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RESEARCH PAPER

Condition Assessment of Civil Structures for Structural Health Monitoring Using Supervised Learning Classification Methods

Alireza Entezami[1,2] · Hashem Shariatmadar[1] · Hassan Sarmadi[1,3]

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Abstract

Structural health monitoring is an essential process for ensuring the safety and serviceability of civil structures. When a structure suffers from damage, it is necessary to implement maintenance programs for returning the structural performance and integrity to its initial normal condition. An important challenge is that the structure of interest may be damaged even after a sophisticated maintenance program. This conveys the great necessity of performing the second level of structural condition assessment and damage detection of maintained structures. To achieve this aim, this article proposes a novel methodology using the concept of supervised learning. The main objective of the proposed methodology is to train various supervised learning classifiers using a training dataset that consists of features regarding both the undamaged and damaged states of the structure before the maintenance program in the first level. Once the classifiers have been trained, one attempts to predict the class labels of test samples associated with the current state of the structure after the maintenance program during the second level. According to the predefined class labels of the training and test samples in the first stage, it is feasible to recognize the current state of the maintained structure in the second level and detect potential damage. The major contribution of this article is to introduce the concept of supervised learning for damage detection in an innovative manner. A numerical concrete beam and an experimental laboratory frame are used to demonstrate the effectiveness and applicability of the proposed methodology. Results show that this methodology is a practical and reliable tool for structural condition assessment and damage detection of maintained structures.

Keywords Structural health monitoring · Damage detection · Statistical pattern recognition · Supervised learning · Classification · Maintained civil structures

1 Introduction

In civil engineering communities, structural health monitoring (SHM) is an essential topic due to the great importance of civil structures and infrastructures. This practical process is mainly intended to evaluate the health and safety of structural systems by condition assessment and damage detection (Brownjohn et al. 2011; Li et al. 2016; Rahami et al. 2018; Qarib and Adeli 2014). There are two general ways of SHM including (1) model-based and (2) data-based methods. The first approach is based on constructing an elaborate finite element model and utilizing model-updating strategies for damage detection, localization, and quantification (Entezami and Shariatmadar 2015; Sarmadi et al. 2016, 2020b; Entezami et al. 2017; Rezaiee-Pajand et al. 2020, 2021; Pedram and Esfandiari 2019; Kaveh et al. 2019). The second method utilizes raw measured data without any model construction and updating procedures. On this basis, it seems that the data-based methods outperform the model-based techniques in terms of simplicity and efficiency. Most of the data-based SHM strategies are based on monitoring damage-sensitive features extracted from measured vibration data that should be related and sensitive to damage and then discriminating

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the normal (undamaged) structural condition from the current state (the potentially damaged condition) (Amezquita-Sanchez and Adeli 2015). To attain this aim, a data-based method is usually implemented in terms of *statistical pattern recognition* paradigm that contains four main steps: (1) operational evaluation, (2) sensing and data acquisition, (3) feature extraction, and (4) statistical decision-making for structural condition assessment and damage detection (Farrar and Worden 2013).

The process of feature extraction is one of the important steps in data-based methods because it significantly influences the final decision on the structural condition classification. The main objective of this step of the statistical pattern recognition is to extract meaningful information (damage-sensitive features) from raw measurements. Autoregressive (AR) modeling (Entezami and Shariatmadar 2018; Entezami et al. 2019a; Safavi et al. 2017; Datteo et al. 2018) and principal component analysis (PCA) (Zhong et al. 2006; Trendafilova et al. 2008; Gharibnezhad et al. 2015) are two well-known approaches to extract damage-sensitive features. On the other hand, the statistical decision-making refers to applying various statistical methods in terms of machine learning algorithms (i.e., supervised learning and unsupervised learning) (Sarmadi and Karamodin 2020; Sarmadi et al. 2020a; Sarmadi and Entezami 2020; Alamdari et al. 2017; Weinstein et al. 2018).

The simple idea behind the algorithms of machine learning is to learn a model (i.e., detector or classifier) using the information (features) of the structure known as training data. If the training data come from multiple classes and the labels for the features or measured data are known, the problem is multi-class or supervised learning. In the context of SHM, this means that the features of both the normal and current (damaged) structural states are used to make the training data. On the contrary, the training data in the unsupervised learning scheme do not have known class labels and it is attempted to learn intrinsic relationships within the known features of data. In other words, the unsupervised learning methods suppose that the information of the current state is unknown, and the model (detector) of interest is only learned by training data, which is comprised of the features of the only normal condition of the structure.

Although it seems that unsupervised learning methods are more beneficial than supervised learning approaches for SHM resulting from the unavailability of information of the current or unknown state of the structure, one can also exploit the capability of supervised learning algorithms. Assume that a structure suffered from damage and unsupervised learning methods were successfully applied to detect damage. In the next step, a maintenance program is implemented to rehabilitate the damaged structure and enhance the structural safety and serviceability. Before this program, it is feasible to measure and retain the information of the damaged condition, in which case the possibility of supervised learning algorithms is plausible. In this regard, suppose that the maintained structure suffers from damage again similar to the event occurred in the Tianjin Yonghe Bridge in China (Li et al. 2014). Under such circumstances, civil engineers are able to exploit supervised learning methods for subsequent condition assessment and damage detection of maintained structures.

Classification is a supervised learning approach to identify the class label of a set of samples (features). This method aims to learn a classifier by training data along with class labels and then predict the label of unseen test data (Alpaydin 2014). The classifier refers to a mathematical function, implemented by a classification algorithm, which maps the training data to a category. For any unknown test data, each classification method possesses a prediction process that generates predictions for the new data. Worden and Manson (2000) employed Kernel discriminant analysis as a damage classifier for the classification of structural state conditions in a ball bearing system and then compared this method with a neural network classifier. Niu et al. (2007) conducted a research as a comparative study of various classification algorithms for fault diagnosis of electric motors using different types of signals. Gaudenzi et al. (2015) applied linear discriminant analysis as a classifier for the detection of delamination in composite structures with the aid of a wavelet packet transform-based algorithm for extracting damage-sensitive features. Addin et al. (2007) used a naive Bayes classifier as one of the most effective classification approaches to simulate damage detection in engineering materials. Sugumaran et al. (2007) applied decision tree as a classification algorithm to choose the best statistical features from a given set of samples for the purpose of classification. In the following, proximal support vector machine was employed to classify faults in roller bearing using the statistical features. Naderpour and Mirrashid (2019) utilized the decision tree to classify the failure modes in ductile and non-ductile concrete joints. They proposed two classification strategies based on the number of classifiers for concrete joints to determine the types of failure mode. Despite the limited applications of supervised learning classification methods, there is no comparative study on investigating them for damage detection and condition assessment of civil structures.

The main objective of this article is to propose a novel methodology by using the concept of supervised learning for structural condition assessment and damage detection of maintained civil structures. For this purpose, various supervised learning classifiers are trained using a training set including the damage-sensitive features of both the undamaged and damaged states of the structure before the maintenance program in the first level. Once the classifiers have been trained, it is attempted to predict the labels of test samples associated with the current state of the structure after the maintenance program during the second level. Based on the predefined class labels of the training and testing samples (i.e., zero for the normal condition and one for the damaged state) in the first level, one can assess the current state of the structure during the second stage. The supervised learning classification methods introduced in this article are linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), naive Bayes (NB), and decision tree (DT). The procedure of feature extraction is also carried out by the AR model and PCA. In this regard, the coefficients of the AR model and principal components (PCs) of the PCA are considered as the main damage-sensitive features. Finally, the effectiveness and performances of the proposed methodology are verified by numerical and experimental benchmark structures. Results demonstrate that this methodology is an effective and practical tool for applying the concept of supervised learning to SHM and conducting structural condition assessment and damage detection of maintained civil structures. Furthermore, it is observed that the LDA and NB have the worst and best classification results.

2 Feature Extraction Methods

2.1 Autoregressive Time Series Model

In statistics, the AR model is a linear stationary (time-invariant) representation. This is a popular and effective tool for feature extraction due to simplicity, sensitivity of its characteristics to damage, independency to excitation loads or input data (Entezami and Shariatmadar 2018). Given the structural response $y(t)$ at time t, the AR model is written as follows:

$$y(t) = \sum_{i=1}^{a} \varphi_i y(t-i) + e(t) \tag{1}$$

where a and $\mathbf{\Phi} = [\varphi_1 \ldots \varphi_a]$ represent the model order and coefficients, respectively. Moreover, $e(t)$ is the model residual at time t. This statistical characteristic of the AR model measures the difference between the structural response $y(t)$ and the predicted data (with the same dimension of the response) obtained from the model. In the context of SHM, both the model coefficients and residuals are taken into account as the reliable and useful damage-sensitive features (Entezami and Shariatmadar 2018).

