IOP Conf. Series: Journal of Physics: Conf. Series **842** (2017) 012019 doi:10.1088/1742-6596/842/1/012019

Ensemble learning as approach for pipeline condition assessment

Jhonatan Camacho-Navarro[1], Magda Ruiz[1], Rodolfo Villamizar[2], Luis Mujica[1], Gustavo Moreno-Beltrán[2]

[1]Universitat Politécnica de Catalunya (UPC) BARCELONATECH, Department of Mathematics, Escola d'Enginyeria de Barcelona Est. (EEBE), Campus Diagonal Besòs, Edifici A, C. Eduard Maristany, 10-14, 08019, Barcelona, Barcelona, Spain

[2]Universidad Industrial de Santander (UIS), Escuela de Ingenierías Eléctrica, Electrónica y de Telecomunicaciones (E3T), Bucaramanga, Colombia

jhonatan.camacho@estudiant.upc.edu, magda.ruiz@upc.edu, rovillam@uis.edu.co luis.eduardo.mujica@upc.edu, Gustavo.moreno4@correo.uis.edu.co

Abstract. The algorithms commonly used for damage condition monitoring present several drawbacks related to unbalanced data, optimal training requirements, low capability to manage feature diversity and low tolerance to errors. In this work, an approach based on ensemble learning is discussed as alternative to obtain more efficient diagnosis. The main advantage of ensemble learning is the use of several algorithms at the same time for a better proficiency. Thereby, combining simplest tree decision algorithms in bagging scheme, the accuracy of damage detection is improved. It takes advantage by combining prediction of preliminary algorithms based on regression models. The methodology is experimentally validated on a carbon steel pipe section, where mass adding conditions are studied as possible failures. Data from an active system based on piezoelectric sensors are stored and characterized through the T^2 and Q statistical indexes. Then, they are the inputs to the ensemble learning. The proposed methodology allows determining the condition assessment and damage localizations in the structure. The results of the studied cases show the feasibility of ensemble learning for detecting occurrence of structural damages with successful results.

1. Introduction

In the last years, a special interest is noted for the condition monitoring of structures such as wings, bridges, oil pipes, towers and sea platforms among others, which are widely used in tasks related to mechanical, civil and aeronautical applications. As a result, new techniques have been developed in the field of Non-Destructive Testing (NDT), in order to detect structural damages due to aging, overloads, fatigue or external disturbances. Thus, when damage is early detected, proper actions can be conducted to repair or reinforce structural elements that minimize accidents risk, economical losses, catastrophic events, and avoid possible human deaths.

The importance of NDT methods has promoted new trends for "*the integration of sensing and possibly also actuation devices to allow the loading and damaging conditions of a structure to be recorded, analysed, localized, and predicted in a way that non-destructive testing (NDT) becomes an integral part of the structure and a material*", which is named as Structural Health Monitoring (SHM) [1]. However, the implementation of SHM demands the management of uncertainty caused by operational and environmental conditions when continuous action is considered [2] and in this way, the

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erroneous diagnostic is minimized. In addition, damage localization strategies that facilitate the failure identification and reduce maintenance costs are included. Examples of SHM techniques comprises statistical analysis with high computational costs and sensitivity to external disturbances. For instance, envelope signals have been used to obtain an approximation of structural damage location [3]. Also, a PZT sensor network has been proposed as an alternative to locate the damage [4], [5].

This work proposes the use of ensemble learning as approach for structural damage assessment, since one of the main requirements to achieve reliable continuous monitoring systems is to minimize false alarms and missing reports. The philosophy of *Ensemble Learning* (EL) is the combination of machine learning algorithms in order to improve the probability of damage identification taking advantage of statistical performance [6]. Also, EL is suitable to manage some issues when large or little data volumes are available by the adaptation of resampling techniques and decision averaging. Additionally, EL is useful to integrate features from diverse information sources, which serves as a simple data fusion scheme. Therefore, the efficiency and accuracy of expert systems for SHM are maximized by using EL.

