Application of Pattern Recognition Techniques to Identify Structural Change in a Laboratory Specimen

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ABSTRACT

Identification of damage in a structure, or structural change in general, has been a challenging problem for the researchers in Structural Health Monitoring (SHM) area. Over the last a few decades, a number of experimental and analytical techniques have been developed and used to solve such problem. It has been has been recently accepted in the literature that the process of damage identification problem is one where statistical pattern recognition techniques can be of use because of the inherent uncertainties of the problem. Time series analysis is one of the methods, which is implemented in statistical pattern recognition applications to SHM. In previous studies, Auto-Regressive (AR) models are highly utilized for this purpose. In this study, AR model coefficients are used with different outlier detection and clustering algorithms to detect the change in the boundary conditions of a steel beam. A number of different boundary conditions are realized by using different types and amounts of elastomeric pads. The advantages and the shortcomings of the methodology are discussed in detail based on the experimental results in terms of the ability of it to detect the structural changes and localize them.

Keywords: Structural health monitoring, statistical pattern recognition, experimental modal analysis, AR-ARX modeling, outlier detection, time series analysis, dynamic testing

1. INTRODUCTION

1.1 Structural Health Monitoring as a Statistical Pattern Recognition Paradigm

Structural Health Monitoring (SHM) is the research area dealing with the condition assessment of the mechanical and civil structures. The earliest application of SHM has been in aerospace engineering. Following the aerospace structures, mechanical structures have become application areas of SHM. For the last two or three decades, SHM has been applied to civil structures, especially civil infrastructures.

Conventional SHM studies have mainly focused on identifying the dynamic properties of the structures and tried to relate the damage to the change in the vibration characteristics of the structure [1]. In theory, the previous sentence is the key for SHM; however, real life applications of SHM involve more challenges than just identifying the dynamic properties of the structures. For example, environmental effects such as temperature change may affect the dynamic properties more than damage. Therefore, statistical analyses may be needed to decrease the number of false positives and false negatives.

Recently, a new definition of SHM was given by Farrar et al. [2] and Sohn et al. [3]. The authors stated that SHM is a statistical pattern recognition process and it is composed of the following four portions; (1) Operational evaluation, (2) Data acquisition, data fusion and cleansing, (3) Feature extraction and (4) Statistical model development. This study focuses on the last three components of this definition by conducting experiments on a laboratory specimen.

1.2 Objective and Scope

The main objective of this study is to examine application of statistical pattern recognition methods in the context of SHM. Different clustering and outlier detection algorithms are applied to identify structural change in a laboratory specimen. Time series analysis, i.e. Auto-Regressive models, in conjunction with K-means clustering and Mahalanobis distance based outlier detection algorithms is used to discriminate different structural conditions. The methodology is applied to laboratory test data where ambient vibration tests are conducted on a steel beam with different boundary conditions. The capability of the methodology is investigated in terms of detecting and locating the damage.

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Furthermore, it is also examined if more than two structural configurations can be differentiated from each other by using the method.

2. THEORETICAL BACKGROUND AND FORMULATIONS

2.1 General Methodology

The analysis procedure applied in this study is similar to the approach used by Sohn et al. [3] in the sense that AR model coefficients are used as features for outlier detection. However, in this analysis Random Decrement (RD) is applied to each channel to normalize the data before constructing the Auto Regressive (AR) models. After normalizing (averaging) the data using RD, AR models are fitted to the averaged data. Then the coefficients of these models are used as the damage indicating features and they are fed to the outlier detection and clustering algorithms (Fig. 1).

