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Application of Hopfield neural network to structural health monitoring

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Abstract

Structural health monitoring (SHM) using artificial neural networks has received increasing attention due to robustness of neural networks, better performance compared to conventional damage detection methods, and influential pattern recognition capability. This article aims to introduce Hopfield neural network (HNN), for the first time, to the SHM community. On this basis, a novel damage identification method by the HNN is proposed to detect damage and estimate damage severity with the aid of measured mode shapes in undamaged and damaged conditions. In this method, these vibration characteristics measured from sensors are used as initial conditions in the HNN. A key benefit of the HNN is that this novel neural network is inherently able to define a threshold value in such a way that any deviation from this value is indicative of damage occurrence. The accuracy and performance of the damage detection problems by the HNN is experimentally verified by the I40 Bridge. Results show that the proposed method is potentially able to detect damage and estimate the damage severity based on the outputs of the HNN.

Keywords: Structural health monitoring; damage detection; artificial neural network; Hopfield network; modal parameters.

1. Introduction

Various adverse changes in structures associated with damage lead to reductions in integrity and safety. Such changes alter the performance of the structures as reductions of stiffness, changes in dynamic characteristics, undesirable stresses and displacements, inappropriate vibrations, failure

and collapse. Structural health monitoring (SHM) is an implementing process using signal processing techniques that are mostly used to evaluate integrity and health of the structures and detect any probable structural damage using vibration data [1]. The process of damage identification in the SHM community generally consists of model-based and response-based methods [2]. A model-based method is one that needs a finite element model, as an analytical or numerical model, to construct the inherent physical properties of the structure such as the mass, stiffness, and damping. The major drawback of these methods is that they require a model updating procedure to correct and calibrate the finite element model of the real structure and reduce uncertainties between test measurements and model predictions. In contrast, a response-based approach normally uses the measured vibration data without applying the analytical or numerical model of the structure to make a decision about damage occurrence.

Modern vibration-based SHM systems are intelligent damage detection methods that rely on soft computing techniques such as Fuzzy logical [3-5], genetic algorithm [6-8], and neural network [9-11]. These methods mainly exploit advanced signal processing and artificial intelligence as analysis tools. The artificial neural network (ANN) techniques are successful approaches to effective damage identification problems due to their salient capability in pattern recognition, influential training process, and ability of implementing complex problems of damage detection [12]. A great advantage of neural-based damage identification methods is that they are a type of the response-based techniques. So, they do not need any numerical or analytical models. In other words, ANNs mainly rely on pattern recognition rules by training a network as the nonlinear relationship between the dynamic characteristics and the damage conditions [13].

Zhang et al. [14] conduced a research on structural damage using an ANN technique. In that article, the authors used measured frequency response functions (FRFs) as input data to the ANN and applied a principal component analysis (PCA)-based data reduction technique to overcome the impracticality of using full-size FRF data with ANNs. Change et al. [15] proposed a structural damage detection method based on parameter identification using an iterative neural network technique. In their article, an neural network model was initially trained off-line using an initial training data set containing structural parameters (flexural rigidity) as outputs and their corresponding dynamic characteristics (modal frequencies and mode shape curvature) as inputs. Sohn et al. [16] applied an auto-associative neural network to remove the influence of operational and environmental variability from damage-sensitive features extracted from autoregressive eXogenous (AR-ARX) model. Lu et al. [17] presented an inverse analysis based on an ANN technique to identify crack in aluminum plates. They employed an information mapping approach to establish the damage parameter database cost-effectively and the generalization performance of the neural network was examined by a process of leave-one-out cross-validation. Park et al. [18] utilized sequential approaches for damage detection in beams applying acceleration signals and modal features such as mode shapes and modal strain energies. First, they proposed an acceleration-based neural network algorithm to detect the occurrence of damage by using cross-covariance functions of acceleration signals. Subsequently, a modal feature-based neural network algorithm was designed to estimate the location and severity of damage. Atashipour et al. [19] proposed an inverse analysis using an ANN technique based on the guided ultrasonic waves to detect damage in thick steel beams for the purpose of structural health monitoring applications. Using a feature extraction technique (damage characteristic points), the authors developed and trained a multilayer feed-forward ANN under supervision of an error-back propagation algorithm.