Since, the main purpose of this work is to evaluate the feasibility of using Ensemble Learning as approach for SHM tasks an EL architecture implemented through a bagging configuration of decision trees is evaluated. The whole methodology combines features obtained from piezo-diagnostics principle in order to build an ensemble with capability for detecting mass adding in a pipe section. As a result, the proposed system is able to condition assessment and predict the location of possible damages using information from guided waves along the structure which is characterized by means of statistical indexes and supervised learning. Experimental tests were conducted over a pipe section with masses emulating potential damages. Thus, the section 2 discuss the methodology framework of the approach used as damage identification system, while experimental results is described in section 3. Finally, section 4 corresponds to the main conclusion of this work. In summary, a promising approach for pipeline damage identification based on ensemble decisions was successful validated with promising results for real world application in structural assessment.

2. Damage condition monitoring methodology

The approach used in this work to detect and locate structural damages is based on piezo-diagnostics principle and ensemble learning approach. The main components of the whole expert system are detailed in next sections. Specifically, pre-processing techniques, data organization and instrumentation scheme, as well as theoretical framework are described.

2.1. Ensemble Learning as approach for SHM

The basic idea of ensemble learning is to combine multiple models to improve prediction performance. They are considered meta-algorithms designed to work on top of existing learning algorithms. Ensemble Learning is also known in the literature with several keywords: ensembles, ensemble methods, ensemble learning methods, model combination, combining models, combining classifiers, multiple classifiers, multiple classifier systems, majority voting or mixtures of experts. This diversity of keywords related to EL hinder the identification of previous works in any application field [6], [7], [8]. Figure 1 shows the concept of the expert system based on Ensemble Learning.

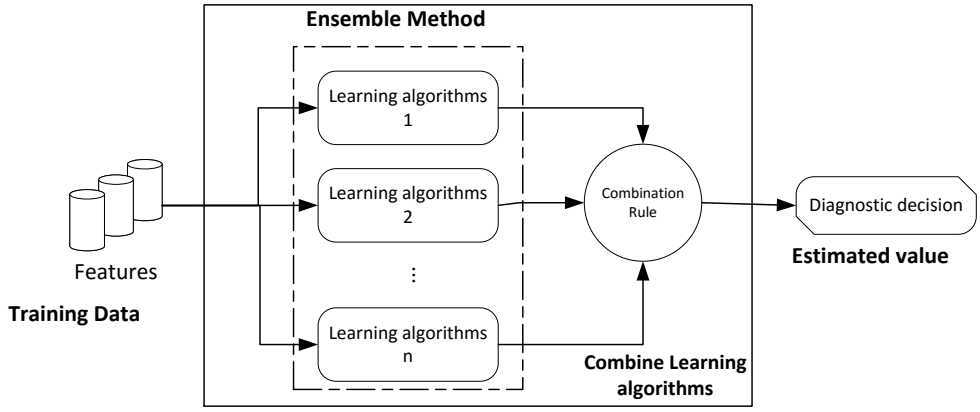


Figure 1. Expert System approach based on Ensemble Learning

According to figure 1, the main components of ensemble approach correspond to multiple learning algorithms organized in a parallel scheme and a combination function (fuser). Thus, the feature inputs are processed and manipulated with the methods selected to construct ensembles in order to obtain the final diagnostic decision. Although figure 1 specifies a parallel architecture, others such a cascading, hierarchical or hybrid can be used as ensemble scheme.

The most popular approaches used to generate ensembles are *Bagging* and *Boosting*. Bagging approach corresponds to Bootstrap Aggregation and it consists on multiple models which are built from different subsamples of the training dataset. In this sense, in bagging a set of models is generated each of which are trained on a random sampling of the data by means of bootstrap resampling where sample of instances with replacement are used. The final output prediction in Bagging ensemble is averaged across the predictions of all of the sub-models, or produced on the concept of voting or weighted average according to the performance of ensemble models [9], [10]:

$$f_{ens}(x) = \sum_{i=1}^{M} w_i \hat{f}_i(x) \tag{1}$$

In equation (1), the combined prediction $f_{ens}(x)$ is obtained from the M models of the ensemble, and the output $\hat{f}_i$ of model ***i*** on an input x. The weights w_i can be seen as the relative confidence in the correctness of the models predictions, and are thus constrained to sum to 1 ($w_i > 0, \sum_{i=1}^{M} w_i = 1$) [11].

