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Implementation of Support Vector Machine Concept for Monitoring with Fiber Optic Sensing

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ABSTRACT: A non-parametric data interpretation approach is explored in conjunction with optical fiber sensors for long-term Structural Health Monitoring. As a result, an innovative hybrid damage detection algorithm is investigated based on strain data captured by Fiber Bragg Grating (FBG) sensors from 4-span bridge model. Three common and critical damage conditions were simulated on the representative bridge model equipped with FBG sensors. Acquired strain data were processed by both Moving Principal Component Analysis (MPCA) and the new developed algorithm so-called Moving Principal Component-Support Vector Machine (MPCA-SVM). The efficiency of the FBG sensors and the new algorithm for detecting and localizing damage as well as time to detection are explored. Based on the findings presented in this paper, the MPCA-SVM is seen to outperform MPCA in terms of time to detection. In fact, MPCA-SVM not only has powerful detectability but also significantly reduces the delay in damage detection associated with MPCA.

1 GENERAL INSTRUCTIONS

Fault detection techniques can be broadly classified into two main categories (Worden 1997). Model-based techniques are based on establishing a mathematical model of structure, in most cases finite element model, and comparing the response between model and measured data from a real structure. Dependency on mathematical model is the main drawback of these techniques. The alternative approach is data-driven methods, which are generally based on pattern recognition techniques or more broadly machine learning methods (Laory 2011, Lanata 2005). Moving principal component analysis (MPCA) is a fully data-driven based damage detection algorithm, which is proven to be very powerful in terms of damage detectability (Laory 2011). However, a critical disadvantage associated with this algorithm is the delay in detecting damage, which in some cases may restrict the application of MPCA. In other words, although MPCA algorithm has been confirmed as one the most powerful algorithm in terms of detectability, it demonstrates significant delayed in detection of the damage. This delay can be life-threatening when dealing with critical structures, including bridges, nuclear plants etc.

The objective of this study is to develop an innovative damage detection algorithm in such a way that it can address the delay issue coupled with MPCA algorithm. In response to this need for decreasing the time to detection criteria, a novel algorithm is designed and proposed by taking advantages of support vector machine (SVM) technique. The new algorithm is developed by integrating MPCA and SVM in a way that the delay in damage detection is significantly reduced. The efficiency of this hybrid damage detection algorithm is tested by simulating three common and critical damage scenarios on a 4-span bridge model structure, which phenomenologically represents a multi-span highway bridge. While this model structure is instrumented with a variety of sensors, the focus will be Fiber Bragg Grating (FBG) sensors that are employed for measuring strain from both the baseline and the damaged structure. Commonly observed bridge damage scenarios will be artificially induced on the bridge to evaluate the detectability and time to detection of MPCA-SVM fault detection algorithm.

The layout of this paper is as follows: Section 2 is devoted to a brief introduction to Fiber Bragg Grating (FBG) sensors. Section 3 is concerned with mathematical background as well as different steps involve in MPCA and also MPCA-SVM algorithm. Experimental setup together with structural configuration, location of sensors and implemented damage scenarios are explained in Section 4. Section 5 is dedicated to interpretation and also comparison of the output results from MPCA and MPCA-SVM. To end with, the paper concludes with some discussion on the merits of the new algorithm, MPCA-SVM.

2 FIBER OPTIC SENSORS (FOS)

2.1 Fiber Bragg Grating (FBG)

There has been a dramatic increase in the FOS implementations in the context of SHM due to advantages brought by these types of sensors, including spatial resolution, durability, stability and immunity to electrical noise (Morey et al.1989). FBG sensors, which are point types of sensors, are among the widely used FOS. The basic working principles of FOS and FBG sensors are reflection and filtration of different wavelengths of light (Morey et al.1989). Beside the FBG sensors, Brillouin Optical Time Domain Analysis **(**BOTDA) and Brillouin Optical Time Domain Reflectometry (BOTDR) two of the widely used distributed types of FOS. For FBG sensors, grating property enables the optical fiber to transmit the entire wavelength except the particular reflected wavelength entitled as grating process. A brief introduction to theory of the optical fiber is presented in the following section.

