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ANALYSES ON STRUCTURAL DAMAGE IDENTIFICATION BASED ON COMBINED PARAMETERS *

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Abstract: *The relative sensitivities of structural dynamical parameters were analyzed using a directive derivation method. The neural network is able to approximate arbitrary non-linear mapping relationship, so it is a powerful damage identification tool for unknown systems. A neural network-based approach was presented for the structural damage detection. The combined parameters were presented as the input vector of the neural network, which computed with the change rates of the several former natural frequencies (C), the change ratios of the frequencies (R), and the assurance criterions of flexibilities (A). Some numerical simulation examples, such as, cantilever and truss with different damage extends and different damage locations were analyzed. The results indicate that the combined parameters are more suitable for the input patterns of neural networks than the other parameters alone.*

Key words: damage detection; neural network; combined parameter; flexibility

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Introduction

Service loads, environmental and accidental actions may cause damage to structures. When the structural damage is small or it is in the interior of the structure, its detection cannot be done visually. Inspection of existing buildings and bridges after catastrophic events, such as earthquakes and hurricanes, as well as under normal operating conditions, is often time consuming and costly because critical members and connections are concealed under cladding and

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other architectural decorations. For many important structures, such as hospitals, fire stations, military control/surveillance centres, major bridges, power stations, and water treatment plants *etc*., it is imperative to assess their healthy state immediately after a major catastrophic event, which has great significance to human lives and properties.

The problem of damage identification is essentially one of pattern recognition. One of the more powerful approaches, currently applied in this area is based on the application of NNs. NNs have been viewed as potential saviors for the solution of the difficult problems in damage identification[1]. NNs are able to treat implicit damage mechanisms, so that it is not necessary to model the structure in detail. The method can also deal with non-linear damage mechanisms easily.

In recent years, research on vibration and NNs based damage identification has been expanding rapidly[1~3]. NNs were developed as a methodology for emulating the human brain, resulting in such systems that can learn by experience. Many researchers have developed various NN models for different purposes[4,5]. In this paper, a multiplayer backpropagation NN (BP-NN)[6] is used for structural damage identification.

A simple NN is formed from interconnected artificial neurons. It consists of an input layer, a hidden, and an output layer as shown in Fig. 1. The network is a feed-forward multiplayer network that has n input nodes, p hidden nodes and m output nodes (n-p-m).

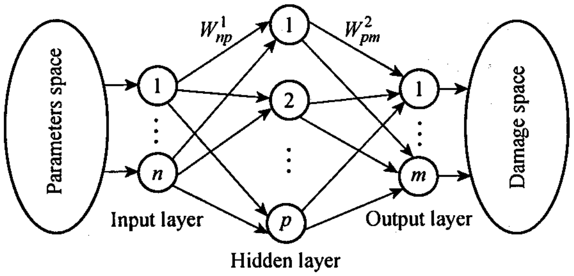


Fig. 1 Architecture of backpropagation NN

Through learning the patterns of input and output, mapping a relationship of the NN's input and output which can be nonlinear as well as linear, and its characteristic information is determined by the weights w^1_{np} and w^1_{pm} assigned to the connections between nodes in two adjacent layers. The basic strategy for developing an NN-based approach to identify the damage of a structure is to train the NNs to map the relationships between structural damages (outputs) and the input patterns.

In this paper, combined parameters that consist of the change rates of the several former natural frequencies, the change ratios of the frequencies and the assurance criterions of the flexibilities are presented as the input parameters of NNs in structural damage identification. Two numerical example analyses on a cantilever and a planar truss are presented to demonstrate the effectiveness of the proposed method. Simulation results indicate that the combined parameters with modal flexibility are more sensitive than natural frequencies or mode shapes alone for damage detection, and the results also illustrate a great promise of using the combined parameters as input patterns of the NNs for detecting damages, and localizing the damage.