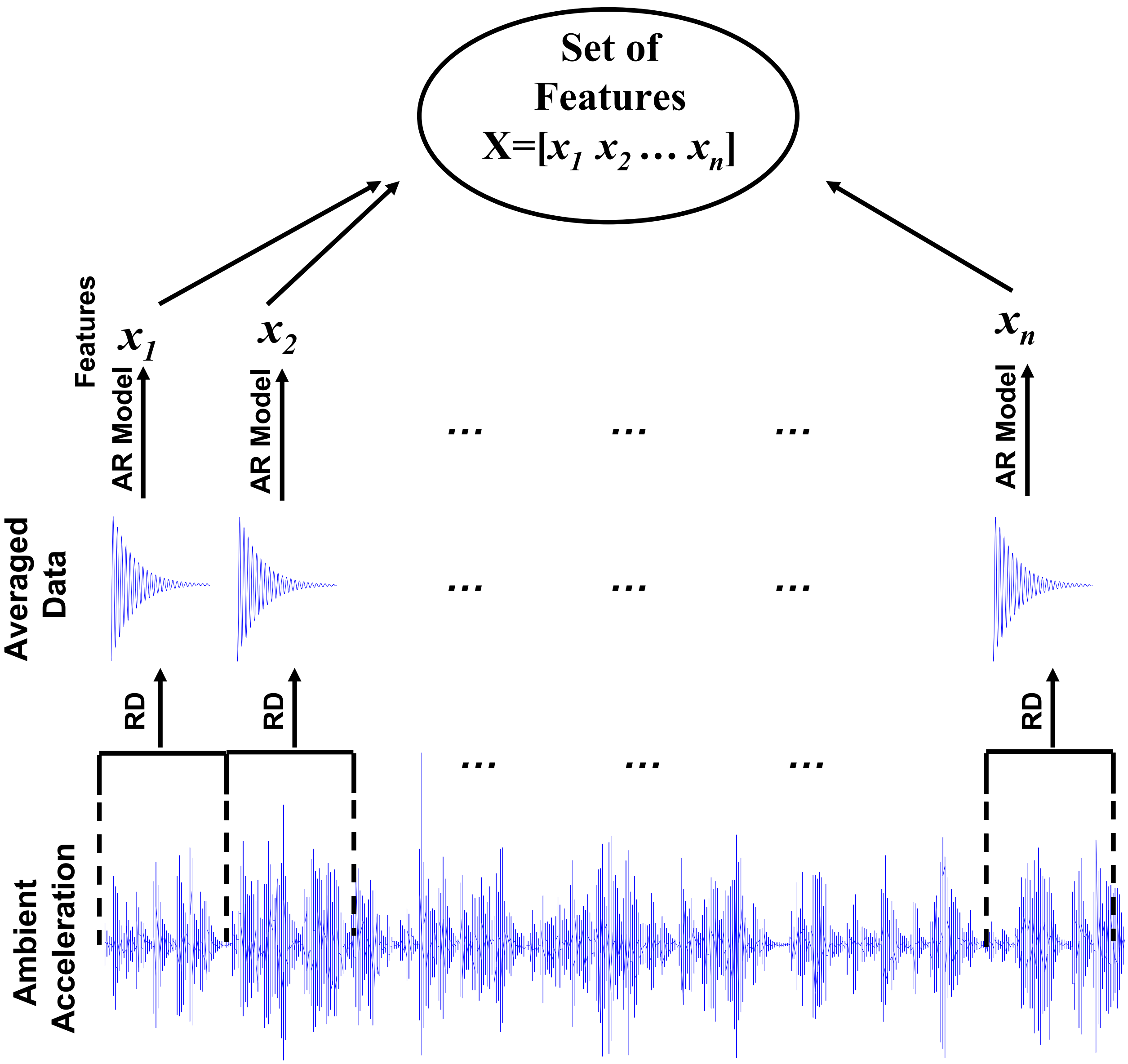


Fig. 1. General Methodology

2.2 Random Decrement (RD) Method

The basic idea behind the method will be briefly summarized in this paragraph, however more comprehensive information about the theory of the method can be found in Asmussen's study [4]. The random response of a system at a particular time consists of three components, which are the step response due to the initial displacements, the impulse response from initial velocity, and a random part due to the load applied to the structure. By taking average of data segments, every time the response has an initial displacement bigger than the trigger level, the random part due to random load will eventually vanish and become negligible. Additionally, since the sign of the initial velocity can be assumed varying randomly in time, the resulting initial velocity will also be zero leaving a pseudo-free response of the system [4]. Detailed discussions about its application for ambient data analysis is given by Gul and Catbas [5] where the authors combined Complex Mode Indicator function (CMIF) with RD method to extract several features from ambient test data, such as modal frequencies, mode shapes, scaled and pseudo flexibilities.

2.3 Time Series Analysis-Auto Regressive (AR) Model

Time series analysis is a common method for novelty detection applications to detect damage [3, 6, 7 and 8]. AR, ARX (Auto Regressive model with eXogenous input) and ARMA (Auto-Regressive Moving Average) models were some of the time series analysis methods employed in that studies. Here, brief description about the theory about AR modeling will be presented because some results related to the AR modeling are presented in the following sections [9].

An AR model estimates a function's value at time t based on a linear combination of prior values. The model order (generally shown with p) determines the number of past values, which will be used to estimate the value at t [10 and 11]. The basic formulation of a p order AR model is defined as follows.

$$x(t) = \sum_{i=1}^{p} \phi_i x(t - i\Delta t) + e(t) \tag{1}$$

The identification of the model requires determining the unknown coefficients of the AR model by using the data points. The AR coefficients can be computed in different ways. The coefficients can be computed from autocorrelation estimates, from partial autocorrelation coefficients, and from least-squares matrix procedures. In this text, the least square formulation will be given as an example. The formulation is summarized in the following paragraph.