2.2 Principal Component Analysis

In statistics, PCA is an important and well-known technique mainly aiming at converting a set of samples (observations) of potentially correlated variables into a set of new samples of linearly uncorrelated variables named as PCs (Gharibnezhad et al. 2015). Despite various applications of PCA, this study considers it as a feature extraction approach. In this regard, the PCs of the structural responses collected into a matrix are considered as the main features for damage detection. Assume that $\mathbf{Y} \epsilon \mathfrak{R}^{n\times m}$ is the matrix of the structural responses, where n and m represent the numbers of response (time series) samples and sensors, respectively. The main goal is to estimate the covariance matrix of $\mathbf{Y}$ and decompose it via the eigenvalue decomposition in the following form:

$$\mathbf{\Sigma}\,\tilde{\mathbf{P}} = \tilde{\mathbf{P}}\mathbf{\Lambda} \tag{2}$$

where $\mathbf{\Sigma} \epsilon \mathfrak{R}^{m\times m}$ stands for the mentioned covariance matrix. This matrix measures the degree of linear relationship within the original dataset between all possible pairs of variables. Meanwhile, the eigenvectors of $\mathbf{\Sigma}$ are the columns of $\tilde{\mathbf{P}}$ and the eigenvalues are the diagonal terms of $\mathbf{\Lambda}$ (the off-diagonal terms are zero). Note that the eigenvector with the highest eigenvalue takes into account as the PC. Therefore, the eigenvectors corresponding to the columns of matrix $\tilde{\mathbf{P}}$ are sorted on the basis of the eigenvalues in descending order. In this way, the new matrix $\mathbf{P}$ (i.e., $\tilde{\mathbf{P}}$ sorted and reduced) can be called as the PCA model.

3 Classification Methods

3.1 Linear Discriminant Analysis

Discriminant analysis is a classification method that is intended to find a linear combination of features that characterizes or separates two or more classes of groups. The basic idea behind this method is to train a linear classifier on the basis of Bayes theorem. In order to perform any classification process, it is essential to define a training set and then predict the classes of test samples by finding its class with the smallest misclassification cost (McLachlan 2005). In the LDA, it is assumed that in a specific class, the probability density function of the feature vector of the training data is Gaussian. The classification rule in the LDA is based on defining a linear score function that consists of a linear discriminant function and the logarithm of the probability of a randomly selected sample in the specific class. The LDA classifies a sample set into a class that has the largest linear score function or the posterior probability (McLachlan 2005). The implementation of the classification process via the LDA is based on some MATLAB default functions (introduced in MATLAB R2014a) such as "`fitcdiscr`" for training or learning the LDA classifier by using a training matrix and a vector of known class labels as well as "predict" for predicting the class labels of test samples.

3.2 Quadratic Discriminant Analysis

The QDA is closely related to the LDA since both of them assume that the samples from each class have Gaussian distribution (McLachlan 2005). The main differences between these classification techniques pertain to their score functions and the parameters of the Gaussian matrix. Unlike the LDA, the QDA does not assume that the covariance of each of the classes is identical. To put it another way, in the LDA, the trained model has the same covariance matrix for each class and the mean values only vary, whereas in the QDA, both the mean and covariance of each class are different at each class. In contrast to the LDA, a quadratic score function is used in the QDA. The classification rule is to train a classifier by the training data and predict the class of the test data with the smallest misclassification cost (the largest quadratic score function or the posterior probability). The implementation of the classification process via the QDA is also based on the MATLAB functions "fitcdiscr" by choosing "quadratic" option and "predict."

3.3 Naive Bayes

The NB is a supervised classification method aiming at classifying test samples on the basis of Bayes theorem (Hastie et al. 2009). This method classifies the mentioned samples using the training data, in which the classifier, developed by the NB, estimates the parameters of a probability distribution under the assumption that the data of interest are conditionally independent. In the following, the method computes the posterior probability of the features belonging to each class for any test data. In other words, the NB classifies the test samples based on the largest posterior probability. To perform the classification procedure, the classification algorithm of the NB estimates the density of the training data with each class and then constructs the posterior probability model on the basis of Bayes rule. Using this model, the algorithm classifies a sample by estimating the posterior probability for each class, and then allocates the observation to the class yielding the maximum posterior probability. The implementation of the classification process via the NB in this article is based on the MATLAB functions (introduced in MATLAB R2014b) "fitcnb" for learning the NB classifier by using a training matrix and a vector of known class labels as well as "predict" for predicting the class labels of test samples.

3.4 Decision Tree

The DT is a supervised classification method applying a tree as a predictive model for the classification. This model is a decision support tool that employs a treelike graph or a model of decisions and their possible consequences. The objective is to create a model from the training data and predict the class of the new data by learning simple decision rules inferred from the data features. Tree models where the target variable can take a finite set of values are called classification trees. In these trees, the leaves represent class labels and the branches indicate conjunctions of features that lead to those class labels. The classification decision tree splits nodes based on either impurity or node error. The common method for impurity is Gini's diversity index or the maximum deviance reduction (also known as cross entropy) (Coppersmith et al. 1999). The implementation of the classification process via the DT is based on the MATLAB functions "fitctree" for learning the DT classifier through a training matrix and a vector of known class labels as well as "predict" for predicting the class labels of test samples.

4 Proposed Methodology for SHM

The proposed methodology of using the supervised learning classification algorithms for structural condition assessment includes two main levels. Figure 1 depicts the flowchart of this methodology. The fundamental principle of the first level is to train classifiers via the LDA, QDA, NB, and DT classification methods in conjunction with the damage-sensitive features extracted from the AR or PCA models (i.e., AR coefficients and PCs). In this stage, one considers that the structure was suffered from damage and the undamaged and damaged states of the structure are known. A maintenance program was also implemented to rehabilitate the damaged structure. Before this program, all information (the damage-sensitive features) of the undamaged and damaged conditions were obtained and retained to use in the second level of damage detection and structural condition assessment. These features and information are useful for producing a matrix of training samples and a vector of known class labels, which are used in the classifiers. In this article, the class labels for the undamaged and damaged states are set as zero and one, respectively.

Assume that $\mathbf{X} \in \mathfrak{R}^{v \times m}$ is the training matrix containing v-dimensional feature samples extracted from m sensors mounted on the structure. It is worth remarking that the v samples of the training matrix are the collection of the features of both the undamaged and damaged conditions. Furthermore, the vector of class labels includes v quantities of zero and one for the undamaged and damaged states, respectively. Using the training matrix and the label vector,

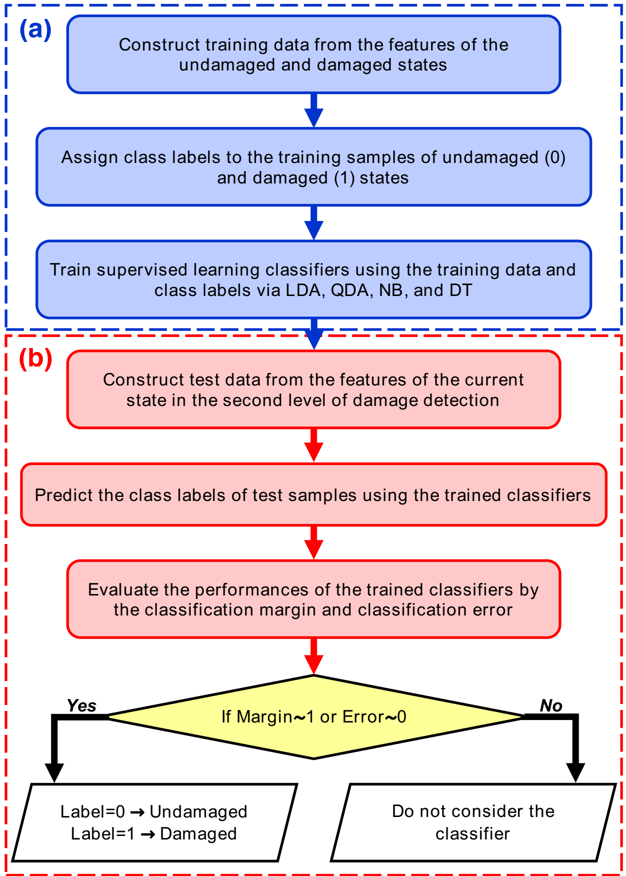

Fig. 1 The flowchart of the proposed methodology: **a** level 1, **b** level 2

four different classifiers on the basis of the LDA, QDA, NB, and DT are trained to predict the labels of test samples in the second level. As explained earlier, the main objective of this article is to supply a new algorithm for damage detection and condition assessment of a structure after a maintenance and rehabilitation program. Therefore, it is attempted to assess the status of the current or unknown state of the maintained structure in the second level.