2.1.1 Theory behind the FBG sensors

FBG system consists of an article interrogator launching infrared light down the core of an optical fiber. As white color, broadband light, travels down the fiber, it passes through grating segments, also identified as FBG, which is a series of article filter. These grating segments can filter certain wavelength or color while letting others pass through. This happens by periodically altering refractive index of fiber dictating which wavelengths can pass and which will get reflected. External factors such as heat and vibration will cause a shift in wavelength of the reflected light. These variations can then translate into physical engineering units such as amplitude, temperature and strain. The principal sensing technology of FBG is illustrated in Figure 1.

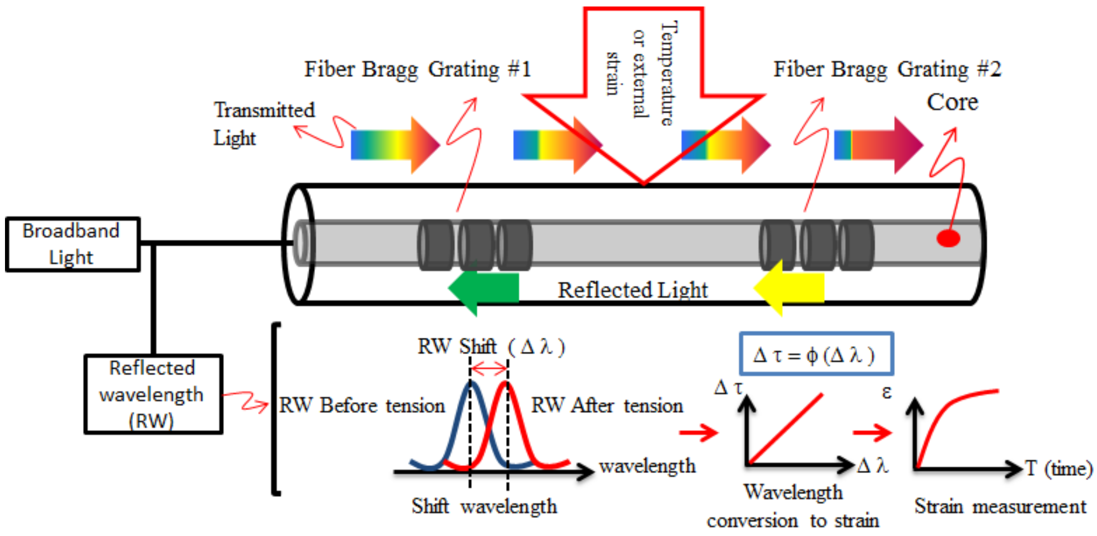

Figure 1-Measurement principal of Fiber Brag Grating (FBG) sensor

3 DAMAGE DETECTION ALGORITHM

3.1 Moving principal component analysis (MPCA)

Two main concerns, delay in abnormality detection along with computational time issue, inspired the revision of classical PCA to make it more practical for long term SHM. Real life employment of SHM involves dealing with large amount of multivariate data. Only a small portion of abnormal data, in comparison to overall data, is available at the time when damage occurs. By means of PCA, the damage will be detectable only when the principal components (eigenvectors) are influenced by the abnormal behavior. Subsequently, eigenvectors are subjected to change only if certain amount of abnormal data captured and possibly affected the overall data set being analyzed. This feature makes PCA less effective for long term SHM implementation. Moving principal component analysis (MPCA) was proposed by (Posenato et al. 2008) to address this challenge. Basically, MPCA computes the PCA within moving windows with a constant size. A sensitive damage index (related to MPCA algorithm) is selected based on PCA outputs. The damage index (Dsi) chosen for this study is simply the square root of the sum of the squares of the first two principal components as shown in Eqn.

$$D_{Si} = \sqrt{(PC_1)_i^2 + (PC_2)_i^2} \tag{1}$$

where (PC1)i and (PC2)i are the first and the second principal components of sensor i respectively. The reason to just incorporate the first two principal components in the damage index is that the most useful information in the data is covered by the first few principal components values. In fact, the first principal component corresponds to the direction in which the projected data has the most variance while the second one is perpendicular to the first component. In other words, since more than 95% of the variance (calculated based on the preliminary study) is covered by the first two principal components, these two components are only incorporated in the damage index. It should be mentioned that the number of principal components that should be considered depends on the data and there is not any prescription for all cases. However in the most cases the most variance is covered by the first two or three components. Therefore, if any damage occurred in structure then it should affect the data and consequently variance of data and should be detected by this damage index.