Let us assume there are m data points. Then, the following set of linear equations can be written by using $m-1$ blocks of data, which consists of $p+1$ data points.

$$\begin{bmatrix} x_1 & x_2 & \cdots & x_p \\ x_2 & x_3 & \cdots & x_{p+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m-p} & x_{m-p+1} & \cdots & x_{m-1} \end{bmatrix} \begin{Bmatrix} \phi_p \\ \phi_{p-1} \\ \vdots \\ \phi_1 \end{Bmatrix} = \begin{Bmatrix} x_{p+1} \\ x_{p+2} \\ \vdots \\ x_m \end{Bmatrix} \Rightarrow [x]\{\phi\} = \{x\} \tag{2}$$

To solve the unknown coefficients,

$$\{\phi\} = \left([x]^T [x]\right)^{-1} [x]\{x\} \tag{3}$$

Here, $\left([x]^T [x]\right)^{-1} [x]$ is so called pseudo inverse (note that $[x]$ is not necessarily square) of $[x]$ and the unknown coefficients can in fact be considered as least square solution.

A very crucial point here is the determination of the model order. Among many model order determination criteria, partial auto-correlation can be applied to determine the model order. For this study, the partial auto-correlation function is defined as the last AR coefficient [11]. To determine the model, the partial auto-correlation function is calculated for increasing p values and the correct model order is set to the p value whose auto-correlation function value is under a pre-set threshold value.

2.4 Clustering and Outlier Detection

Clustering can be described as defining groups in the data set where the data points in the same groups (clusters) are similar to each other and dissimilar to the data points in the other clusters. More details about the topic and different clustering approaches can be found in the studies by Jain et al. [12] and Xu et al. [13]. Outlier detection, however, is detection of clusters, which deviate from other clusters so that they are assumed to be generated by another system or mechanism. Outlier detection is one of the most common pattern recognition concepts in those applied to SHM problem as it can be found in aforementioned studies. In this text, first K-Means clustering and then Mahalanobis distance based outlier detection will be mentioned briefly.