Instead, boosting method constructs models in an iterative manner, where new models learns to fix the prediction errors of a prior model in the chain. Thus, *boosting* ensemble algorithms creates a sequence of models that attempt to correct the mistakes of the models before them in the sequence. There are several variants of boosting algorithm such a AdaBoost, LogitBoost, GentleBoost, and LPBoost. Specifically, LSBoost (least squares boosting) is used to fit regression ensembles by minimizing mean-squared error [12]. In this case, the ensemble fits new learners to the difference between the observed response and the aggregated prediction of all learners grown previously.

On the other hand, a typical example of ensemble machine learning algorithms is the decision trees [10]. A tree model is a set of rules for predicting the target, which are constructed by recursively partitioning a learning sample of data and represented by a node in the tree. For instance, a linear tree model implements a general linear function by means of piecewise linear approximation to the target function. Therefore, the final tree model consists of a tree with linear regression functions at the leaves. In the same way, the prediction for an instance is obtained by sorting it down to a leaf and using the prediction of the linear model associated with that leaf [11].

EL has not been applied sparingly in SHM despite the advantages of its use for task related to pattern recognition. As an illustration, support vector machines and neural networks have been used in combination to detect and classify two damage types in the aircraft fuselage [13]. Other example is detailed in [14], where a classifier is proposed as fusion strategy to manage different sources of information from acoustic emissions, ultrasound tests and flows measurements. The aim of this system is to improve leak detection in pipeline structures. A similar application is described in [15], where independent classifiers are used to combine measurements from different type of sensors in order to obtain higher level diagnostic responses. In this sense, a vote majority scheme is implemented to identify pipe damages as an approach in nondestructive testing. Other example is discussed in [16], where the authors present results of full-scale fatigue test (FSFT), which are analyzed by means of an ensemble of Artificial Neural Networks (ANNs). This last approach allows compensating temperature and environmental effects present during acquisition of Lamb-wave signals.

2.2. Piezo-diagnostic feature extraction

The features input for the structural damage identification methodology previously described are obtained by means of piezo-diagnostics principle. Hence, guided waves travelling along the structure are statistically characterized and implemented through piezoelectric devices. The suitability of piezo-diagnostic principle to find patterns with high sensitivity in structural damages has been previously demonstrated. Therefore, it has been successfully implemented for analyzing experimental data from aircraft wings, pipe bench tests, and plate structures, among others [17], [18]. The main components of feature extraction methodology based on piezo-diagnostics are summarized in figure 2.

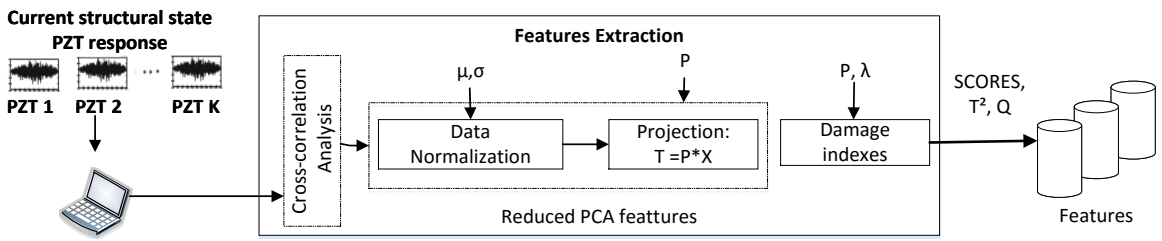


Figure 2. Piezo-diagnostic approach

According to figure 2, an active piezoelectric scheme is implemented in order to acquire the signature response of the structure to the scattering, reflection, and mode conversion from elastic wave travelling, caused by the presence of discontinuities [19]. Also, a pre-processing stage by using cross-correlation analysis and data normalization is included in order to minimize the influence of outliers and atypical data, as well as to facilitate data cleansing and common external noise filtering.