In the soft computing techniques, Hopfield neural network (HNN) is a form of recurrent artificial neural network in the sense of a network with feedback. By comparing the HNN with other ANNs, it can be argued that this recurrent network provides better performance in comparison with the other neural networks due to higher accuracy and faster convergence rate. In addition, the HNN is a robust neural network in the damage detection problems as a result of equilibrium nodes and dynamic network structure [20-23]. However, this artificial neural network has been paid less attention in the SHM community. Therefore, the main objective of this article is to

present the HNN for the first time in the problems of damage identification. A response-based damage detection method using the HNN is proposed to assess the current condition of the structure, called early damage detection, and estimate the level of damage severity. In this method, the measured modal displacements are used as vibration responses, which are applied as the initial condition to the HNN. The performance and capability of the proposed damage detection method using the HNN are experimentally verified by the full-scale I-40 Bridge. Results demonstrate that the HNN has an acceptable ability when used in damage detection problems based on the response-based class.

2. Theory

2.1 Hopfield neural network (HNN)

The Hopfield model is a dynamic recurrent neural network that is biologically plausible since it functions much like the human brain [24, 25]. The model is normally represented by using a J-J layered architecture as depicted in Fig. 1.

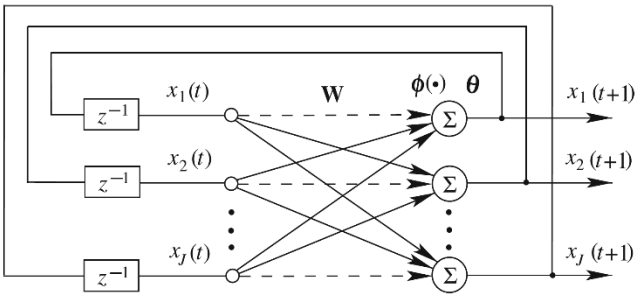

Figure 1. Architecture of the Hopfield neural network

The input layer only collects and distributes feedback neural signals from the output layer. The network has a symmetric architecture with a symmetric zero-diagonal real weight matrix; that is, $\omega_{ij} = \omega_{ji}$ and $\omega_{ji} = 0$. Each neuron in the second layer sums the weighted inputs from all the other neurons to calculate its current net activation net_i, then employs an activation function to net_i and broadcasts the result along the connections to all the other neurons. In Fig. 1, $\omega_{ji} = 0$ can be observed by a dashed line; $\boldsymbol{\phi}(.)$ and $\boldsymbol{\theta}$ are a vector comprising the activation functions for all the neurons and a vector comprising the biases for all the neurons, respectively. The HNN operates in an unsupervised manner, which means that it trains a network only by training data set. The dynamics of the network are described by a system of nonlinear ordinary differential equations. The discrete form of the dynamic is defined by:

$$net_i(t+1) = \sum_{j=1}^{J} \omega_{ji} x_j(t) + \theta_i \tag{1}$$

$$x_i(t+1) = \varphi\left(net_i(t+1)\right) \tag{2}$$

where net_i is the weighted net input of the ith neuron, $x_i(t)$ is the output of the ith neuron, θ_i is a bias to the neuron, and $\varphi(.)$ is the sigmoidal function. The discrete time variable t in Eqs (1) and (2) takes values 0,1,2,…. For the continuous form of the dynamics, the Hopfield model is given by:

$$\frac{\mathrm{d}\, net_i(t+1)}{\mathrm{d}t} = \sum_{j=1}^{J} \omega_{ji} x_j(t) + \theta_i \tag{3}$$

where t denotes the continuous-time variable. In order to specify the performance of the network, the concept of energy is used as the following form:

$$E = -\frac{1}{2}\sum_{i=1}^{J}\sum_{j=1}^{J}\omega_{ji}x_i x_j - \sum_{i=1}^{J}\theta_i x_i = -\frac{1}{2}\boldsymbol{x}^T\mathbf{W}\boldsymbol{x} - \boldsymbol{x}^T\boldsymbol{\theta}. \tag{4}$$

In this equation, $\boldsymbol{x} = (x_1, x_2, \ldots, x_J)^T$ is the input and state vector, and $\boldsymbol{\theta} = (\theta_1, \theta_2, \ldots, \theta_J)^T$ is the bias vector. The theory of stability (Lyapunov's theorem) of the neural network proves that the continuous-time Hopfield network always converges to a local minimum; therefore, it is stable.