3.2 Moving principal component analysis-Support vector machine (MPCA-SVM)

3.2.1 Support vector machine (SVM)

Support vector machine (SVM) is a powerful supervised machine learning algorithm, which are commonly used for classification, pattern recognition and also regression analysis (Cortes et al.1995). Linear SVM (LSVM) is the most preliminary form of SVM. In fact, a hyperplane or sets of hyperplanes are constructed by SVMs algorithm in such a way that they can be used for classification and in general for separation of different classes of data. LSVM is applicable only for the data which are linearly separable in the original feature space. However, since this is not the case in most of the real-life problems, the applications of LSVM are limited. For this reason, nonlinear support vector machine (NSVM) was proposed in order to deal with the data which are not linearly separable in original feature space. In order to perform such an analysis, in the first step, the data should be mapped from the original finite-dimensional space into much higher-dimensional space by taking advantages of kernel functions. Supposedly, this transformation should make the separation of the data much more feasible.

3.2.2 Innovative damage detection algorithm (MPCA-SVM)

As it is was discussed throughout section 3.1, although MPCA has exposed a reliable performance in terms of damage detectibility in comparison with other non-parametric damage detection algorithms, it still requires to be significantly improved particularly in terms of its time to detection aspect. In response to this demand, a new non-parametric damage detection algorithm is proposed by integrating the advantages of both MPCA and SVM methods. In fact, this new data interpretation approach consists of two distinctive phases, including feature extraction and pattern recognition. The objective of the preliminary phase (MPCA) is to extract the most informative features out of the raw data, whereas the second phase (SVM) is designed to recognize the pattern throughout the previously extracted features.

The procedure for the first step is the same as the MPCA algorithm which was explained through the section 3.1. However, the second stage, SVM, is the new step, which is added to the MPCA algorithm to reduce the associated delay. To begin with, the time series of principal components corresponding to the individual sensors should be identified by taking the benefits of the MPCA algorithm. In order to carry out the MPCA, an appropriate moving window should be determined and consistently moved along the time to extract the datasets. In the next step, covariance matrix is computed for the extracted datasets. Consequently, the eigenvalues and eigenvectors of the covariance matrix are derived. The time series of eigenvectors corresponded to each sensor, are then fed into SVM algorithm (second phase) for further computation. The second phase (SVM) by itself, involves in several sub steps. Initially, the time series (eigenvectors) pairs that have higher correlation than correlation threshold should be identified and stored. Later, additional moving window is defined and moved along each pairs individually to extract dataset.

Afterward, each of the extracted dataset is fed separately into SVM in order to train the algorithm. Therefore, for each dataset from each additional moving window (during the training phase) a hyperplane is determined. Finally, intercept of the hyperplane is considered as damage index. In other words, a confidence interval is established for dataset during the training phase and based on the intercept of hyperplane, which in turn is used in the monitoring phase as damage criteria. A summary of the aforementioned procedure is presented in Figure 2.