In the second level of damage detection, as shown in Fig. 1b, suppose that $\mathbf{Z} \in \Re^{u \times m}$ is the mentioned test data, where u denotes the features (i.e., the AR coefficients or PCs) of the current state of the maintained structure. The underlying aim is to predict the labels of u test samples (i.e., 0 or 1) by the classifiers trained by the training matrix and the class label vector in the first level. Before making the final decision about the status of the current state in the second level of damage detection, it is important to ensure the accuracy of classification. This is because it is reasonable that some classifiers may not be sufficiently effective for an accurate classification and structural condition assessment. Thus, the performances of the proposed classifiers are evaluated by some criteria such as the classification margin and classification error. These criteria can be implemented by the MATLAB default functions "`margin`" and "`loss`." The classification margin is a measure that indicates the difference between the posterior probability for the true class and maximal posterior probability for the false class (Allwein et al. 2000). A small classification error near to zero and a large margin value close to one are indicative of the true classification.

If these criteria are acceptable, one can ensure that the classifier of interest performs well and the predicted labels are correct. In such a case, the predicted class label equal to one means that the structure in the second level suffers from damage; otherwise, it still behaves as normal. If the criteria are not acceptable, the classifier does not consider making the final decision about the current state of the structure. In case of accurate classification results (i.e., Margin ~ 1 and Error ~ 0) for more than one classifier, the one that has the best performance in terms of the smallest classification error or the classification margin closer to one is chosen to implement structural condition assessment.

5 Application to Benchmark Structures

5.1 A Numerical Concrete Beam

To verify the performance and capability of the proposed methodology, a numerical benchmark model of a concrete beam (Kullaa et al. 2013) is initially used as shown in Fig. 2. The model is a simply supported beam with length 5 m, height 0.5 m, and width 0.01 m constructed on the basis of Euler–Bernoulli beam theory. It was assumed that similar damping mechanisms were distributed throughout the beam; hence, Rayleigh damping was applied to establish a full damping matrix. The numerical beam was modeled with 4-node linear 2D elements with reduced integration, and ABAQUS Explicit finite element code was used for the simulations. In the simulation process, the fifteen sensors ($m = 15$) were separately installed at the top and bottom surfaces of the beam. These sensors measured acceleration time histories in the vertical direction caused by a uniform random excitation applied to the top surface of the beam. The load histories were low-pass

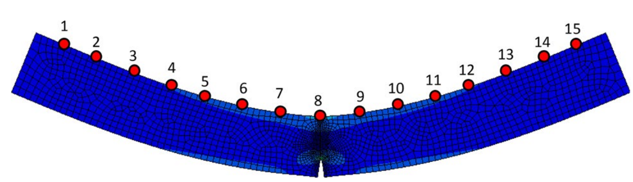

Fig. 2 The numerical benchmark model of the concrete beam along with the simulated damage scenario as a single vertical crack at the middle span of the beam (Kullaa et al. 2013) (Note that the red circles are the simulated sensors mounted on the top of the beam.)

filtered below 1000 Hz, resulting in five active dynamic modes of the structure.

In order to simulate damage, a single vertical crack was modeled at the middle span of the beam (i.e., at the bottom surface of the sensor 8). This damage was the simulation of the breathing crack as a realistic damage scenario in many concrete beam elements. Table 1 lists the different cases of the crack length with incremental damage severities (Cases 2–7) as well as the normal condition (Case 1). The vibration response of each case consists of two test measurements with the 4001 time series points ($n = 4001$) sampled at 4 s (Entezami et al. 2019b). Noise with 30 dB signal-to-noise ratio was also added to the acceleration responses for each test measurement. For example, Fig. 3 indicates the acceleration time histories at the sensor 8 in Cases 1 and 2. According to the proposed methodology, the first test measurement of all cases is considered in the first level. Hence, one adopts that the states of Cases 2–7 are known; that is, those are indicative of the damaged conditions of the beam. It is assumed that a maintenance program is applied to rehabilitate the beam during the first stage. Subsequently, one supposes that the acceleration time histories of the second test measurement are related to the second level after the maintenance program. In this situation, one attempts to classify the labels of Cases 2–7 by the proposed classification methods.

Table 1 The different cases of the concrete beam

Case	Structural state	Description
1	Undamaged	No crack
2	Damaged	Crack length = 10 mm
3	Damaged	Crack length = 20 mm
4	Damaged	Crack length = 30 mm
5	Damaged	Crack length = 50 mm
6	Damaged	Crack length = 100 mm
7	Damaged	Crack length = 150 mm

5.1.1 Feature Extraction

The process of feature extraction is based on estimating the AR coefficients and obtaining the PCs from the PCA via the acceleration response of each sensor. Due to the importance of determining the adequate and accurate order of the AR model (Entezami and Shariatmadar 2018; Entezami et al. 2019b), this article utilizes the Bayesian information criterion (BIC). On this basis, the most appropriate order of the AR model is equal to 23. Note that this procedure is only implemented by using the vibration data of the undamaged condition or Case 1. The least-squares technique is then applied to estimate the 23 coefficients of the AR model at each sensor of Cases 1–7. As a sample, Fig. 4 illustrates the model coefficients regarding the sensors 1, 3, 5, and 8 in Case 1.

For using the PCs of the PCA as the damage-sensitive features, it is initially necessary to perform a standardization process on the acceleration time histories so as to obtain standardized time series data with zero mean and unit

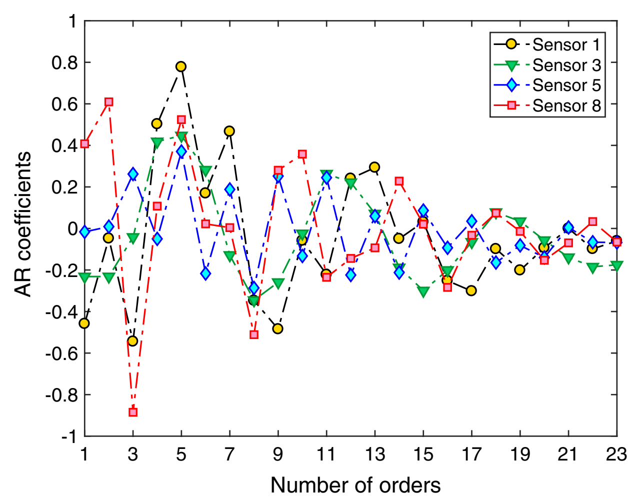

Fig. 4 The coefficients of AR(23) at the sensors 1, 3, 5, and 8 in Case 1

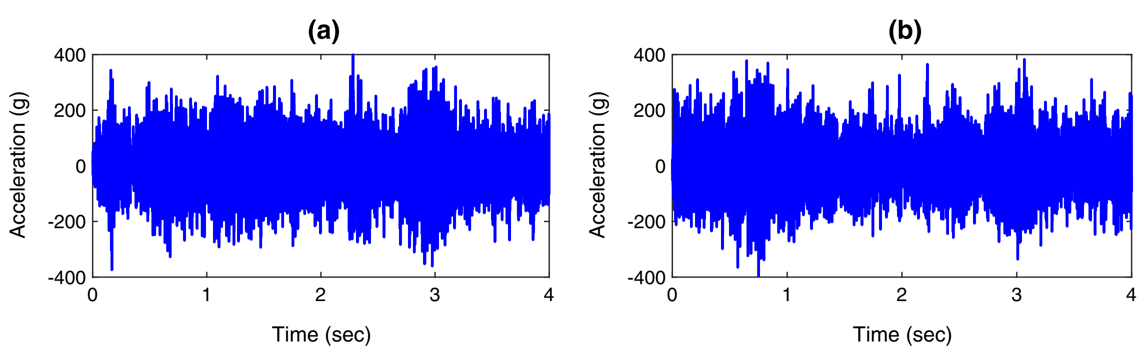

Fig. 3 The acceleration time histories at the sensor 8 in the numerical beam: **a** Case 1, **b** Case 2