The data-driven strategy illustrated in figure 2 is implemented in two phases. In the first phase, a baseline model is obtained by processing data from repetitions of undamaged structural condition. As a result, the data matrix (***X***) corresponding to cross-correlated functions from PZT sensor measurements are represented in a reduced space according to Principal Component Analysis (PCA) procedure:

$$X = TP^{'} + E = \mathrm{mod}\,el + noise \tag{2}$$

The baseline model expressed in equation (2) is a representation of the pristine structural condition with minimal redundancy. In equation (2), T is the projection of X to the reduced space (SCORES), P is a linear transformation matrix which denotes the conserve r principal components and E corresponds to the noise matrix describing the residual variance neglected by the reduced baseline model.

PCA procedure is an efficient data reduction method, also known as Karhunen-Loμeve decomposition or Proper Orthogonal Decomposition. If data X processed by using PCA lie in the Hilbert space, then it can be approximated by orthonormal basis functions φ_i as stated in equation (3) [20]:

$$X = \sum_{i \in \mathbb{I}} (X, \varphi_i) \varphi_i \tag{3}$$

In theorem (3) the real numbers (X, φ_i) are referred as the *Fourier coefficients* of X in the basis $\{\varphi_i\}_{i \in \mathbb{I}}$ [20], where $\mathbb{I}$ is a countable index set and the relative contribution of each term decreases with increasing i. Such series will be referred as a Fourier expansion, used to approximate X data, which corresponds to a similar compact representation of statistical model in (2) [21].

On the other hand, the second phase consists of determining the current structural condition by processing new PZT measurements. For this purpose, the row vector of new PZT measurements is projected onto the reduced space by using the statistical model (2). Then, two statistical indexes are computed in order to identify differences between baseline model and current state: T-squared statistic (T^2) and squared prediction error (Q) [5].

$$T^2 = T' \lambda^{-1} T \tag{4}$$

$$Q = \sum_j \left(e_j \right)^2 \tag{5}$$

Where, e_j is the residual error for each $j - th$ principal component used to reconstruct the trial experiment and λ are the respective variances of the space determined by principal components.

3. Experimental Results

A carbon steel pipe section of 100 length, 2.54 diameter and 0.3 cm thickness, was used as structural lab model in order to conduct experimental tests. The test specimen was instrumented with two piezoelectric devices, which work in a pitch–catch mode. Other components comprising the instrumentation equipment consist of fine-tuning filters, high wide-band amplifiers and acquisition elements, among others. The test structure is depicted in figure 3, where PZT actuator and sensor can be identified.

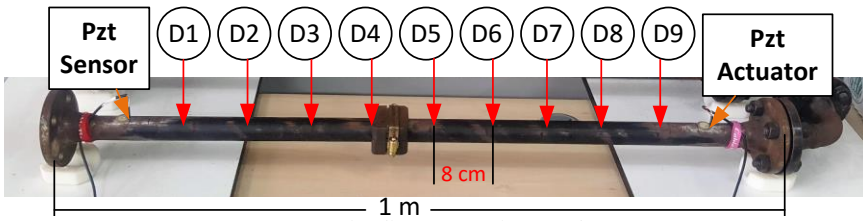


Figure 3. Pipeline experimental set-up

Also, figure 3, show a special shaped accessory added to the surface pipe section, which is used to simulate a damage type, corresponding to added mass at different locations of the structure surface. In this sense, nine damages cases were produced by positioning the mass accessory every 8 cm (tagged with labels from D1 until D9). The mass size is 5 cm, which is taken into account as uncertainty in the damage position. Thus, repetitions of each scenario are randomly labelled in the range [-2.5, 2.5] cm respect to the middle point of the shaped accessory.

