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Invited/Review Article

Feature extraction and classification techniques for health monitoring of structures

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Abstract. Damage identification in Structural Health Monitoring (SHM) involves three main steps: signal acquisition, signal processing, and feature extraction and interpretation. Recently, the authors presented a review of recent articles on signal processing techniques for vibration-based SHM. This article presents a review of journal articles on feature extraction and classification techniques in order to assess the health condition of a structure in an automated manner. This review is limited to civil structures such as buildings and bridges. The methods reviewed are neural networks, wavelets, fuzzy logic, support vector machine, linear discriminant analysis, clustering algorithms, Bayesian classifiers, and hybrid methods. Further, two novel algorithms with potential for feature classification in SHM are suggested.

1. Introduction

Civil infrastructures, such as buildings and bridges, can deteriorate during their service life due to different causes, such as corrosion, fatigue, and sudden accidental loads, as well as natural hazards, such as earthquakes and high winds [1,2]. To ensure their safety and reliability and to prevent human losses and minimize economic losses, it is highly desirable to have an automated monitoring system capable of assessing the structural performance and detecting, locating, and quantifying damage severity in an early stage [3,4]. In the past two decades, Structural Health Monitoring (SHM) has become an important and growing research topic on aeronautical, mechanical, and civil structures with the aim of evaluating the health condition and the dynamic characteristics of the structure in real time. Qarib and Adeli [5] presented a review of recent advances made in vibration-based SHM using responses of the structure to an excitation. They discussed sensor layout and data collection strategies, integration of SHM with vibration control of structures [6], wireless monitoring, and application of LIDAR [7-8].

Damage identification in an SHM system involves three main steps: signal acquisition, signal processing, and feature extraction and interpretation (Figure 1). Recently, Amezquita and Adeli [9] presented a review of recent articles on signal processing techniques for vibration-based SHM. This article focuses on the last step and presents a review of journal articles on feature extraction and classification techniques in order to assess the health condition of a structure in an automated manner. This review is limited to civil structures including buildings and bridges.

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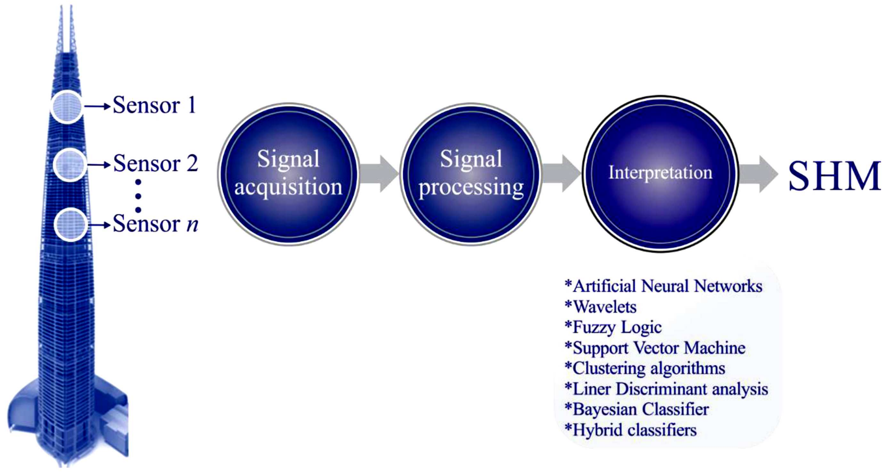

Figure 1. Steps in a structural health monitoring system.

2. Artificial neural networks

Artificial Neural Networks (ANN) are computational models inspired by the interconnected neurological structure of the human brain in order to learn and solve problems through pattern recognition [10-12]. Different ANN architectures have been proposed with the feedforward architecture to be the most commonly-used in numerous applications, such as pattern matching [13-15], classification [16,17], forecasting [18], system identification [17,19,20], and data clustering [21-23]. Figure 2 shows a typical feedforward architecture consisting of an input layer, one or more hidden layers, and an output layer where each layer is composed of a number of nodes. In this architecture, the input information moves in one direction only, from the input nodes through the hidden nodes and to the output nodes.