K-means clustering is a very simple, yet powerful, unsupervised learning algorithm to cluster a given data set. The basic idea behind the method is to define *k* clusters in the data set by minimizing the following objective function

$$V = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\| \tag{4}$$

where $x_i^{(j)}$ is i^{th} data point in cluster j and c_j is the center of the cluster j. First, an initial partition with k clusters is selected. Then new partitions are generated by assigning each data point to its closest cluster. Afterwards, new clusters are recorded and the centers of the new clusters are calculated. This procedure is repeated until the cluster membership is stabilized [14].

The outlier detection problem for univariate (1D) data is relatively straightforward meaning that the outliers must be removed from one end or the other of the data set distribution. There are several discordance tests but one of the most common is based on deviation statistics and it is given by the following

$$z_\xi = \frac{x_\xi - \bar{x}}{\sigma} \tag{5}$$

where x_ξ is the potential outlier and $\bar{x}$ and σ are the sample mean and standard deviation, respectively. The multivariate equivalent of this discordance test is known as the Mahalanobis squared distance [15] (will be referred as Mahalanobis distance after this point) and given as

$$Z_\xi = (x_\xi - \bar{x})^T \Sigma^{-1} (x_\xi - \bar{x}) \tag{6}$$

where x_ξ is the potential outlier vector and $\bar{x}$ is the mean vector and Σ is the sample covariance matrix. By using the above equations, the outliers can be detected if the Mahalanobis distance of a data vector is bigger than a pre-set threshold level. The determination of this threshold level is critical and can be determined by using previous observations or simulations [3].

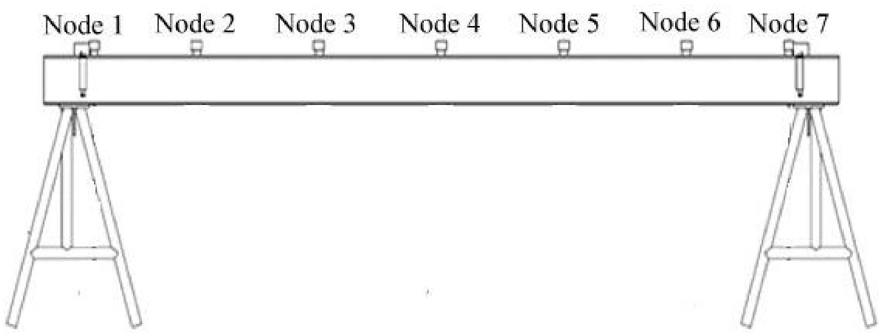
3. EXPERIMENTAL STUDIES

3.1 Test Setup

The model used for the experimental tests is a simply supported steel W8x13 I-beam. The overall length of the beam is 156 in, while the clear span is 144 in. The beam rests on two steel sawhorses each measuring 3 feet in height. The setup can be seen in Fig. 2 and more information about the tests can be found in the study by Francoforte et al. [16].

Although it is a simple laboratory specimen, a very interesting aspect of this study is that the beam is densely instrumented with a number of sensors and it is tested for many different structural configurations (different boundary conditions). The total number of dynamic and static sensors is 29 (seven accelerometers, seven displacement gages, seven tiltmeters and eight strain gages); however only the results obtained with data coming from accelerometers will be presented in this text.

