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Identification and damage detection of beam-like structure using vibration signals based on simulated model, real healthy state and deep convolutional neural network

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ABSTRACT: Condition monitoring of mechanical systems, such as structures and rotating machines is always a major challenge. This paper is presented a new method for damage detection of real mechanical systems in presence of the uncertainties such as modeling errors, measurement errors, varying loading conditions, and environmental noises based on a simulated model and real healthy state. In this method, data of a real healthy system is used to updating the parameters of the simulated model. Some parts of the signals that are not related to the nature of the system are removed using the complete ensemble empirical mode decomposition method. A deep convolutional network is designed to learn damage-sensitive features from raw frequency data of simulated model and real healthy state. Raw frequency data is extracted from vibration signals using the power spectral density method. In order to train the proposed deep network, raw frequency data of the simulated model and real healthy state are used. Then, raw frequency data of the real model are used to test the proposed deep network. The proposed method is validated using an experimental beam structure. The results show that using the proposed algorithm for identification and damage detection of the beam-like structure has more accuracy with respect to the other comparative methods.

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1- Introduction

Mechanical systems are widely used in the industrial sector and are key and important equipment. Condition monitoring of these systems is always a major challenge and can extend their lifespan. The vibrational signals extracted from mechanical systems contain useful information, and by examining the physical characteristics of these signals, damages can be detected in different parts of them. The forces applied to mechanical systems are subjected to many changes; therefore, data acquisitioning from mechanical systems under different loads is difficult and expensive. Also, in mechanical systems, the extraction of damage data is not really cost-effective, and generally only data on a healthy state is available; so, using artificial damage data based on simulated model instead of real ones is a feasible approach to addressing the problem [1].

Feature extraction plays a crucial role in the damage detection of mechanical systems. Traditional feature extraction methods are not well capable of extracting damage-sensitive features [2]. In recent years, the use of deep neural networks to extract the effective features has attracted the attention of many researchers [3]. Deep neural networks have been widely and successfully used for image and signal processing in the time and frequency domain [2, 4-5].

In this paper, a new method for damage detection of mechanical systems is presented. The first purpose of this paper is to present a method for damage detection of mechanical systems in presence of the uncertainties such as modeling errors, measurement errors, varying loading conditions and environmental noises. The second purpose of this paper is to design a deep convolutional neural network in order to learn the damage-sensitive features from raw

frequency data of the simulated model and real healthy state despite the various uncertainties. The third aim of this paper is to train the proposed deep network based on frequency data of the simulated model under simple loading condition and real healthy state, and then to evaluate the deep network with frequency data of real model under complex loading condition (for more realistic assumptions). In the proposed method, the simulated model parameters are updated based on the real model data. Some parts of the vibration signals that are not related to the nature of the system have been removed using the Complete Ensemble Empirical Mode Decomposition (CEEMD) method. Frequency data are obtained from the vibration signals using the Power Spectral Density (PSD) method. To evaluate the proposed method, a beam-like structure in a laboratory environment has been used as a case study.

2- Methodology

In this section, at first the Finite Element (FE) and experimental models of the beam structure is explained. Then, the proposed algorithm for damage detection of the beam structure is expressed.

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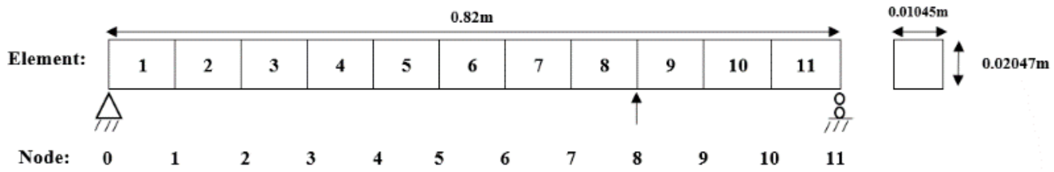

Fig. 1. The FE beam model.