2.2 Outline of structural of health monitoring by HNN

To implement the process of structural health monitoring by the HNN, it is necessary to establish a damage detection algorithm containing the vibration features, neural network, and a damage indicator for detecting damage. Unlike most of the artificial neural networks, the input layer of the HNN only collects and distributes feedback signals from the output layer. Therefore, the vibration features, including the modal parameters, used in the HNN are applied as initial conditions. The initial conditions are applied as a column vector by transforming the matrix of measured mode shapes in each pattern to a column vector by a vectorization procedure. In linear algebra and matrix theory, the vectorization of a matrix is a linear transformation that converts a matrix into a column vector. For example, the vectorization of the *n*-by-*m* mode shape matrix, where *n* and *m* denotes the number of sensors and measured modes, is a column vector with *nm* elements obtained by stacking the columns of the mode shape matrix on top of one another. To train a network by the HNN, one needs to combine the column vector of the mode shapes in each damage pattern with the column vector of the measured mode shapes in the healthy state. Therefore, the initial condition induced to the HNN is a column vector with *2nm* elements, where the first *nm* elements represent the mode shape vector of the healthy conditions and the second *nm* elements pertain to the damaged conditions. For the damage detection process, the outputs of HNN and its convergence rate provide reliable criteria to detect damage and estimate its severity.

3. Experimental procedure

In order to demonstrate the capability and performance of the proposed damage identification based on the HNN, the experimental data of the full-scale I-40 Bridge is applied. The bridge was located along Interstate Highway 40 across the Rio Grande River in Albuquerque, New Mexico as shown in Fig. 2(a). The bridge was constructed of a concrete deck approximately 13.3 m wide and 17.8 cm thick, supported by two steel plate girders, each 3.05 m high, and three steel stringers as depicted in Fig. 2(b). A series of modal tests was performed on this bridge after it had been closed to traffic prior to demolition in 1993. The section of the bridge that was instrumented for this series of modal tests consisted of three spans with a combined length of about 130 m. The instrumentation consisted of 13 accelerometers mounted to each of the two plate girders along the length of the three spans, for a total of 26 response measurements.

The damage scenario in the bridge was intended to simulate fatigue cracking that can be observed in most plate-girder bridges. Four levels of damage were introduced by making various torch cuts in the web and flange of the girder, as shown in Fig. 3(a). The first level of damage, designated E-1, consisted of a 61-cm-long, 10-mm-wide cut through the web centred at mid-height of the web. This cut was continued to the bottom of the web to produce a second level of damage designated E-2. For the third level of damage, E-3, the flange was then cut halfway in from either side directly below the cut in the web. Finally, the flange was cut completely through for damage case E-4 leaving the top 1.22 m of the web and the top flange to carry the load at this location. Figs. 3(a) and 3(b) illustrate the damage patterns and sensor layouts in the I-40 Bridge.

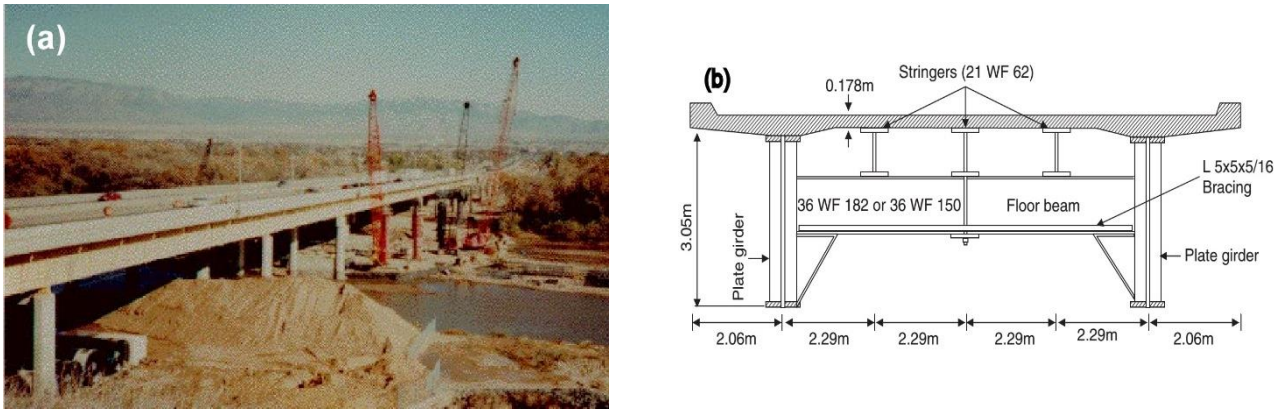

Figure 2. The I40 Bridge: (a) the actual photo, (b) the geometrical cross-section