In order to evaluate the capability of the methodology for damage assessment, 100 experiment repetitions of each damage scenario were acquired, while 1500 repetitions of undamaged condition (tagged as *'orig'*) were used to build the baseline model. The piezoelectric actuator device is excited with a 1s periodic high frequency (~100 Khz) burst type signal to induce guided waves. Linear trends

and bias issues are removed from piezo-electrical measurements in order to reduce artefacts noise and low frequency disturbances. The cross-correlation between sensing and actuation signals obtained from the 1500 piezoelectric measurements used to build the baseline model are depicted in figure 4.

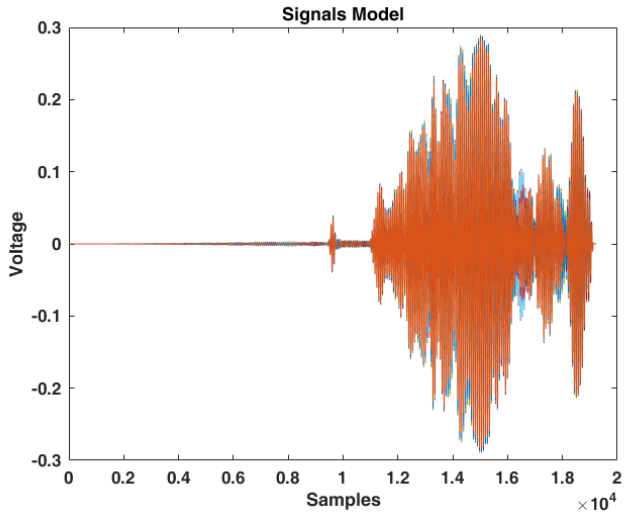


Figure 4. Cross-correlation signals used for baseline modelling.

According to figure 4, the most significant differences are regarding to amplitude variations and possible mode conversions between guided wave packages, which represent the structural response of pristine condition.

Then, the baseline model was built by estimating 25 principal components and considering as healthy structure, the pipe section including bolts and other elements attached to the pipe structure. The input feature vector is formed by concatenating 8 of the first scores with the statistical indexes (T^2 and Q). In this augmented feature vector, only scores from 2 to 8 are included (the first is omitted since it contains amplitude influence), thus, scaling issues are minimized by excluding the first major component. Above influence is demonstrated according to results in figure 5, where baseline model variances for cross-correlation signals in figure 4 as well as contribution of each component are detailed.

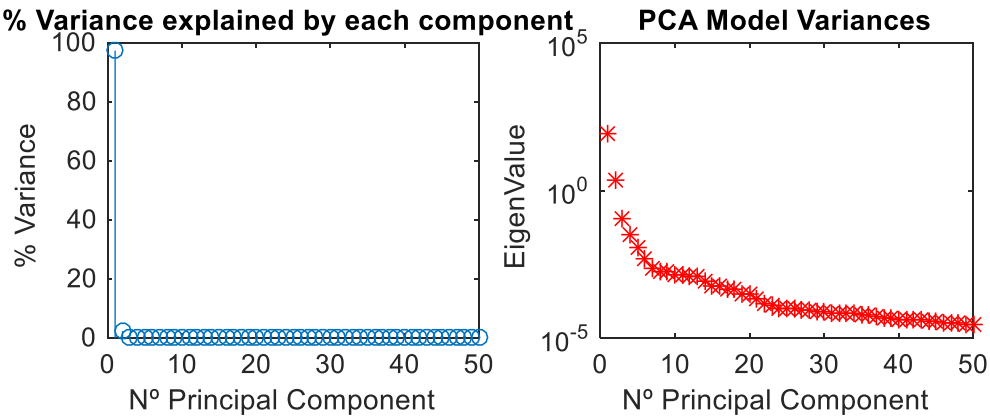


Figure 5. Variance of baseline modelling.