Since the publication of the first journal article on civil engineering application of neural networks by Adeli and Yeh [24], neural networks have been used extensively in different fields of civil engineering, such as transportation engineering [25,26], earthquake prediction [27-29], vibration control [30], structural design optimization [31-35], construction engineering [36,37], among others.

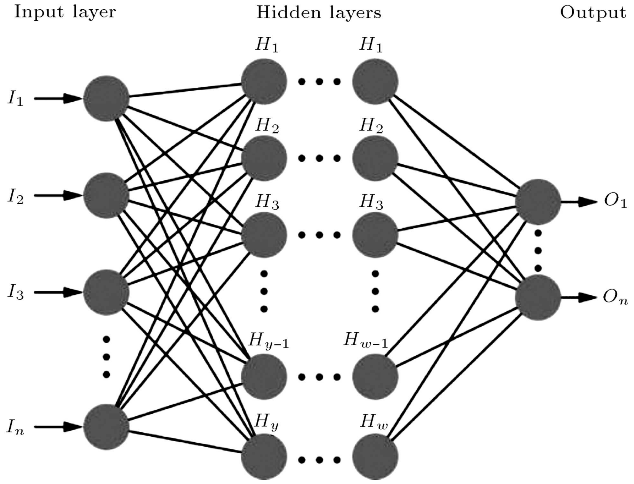

Figure 2. Feedforward architecture of a neural network.

In recent years, many researchers have used an ANN approach for system identification and damage detection of civil structures. Ni et al. [38] combined Frequency Response Function (FRF) [39], Principal Component Analysis (PCA) [40,41], and multilayer perceptron NN [24] to identify and locate damage in the scaled model of a 38-story RC structure. Li et al. [42] also employed FRF-PCA-ANN for monitoring the health condition of a beam subjected to forced excitations. Mehrjoo et al. [43] used a multilayer perceptron NN to detect damage severity in the joints of two truss bridge structures subjected to dynamic excitations. The natural frequencies and mode shapes of structures were used as inputs to train the neural network for damage detection.

Probabilistic NN (PNN) [29,44] provides a relatively quick training, good network fault tolerance, and strong pattern classification ability compared with the multilayer perceptron and backpropagation NN. Li [45] compared PNN and Learning Vector Quantization (LVQ) neural network to locate damage in a simple plate and concluded that PNN was more efficient in locating damage in the structure compared with LVQ-NN. Jiang et al. [46] used PNN to detect and locate single- and multi-damage patterns in a 2D 7-story steel model. Recently, Zhou et al. [47] used PNN for assessing the heath condition of a cable-supported bridge. The first 20 modal frequencies were used to train the PNN. The authors concluded that the method could detect and locate damage with an accuracy of 90% when the signal was not noisy; but when the signal was noisy, the accuracy fell below 85%.

Butcher et al. [48] used a recurrent neural network for electromagnetic anomaly detection of defects in reinforced concrete. Story and Fry [49] used a competitive array of neural networks to detect impairment in a 100-year old railroad drawbridge based on the analysis of digital data streams of electronic sensors attached to its critical components.

3. Wavelets

In recent years, the Wavelet Transform (WT) [50] has been used as a powerful signal processing approach in different structural engineering applications, such as analysis of seismic signals [51], structural control [52-54], and reliability analysis [55]. In the parametric approach to SHM, a key point is accurate estimation of the modal parameters of a structure. Su et al. [56] integrated the time series Auto-Regressive (AR) method with the wavelet packet [57] transform to determine the modal parameters of a structure from its ambient vibration responses. When combined with a classification approach, WT can be a powerful tool for feature extraction. Examples of such integration will be presented in the section Hybrid Approaches.

