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Damage Diagnostic Technique Combining Machine Learning Approach With a Sensor Swarm

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ABSTRACT

A Model-free approach is particularly valuable for Structural Health Monitoring because real structures are often too complex to be modelled accurately, requiring anyhow a large quantity of sensor data to be processed. In this context, this paper presents a machine learning technique that analyses data acquired by swarm of a sensor. The proposed algorithm uses unsupervised learning and is based on the use principal component analysis and symbolic data analysis: PCA extracts features from the acquired data and use them as a template for clustering. The algorithm is tested with numerical experiments. A truss bridge is modelled by a finite element model, and structural response is produced in healthy and several damaged scenarios. The present research shows also the importance of considering a sufficient number of measurements points along the structure, i.e. the swarm of sensors. This technology, which nowadays is easily attainable with the application of optical Fiber Bragg Grating strain sensors. The difficulties related to the early stage damage detection in complex structures can be skipped, especially when ambient, narrow band, moving loads are considered, enhancing the prediction capabilities of the proposed algorithm.

Keywords: Structural health monitoring, machine learning, model free
I-INCE Classification of Subject Number: 74

1. INTRODUCTION

Structural health monitoring (SHM) deals with the real-time characterization of structural performance in order to enhance structural safety and to optimise the maintenance procedures. Thus, at the core of SHM is the early stage damage detection that is generally carried out analysing vibration data coming from the monitored structure [1-6].

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Sensors for infrastructure monitoring and evaluation are placed at strategic locations to monitor the behaviour of large structures and provides valuable data such as strain, temperature, and vibration [7]. A high-density sensor network helps in identifying structural problems at early stages, increasing the life of these structures, and improving public safety.

Many techniques employed in SHM are based on the determination of modal properties through an identification process [1-3]. However the procedures involved for the identification of modal parameters imply the filtering of the signal, which generally mask the damage signature in respect to the raw data. In addition, modal components are essentially describing an equivalent linear behaviour, which may be not exact for the analysis of damaged systems. To overcome the problem, several damage detection methods presented in recent years are based on signature principles, which generally require a time-frequency analysis of the acquired signal [2-3]. They generally provide better performances regarding the early stage detection. However, their results are still hard to be generalised in an automatic detection procedure when real life structures are considered. In addition, working with raw data implies large data sets, which make the analysis process very demanding.

This paper provides a solution to these problems for the damage detection level 1 problem, according to Rytter's classification [8], which involves data compression, to limit the dimensionality of the problem, and data clustering, for an easy implementation of an automatic detection procedure. The present paper proposes an unsupervised early-stage damage detection method, which relies on the combined application of Principal Component Analysis and Symbolic Data Analysis. The algorithm processes vibration data acquired by a number of sensors embedded within the structure, excited by ambient loads. To test and validate the performance of the proposed algorithm, strain signals are numerically generated from the Finite Element Model (FEM) of a truss bridge.

2. THEORETICAL INTRODUCTION TO THE UNSUPERVISED METHOD FOR DAMAGE DETECTION

2.1 Brief resume of Principal Components Analysis

Data from a number of sensors embedded within the structure are analysed, in order to maximise the early stage damage detection capability, so a technique for dimensionality reduction has to be envisage. In this respect, Principal Component Analysis (PCA) is one of the most acknowledged techniques for exploratory data analyses [9]. This statistical procedure employs an orthogonal transformation to change a set of observations of possibly correlated variables, into a set of linearly uncorrelated variables, which are the principal components.

Considering an array of n measurement points of the analysed structure and consider s time samples for each measurement, the observation matrix $\mathbf{M}_{sxn}$ is introduced: rows of matrix $\mathbf{M}$ are the vibration data corresponding to a given time obtained from all measurement points. The goal of PCA is to find a reduced order data matrix whose columns are an optimal orthonormal basis vector set. The term optimal stresses the basis is with the maximum data set projection on it. The columns of the observation matrix are normalized by subtracting the time mean value, for the sake of notation the symbol $\mathbf{M}_{sxn}$ is here used also for the normalised matrix.