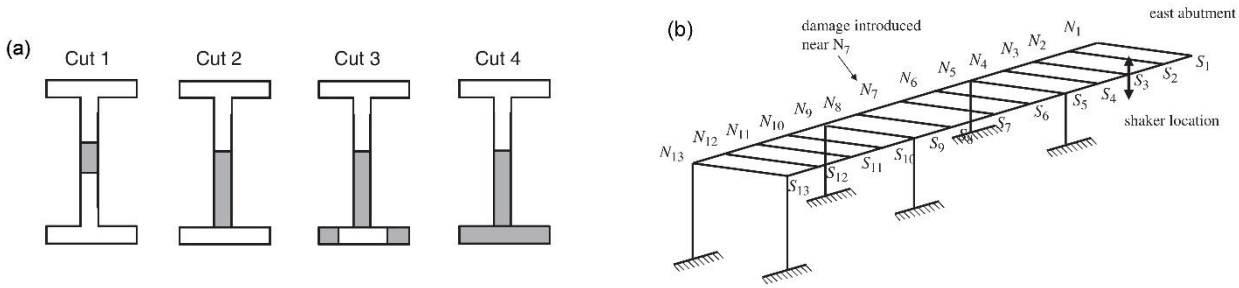

Figure 3. Damage in the I-40 Bridge: (a) the damage patterns, (b) the damage location and sensor networks (N: North and S: South)

The measured mode shapes of the I-40 Bridge are used as the initial conditions in the HNN for each damage pattern. Based on the four damage scenarios in the I-40 Bridge, four HNNs are trained by using the column vectors of the measured mode shapes in each pattern. Before applying the mode shapes to the HNN, it is necessary to normalize the vector of mode shapes to vary between -1 and 1. Fig. 4 indicates the comparison of the measured first mode shapes of the healthy and damaged conditions (cases 2 and 4).

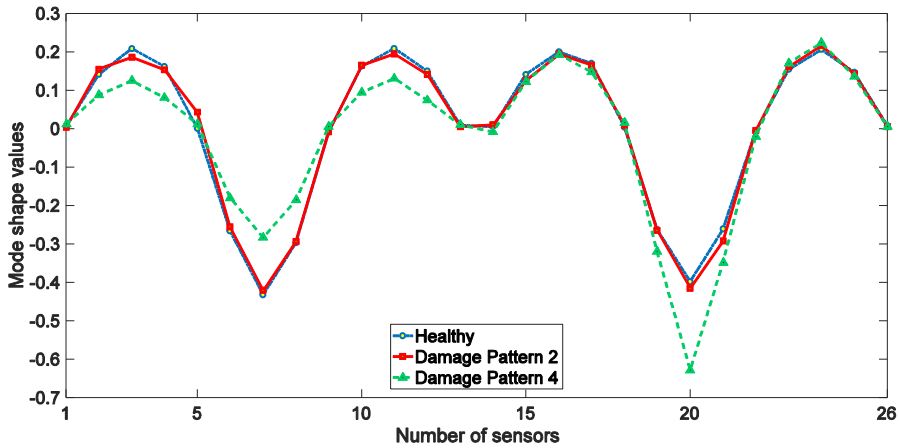

Figure 4. The measured first mode shapes in the healthy and damage patterns (cases 2 and 4)

It is obvious in Fig. 4 that there are deviations of the measured mode shapes in the damaged conditions from the undamaged one, particularly in the damage pattern #4. However, the comparison of the mode shapes between the healthy and damaged case #2 demonstrates small and unclear differences. This result confirms the necessity of using robust methods for the problems of damage identification even for the simplest problem (early damage detection).