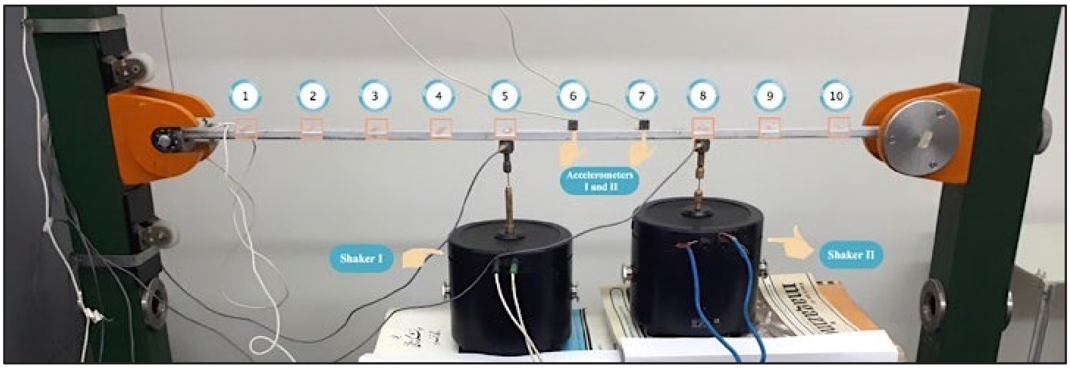

Fig. 2. The experimental setup of the beam-like structure.

2-1- FE model

Considering the small deformations and linear behavior of the system, a FE model of the simply supported Euler–Bernoulli beam structure is created. The vibration equation of the beam can be written as follows [6-8]:

$$M_b\ddot{Z}+C_b\dot{Z}+K_bZ=F(t)$$

where Z, $\dot{Z}$ and $\ddot{Z}$ are the displacement, velocity and acceleration vectors of the beam structure and M_b, K_b and C_b displays the mass, stiffness and damping matrices of the whole structure, respectively. To solve the Eq. (1), the ode45 method is used in MATLAB software. The FE beam model is shown in Fig. 1.

The FE beam model is excited only from one point at node No. 8 with random excitation which is generated with white Gaussian noise.

2-2- Experimental model

Fig. 2 shows the experimental setup of the beam structure. Two shakers I and II are connected to the structure at nodes No. 5 and No. 8 to excite the structure. The uncorrelated forces used for excitation are white Gaussian noise. Two accelerometers I and II are mounted along the beam at nodes No. 6 and No. 7 for extracting the dynamic responses of the structure.

2-3- The proposed algorithm

In this section, the main procedure of the proposed algorithm based on deep learning is listed as follows (see Fig. 3):

(a)Extracting the dynamic responses corresponding to different states of experimental and FE models.
(b) Data preprocessing.
(c)Removing some of the signal parts using the CEEMD method [9] and reconstructing the signals using the proper Intrinsic Mode Functions (IMFs).
(d) Generating raw frequency data from dynamic responses using PSD method.
(e)Dividing the data into three parts, namely training data based on FE model and experimental healthy state, validation data and testing data based on the experimental model.
(f)Designing a deep convolutional neural network in order to learn the damage-sensitive features from raw frequency data of the FE model and experimental healthy state.
(g) Investigating the performance of the proposed deep network to damage detection of experimental structure.

3- Results and Discussion

In this section, the damage detection of the beam structure under complex loading conditions with two random excitations using the proposed algorithm is checked after evaluating the accuracy of the FE model. In order to evaluate the accuracy of the FE model, the natural frequencies of the healthy structure are obtained and compared with each other using different methods [10] (see Table 1).

After ensuring that the FE model is accurate, the frequency data of the reconstructed signals of the FE model under a random excitation and the experimental healthy state is used as the training data of the proposed deep network to extracting the damage-sensitive features. Then, the frequency data of the reconstructed signals of the experimental model under two random excitations is used to evaluating the proposed deep network. The confusion matrix of the proposed algorithm is shown in Table 2. A network [11] with two hidden layers is used to compare the results of the proposed algorithm. Table 3 presents the accuracy of the proposed algorithm compared to the other methods. The results show that the proposed method is able to detect the damages of the real structure with more accuracy with respect to the other comparative methods.