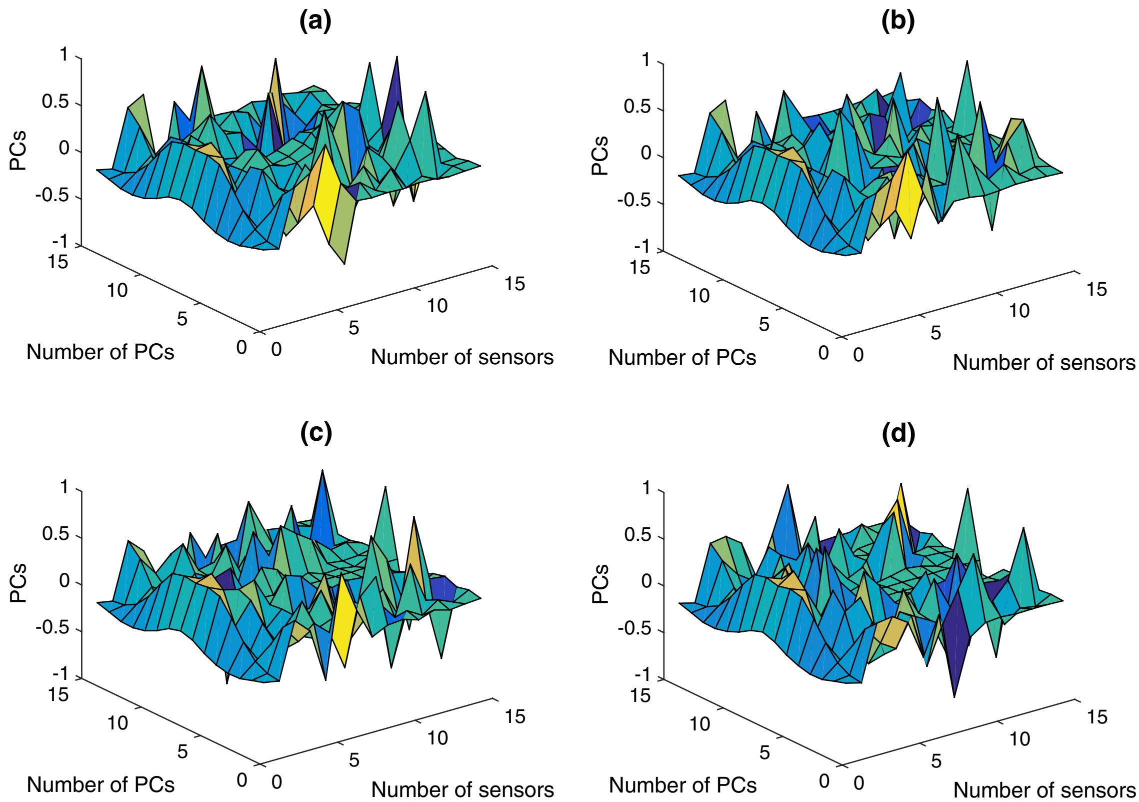

Fig. 5 The PCs of the response matrix **Y** of the numerical beam: **a** Case 1, **b** Case 3, **c** Case 5, **d** Case 7

variance. The standardized time series samples of all sensors are collected to make the matrix of vibration responses $\mathbf{Y}\epsilon\mathfrak{R}^{4001\times15}$. Subsequently, the eigenvalue decomposition is used to decompose the covariance matrix of **Y** for each case. Hence, the main objective is to compute the matrix **P** whose columns are the PCs. Figure 5 shows the PCs of the response matrices of Cases 1, 3, 5, and 7.

5.1.2 Classification

Once the damage-sensitive features have been obtained, one needs to make two kinds of the training datasets. As explained earlier, these sets are the matrices of the AR coefficients and PCs associated with Case 1 and Cases 2–7. For the first type of the damage-sensitive features (i.e., the AR coefficients), the training set is the matrix $\mathbf{X}_{\mathrm{AR}}\epsilon\mathfrak{R}^{161\times15}$, where $v=161$ is determined by multiplying the number of AR coefficients (23) and the number of the undamaged and damaged cases (7). For the second type of the damage-sensitive features (i.e., the PCs of the PCA), the training set is the matrix $\mathbf{X}_{\mathrm{PCA}}\epsilon\mathfrak{R}^{105\times15}$, where $v=105$ is obtained from multiplying the number of PCs (15) by the number of cases (7).

The other important requirement of the classification methods is to prepare the vector of class labels for the feature samples of the undamaged and damaged states. Based on the descriptions in Sect. 4, the labels zero and one are allocated to the features of the undamaged and damaged conditions, respectively. In this regard, the first 23 and the remaining 138 labels for the first training matrix are set as zero and one, respectively. In a similar manner, the first 15 and the remaining 90 labels concerning the second training matrix are identical to zero and one, respectively. Finally, the training matrices and the vectors of class labels are utilized to train the LDA, QDA, NB, and DT classifiers.

In the second level of damage detection by considering that the maintained beam suffered from the damage once again, it is attempted to predict the labels of test samples, which are the damage-sensitive features extracted from the vibration responses of the beam in Cases 2–7 for the second test measurement. Using the same numbers of the AR coefficients and PCs and neglecting the features of the undamaged state, the testing sets for the AR and PCA are the matrices $\mathbf{Z}_{\mathrm{AR}}\epsilon\mathfrak{R}^{138\times15}$ and $\mathbf{Z}_{\mathrm{PCA}}\epsilon\mathfrak{R}^{90\times15}$, respectively. Before making the decisions on Cases 2–7, it is necessary to evaluate the performances of the proposed classifiers through the classification margin and classification error. In this regard, Figs. 6 and 7 demonstrate the margin values of the LDA, QDA, NB, and DT for the AR coefficients and PCs, respectively. Additionally, Table 2 presents the classification errors of these classifiers.

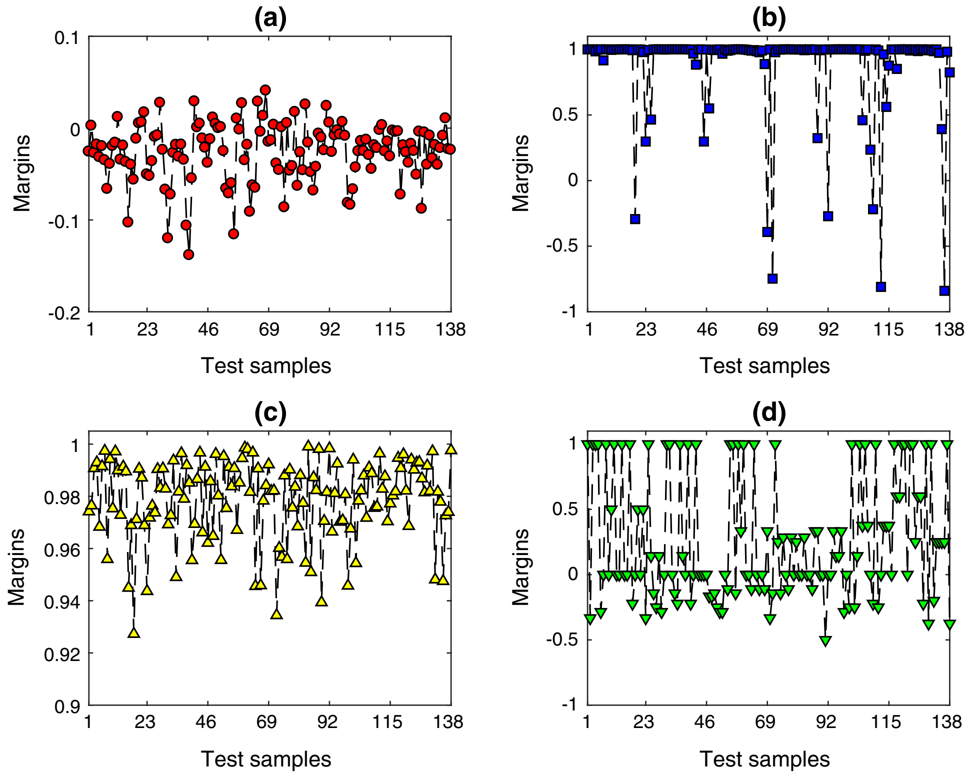

Fig. 6 Margin values of the classification methods in the concrete beam using the AR coefficients: **a** LDA, **b** QDA, **c** NB, **d** DT