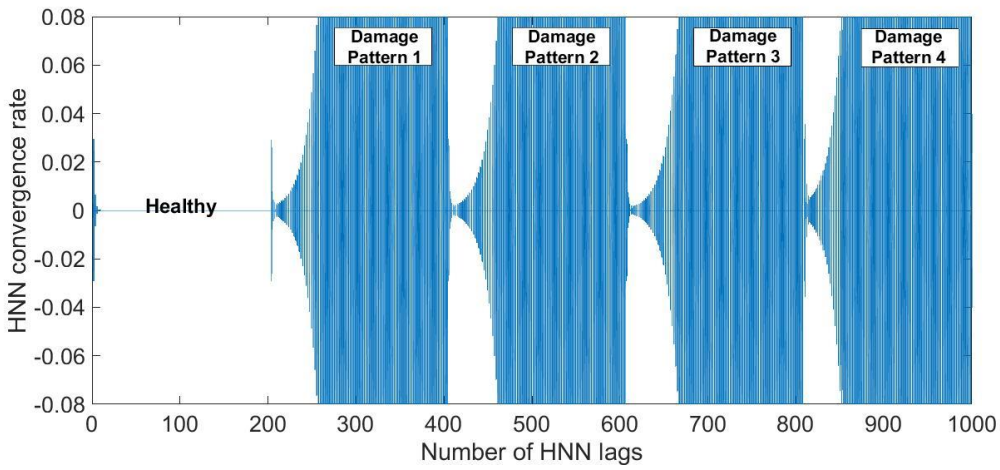

Figure 5. The HNN convergence rate

Fig. 5 indicates the results of HNN convergence rate in the healthy and damaged conditions obtained from the HNN. However, this figure demonstrates how the initial conditions (mode shape vectors) applied to the HNNs converge that it is possible to use this result of HNN for detecting damage. In this figure, there are distinctive differences between the healthy and damaged conditions, which indicate that the HNN convergence rate can detect discrepancies between two states of the structure including the undamaged and damaged conditions. Nevertheless, the HNN convergence rate fails to estimate the level of damage severity.

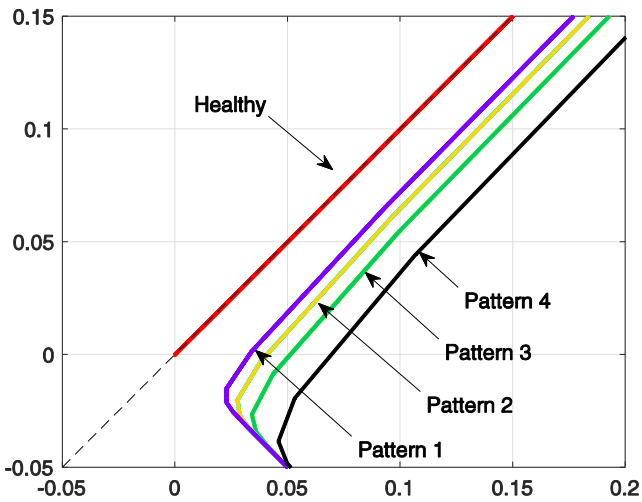

Figure 6. The HNN plot

Fig. 6 illustrates the results of early damage detection in the I-40 Bridge using the individual plot of the HNN in all damage patterns. In this figure, the dashed line shows the threshold level inherently gained by the HHN. In the plot of HNN, the lines under the threshold level are indicative of damage occurrence and the distance of each line from the threshold line represents the level of damage severity in the structure. As can be observed in Fig. 6, the healthy state of the bridge coincides with the threshold level, whereas all of the damage patterns are under the threshold line. Furthermore, the highest level of damage (the pattern #4) has the farthest distance compared with the other damaged conditions. All of the obtained results lead to the conclusion that the proposed damage identification algorithm using the HNN can effectively detect the damage and qualitatively estimate the damage severity.

4. Conclusion

The main objective of this article was to propose a novel damage identification method using Hopfield neural network (HNN) presented for the first time in the SHM applications. The major contribution of this method was to detect early damage and estimate the level of damage severity. The proposed method is based on applying the initial conditions to the HNN and extracting network outputs as the damage indicators. The initial conditions are vibration features as a column vector including the features of undamaged and damaged conditions. In this study, the measured mode shapes were utilized as the vibration features. To verify the proposed method, the measured mode shapes of the full-scale I-40 Bridge were used. The results demonstrated that the convergence rate of the HNN can be an appropriate criterion to distinguish the healthy state from the damaged one. Furthermore, it was seen that the outputs of HNN (its plot) can effectively detect damage so that the healthy state coincides with the threshold level and the damaged conditions are under the threshold line. The results also confirmed that the proposed method is able to estimate the level of damage severity.

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