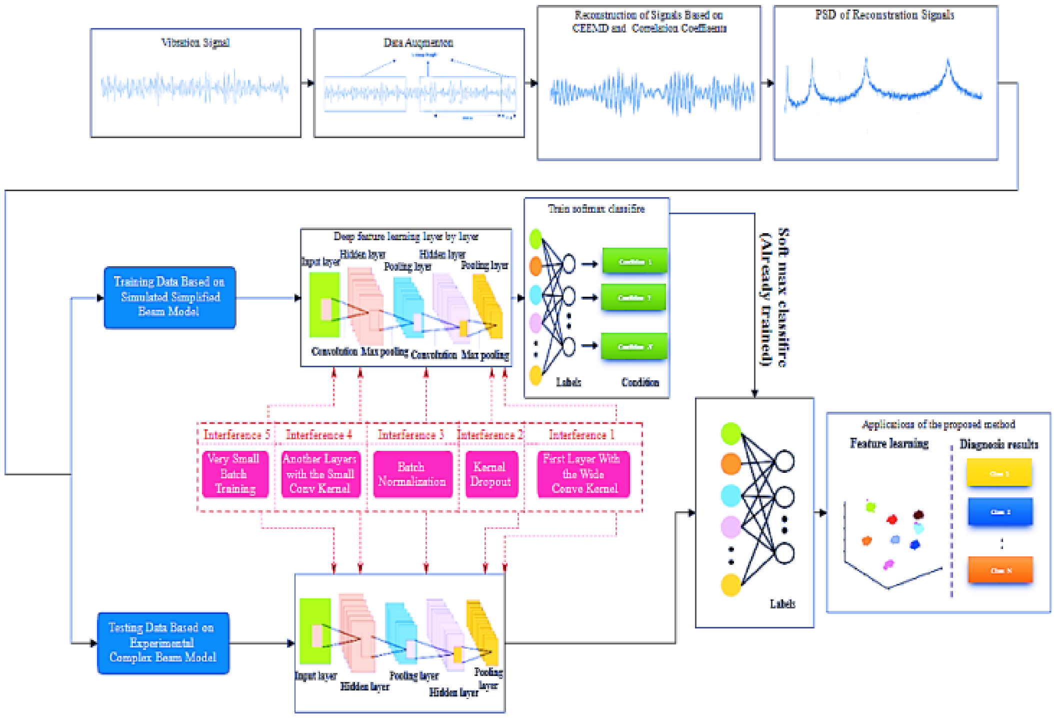

Fig. 3. The block diagram of the proposed algorithm.

Table 1. Comparison of the obtained natural frequencies for the healthy structure using different methods.

	Natural Frequency (Hz)			Error (%)		
Mode No.	Analytical Solution	Experimental Model	FE Model	Experimental Model	FE Model	FE compared with Experimental
		PSD	PSD	PSD - Analytical	PSD – Analytical	PSD-PSD
1	35.81	38	38	6.11	6.11	0.0
2	143.26	136	140	5.06	2.27	2.9
3	322.34	344	324	6.71	0.51	5.8
4	473.06	472	472	0.2	0.2	0.0
5	895.41	880	880	1.7	1.7	0.0

Table 2. Classes and lumped become non-italic.

Considered States	Classes	Class 1	Class 2	Class 3	Class 4	Class 5	Accuracy%
Healthy	Class 1	106	0	0	0	0	100
Damaged (Added lumped mass with severity 0.1 kg in element 3)	Class 2	0	106	0	0	0	100
Damaged (Added lumped mass with severity 0.2 kg in element 3)	Class 3	0	0	105	0	0	99.06
Damaged (Added lumped mass with severity 0.1 kg in element 8)	Class 4	0	0	0	106	0	100
Damaged (Added lumped mass with severity 0.2 kg in element 8)	Class 5	0	0	0	5	101	95.28

Table. 3. The accuracy of the proposed algorithm compared to the comparative methods.

Methods	Feature learning from raw data	Accuracy%
Perceptron Network	Frequency data of vibration signals	75.85 ± 2.2
Perceptron Network	Frequency data of reconstructed vibration signals	81.70 ± 2.5
Proposed Network	Frequency data of vibration signals	94.53 ± 4.1
Proposed Network	Frequency data of reconstructed vibration signals	$\mathbf{98.87 \pm 5.3}$

4- Conclusions

This paper is proposed a new method for damage detection of mechanical systems in the presence of different uncertainties based on the FE model, real healthy state, and deep neural network. The FE model parameters are updated on the basis of a real healthy state. Some parts of the signals which are not related to the nature of the system are removed using the CEEMD method. To train the proposed deep network, only the frequency data of the FE model and the real healthy state are used. After that, the frequency data of the real model are used to evaluate the proposed network. Frequency data is extracted from vibration signals using PSD method. Two major interferences affect the proposed network, namely the wide kernel in the first convolution layer and the small kernels in the remaining convolutional layers. A beam structure in the laboratory environment is used to evaluate the proposed method. The results show that the proposed network is able to detect the damages of the real structure using the FE model data and the real healthy state.

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