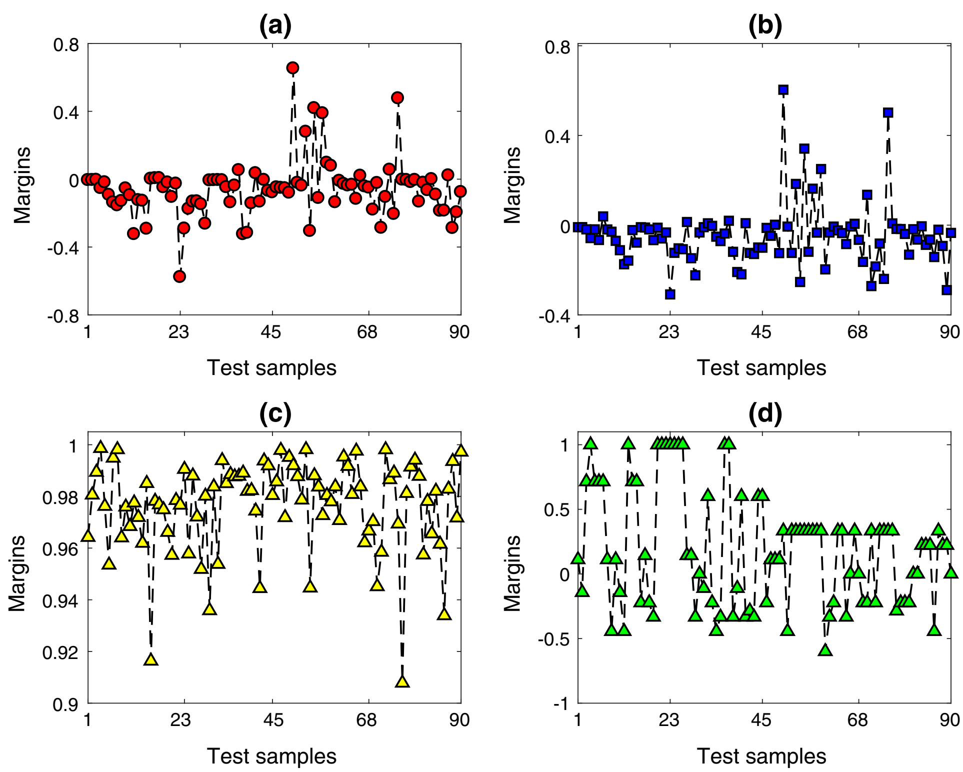

Fig. 7 Margin values of the classification methods in the concrete beam using the PCs: **a** LDA, **b** QDA, **c** NB, **d** DT

As can be observed in Figs. 6a and 7a, the LDA fails in classifying Cases 2–7 as the damaged states properly due to numerous margin values near to zero. Both QDA and NB methods in Fig. 6b, c show the excellent classification results using the AR coefficients owing to the margin quantities close to one, particularly the NB method. The same

Table 2 Classification errors in the proposed classifiers using the AR coefficients and PCs

Classifier	Damage-sensitive feature	
	AR coefficients (%)	PCs (%)
LDA	80.43	83.34
QDA	5.07	83.34
NB	0	0
DT	41.30	37.78

conclusion can be observable in Fig. 7c regarding the NB method through the PCs, while the QDA in Fig. 7b is not successful in classifying Cases 2–7 resulting from its margin quantities near to zero. Additionally, the results of DT in Figs. 6d and 7d are not as good as the NB method, and there are some margin values close to zero implying the unreliable classification.

From the data listed in Table 2, one can deduce that the best performance of classification in terms of the smallest rate of error correlates with the NB method for both types of the damage-sensitive features. With the exception of this approach, the other classification techniques fail in providing the reliable classification decisions. The amounts of classification errors also reveal that the AR coefficients outperform the PCs due to smaller errors. All the obtained results in Figs. 6 and 7 as well as Table 2 lead to the conclusion that the NB method is the only reliable and capable tool for classification and structural condition assessment in the second level by using both the AR coefficients and PCs.

After evaluating the performances of the proposed classifiers, Figs. 8 and 9 show the results of damage detection in the second level by the predicted class labels of the test samples. The predicted labels equal to zero and one are representative of the undamaged and damaged conditions, respectively. Based on the best performance of the NB method, it is expected that this approach accurately detects the states of Cases 2–7. For the comparison, the labels associated with the LDA, QDA, and DT are also presented in Figs. 8 and 9. As can be observed, all the predicted labels of the test samples of Cases 2–7 for the NB method are identical to one in the sense that this approach correctly detects these cases as the damaged conditions. In contrast, the other classification techniques, particularly the LDA and QDA, yield inaccurate predictions (i.e., labels equal to zero for the damaged state) of the labels of the test samples concerning Cases 2–7.

5.2 An Experimental Laboratory Aluminum Frame

For further verification, an experimental benchmark model is applied to demonstrate the effectiveness and reliability of the proposed methodology. This model is a three-story laboratory aluminum frame constructed at the Engineering Institute of Los Alamos National Laboratory (Figueiredo et al. 2009). The frame schematic and sensor locations are

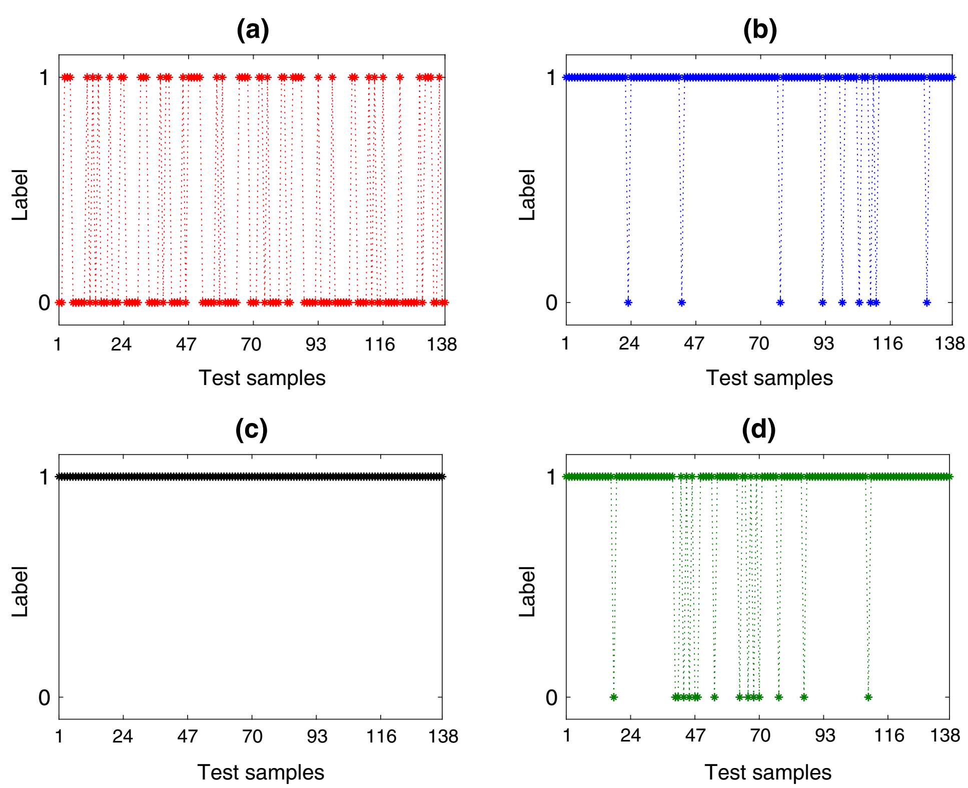

Fig. 8 Predicted class labels of the test samples for structural condition assessment in the concrete beam by the AR coefficients: **a** LDA, **b** QDA, **c** NB, **d** DT

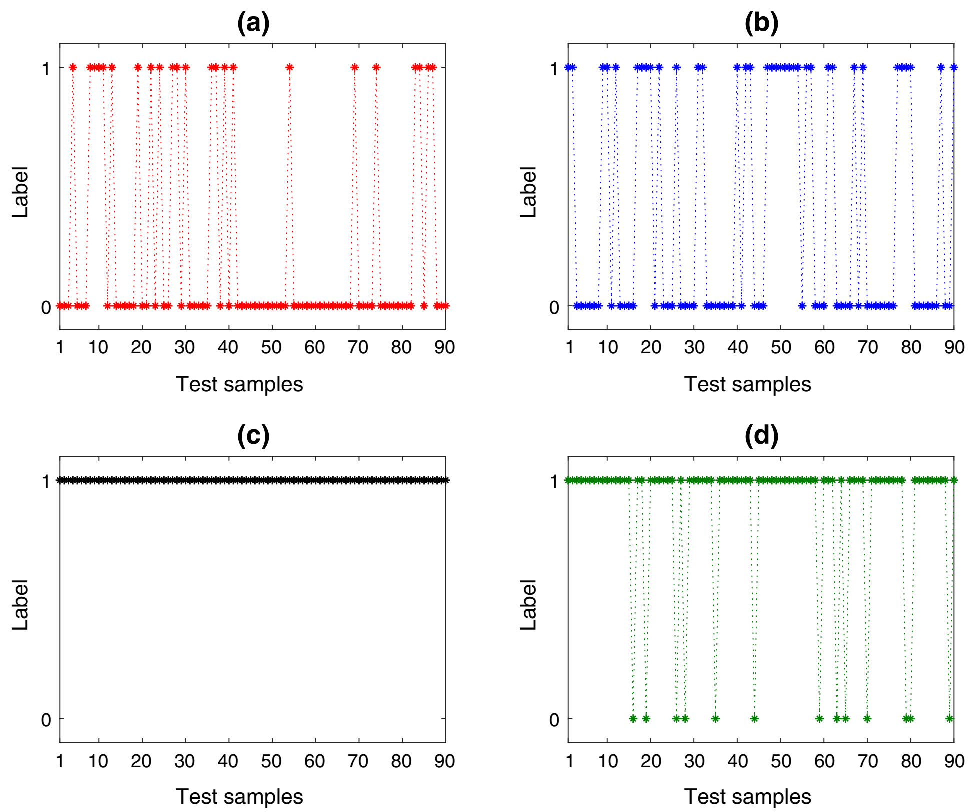

Fig. 9 Predicted class labels of the test samples for structural condition assessment in the concrete beam by the PCs: **a** LDA, **b** QDA, **c** NB, **d** DT

shown in Fig. 10. A random vibration load was applied by means of an electrodynamics shaker to the base floor along the centerline of the frame. The structure was instrumented with four sensors ($m = 4$) mounted at the centerline of each floor on the opposite side from the excitation source to measure the acceleration time-domain response. The shaker and frame were mounted together on an aluminum baseplate and the entire system rested on rigid foam. The acceleration time histories were sampled at 320 Hz for 25.6 s in duration, which are discretized into 8192 time series samples ($n = 8192$) at 3.125 microsecond intervals.