4. Support vector machine

Introduced by Vapnik [58], Support Vector Machine (SVM) is a statistical machine learning method for distinguishing different classes. SVM classifies data by finding the optimal hyperplane with the largest margin between the classes in a high dimensional feature space [59]. Complex problems cannot be classified using simple hyperplanes. To overcome this problem, a nonlinear SVM classifier can be used, which employs a nonlinear kernel, usually a Gaussian Function (GF) or Radial Basis Function (RBF) [60]. Figure 3 graphically shows examples of linear and nonlinear SVM classification.

SVM has attracted SHM researchers, because it does not require a large number of training data sets and seems to suffer less from the data over-fitting issue plaguing some of the ANN models. Park et al. [61] used RBF SVM for classification of crack damage on a 1/8 scale model of a vertical truss member of Seongsu Bridge, Seoul, Korea, which collapsed in 1994.

Despite promising results on small-scale structures, an SVM model can only detect if the structure is damaged or not, that is a binary classifier. It has been applied mostly to simple structures and academic exercises. Chong et al. [62] presented a nonlinear multiclass SVM known as one-versus-the-rest for health monitoring of a 2D three-story frame structure equipped with an MR damper subjected to ambient vibrations. For larger real-life applications, SVM has been combined with other approaches, such as WT, that is discussed in the section of Hybrid Approaches.

5. Linear discriminant analysis

Linear Discriminant Analysis (LDA), also known as Fisher's discriminant, is a statistical classification method which minimizes the interclass variance while maximizing the distance between two classes through a linear hyperplane [63]. For a multiple-class classification, a generalization of LDA, known as Multiple Discriminant Analysis (MDA), uses several linear hyperplanes to separate all classes [64]. Advantages of LDA are ease of the implementation and computational efficiency [65].

Farrar et al. [65] used LDA for health monitoring of a concrete bridge column subjected to dynamic excitations produced by an electromagnetic shaker. The results showed that LDA can distinguish the undamaged structure from the damaged one, but cannot locate and quantify damage severity which is of vital importance in SHM. Other applications of LDA have been reported by Sohn et al. [66] and Lynch [67]. LDA, however, cannot solve nonlinear classification problems, effectively, which occur commonly in SHM.

6. Clustering algorithms

Clustering refers to classification of similar objects into different groups or clusters based on their features [68-69]. Its intention is to classify a dataset into a set of groups which contain similar data items according to some defined distance measure [70-72]. Different types

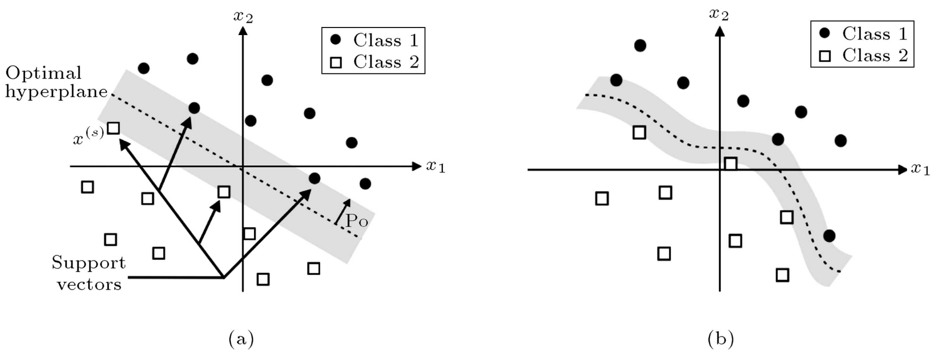

Figure 3. (a) Linear- and (b) nonlinear-SVM classification.

of clustering algorithms, such as k-means (KM) [73], Fuzzy C-Means (FCM) [74], and Partitioning Around Medoids (PAM) [75], have been proposed. Among them, KM and FCM are the most widely-used in SHM, primarily because of the ease of implementation.