The problem can be stated with the following matrix equation:

$$\boldsymbol{A}_{sxn} = \boldsymbol{U}_{nxn}\boldsymbol{M}_{sxn}^{\boldsymbol{T}} \qquad (1)$$

where $\boldsymbol{A}_{sxn}$ is the principal component matrix, and the orthonormal linear transformation matrix $\boldsymbol{U}_{nxn}$ is obtained by the solution of an eigenproblem on the correlation matrix $\boldsymbol{C}_{nxn}$, obtained from the observation matrix $\mathbf{M}_{sxn}$:

$$\boldsymbol{C}_{nxn}\boldsymbol{U}_{nxn} = \boldsymbol{\Lambda}_{nxn}\boldsymbol{U}_{nxn} \quad (2)$$

$\boldsymbol{\Lambda}_{nxn}$is a diagonal matrix whose elements are the eigenvalues of $\boldsymbol{C}_{nxn}$, which are positive or null values. Eq. (1) allows each principal components, the columns of $\boldsymbol{U}_{nxn}$, to have the highest correlation and to be orthogonal to the original components. The eigenvalues are referred as active energies and express the relative importance of each principal component in respect to the whole data set, generally sorted in descending order [10].

2.2 Notes on Symbolic Data Analysis

Data clustering is a technique for statistical data analysis, which has gained popularity in many fields, such as machine learning, data mining, and also in structural health monitoring [11]. It represents a way of classifying a number of objects into different groups, namely it is the procedure of partitioning a data set into subsets or clusters, in order to the elements in each subset have some common features. To obtain a meaningful cluster, the so called within-cluster variation has to be minimized, to get homogeneous elements within each cluster and, analogously, the inter-cluster variation is also maximised to obtain the most dissimilar clusters. To this scope, suitable dissimilarity measures need to be introduced.

Let introduce the cluster set $(C_1, C_2, \dots, C_p)$, the realization of this set is determined by a particular dissimilarity measure, which provides numerical values that show the distance between two objects. The lower these values are the more similar the objects are, and then the two objects can be collected in the same cluster; on the contrary, objects into different clusters are the ones which have greater distances between them [12]. In this respect, a distance measure can be used to quantify similarities and dissimilarities, and some applications might require specific ones. For any clustering method a suitable dissimilarity measure has to be considered, since it will influence the shape of the clusters. In fact given two objects they may be close in respect to a certain distance measure and far away separated in respect to another distance. In particular, let indicate with T_i and T_j the pair of objects, among a total number of n-tests, in this work we will use the Euclidean distance $\varphi(T_i, T_j)$ between them. The within cluster variation of a cluster C_k containing tests denoted by T_i is evaluated as follows:

$$I(C_k) = \frac{1}{nn_k}\sum_{i=1}^{n_k}\sum_{j>i=1}^{n_k}\varphi^2(T_i, T_j) \quad (3)$$

Where n_k is the number of tests within cluster C_k. Considering a given partition $P_p = (C_1, C_2, \dots, C_p)$, as explained in (ref. 13) the total within-cluster variation is the sum of all within-cluster variations, as defined ahead:

$$W(P_p) = \frac{1}{p}\sum_{k=1}^{p} I(C_k) \quad (4)$$

Where p is the total number of cluster considered. Indicating with Q the global set of tests, the inter-cluster variation is also introduced as follows:

$$V(P_p) = W(Q) - W(P_p) \quad (5)$$

The clustering methods used in the present work are K-means clustering and Hierarchical agglomerative clustering. The former method partitions the objects into K mutually exclusive clusters, such that objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible, as conceptually explained with equations [11-13]. In fact, each cluster is characterized by its centroid, K-Means clustering uses an iterative algorithm [14] that assigns objects to clusters so that the sum of distances from each object to its cluster centroid, over all clusters, is a minimum.

Hierarchical clustering permits to examine grouping in your data, together with a wide range of scales of distance, employing a cluster tree. In this case, the tree is not a single set of clusters, as it happens with in K-Means algorithm, instead it is a multi-level hierarchy, where clusters at one level are combined with clusters at the next higher level. This allows to select which scale or level of clustering is most appropriate. The process starts with *p* clusters containing one single test and continues by merging two sub-clusters, e.g. C_1 and C_2, into one new cluster C. C_1 and C_2 are merged following the previously introduced criteria for minimizing the within-cluster variation and then for maximizing the inter-cluster variation [15]. With this method a difference in height is introduced to evaluate the similarity between clusters.

3. CASE STUDY: A BRIDGE TRUSS

3.1 The structure analysed

The considered test structure is a bridge 144 m long and 40 m tall, shown in Figure 1. The structure is excited by a load that runs over the upper section of the beam with a speed within the interval [19.5-20.6 m/s].