(a) Instrumented steel beam



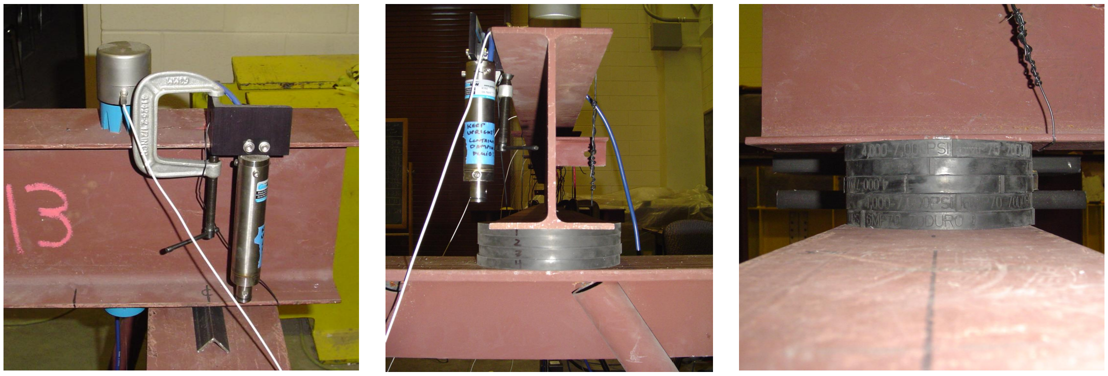
(b) Node numbers

Fig. 2. Test setup

The Boundary Conditions (BC) of the structure are modified by changing the material that sits on the support (between the sawhorses and the beam). The material can be a neoprene pads (different configurations of two types of pads) or a steel angle. Although a number of BC is applied during the tests, only four of them are used in this study and they are summarized in Table 1. It should be noted that the first BC could also be referred as the baseline case.

Table 1. The BC applied to the test beam

Name	Boundary Condition
BC1	Pin supports at each support
BC2	4 Duro50 pads at node 1; Pin/shims at node 7
BC3	5 Duro50 pads at each support
BC4	5 Duro70 pads at each support



(a) (b) (c)

Fig. 3. Example pictures showing different BC (a) The pin support for BC1 (b) Four Duro50 pads for BC2 (c) Five Duro70 pads for BC4

Please note from Fig. 3 (a) that the accelerometers are not placed exactly on the supports. The reason for this is that the accelerometers were positioned right above the displacement gages and the displacement gages could not be placed under the supports. Therefore, when the term 'support points' are used in the following sections, the reader should understand 'the points at the vicinity of the supports'. Fig. 3 (b) and (c) show some of the other BC.

3.2 Dynamic Testing

Two types of dynamic tests were conducted during the experimental phase of the study. For all of the BC, impact and ambient tests were performed. An impact hammer was used for impact testing whereas ambient excitation was created with hand tips as it can be seen from Fig. 4 (a) and (b). Since the primary objective of this study is to present statistical analysis of ambient vibration data, results of impact tests are not given in this text for the sake of brevity. However, results obtained from impact tests can be found in Francoforte et al. [16].

(a) (b)

Fig. 4. Dynamic testing (a) Impact tests (b) Ambient test

4. FRAMEWORK OF THE ANALYSIS AND RESULTS

As explained before, the ambient data is first processed (averaged) by using random decrement method. A pseudo-free response of the system is obtained when RD is applied to data. Then, the AR models are fitted to the averaged data to obtain the damage indicating features (please refer to Fig. 1).

There are a number of different crucial parameters for the analysis such as the size of the data blocks, the reference channel for RD and the model order of AR models. A sensitivity analysis concerning these parameters can reveal important information, however, it is beyond the scope of this study. The ambient data is collected from each channel for approximately 10 minutes with a sampling frequency of 800 Hz. 18 blocks of 50000 points with no overlap are used for each BC. Reference channel for RD is node 2 and each data block has 1024 points after averaging with RD. The model order p for AR models is 10 and obtained by using partial auto-correlation function [11]. Fig. 5 (a) shows an example of the ambient data collected from the beam. In Fig. 5 (b), two graphs are overlaid one of which is the pseudo-impulse response function estimated with RD. The same figure also shows the data estimated by using the AR model. As it can be seen from Fig. 5 (b) and (c), the averaged and estimated data match almost perfectly, which indicates that the AR model fitted to the data is working reasonably well.

After constructing the AR models, the coefficients of these models are used as the damage indicating features. Please note that, for each BC, there are 18 data blocks, which means there are 18 sets of feature vectors each containing 10 AR coefficients. Then, all of these features are used to calculate the Mahalanobis distance between the features coming from different BC. The same features are also fed to K-Means to see if the data coming from different BC can be clustered properly.