Cen et al. [76] presented a grey-box neural network approach for model identification in nonlinear dynamic systems. Park et al. [77] used the KM algorithm for classifying the frequency variations in vibration signals in order to detect loosening of bolts in joints for an aluminum beam subjected to forced excitations. The authors concluded that it was necessary to combine the KM algorithm with supervised pattern recognition tools such as FLC, SVM, and ANN for health monitoring of more complex structures. Silva et al. [78] combined the AR-ARX model and FCM algorithm for classifying the level of damage in a 3D scaled model of a four-story two-bay by two-bay braced steel frame subjected to band-limited noise as excitation. da Silva et al. [79] compared the FCM and Gustafson-Kessel (GK), another clustering algorithm, to identify different damage states (bolts and bracket completely removed) for a 3D three-story steel frame subjected to forced excitation produced by an electrodynamic shaker and concluded that the GK algorithm is slightly better than the FCM algorithm for condition assessment of the structure.

Despite providing useful results, the aforementioned works have been limited to academic and small example structures only. Health monitoring of large real-life structures represents a major challenge, because the measured signals include nonlinear and non-stationary properties. Carden and Brownjohn [80] examined the FCM algorithm for health monitoring of a large real-life structure, the 66-story Republic Plaza Office in Singapore, subjected to ambient dynamic excitations (Figure 4). Yu et al. [81] combined FRF-PCA-FCM for health monitoring of the scaled model of a 3D aluminum six-bay truss bridge subjected to forced excitations produced by a shaker.

KM and FCM methods are sensitive to the initial choice of cluster centers which can produce erroneous classification. Compared with the KM algorithm, the FCM algorithm is computationally more intensive, but usually yields better results.

7. Bayesian classifiers

A Bayesian Classifier (BC) sets the decision boundaries based on probabilities [82]. A few applications of BC have been reported for damage detection in recent years. Lin et al. [83] examined the BC for health monitoring of a scaled model of a 3D six-story steel structure subjected to ambient dynamic excitations. The authors reported an accuracy of 90%, but the method could not estimate the damage location. The BC method requires a previous calibration [84]. Huang et al. [85] investigated a Bayesian compressive sensing approach that used sparse Bayesian learning to reconstruct signals from a compressive sensor and present ideas to improve its robustness.

Figure 4. Republic Plaza Office Tower (adapted from Carden and Brownjohn [80]).

8. Hybrid approaches

SHM of large real-life structures is complicated. For solution of such complicated problems, a single Computational Intelligence (CI) or classification technique is not sufficient. Two decades ago, Adeli and Hung [86] advocated the integration of three CI approaches, neural networks, Genetic Algorithm (GA) [87-89], and fuzzy logic [90] as a more powerful tool for solution of complicated pattern recognition problems. Since then, hybridization has been a major research trend. The goal of hybridization is to improve accuracy, efficiency, and stability of the resulting algorithm.

Jiang and Adeli [91] presented a novel multi-paradigm model for damage detection of highrise building structures subjected to seismic excitations using the non-parametric dynamic fuzzy Wavelet Neural Network (WNN) model developed by them earlier [92]. They introduced a new damage evaluation method based on a power density spectrum method, called pseudospectrum, and employed the multiple signal classification (MUSIC) method to compute the pseudospectrum from the structural response time series. In order to reduce errors produced by a noisy signal, they applied the method to the scaled model of a 38-

story reinforced concrete subjected to synthetic seismic excitations. Osornio-Rios et al. [93] combined MUSIC and multilayer perceptron ANN for monitoring the health condition of a 3D truss-type structure with 70 members subjected to forced excitations. A damage indicator based on the amplitude variation of natural frequencies estimated by MUSIC algorithm was used as input to train the ANN.

He and Yan [94] combined WT and SVM for damage detection of a single-layer spherical lattice dome subjected to ambient excitations. They employed the wavelet energy rate index as input of the SVM classifier for damage detection in the structure. Oh and Sohn [95] combined three algorithms, PCA, autoregressive, and autoregressive with exogenous inputs (AR-ARX) and SVM for damage detection in an eight-degree freedom mass-spring system subjected to random excitations produced by an electrodynamic shaker. The method compared the AR-ARX coefficients obtained from the undamaged and damaged dynamic systems. Jiang and Mahadevan [96] used a Bayesian wavelet probabilistic methodology for damage detection of a 3D 5-story steel frame and the scaled model of a 38-story concrete building subjected to the Kobe and synthetic earthquakes, respectively.