1 Inputs to Neural Network

For the method of damage detection based on the NNs, the question what input patterns are more suitable for the NN, there is still not a good answer[7]. In the process of structural damage identification, the input patterns must be chosen first of all in order to characterize the changes of structural states. As the damage identification index, choosing proper parameters may increase the accuracy and reliability of identification, so it is the most important problem for damage identification. Several researchers have used the various input patterns suitable for their purpose. Such as, Wu X, *et al*.[2] used the frequency spectrum, simulation results showed that was not effective. Yun Chungbang, *et al*.[5] used the natural frequencies and modes. Fox[8] showed that mode shape changes were relatively insensitive to damage in a beam with a saw cut. Using the natural frequencies or mode shapes alone for damage detection, may reduce the efficiency and accuracy of the damage identification.

Recently, some researchers have found experimentally that the modal flexibility is a more sensitive parameter than natural frequencies or mode shapes alone for structural monitoring and damage detection in bridges[9~11], because the modal flexibility involves functions of both the natural frequencies and more shapes. In this paper, the combined parameters are presented as input patterns of NNs in structural damage identification, which are computed with change rates of the several former natural frequencies (CRF), change ratios of the frequencies (RAF) and the assurance criterions of the flexibilities (ACF).

Definitions of the CRF and RAF are as follows:

$$C(i) = \Delta\omega_i/\omega_i, \tag{1}$$

$$R(i,j) = \Delta\omega_i/\Delta\omega_j, \tag{2}$$

where $\Delta\omega_i$, ω_i means the change of the ith mode natural frequency and the ith mode natural frequency, respectively.

For a structural system with n degrees of freedom, the natural frequencies are $\omega_1, \omega_2, \cdots, \omega_n$, and mode shapes are $\boldsymbol{\phi} = [\phi_1, \phi_2, \cdots, \phi_n]$, which are normalized by mass matrix. The modal flexibility matrix is defined as

$$\boldsymbol{F} = \boldsymbol{\phi}^{\mathrm{T}}\boldsymbol{\lambda}\boldsymbol{\phi} = [f_1, f_2, \cdots, f_n], \tag{3}$$

where $\boldsymbol{\phi}^{\mathrm{T}}$ is the transpose of $\boldsymbol{\phi}$, and $\boldsymbol{\lambda} = \begin{bmatrix} 1/\omega_1^2 & 0 & \cdots & 0 \\ 0 & 1/\omega_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & \cdots & 0 & 1/\omega_n^2 \end{bmatrix}$.

Definition of the ACF is given by

$$A(i,j) = \frac{[(f_i^A)^{\mathrm{T}} f_j^B]^2}{(f_i^A)^{\mathrm{T}} f_j^A (f_i^B)^{\mathrm{T}} f_j^B}, \tag{4}$$

where f_i^A, f_j^B means ith modal flexibility vector before and after the damage occurs, respectively.

The input vector of the combined parameters is defined as

$$\boldsymbol{I}_{\mathrm{in}} = \{C(i), R(i,i), A(i,i)\} \qquad (i = 1, \cdots, m), \tag{5}$$

where m is the number of modes to be included in the identification.

2 Numerical Examples

The structures considered here to illustrate the effectiveness of the proposed approach are modelled as a planar truss and a cantilever. Structural damage is simulated by the reduction in Young's modulus.

2.1 Cantilever structure

An example of cantilever, which contains 10 elements, 11 nodes and 20 nodal DOFs, is shown in Fig. 2. it is assumed that the baseline parameters are known. Values for the material and geometric properties are listed in Table 1.

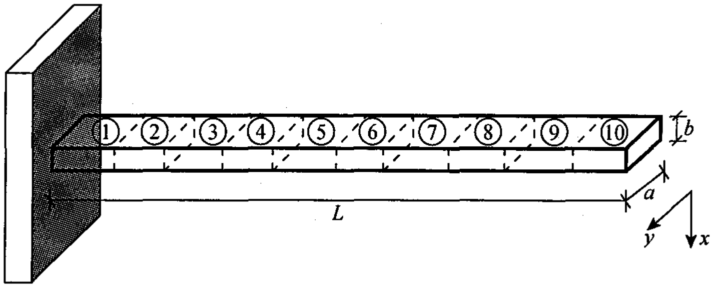


Fig. 2 Cantilever structure model

Table 1 Material and geometric properties of the cantilever

Modulus E /(kN/m^2)	Density ρ /(t/m^3)	Moment of inertia I /(m^4)	Width a /(m)	Height b /(m)	Length L /(m)
2.0E7	2.5	1.35E-7	6.0E-2	3.0E-2	1.9

