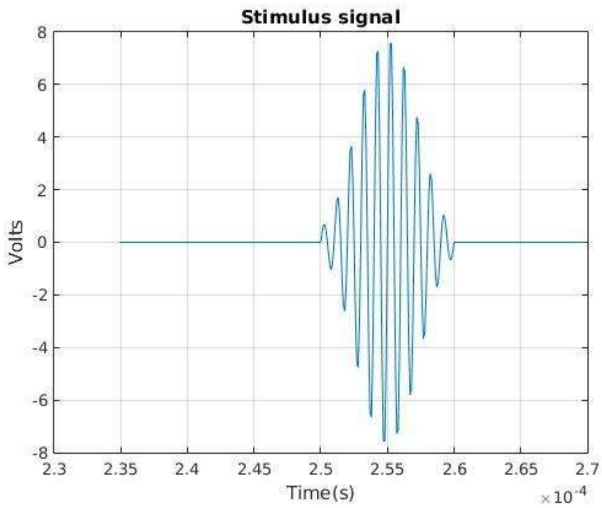



Figure 3: Stimulus signal.

Three damages were simulated in the structure by adding magnets in order to change the structure and the information collected by the sensors. Each damage correspond to the added mass as in Figure 2.

## 5. EXPERIMENTAL RESULTS

This section presents the results in the application of the machine learning based approach. Figure 4a shows the acquired signal in the actuation phase 1 from the healthy structure. In addition, to evaluate the results in the algorithm with noise, Figure 4b shows the signal with Gaussian noise by adding 5 dB of noise with a sample rate of 2 Msps.

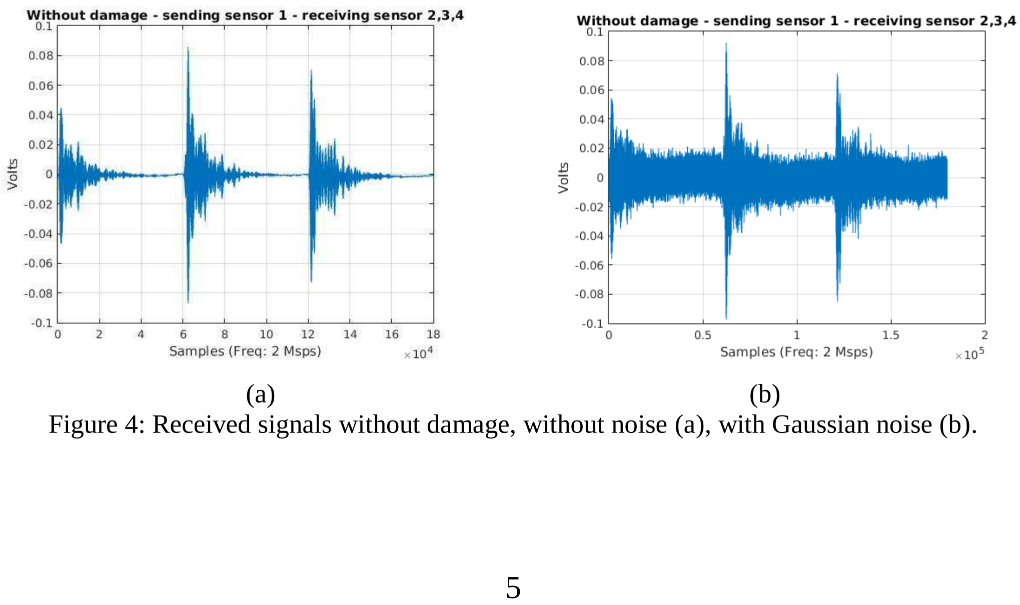
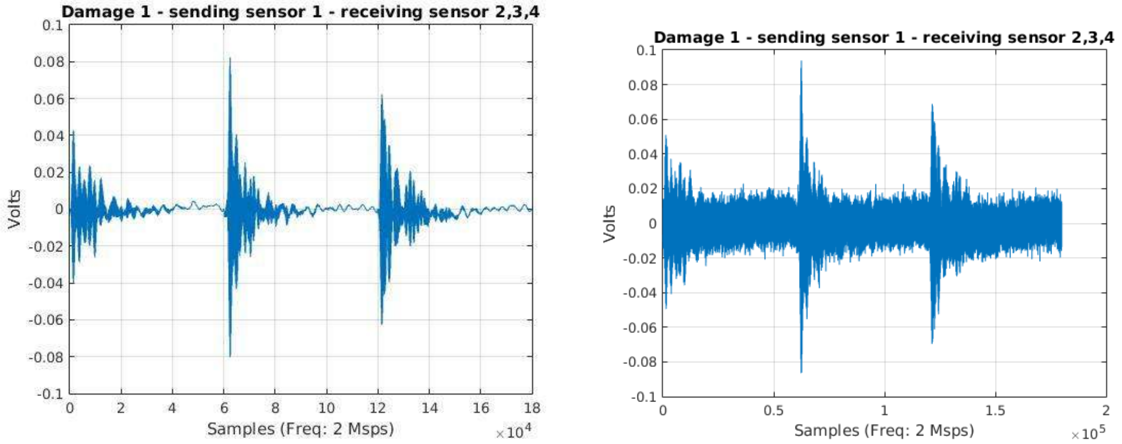