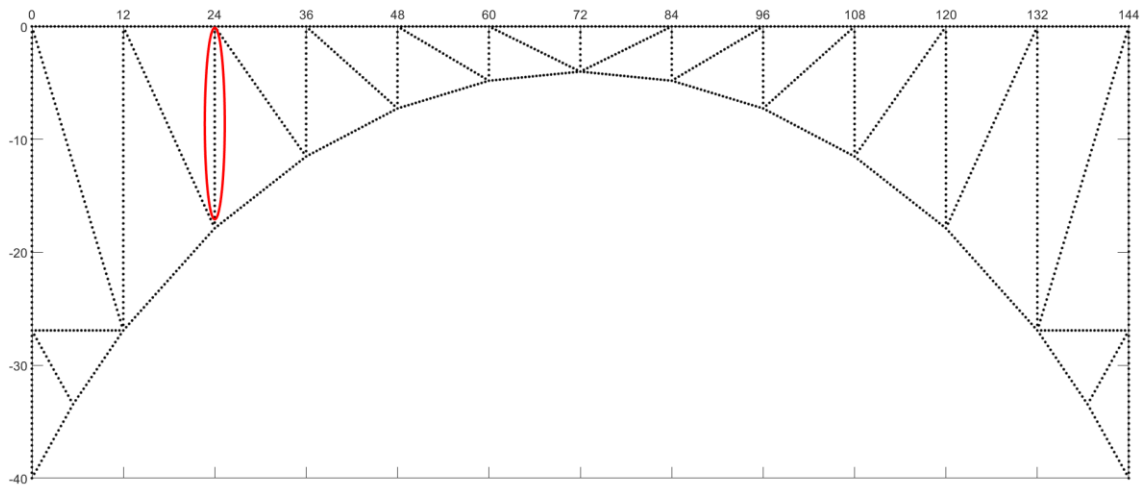


Figure 1: Test bed. Position of the damage

The damage is simulated by four different thickness reductions (10%, 20%, 30% and 40%) of one piers of the bridge show in Figure 1. The cross sections of the structure are shown in Table 1.

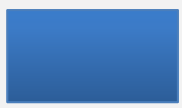
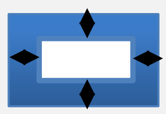
	Deck section	*Bridge section*
		

Table 1: Cross Sections

Ten different sets of observation points are selected, distributed along the structure as shown in Figure 2.