To induce nonlinear damage, a center column was suspended from the third floor. This column has contacted a bumper with an adjustable gap mounted on the second floor, which enabled to define diverse severities of damage. The source of damage is the simulation of a breathing crack to produce nonlinear behavior through opening and closing under excitation forces. The acceleration time-domain responses of the four sensors were measured under 17 structural state conditions as listed in Table 3. These conditions were categorized into the four main groups including the baseline condition (State 1), the undamaged conditions with the operational and environmental variations (States 2–3 and 4–9), the damaged conditions (States 10–14), and the damaged conditions with the environmental and operational variability (States 15–17). In State 1, there is no change in the laboratory frame implying an ideal condition is the SHM community. Moreover, one test measurement of all structural states is considered in the first level, for which it is known that States 1–9 and States 10–17 are representative of the undamaged and damaged conditions with the class labels zero and one, respectively. Another test measurement is incorporated in the second level of damage detection with the assumption that States 10–17 are the current conditions of the frame. Therefore, it is attempted to predict their class labels by the proposed methodology and two kinds of the damage-sensitive features.

5.2.1 Feature Extraction

Similar to the numerical beam, the process of feature extraction is performed by the AR and PCA models for extracting the AR coefficients and PCs as the damage-sensitive features. Applying the BIC technique, the AR order is set as 20. Figure 11 illustrates the coefficients of AR(20) at all sensors of the laboratory frame in State 1. After the standardization of the acceleration time histories collected into the response matrix $\mathbf{Y} \in \Re^{8192 \times 4}$, the covariance matrix of $\mathbf{Y}$ for each state is estimated to obtain the PCs. Figure 12 shows these features associated with Sates 1, 5, 14, and 17, respectively.

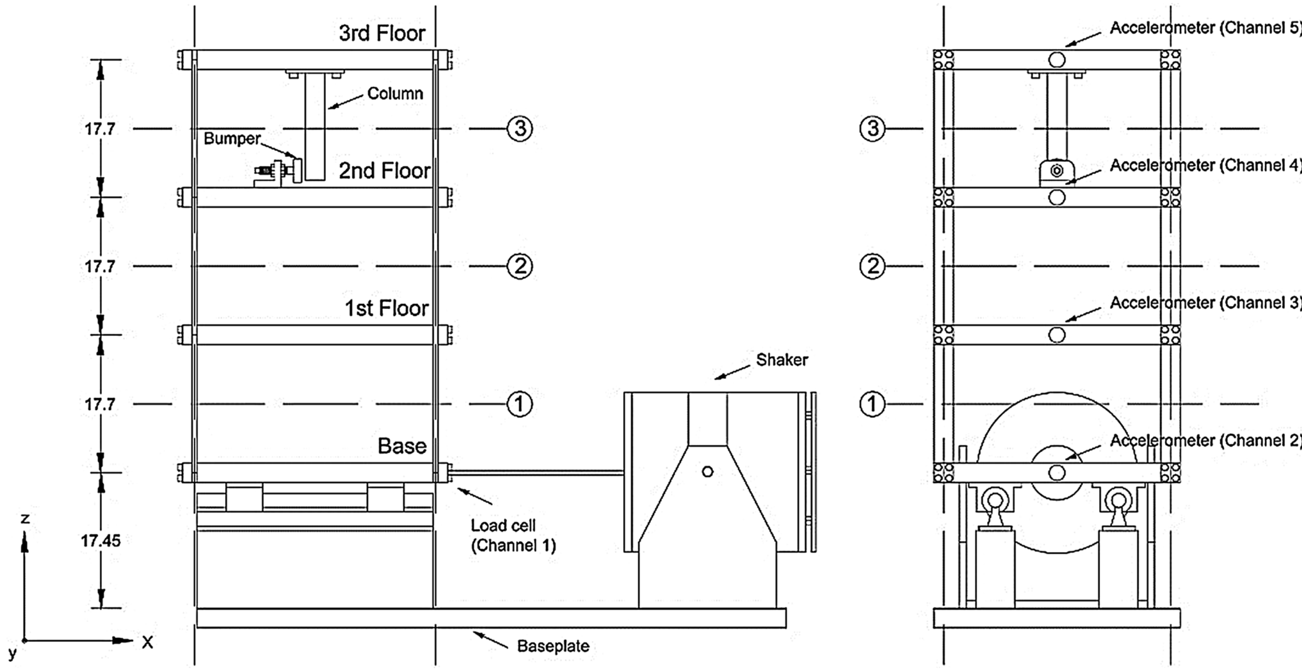

Fig. 10 The three-story laboratory aluminum frame (Figueiredo et al. 2009)

Table 3 The structural state conditions of the laboratory frame (Figueiredo et al. 2009)

States	Condition	Description
1	Undamaged	Baseline condition without damage and environmental and operational variability
2–3	Undamaged	Simulated operational variability by adding a concentrated mass (1.2 kg) on the base and first floors
4–9	Undamaged	Simulated environmental variability by decreasing structural stiffness at the first, second, and third floors
10–14	Damaged	Nonlinear damage (Gap = 0.20, 0.15, 0.13, 0.10, and 0.05 mm)
15–17	Damaged	Nonlinear damage (Gap = 0.20, 0.20, and 0.10 mm) with simulated operational variability at the base and first floors

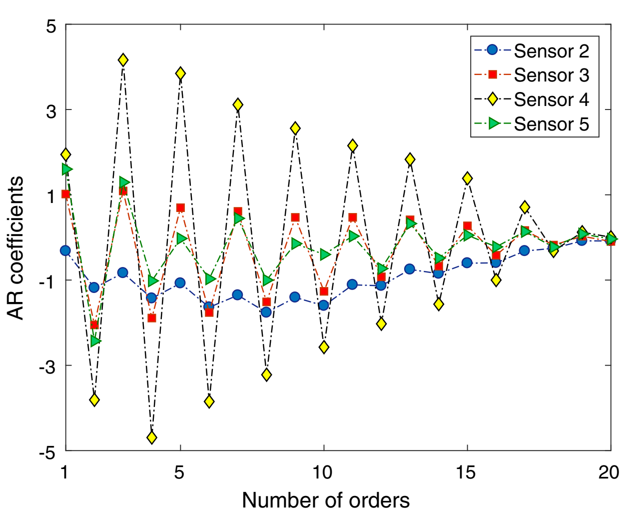

Fig. 11 The coefficients of AR(20) in State 1

5.2.2 Classification

Using the extracted damage-sensitive features, one needs to make two kinds of the training matrices by the AR coefficients $\mathbf{X}_{\mathrm{AR}} \epsilon \Re^{340\times4}$ and PCs $\mathbf{X}_{\mathrm{PCA}} \epsilon \Re^{68\times4}$. These matrices are composed of the features of both the undamaged and damaged states in the first level. Moreover, the labels zero and one are assigned to the features of the undamaged and damaged conditions in order to produce two label vectors with 340 and 68 samples, where the first 180 and the remaining 160 labels of $\mathbf{X}_{\mathrm{AR}}$ and the first 36 and the remaining 32 labels of $\mathbf{X}_{\mathrm{PCA}}$ are related to States 1–9 and 10–17, respectively. Finally, the training matrices and the vectors of class labels are applied to train the LDA, QDA, NB, and DT classifiers. In the second level of damage detection, it is necessary to predict the class labels of States 10–17 by using the trained classifiers and the testing matrices $\mathbf{Z}_{\mathrm{AR}} \epsilon \Re^{160\times4}$ and