Fig. 6 compares the features coming from BC1 and BC2 for the seven nodes. The first half of the features (blue stars) is coming from BC1 whereas second half of them (red circles) represents the BC2. It is clearly seen from Fig. 6 (a) that the two BC can be well separated by using Mahalanobis distance. However, Fig. 6 (b) shows that the same BC cannot be differentiated with the same features by using K-Means clustering. Mahalanobis distance works also quite well for classifying BC1 and BC3 as it is shown in Fig. 6 (c). Unlike the previous case, K-Means works reasonably good for these cases (Fig. 6 (d)) yet it does not perform as well as Mahalanobis distance. For example, patterns could not be classified correctly for nodes 3 and 7.

(a)
(b)
(c)

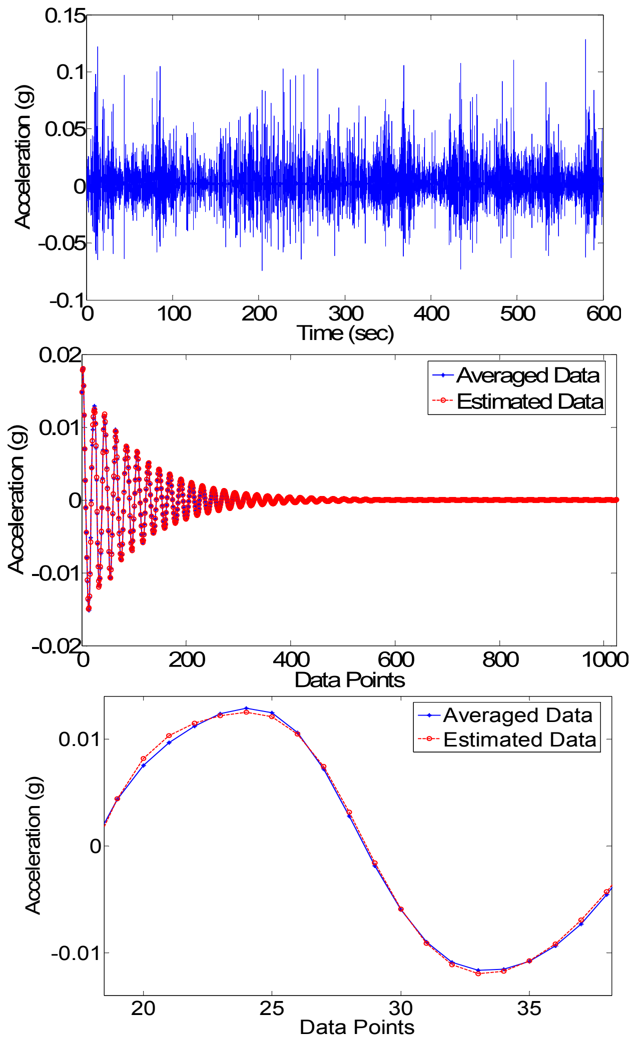


Fig. 5. Time history data (a) Ambient data (b) Data after averaging with RD plotted with the data estimated with AR (c) A closer look at the figure in (b)