In a Fuzzy Logic (FL) system, inputs are assessed through membership functions in order to determine their degree of association to a specific fuzzy event set [97]. The consequent or output of the fuzzy system is obtained through a series of logical operations known as fuzzy rules [98]. A few applications of fuzzy logic classifier combined with other approaches have been reported for damage detection in simple systems in the last decade. Altunok et al. [98] combined WT with an FLC for detection and quantification of damage severity in a 3D scaled model steel bridge subjected to ambient dynamic excitations. FL uses the energy estimated by WT to assess the condition of the structure. Chandrashekhar and Ganguli [99] discussed uncertainty handling in structural damage detection using FL and probabilistic simulation in a cantilever beam model. The first six natural frequencies values were used as input of the FL. Based on results obtained for a simple beam, the authors concluded that the use of natural frequencies caused uncertainty in damage detection for symmetric structures having two different symmetric damage states. Beena and Ganguli [100] combined fuzzy cognitive maps with a Hebbian learning algorithm to detect damage in a cantilever beam. ud Darain et al. [101] used FL to identify cracks in a reinforced concrete beam subjected to testing load.

Jiang et al. [102] used a combined ANN-FL algorithm known as Adaptive Neuro-Fuzzy Inference System (ANFIS) for damage detection in a 2D seven-story shear-beam type building model. The authors concluded that the combined model is superior to ANN or FL, used individually. Graf et al. [103] used a combination of recurrent neural network and FL to model uncertain time-dependent structural behavior. Zheng et al. [104] presented a genetic fuzzy radial basis function neural network for SHM of a composite laminated beam through integration of ANN and FL with Genetic Algorithm (GA) [105-107].

9. New algorithms for feature classification

In this section, recently-developed intelligent classification techniques are reviewed with potential for structural engineering application and SHM.

9.1. Enhanced probabilistic neural network

In order to obtain the best performance for PNN, the value of the spread parameter which determines the width of the kernel should be selected. This is usually done by trial and error which does not guarantee the best performance. In order to overcome this problem and improve the accuracy and robustness of PNN, Ahmadlou and Adeli [108] developed a novel Enhanced Probabilistic Neural Network (EPNN) using local decision circles to take into account and model local information and non-homogeneity existing in the training population. They showed the superiority of the model compared with PNN using three different benchmark classification problems: iris data, diabetic data, and breast cancer data. EPNN has been used for computer-aided diagnosis of the Parkinson's disease [109]. To the best of the authors' knowledge, no structural engineering application of EPNN has been reported in the literature. The authors believe, however, that EPNN has great potentials and should be explored for SHM.

9.2. Spiking neural networks

Spiking Neural Networks (SNN) are referred to as 3rd generation ANN. Compared to conventional ANN, such as multilayer perceptron, SNN is characterized by an internal state which changes with time and each postsynaptic neuron fires an action potential or spike at the time instance its internal state exceeds the neuron threshold [110]. SNN is a more realistic representation of real neurons than traditional ANN, but its training is more complicated and intensive, computationally. Ghosh-Dastidar and Adeli [111,112] presented a new multi-spiking neural network model where the information from one neuron was transmitted to the next in the form of multiple spikes via multiple synapses. Further, they presented a new supervised learning algorithm called Multi-SpikeProp with heuristic rules for training the network. The proposed SNN was used to classify three pattern recognition problems: XOR problem, the Fisher iris classification problem, and the epilepsy and seizure detection (EEG classification) problem.

10. Final comments

This paper presented an overview of the main feature extraction and classification techniques used in SHM. It also suggested two recently-developed models for potential applications in SHM. These algorithms are worth being researched for health monitoring of large, real-life structures. Significant additional research is needed on automated feature detection for SHM technology to be realized for large real-life structures such as bridge and highrise building structures.

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