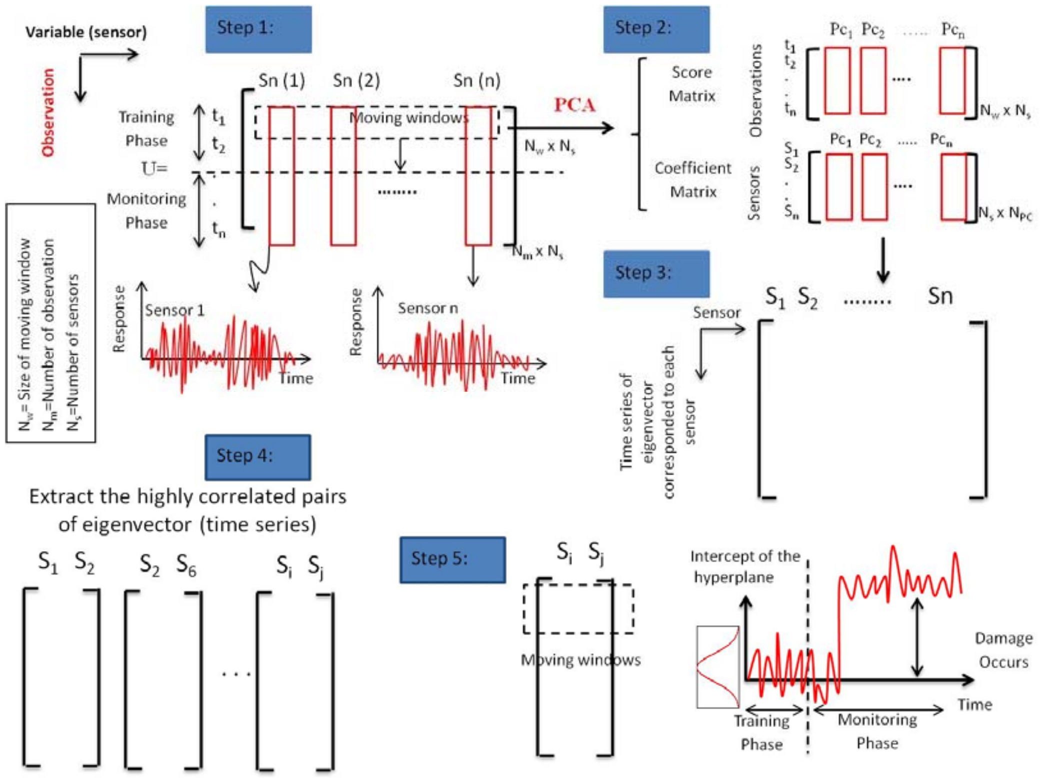

Figure 2- Procedures for long term SHM using MPCA-SVM algorithm

4 EXPERIMENTAL STUDIES

4.1 Structural description and instrumentation (UCF 4-span bridge)

For the sake of evaluating these algorithms using FBG sensors, several experiments with a laboratory bridge model were designed and conducted taking three common damage scenarios into consideration. The structure consists of two 120 cm approach (end) spans and two 304.8 cm main spans with a 3.18 mm thick, 120 cm wide steel deck supported by two HSS 25x25x3 girders separated 60.96 cm from each other. Using the 4-span bridge model in the UCF structural laboratory (Figure 3), it is feasible to simulate and test a variety of damage scenarios that are commonly observed in bridge type structures. It is possible to simulate most of the common boundary conditions, including rollers, pin, and fixed support. It should be pointed out that even though the structure is not a scaled down model of a specific bridge, its responses are representative of typical values for medium-span bridges.

4.2 Damage scenarios

Based on the discussions with the Department of Transportation (DOT) engineers, three critical and common damage scenarios were identified and simulated on the 4-span bridge model. A crucial type of damage which was observed in bridges is alterations in the boundary conditions. These types of alterations may cause stress redistributions and in most cases it may result in additional load in different elements. Therefore, three cases were devoted to this type of damage using the advantage of the ability to shift from pinned to fix or roller condition or vice versa. The damage scenarios implemented in this study are illustrated in Figure 3.

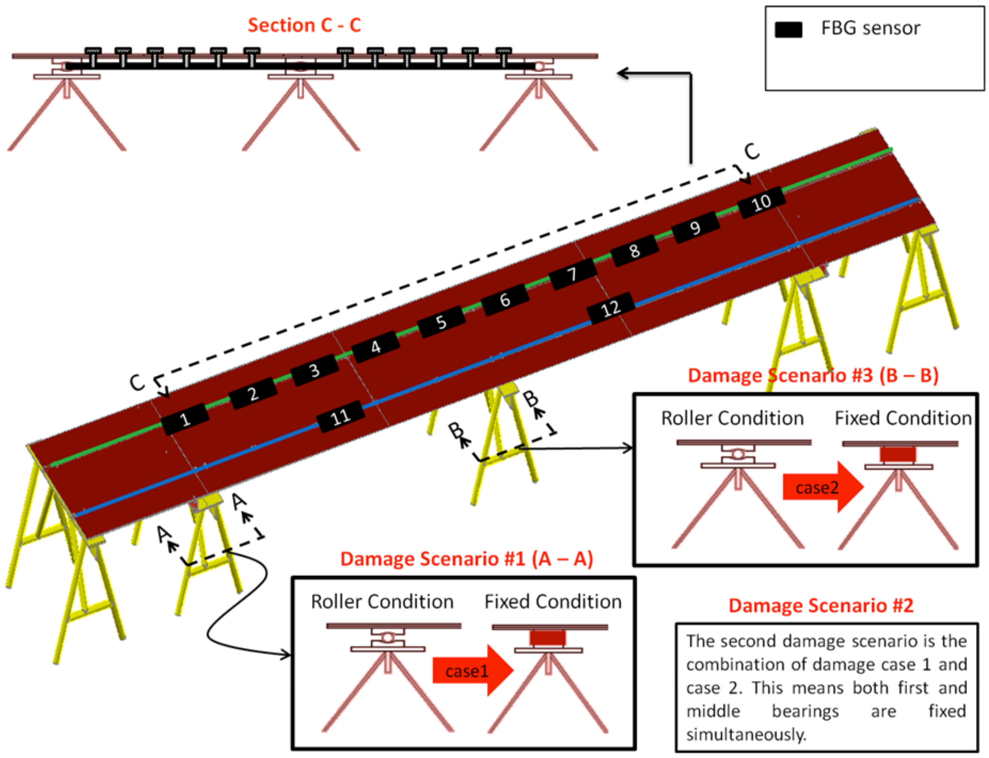

Figure 3- Location of sensors and simulated damage (UCF 4-span Bridge)