The mode shapes are assumed to be measured only in the x-direction, and only the first 6-orders of the natural frequencies are available from the test DOFs. The first six CRFs (see Eq. (1)) are used as input patterns to the NNs, so the dimension of the input vector will be six. The output patterns are defined as

$$\boldsymbol{O}_{\text{out}} = \{o_1, o_2, \cdots, o_i, \cdots, o_m\}, \tag{6}$$

where o_i means the damage extent and location of the ith element, m denotes all numbers of the elements.

Using the NN(6-10-30-10), which consists of one input layer (6 nodes), two hidden layers (10 nodes, 30 nodes), and one output layer (10 nodes), the training of the NN was accomplished by using Levenberg-Marquardt (L-M) algorithm[12]. The training and testing data sets are prepared for the case with 1%, 10%, 40% and 60% reduction of the modulus (element 1 to element 10), respectively. Examples (due to 3%, 15%, 30% and 55% reduction in element 1, 3% and 25% reduction in element 6) of the tested output are shown in the Fig. 3(a) to Fig. 3(d), and Fig. 4(a) to Fig. 4(b).

Figures 3(a) ~ (d) show that the estimation errors for the simulation data (element 1) are 0.5% ~ 7% for the case of single damage. It also can be seen that with the damage increasing, the identification errors increasing correspondingly, even fault identification occurs, such as element 4 damaged 6% (see Fig. 3(c)), and element 10 damaged 18% (see Fig. 3(d)).

Figures.4(a) ~ 4(b) show that estimation errors are 0.7% ~ 4% (for element 6). But, it also has fault identification, such as element 10 damaged 5% (see Fig.4(b)).

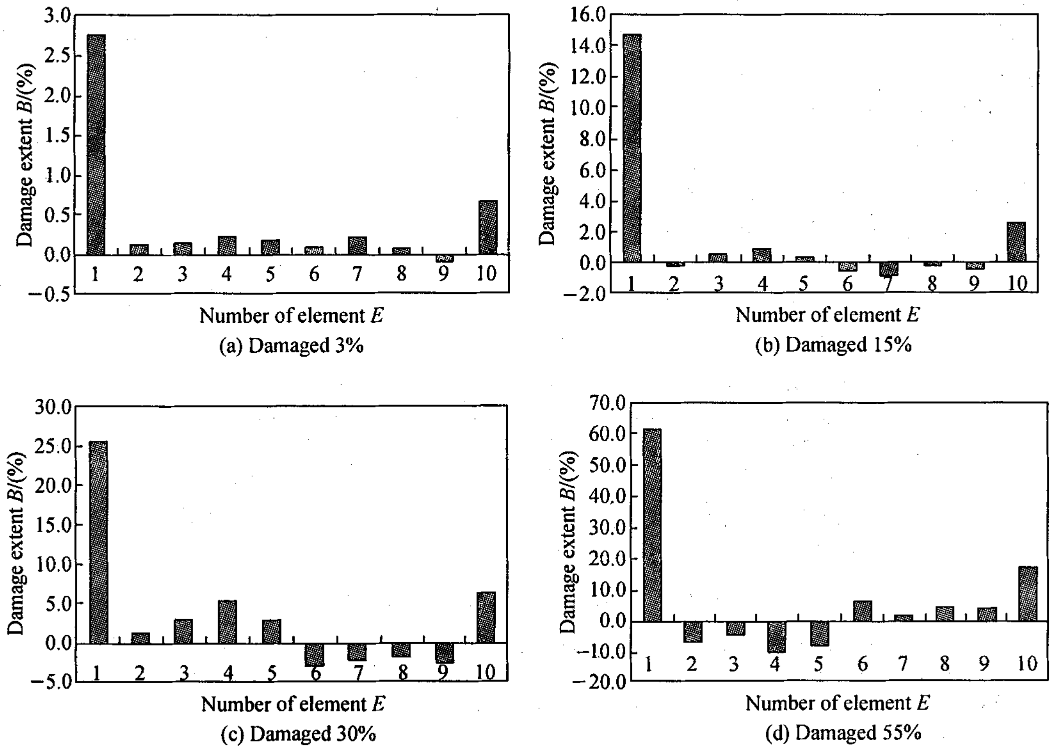


Fig.3 Example of NN outputs (single damage of element 1)