Figure 5a (left) shows that first component mask the contribution of remaining principal components and additionally, percentage variance (figure 5a-left) is not a good indicator of the principal component importance. While, cumulative variance does not allow establishing a meaning significance, there exists a relative variance that can be comparable through the eigenvalues magnitude in a semi-log scale (figure

5b-rigth). Above behaviour indicates that by excluding the first principal component from the augmented feature vector, structural response can be suitable to be represented. Plots of the first fourth Fourier modes are given in figure 6.

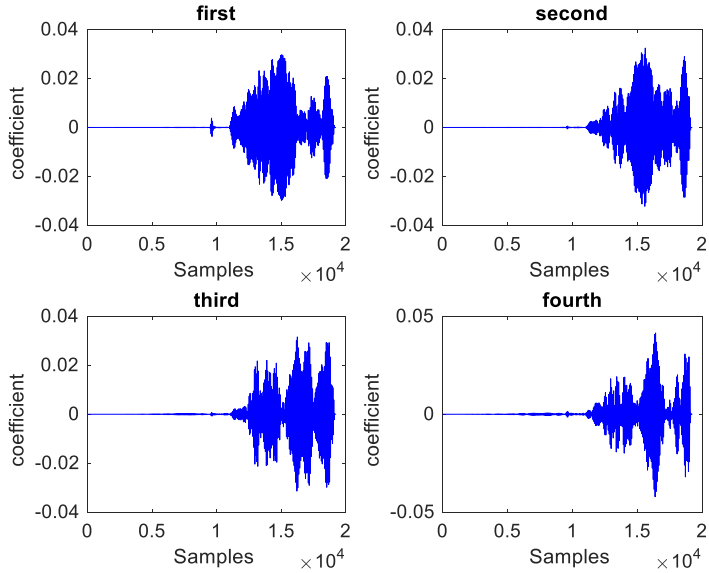


Figure 6. Fourier modes of baseline model.

In figure 6 it is observed that first component is a smoothed-roughly approximation of signals used to build the baseline model (figure 4). Besides, the other principal components capture high variation of baseline model signals. It confirms that first component is highly influenced by amplitude and scaling variations as was previously mentioned.

On the other hand, an iterative analysis was performed to examine the performance of Mean Square Error (MSE) of the estimated damage location. In this way, a proper number of ensembles are used to identify a suitable method to construct ensemble are performed. Figure 7 shows the evolution of the MSE for the Bag (Bagging) and LSBoost methods.

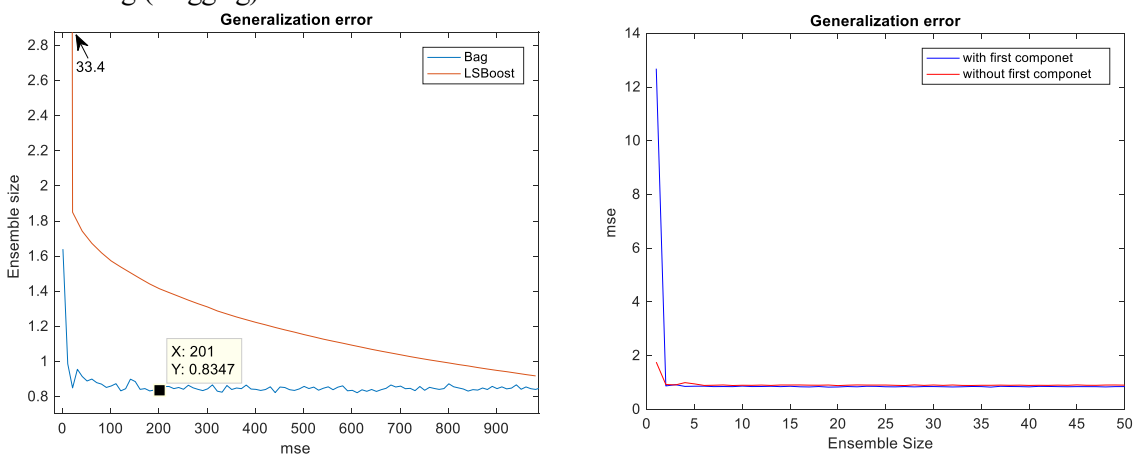


Figure 7. MSE evolution for ensemble methods

According to figure 7, the Bag method show better performance and more stable behaviour with a lower ensemble size. Consequently from now, the results are computed by using Bagging method with 200 ensembles.