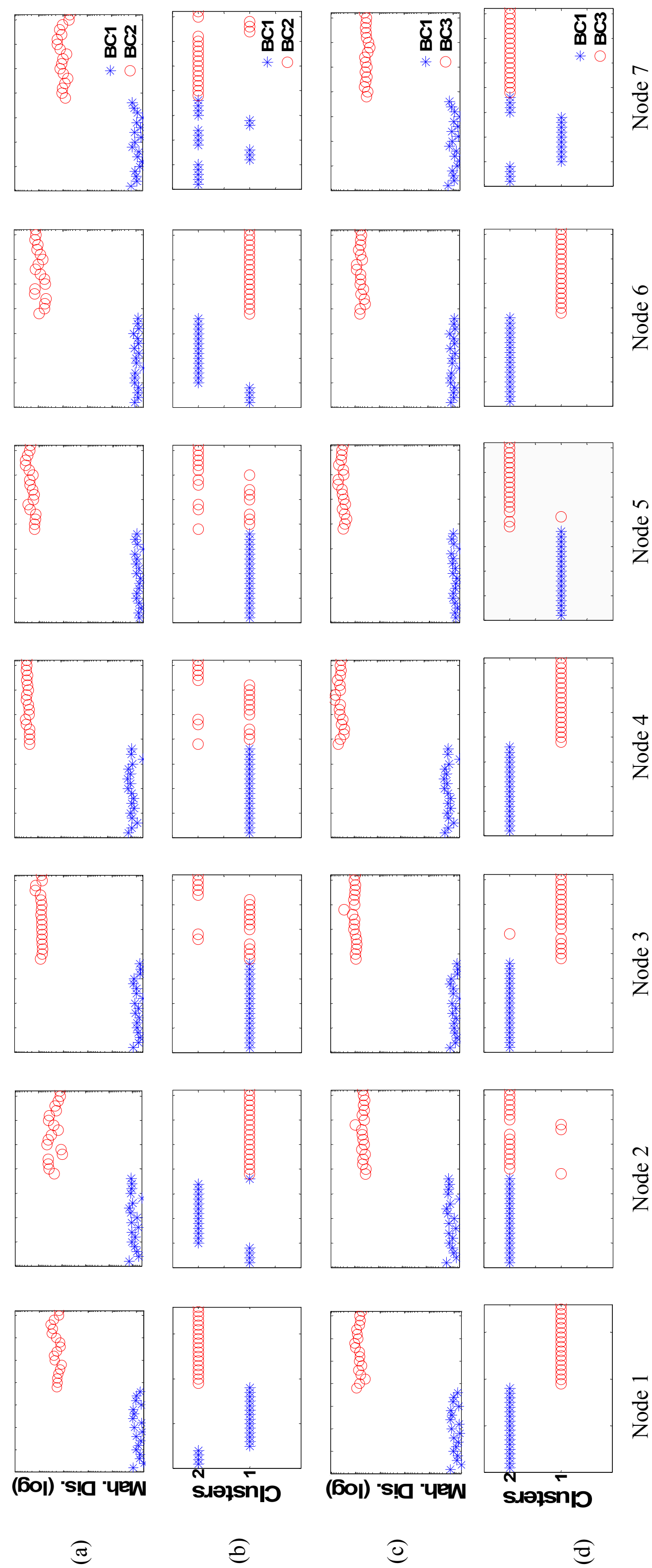
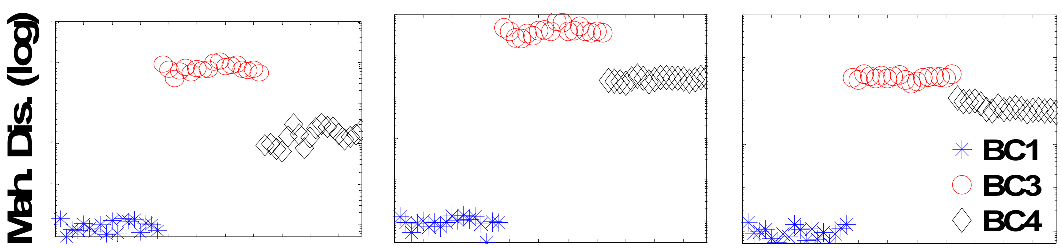