5 DAMAGE ASSESSMENT

Total number of 30 data sets, 15 from baseline condition and 15 from damage condition, has been considered in this study. Each data set consisted of approximately 10000 to 13000 data points. This results in a main matrix with 360175 rows (data points or measurements) and 12 columns (number of FBG sensors or variables). Taking this information into account, the size of the moving window was chosen as 13000 x 12 while the moving rate (or window overlap) is selected as 2000 points. Since this is multivariate data analysis, the results of selective sensors are presented instead of individual sensors. For that reason, only the results for the sensors close to damage location will be considered as illustration purpose.

5.1 First damage scenario

The main idea behind this damage case is to simulate one of the most common faults in bridge type structures, which is altering the boundary condition from roller condition to fixed condition. In fact, this type of change will result in redistribution of force in the structure and may cause unexpected bending moment at boundary location, which can have detrimental effect on the performance of the structure. The corresponding results for the MPCA and MPCA-SVM are presented separately in Figure 4. As it is shown in this Figure, both methods (MPCA and MPCA-SVM) show reliable performance in detecting the damage. In fact, there is a significant separation in damage index due damage. However, MPCA detects the damage after 35000 data points from the exact occurrence of damage while MPCA-SVM reduces the delay to 16700 data points. This can be considered as a significant improvement in terms of time to detection. In other words, MPCA-SVM not only has a reliable and powerful detectability but also has the advantages of detecting damage faster than MPCA. This feature will be further evaluated by the other two damage scenarios.

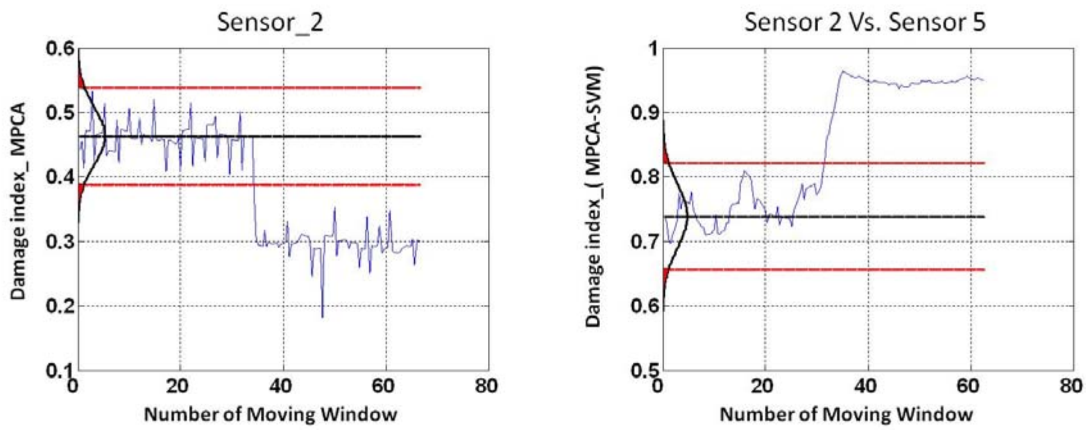

Figure 4- Results for MPCA (left) and MPCA-SVM (right) and case scenario1

5.2 Second damage scenario

The second damage scenario was designed and implemented to simulate the situation in which a number of bearings are experiencing the fixing issue. For that reason, the middle bearing was fixed in addition to the first one. The results for this case are summarized in Figure 5. The results corresponded to sensor 5 are presented for both MPCA and MPCA-SVM algorithm. Similar to the first case, here also, damage indeces for both algorithms exceed the confidence interval immediately after the introduction of the damage. Likewise scenario 1, MPCA detects the damage after 42560 data points whereas MPCA-SVM is able to detect damage only after 176543 data points.