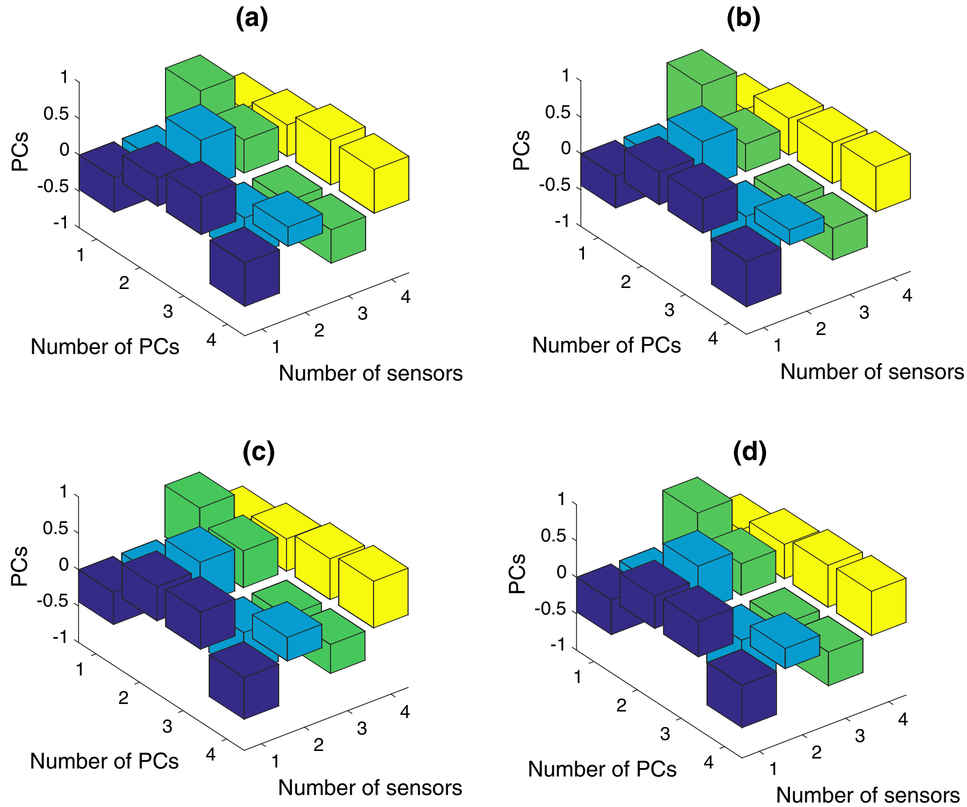

Fig. 12 The PCs of the response matrix **Y** of the laboratory frame: **a** State 1, **b** State 5, **c** State 14, **d** State 17

$\mathbf{Z}_{PCA} \in \mathfrak{R}^{32\times4}$. Figures 13 and 14 illustrate the margin values of the test samples of States 10–17, where each of the 20 and 4 test samples is related to one damaged state of the frame. In addition, Table 4 lists the classification errors of the proposed classifiers in predicting the class labels of the test samples.

As can be seen in Figs. 13c and 14c, the NB method provides the accurate and reliable results of the classification in comparison with the other techniques due to its margin values close to one. Both of the discriminant analysis methods, LDA and QDA, have the low margin amounts in Figs. 13a, b and 14a, b. In addition, the results of classification in Figs. 13d and 14d concerning the DT method demonstrate its unreliable classifications resulting from several margin quantities, which are far away from one. The same conclusions can be reached by the classification errors in Table 4, where the NB method does not have any error indicating its excellent performance compared to the other classification techniques. Furthermore, one can realize that the classification errors in the AR coefficients are roughly smaller than that of the PCs.

In the following, the predicted class labels of the test samples in the second level of damage detection and structural condition assessment are shown in Figs. 15 and 16. According to the excellent performance of the NB method, one expects that the predicted labels of the test samples regarding States 10–17 are equal to one. For the comparison, the labels of the test samples of the other classification methods are also depicted in Figs. 15 and 16. As can be observed, all the predicted labels of the test samples concerning States 10–17 for the NB method correspond to one, which means that this approach accurately detects these states as the damaged conditions. On the other hand, it is seen that the other classification techniques do not have the best results similar to the NB method.

6 Discussion

This article proposes a novel methodology for damage detection and structural condition assessment of maintained civil structures using the concept of supervised learning. The main premise behind this methodology is that the maintained structures may suffer from damage such as the event occurred in the Tianjin Yonghe Bridge in China (Li et al. 2014). During usual inspections, some damages were found in the deck and cables of this bridge. A sophisticated SHM and sensing program was performed to measure environmental and vibration data of the undamaged and damaged states. After the maintenance of the bridge, new damage scenarios were observed once again. Accordingly, the proposed methodology in this article develops an effective and practical framework to apply supervised learning algorithms, which are not usually utilized in SHM problems.

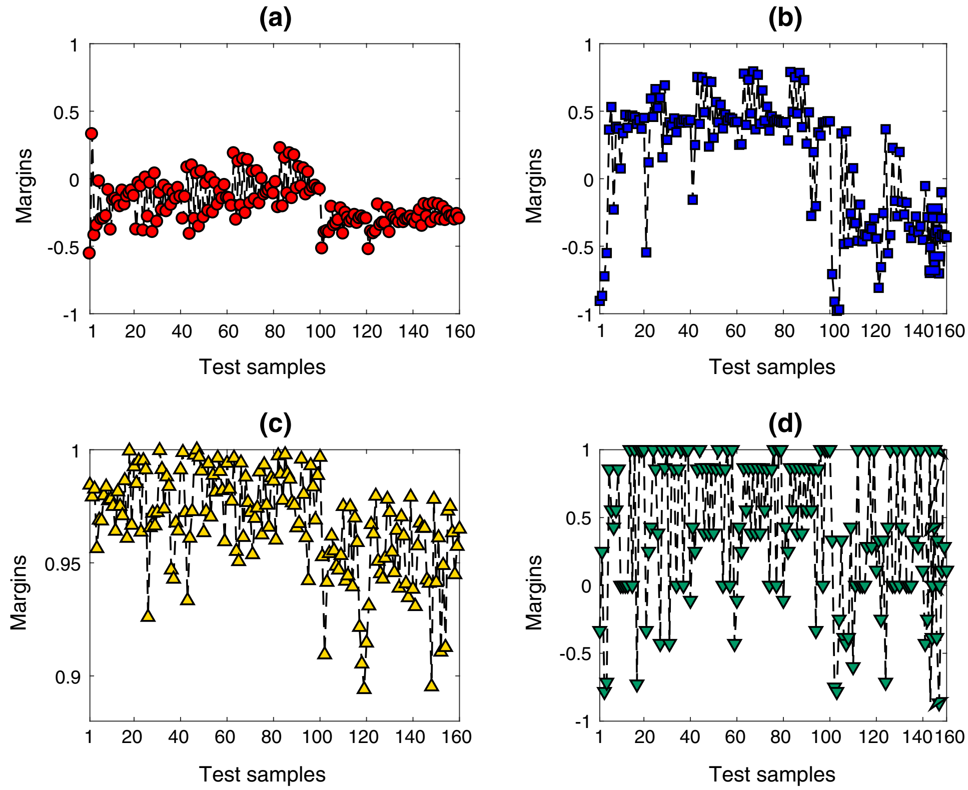

Fig. 13 Margin values of the classification methods in the laboratory frame by the AR coefficients: **a** LDA, **b** QDA, **c** NB, **d** DT

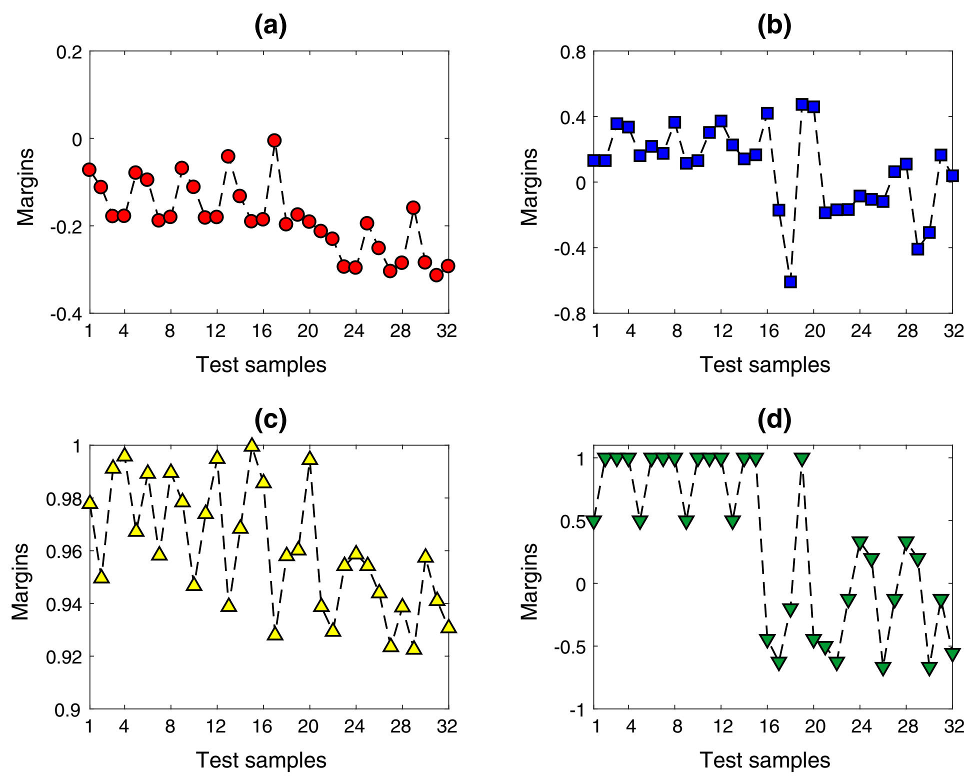

Fig. 14 Margin values of the classification methods in the laboratory frame by the PCs: **a** LDA, **b** QDA, **c** NB, **d** DT