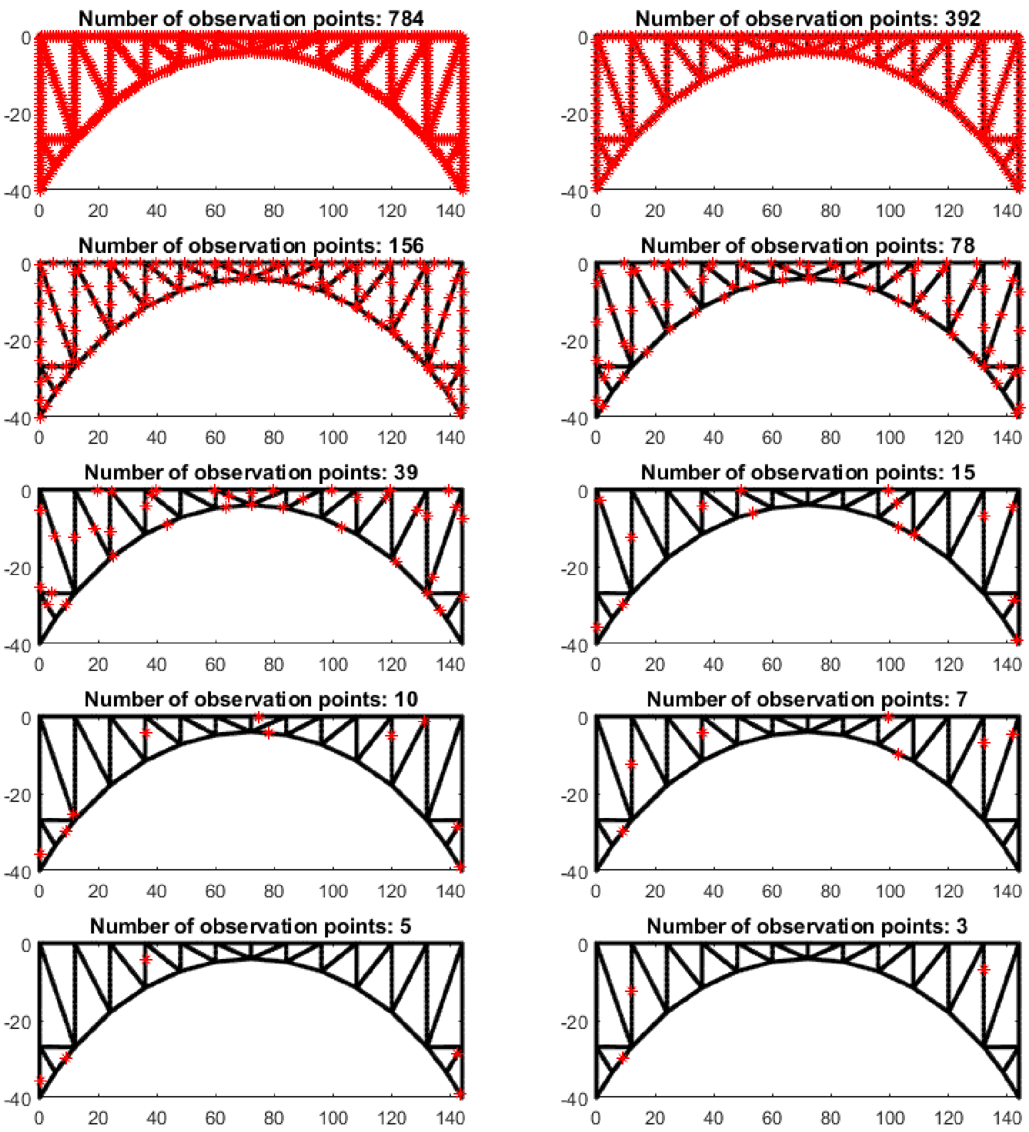


Figure 2: Test structure. The red marker shows the sensor distribution on the structure for each considered test

3.2 Description of the numerical simulations

The Finite Element Model of the structure is built to calculate N_m natural frequencies, ω_n, and eigenvectors, Φ_n. The response, $w(x_o,t)$, at each observation point is calculated by using the modal analysis:

$$w(x_0,t) = \sum_{n=1}^{N_m} \Phi_n(x_o) q_n(t) \tag{6}$$

The modal coordinates, q_n, are calculated by [16-17]: .

$$\ddot{q}_n + 2\delta_n \omega_n \dot{q}_n + \omega_n^2 q_n = F \int_0^L \frac{\Phi_n(x_o)}{\left[d_0^2 + (x_0 - Ut)^2\right]^2} dx_o \tag{7}$$

where U is the velocity of the load and d is its radius.

This response is polluted by a random noise proportional to the 3% of the standard deviation of the signal.