5.3 Third damage scenario

MPCA and MPCA-SVM outcomes for the third case are plotted in Figure 6. Since only the middle boundary condition is altered, only sensor 5 experienced a significant change. This scenario is also confirmed the advantages of MPCA-SVM than MPCA in terms of time to detection.

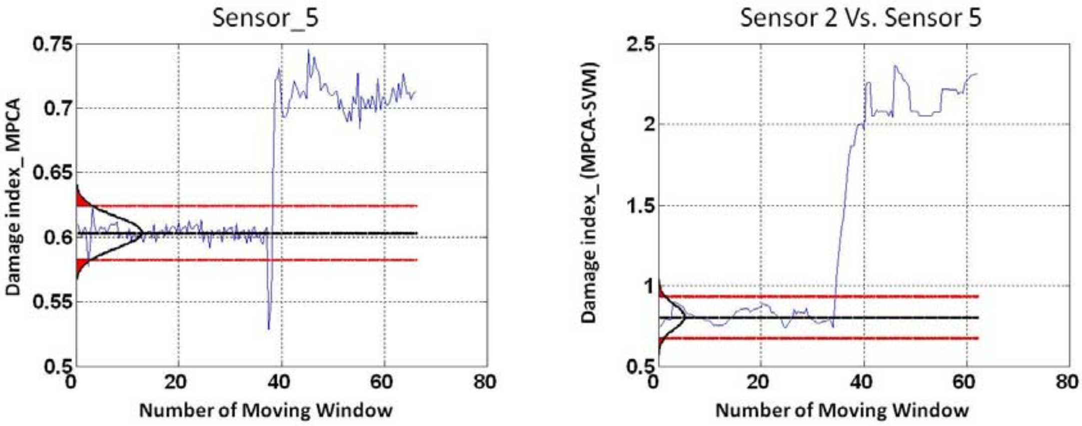

Figure 5- Results for MPCA (left) and MPCA-SVM (right) and case scenario2

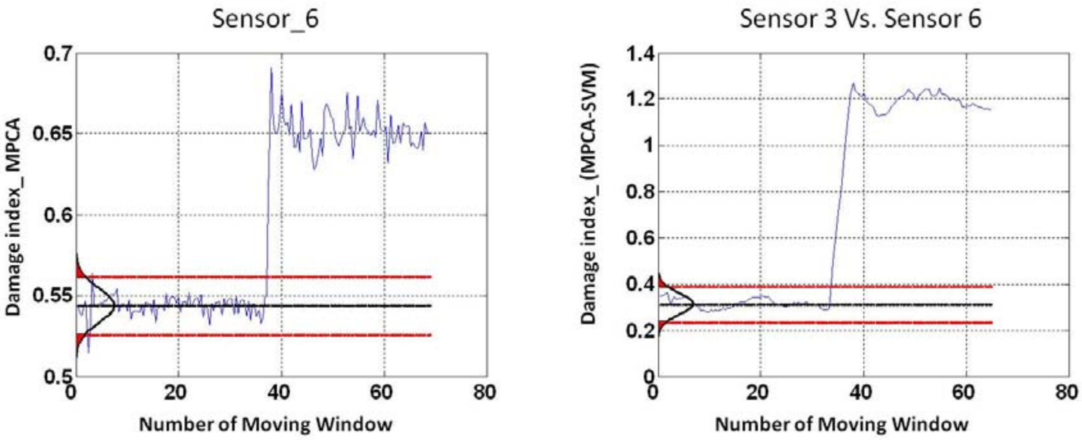

Figure 6- Results for MPCA (left) and MPCA-SVM (right) and case scenario3

6 CONCLUSION

In this study, an algorithm is developed by integrating two powerful machine learning techniques including, Moving Principle Component Analysis (MPCA) and Support Vector Machine (SVM) techniques. In the first stage, the time series of eigenvectors associated with each sensor (variable) should be determined by taking advantage of MPCA, while in the second phase, these eigenvectors are fed into SVM algorithm. The intercept of hyperplane is considered as damage index for the MPCA-SVM method. In order to evaluate the advantages of MPCA-SVM than MPCA, three of the most common damage scenarios are designed and simulated on the 4-span bridge model. The data are collected using an in-house developed FBG system and a network of FBG sensors, which are distributed all over the structure. Comparing the results obtained for MPCA and MPCA-SVM reveals the fact that the new data interpretation approach significantly reduces the time to detection while it also has good performance in terms of detectability.

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