In addition, the T-squared and Q-statistical indices as well as the variance of the PCA baseline model are depicted in figure 8.

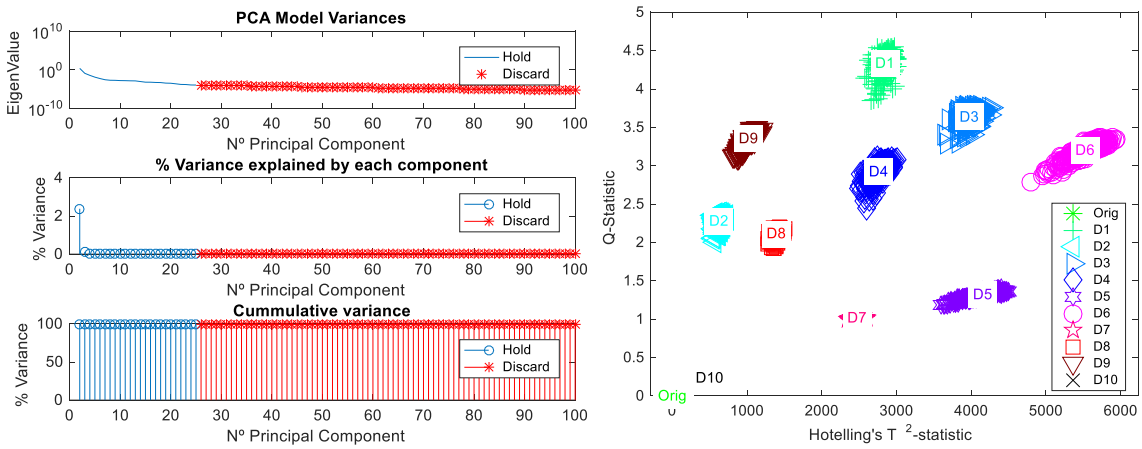
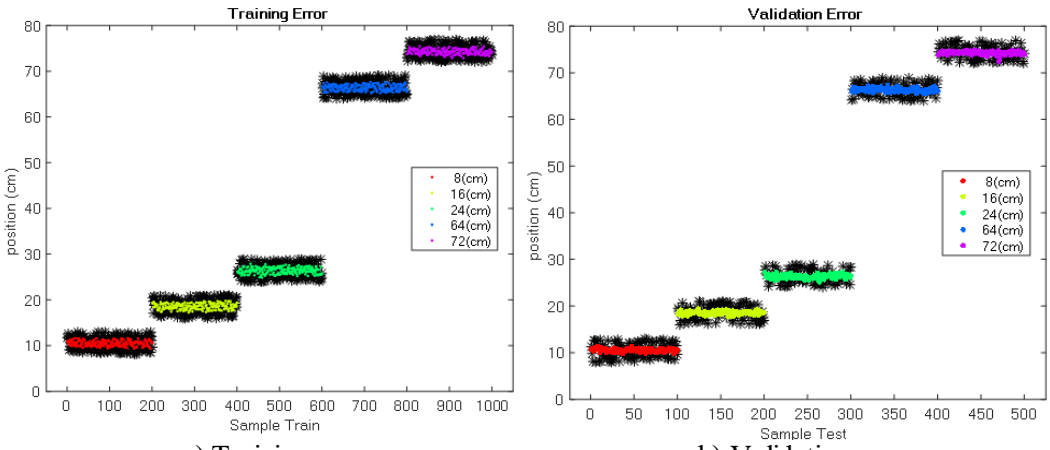


Figure 8. PCA results a) Baseline model variance b) Damage statistical indexes

Figure 8a (left) shows that the first 25 components retain more than 99% of cumulative variance, which is statistically significant to describe the normal (healthy) condition of the structure. Also, different damage types (locations) are clearly separated by boundaries between clusters generated by the T^2 and Q statistical indexes (see figure 8b - right). Thus, damage detection is achieved in a simple way by the examination of scatter plot of damage indexes, while automation of this task can be implemented through proper thresholds definition.