4. THE STRUCTURAL HEALTH MONITORING TECHNIQUE

The developed method for the early stage detection of damage is discussed using four damage level, considering a section reduction of 10%, 20%, 30% and 40% of the thickness. In this preliminary study only one position for damage has been investigated in correspondence of one piers of the bridge, however a test campaign with several damage positions is under investigations.

Figure 3 shows the absolute value of the first six principal components evaluated from the strain acquired by a set of 78 sensors among all those considered and for different damage levels.

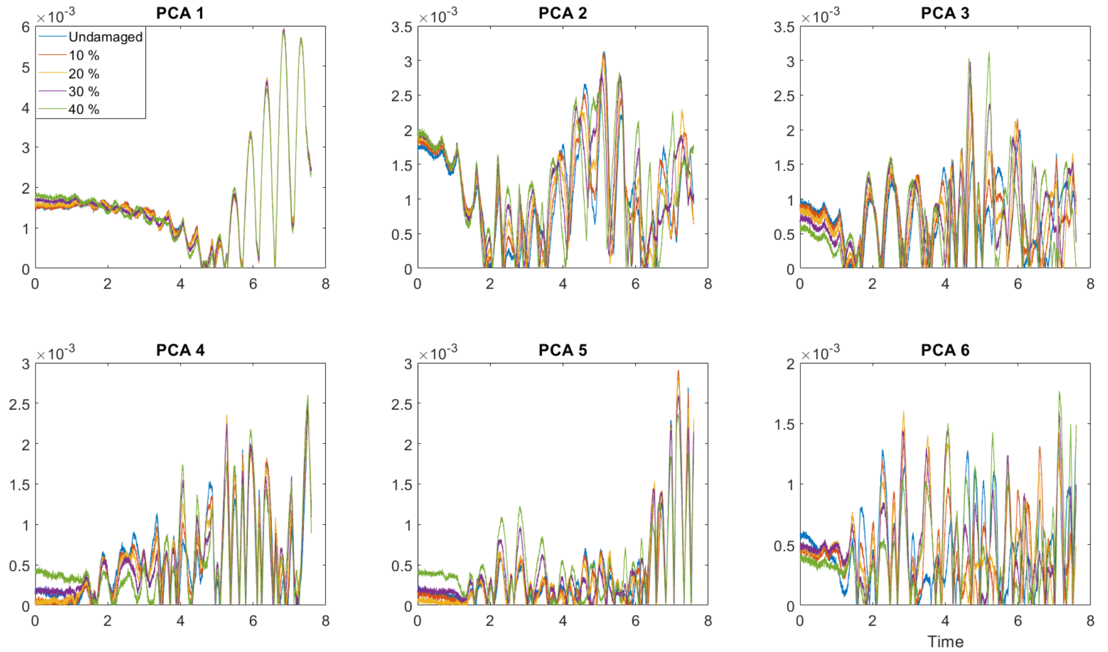


Figure 3: First six PCA vs time computed for 78 sensors

In order to select the principal components that are more sensitive to damage, the Root Mean Squared Error (RMSE) of the normalised principal components is introduced:

$$RMSE_k = \sqrt{\frac{1}{s}\sum_{i=1}^{s}\left[PC_k(t_i) - PC_{damage\_k}(t_i)\right]^2} \qquad (8)$$

where k=*1, 2, .. n*, and n is the total number of sensors, and where $PC_k(t_i)$ is the normalised principal components, i.e. $(x(t_i) - \overline{x(t_i)})/\sigma_x$, where the mean and the standard deviation are performed over time samples. Therefore $RMSE_k$ measures the relative average distance between the *k-th* normalised principal component evaluated in absence, PC_k, and in presence, PC_{damage_k} , of the damage. Figure 4 shows the sets of $RMSE_k$ for different damage levels and varying the number of the considered sensors. The first two principal components are almost insensitive to damage up to 15 sensors, while starting from 39 sensors an higher sensitive is observed over the first modes. $RMSE_k$ generally increases as the number of sensors does.

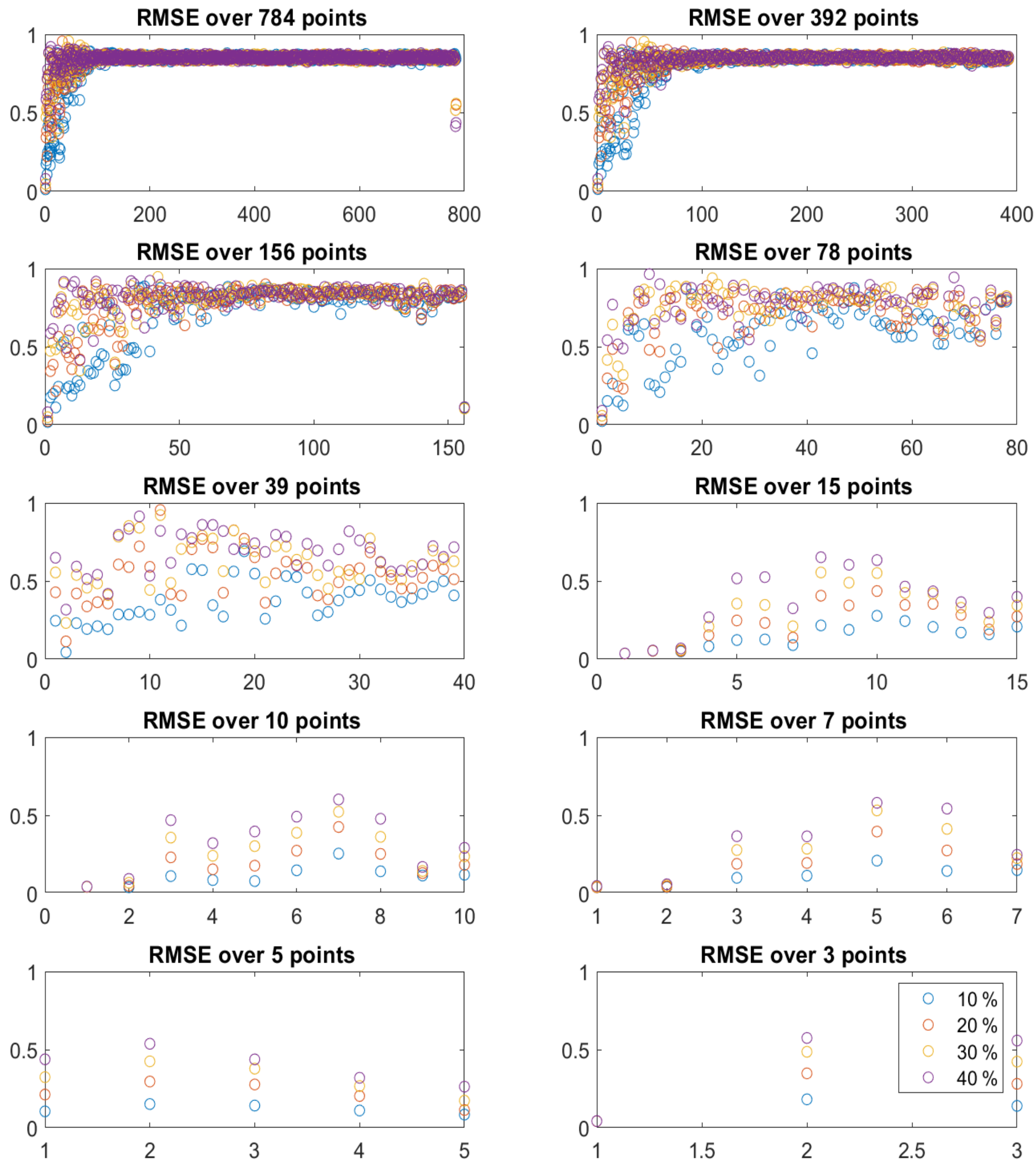


Figure 4: RMSE plotted versus the PCA number for different number of sensors.

An explanation for this phenomenon is that, as the number of sensor increases, a relevant number of sensors fall in the neighbourhood of the damaged area, thus the signature of the damage emerges clearly over many sensors, while when a few sensor are considered, most or all of them are far from the damage position and its effect is perceived only on higher principal components, that have however low energies, as shown in Figure 5. For over 78 sensors, the vast majority of the principal components become highly sensitive to the damage presence, even if their energies become quickly negligible, as shown in Figure 5. For the forthcoming analysis a good compromise between the need of considering a number of sensor reasonably small and having an high sensitivity to damage over the firsts principal components is to consider 39 sensors; in this case only the first ten principal components will be analysed, because the higher ones have a negligible level of energies, as shown in Figure 5.