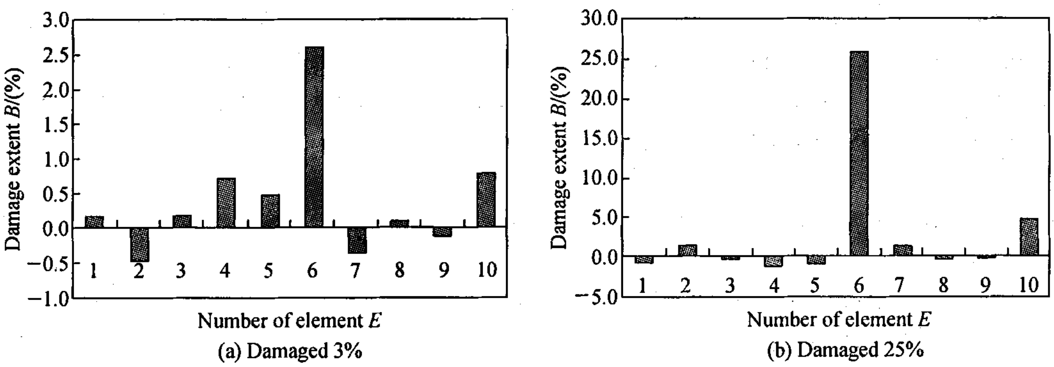


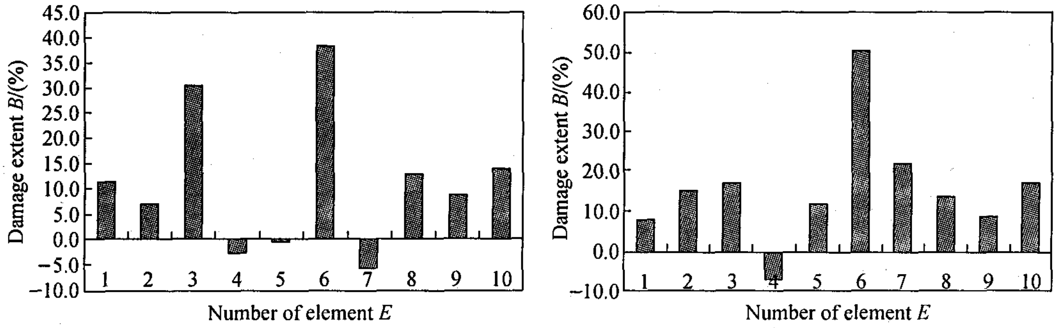
Fig.4 Example of NN outputs (single damage of element 6)

For the multi-damage problem, examples (elements 3,6 damaged 20%,35% respectively, and elements 1,6 damaged 15%, 40% respectively) of the tested output are shown in Fig.5(a) and Fig.5(b).

Figure 5 shows that the estimation errors increase distinctly. The maximum error for Fig.5 (b) is 15%. Which have more fault identifications for multi-damage case than single damage case.

The examples of the cantilever indicate that the NNs approach which employs the partial

CRFs data to identify damage is efficient for single damage. But, it also can be seen that with the damage increasing, the identification errors increasing correspondingly. For multi-damage case, more fault identifications occurred, even though for small damage case.



(a) Elements 3,6 damaged 20%,35%, respectively (b) Elements1,6 damaged15%,40%, respectively

Fig.5 Example of NN outputs (multi-damage)

2.2 Truss structure

To overcome the disadvantages of above input vector by using CRFs, an example of truss is presented in this section, which indicates that the combined parameters proposed in this paper will be more suitable for the input patterns of NNs than the other parameters alone.