Figure 4: Received signals without damage, without noise (a), with Gaussian noise (b).

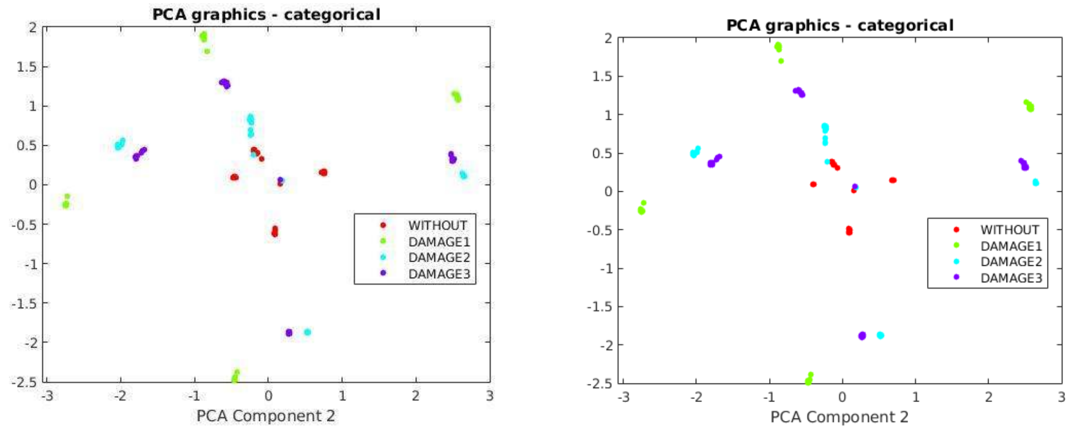
Figure 5a and 5b show the same signal when damage 1 is considered with and without noise.




(a) (b)

Figure 5: Received signals damage [1], without noise (a), with Gaussian noise (b).

Both signals were introduced to PCA and two components were obtained. After that, the machines are trained with these values; results are included in Figures 6a and 6b.




(a) (b)

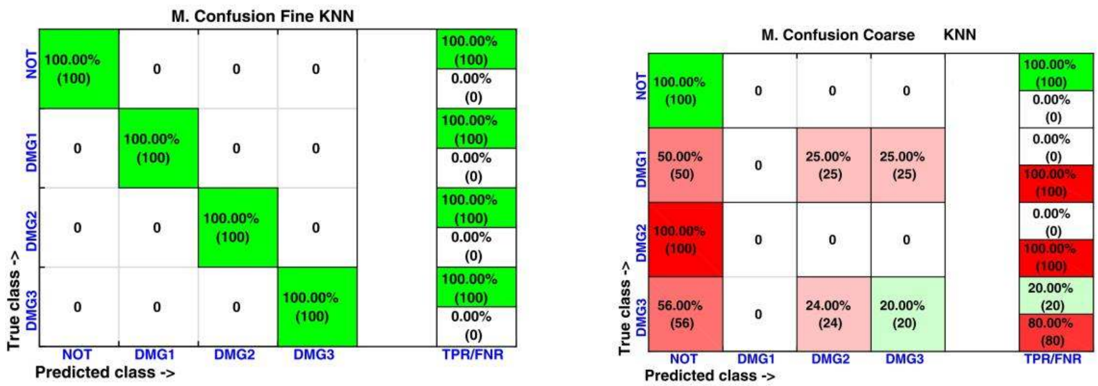
Figure 6: Two component of PCA, without noise (a), with Gaussian noise (b).