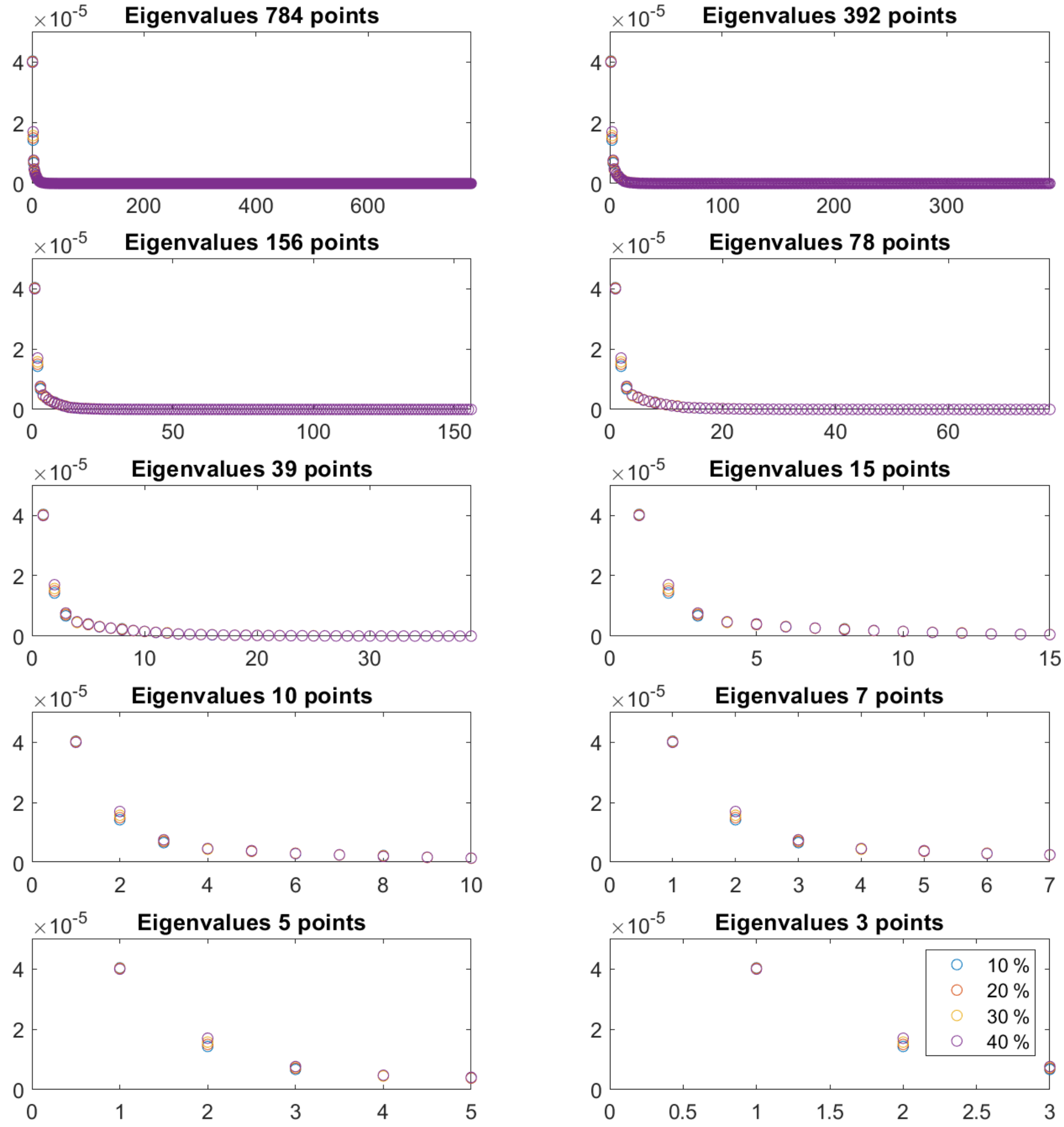


Figure 5: Eigenvalues of the PCA plotted versus the PCA number for different number of sensors.

Having set the number of sensors and the principal components that will be analysed, a dataset of trials is created, varying randomly the speed of the traveling load within the interval [19.5-20.6 m/s]: a number of 30 cases are considered, 20 in absence of damage, labelled from 1 to 20, and 10 in presence of a 40 % damage, labelled from 21 to 30, results are shown in Fig.s 6-7.

Figure 6 shows K-means and Hierarchical agglomerative clustering for principal component number 1. The latter method separates correctly the damaged from intact cases, all the undamaged samples with label from 1 to 20 are grouped in the dendrogram cluster 2, while the damaged samples with label from 21 to 30 are grouped in the dendrogram cluster 1 on the right: the root node in this tree is much higher than the remaining nodes, confirming that there are two large, distinct groups of observations.

Within each of those two groups, you can see that lower levels of groups emerge as you consider smaller and smaller scales in distance, due to the perturbations introduced by the random variation of the velocity of the load. It is interesting to notice that K-means method separates the samples in two cluster of exactly 10 and 20 components, but the labels within them are not related to damaged and undamaged cases: in fact all the damaged labels are grouped into the cluster 2 and are mixed with the labels from 15 to 20 that refers to undamaged cases.

Figure 7 shows the same plots for principal component number 2. In this case both methods fail to separate correctly damaged from intact cases, which instead are mixed in cluster 1 and 2. Concerning the dendrogram the height of the root node is reduced in respect to the cases in the previous figures.

Similar results can be obtained also for a damage of 20%, whilst both methods fail when the damage is 10%.

At the end Hierarchical agglomerative clustering have shown better performances than K-means, the principal component that have shown the best performance to highlight the presence of damage are 1 and 8, being number 8 a good candidate as well when Hierarchical agglomerative clustering is employed.