The second example is a truss as shown in Fig.6, which contains 13 elements, 8 nodes and 13 nodal DOFs. The main parameters are listed in Table 2.

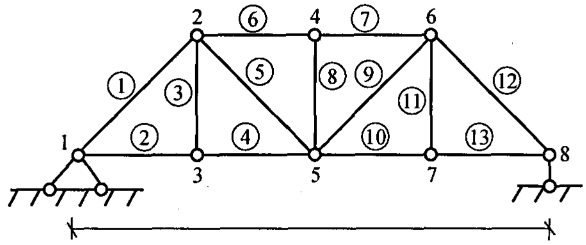


Fig.6 Truss structure model

Table 2 Material and geometric properties of the truss

Modulus E /(kN/m^2)	Density p /(t/m^3)	Sectional area A /(m^2)	Class ① Length l_1 /(m)	Class ② Length l_2 /(m)
2.0E7	2.5	4.0E-3	4.24	3

Using the NN (12-25-13), which consists of one input layer (12 nodes), one hidden layer (25 nodes), and one output layer (13 nodes). The training and testing data sets are prepared for the case with 2%, 10%, 25%, 40% and 60% reduction of the modulus. The first four order parameters (see Equation 5) are used as input patterns to the NNs, example (single damage case, due to 5%, 15% and 30% reduction in element 3, element 7, and element 10, respectively) of the tested outputs is shown in the Fig.7, and another example (multi-damage case, due to 10% and 20% reduction in element 5 and element 11, respectively) of the tested outputs is shown in

Fig.8.

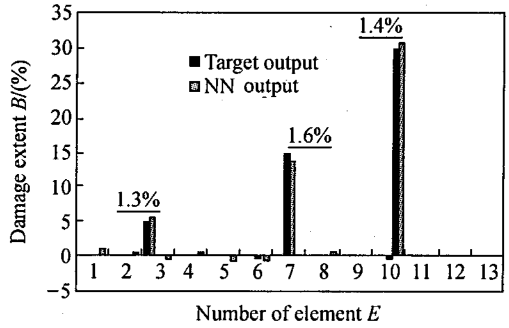


Fig.7 Example of NN outputs using the combined parameters (single damage) (Elements 3, 7, 10 damaged 5%, 15%, and 30%, respectively)

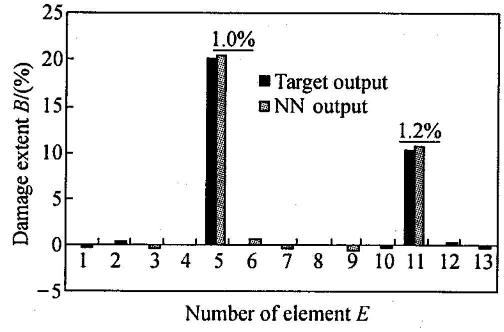


Fig.8 Example of NN outputs using the combined parameters (multi-damage) (Elements 5,11 damaged 20%,10%, respectively)

Figures 7 and 8 show that the NNs approach, which employs the combined parameters (Eq. (5)) data as input patterns to identify damage (location, extent), is more efficient for single- and multi-damage than the other parameters alone (see the cantilever example); with the damage increasing, the identification errors keeping almost no changes correspondingly. The maximum error for Fig.7 (single damage case) is only 1.6%, and for Fig.8 (multi-damage) is only 1.2%.

3 Summary

For the problem of structural damage identification based on the NNs, the combined parameters are presented as the input patterns of the NNs in this paper, which consist of change rates of the several former natural frequencies, the change ratios of the frequencies and the assurance criterions of the flexibilities. Some numerical simulation examples, such as, cantilever and truss with different damage extents and locations are analysed, which indicate that the combined damage parameters will be more suitable for the input patterns of NNs than the other parameters alone, not only for the case of single damage, but also for the multi-damage. Especially, for the case of multi-damage, the data simulation proved the proposed method more effectiveness.

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