In this work the Classification Learner toolbox from Matlab was used. This toolbox includes the following machines:

| **Decision trees:** | **Nearest neighbor classifiers** | **Support vector machines** | **Ensemble classifiers** |
|---|---|---|---|
| Simple tree | Fine KNN | Linear SVM | Boosted trees |
| Medium tree | Cubic SVM | Fine Gaussian SVM | Bagged trees |
| Complex Tree | Medium KNN | Medium Gaussian SVM | Subspace KNN |
| | Coarse KNN | Coarse Gaussian SVM | Subspace discriminant |
| | Cosine KNN | Quadratic SVM | RUSBoosted Trees |
| | Weighted KNN | Cubic SVM | |

Table 1: Classification Learner – machine options

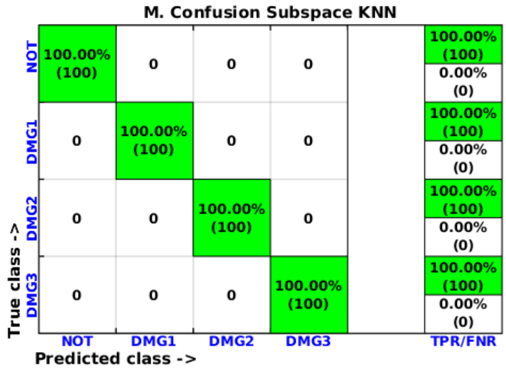
All the methods were evaluated; Figure 7a presents one of the obtained machines with good results. This machine found 100% of the damages, in both cases, without noise and with noise. Figure 7b, shows one of the worst machines, its classification capacity was too poor, although achievement detecting 100% of the signals without damage, it cannot detect damage in general only 20% the signals with damage 3 .



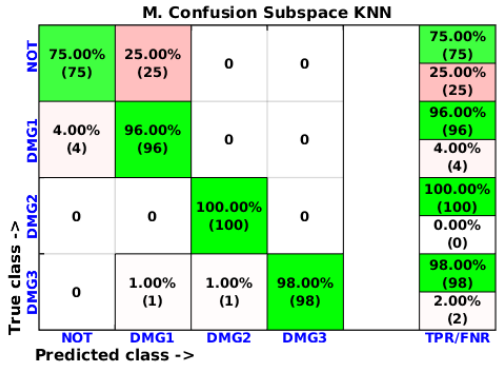

(a) (b)

Figure 7: Matrix confusion, Fine KNN (a), Coarse KNN (b).

Other machines showed better sensitivity to noise, for example subspace KNN presented a hundred percent of effectively as is shown in Figure 8a, but fail with the signals with added noise (Figure 8b).




(a)




(b)

Figure 8: Matrix confusion, Subspace KNN without noise (a), Subspace KNN with noise (b).

## 6 CONCLUSIONS

A damage detection and classification methodology was introduced with excellent results. Results of this study showed that all the structural states were properly classified in spite of the Gaussian noise added to the signals acquired from the structure. Among the classifiers used, best results were obtained with Subspace KNN, Bagged Trees, Weighted KNN and Fine KNN while worst results were obtained by Coarse KNN, Subspace Discriminant and Rusboosted Trees.

Other cases such as subspace KNN showed great sensitivity to noise and starts to produce a bad classification when it is added. From this point of view, is evident the importance of find a methodology suitable for detecting and classifying the damage with some immunity to noise and temperature, two of the most common factors in real structures. On the other hand it is also important to consider the computational load that provides the methodology, which is a factor to consider when the system wants to be portable or devices with low capacity but economic. More test need to be evaluated with different quantity of sensors to calculate the computational cost, however the four sensors used, allowed performing the detection and classification process with a low computational cost.

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