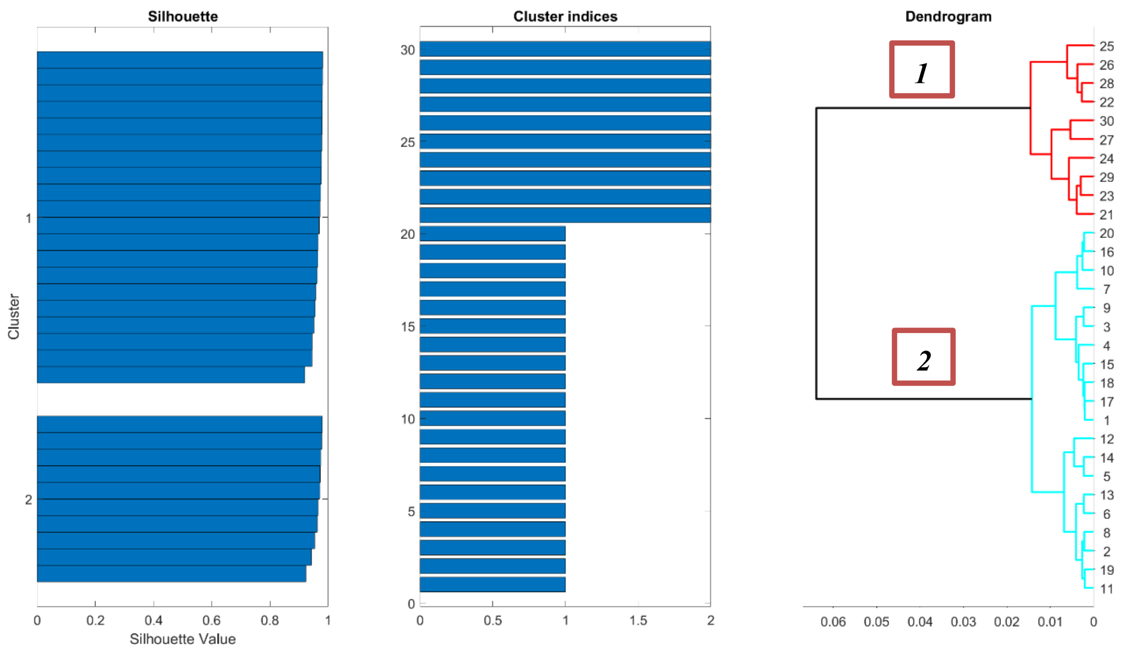


Figure 6: Principal component number 1, on the left silhouette plot for the k-means method, it displays a measure of how close, on a scale form 0 to 1, each point in one cluster is to points in the neighbouring clusters; labels are within the data tip. On the right dendrogram plot, labels are plotted on the y axis.

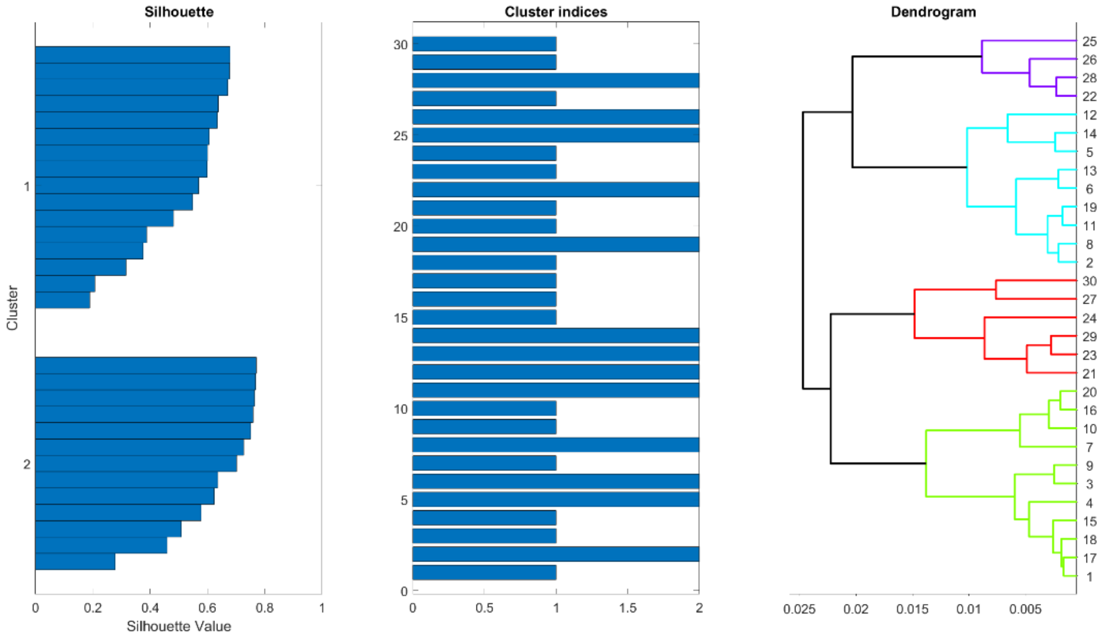


Figure 7: Principal component number 2, same symbolism than Figure 6.

5. CONCLUSIONS

A novel technique for the early stage damage detection is here presented, which is based on the combinate use of principal component analysis and symbolic data analysis and it uses ambient load vibrations induced by a travelling load acquired over a number of sensors. An experimental application containing five structural states of a truss bridge has been numerically analysed by the uses of FEM. The goal was to use clustering methods applied to the principal component of the data in order to separate the intact structure from the damaged one.

The effect of the number of sensors has been initially analysed, studying how the principal components are sensitive to the damage presence varying the number of the measurement points along the structure. It has been shown that the first two principal components are almost insensitive to damage up to 15 sensors, while starting from 39 an higher sensitivity to damage is observed over the first modes. This can be explained observing that, the measurement points that fall in the neighbourhood of the damaged area is a fraction of the total number of sensors, thus the signature of the damage emerges clearly over a sufficient number of measurements and this information can be recovered over the principal components that have higher active energies. For the rest of the study 39 measurement points have been considered.

The obtained results obtained are promising and they showed that the symbolic employed data analysis methods were able to classify structural modifications with a damage as low as 20 % of the thickness. The use of Hierarchical agglomerative clustering has shown better performances than K-means.

At present a depth study concerning how the velocity of the moving load and the damage position affect the damage detection capabilities of the proposed technique has been carried out and it will be the object of future publications.

6. ACKNOWLEDGEMENTS

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