However, in order to solve the damage location problem, complementary information is required. It can be supplied using the first scores computed by the baseline model. Hence, information about deviations respect to healthy condition is included in the augmented feature input vector, then the ensemble tree is trained with supervised learning. Figure 9 shows the performance of training and validation errors, where black dots correspond to original data used to evaluate the regression algorithm and color points to the respective ensemble response.



a) Training error. b) Validation error

Figure 9. Ensemble tree performance

Besides, in figure 9 is observed the results obtained within the uncertainty range. Small errors and low dispersion were obtained since data used for training (Figure 9a) and validation (Figure 9b) purposes, corresponds to same damage location biasing the capacity of the algorithm. In this way for a new set of data (Prediction) the error estimate is calculated and illustrated in figure 10.

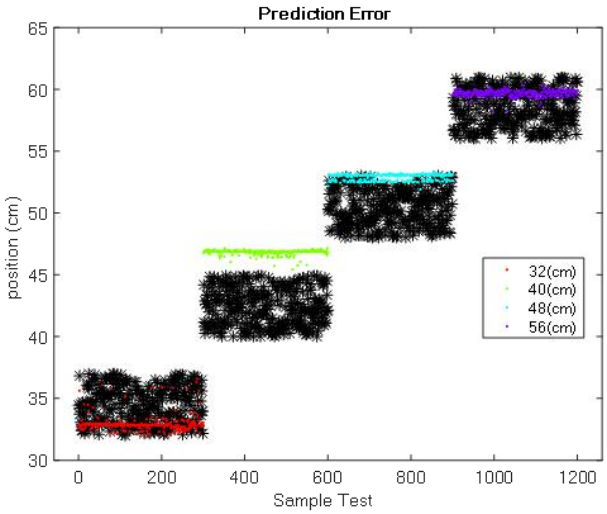


Figure 10. Ensemble prediction error.

Figure 10 shows the position of intermediate damage locations predicted by the ensemble. Although, error can be considered as minimum since it is lower than the size of the element used to simulate damages (damage quantification < 5cm).

4. Conclusions

In this paper an ensemble machine learning approach for improving the performance of models on SHM problem was detailed. The feasibility of combining different learning algorithms, in an ensemble scheme, for monitoring mass aggregation damages in pipe like structures was experimentally validated.

The damage detection is properly performed by the statistical indexes and the scores of PZT measurements. Nevertheless, with the methodology developed in this work, statistical modelling through PCA, piezo-diagnostics approach for damage characterization and bagging method to construct ensembles, the damage location is performed with mean square errors lower than 0.8.

The capability of prediction could be limited to be reliable only in the range within the experimental uncertainty. However, in the Predictive step is recommended to perform additional experiments that do not match with those used during the validation step. On the contrary, the capability of prediction could be limited.

In general, the decision making process for the experiment conditions and the approach based on ensemble learning proposed in this paper has been suitable. As future work, environmental and operational variations should be included, as well as methods to manage unsupervised algorithms, which probably would improve the generalization errors.

5. Acknowledgement

The results in this paper were obtained as a collaborative work between the "Universidad Industrial de Santander –UIS- (Colombia)" and "Universitat Politécnica de Catalunya -UPC- (Spain)". It has been partially funded by the Spanish Ministry of Economy and Competitiveness through the research projects DPI2014-58427-C2-1-R and also it corresponds to a continuation of the "Monitorización y detección de defectos en estructuras usando algoritmos expertos embebidos" research project, financed by the "Departamento administrativo de ciencia y tecnología Francisco José de Caldas – COLCIENCIAS" and "Banca Mundial".

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