Table 4 Classification errors in the proposed classifiers using the AR coefficients and PCs

Classifier	Damage-sensitive feature	
	AR coefficients (%)	PCs (%)
LDA	86.87	100
QDA	39.37	31.25
NB	0	0
DT	24.37	37.5

This is because these algorithms require the information of both the undamaged and damaged conditions for training a classifier. For complex and expensive civil structures, it is not reasonable and economical to damage them in order to prepare the information of the damaged state. However, this article indicated that it is feasible to apply the concept of supervised learning for structural condition assessment and damage detection of maintained civil structures.

On this basis, it is only necessary to prepare some information of the structural states in the first and second levels before and after the maintenance programs. In the first level, one supposes that the information (the damage-sensitive features) of the undamaged and damaged states is available. During the second level, one attempts to predict the class label of the current state of the maintained structure. In order to guarantee the reliability of classification, this article recommends applying different supervised learning classifiers and evaluating their performances by some classification criteria (i.e., the classification margin and error) so as to choose the best classifiers. Using the predicted class labels of the test samples regarding the most appropriate classifiers, it is possible to recognize the current state of the maintained structure in terms of being undamaged (label = 0) or damaged (label = 1).

7 Conclusions

In this article, a novel supervised learning methodology was proposed to assess the structural condition and detect potential damage in maintained civil structures. The LDA, QDA, NB, and DT classification methods in conjunction with two kinds of the damage-sensitive features extracted from the AR and PCA models were introduced to evaluate the effectiveness and applicability of the proposed methodology. Based on the numerical concrete beam and the experimental laboratory frame, the following conclusions are drawn: (1) The proposed methodology is a reliable tool for structural condition assessment and damage detection of maintained structures using the concept of supervised learning. (2) The best performance of classification and damage detection is related to the NB method in both types of the

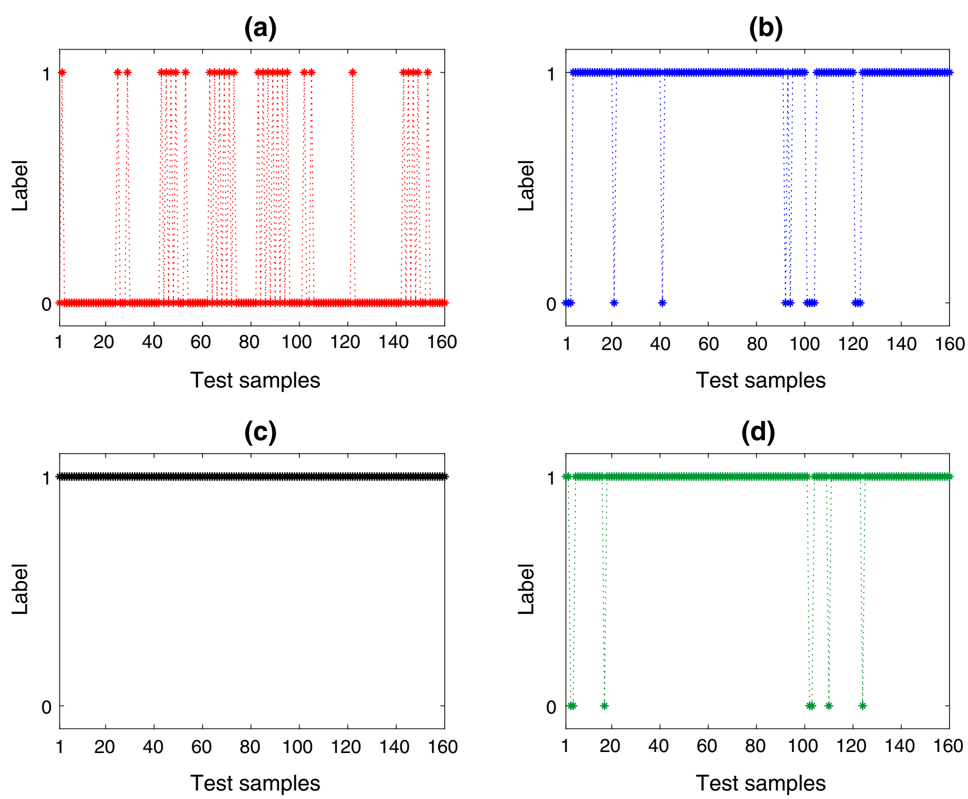

Fig. 15 Predicted class labels of the test samples for structural condition assessment in the laboratory frame by the AR coefficients: **a** LDA, **b** QDA, **c** NB, **d** DT

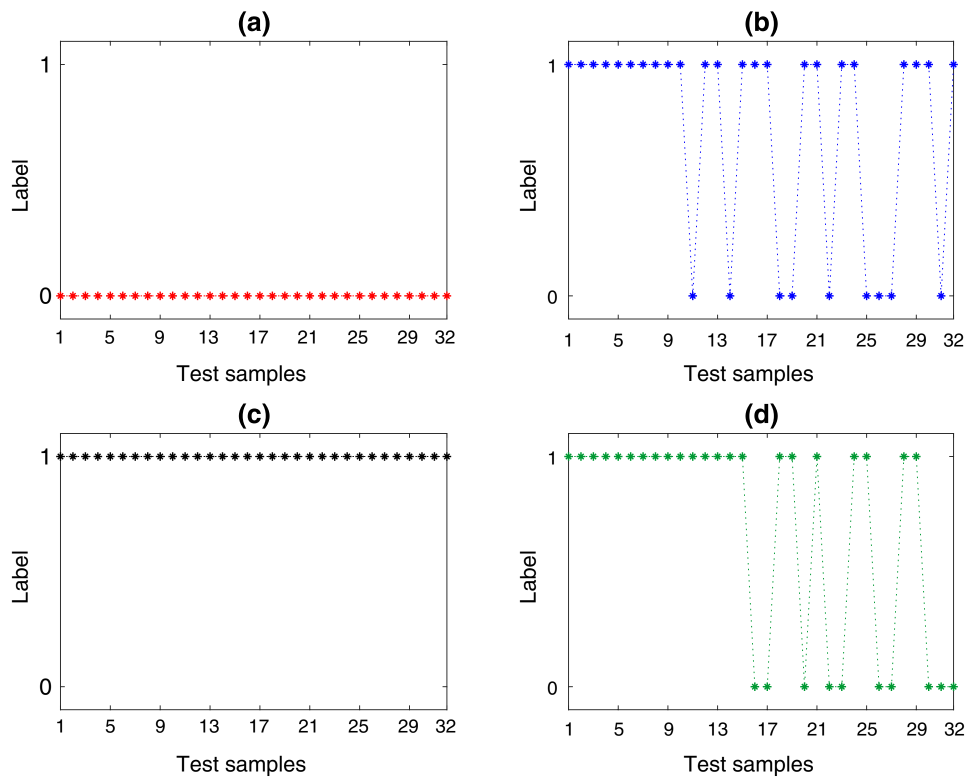

Fig. 16 Predicted class labels of the test samples for structural condition assessment in the laboratory frame by the PCs: **a** LDA, **b** QDA, **c** NB, **d** DT

damage-sensitive features. (3) This method successfully predicted the class labels of the test samples of the damaged states. (4) The LDA and QDA were not successful in the classification and damage detection due to their inappropriate results. (5) It was observed that the DT technique outperforms the LDA and QDA but not as good as the NB method. (6) The comparison of the classification errors revealed that it is better to apply the AR coefficients than the PCs as the damage-sensitive features.

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