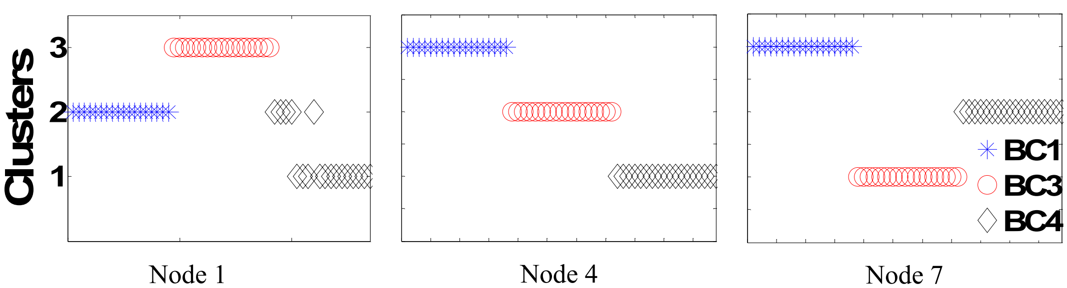
Fig. 6. Analysis results for BC1, BC2 and BC3 (a) Mahalanobis distance of the AR coefficients for BC1 and BC2 (b) Clustering of the AR coefficients for BC1 and BC2 (c) Mahalanobis distance of the AR coefficients for BC1 and BC3 (d) Clustering of the AR coefficients for BC1 and BC3 (each point in the figures is coming from one data block)

Another important thing we should notice from Fig. 6 (a) and (c) is that although the difference between data sets are clearly seen with Mahalanobis Distance, no information about the location of the change is obtained. This is a very important point and it should be explored with further investigation in future studies.

Now, the same algorithms are used to see if three different BC can be separated from each other. The previous analysis results showed that there was a change in the structure. However, here it is not only shown that there have been changes in the data but also these changes are different from each other. Fig. 7 (a) the Mahalanobis distances for BC1, BC3 and BC4 for node 1, 4 and 7. Then, the Mahalanobis distance are used as patters for classification to see if they can be separated by using K-Means clustering. It is worth to emphasize that for Fig. 6 K-Means was used to cluster the AR model coefficients, however here it is used to cluster the Mahalanobis distances. Fig. 7 (b) shows that there different cases can be identified by using Mahalanobis distance based outlier detection in conjunction with K-Means clustering for most of the cases.



(a) Mahalanobis distance of the AR coefficients for BC1, BC3 and BC4



(b) Clustering of the Mahalanobis distances for BC1, BC3 and BC4.

Fig. 7. Analysis results for BC1, BC3 and BC4 (each point in the figures is coming from one data block)

5. COMMENTS AND CONCLUSIONS

In this study, laboratory studies are conducted to investigate statistical pattern recognition applications to damage detection problem in the context of SHM. The test specimen used in the study is a simply supported beam with different BC. Ambient acceleration data is collected from seven channels for each BC.

The methodology investigated in this study accompanies time series modeling with outlier detection and clustering algorithms. AR models of the ambient acceleration data is constructed after averaging each data block with RD. Then the coefficients of these AR models are used as damage indicating features and fed to the Mahalanobis distance based outlier detection algorithm and K-Means clustering algorithm.

It is shown that Mahalanobis distance is quite successful in detecting the structural change whereas K-Means clustering may give wrong results for some other cases although it works quite well for some other cases. The authors believe that Mahalanobis distance based outlier detection works better since it takes into consideration not only the means of the data but the variances of the data, too.

Another important point explored in the study is the localization of the structural change. The analysis results show that there is not enough evidence to locate the structural change even for the cases where the change was clearly identified. Therefore, it is an important task to improve the methodology to pinpoint the location of the change. Data fusion techniques may be used for this purpose by combining different types of data sets, i.e. acceleration, strain or rotation, to locate the change. Moreover, the data may be analyzed by considering the correlation of each channel with each other instead of analyzing each channel independently.

Finally, after seeing that Mahalanobis distance is very well capable of identifying the structural change, it is investigated if the same methodology can be used to differentiate more that two structural configurations. It is shown that three different structural configurations can be clearly identified by using Mahalanobis distance, which is a very promising aspect of the methodology.

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