

Multi-Stage Approach for Damage Identification of Bridge Structure Based on RBF Neural Network

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Abstract: A multi-stage approach based on radial basis function (*RBF*) neural network for damage identification of bridges structures is proposed. In this approach, the identification of structural damage is divided into three steps. Firstly, anomalous damage filter is established by the *RBF* neural network to provide alert of the damage. And then, the damage is located by inputting a composite indicator combining the natural frequency and vertical modal displacement into the neural network. Finally, the damage severity is estimated by input changing ratio of squared frequencies (*RNF*) into the neural network. According to different purpose of identification, appropriate damage parameters are selected respectively as the input of the neural network, and the effects of different noise levels on the identification results are discussed. A simulation of a three-span reinforced concrete continuous girder bridge shows that within a certain range of measurement noise, the proposed approach exhibits a good performance. Copyright © 2013 IFSA.

Keywords: Neural network, Damage identification, Damage index, Measurement noise, Multi-stage approach.

1. Introduction

Damage identification is one of hot research issues in bridge engineering. Recently, a variety of bridge structural failures have shown that the bridge structural due to long-term accumulative damage is very dangerous and may induce serious disaster. Therefore, to monitor the health status of bridges in real time, identify the damage of bridge structures and quantify the damage severities is of critical importance [1-3].

Vibration-based method is one of the main methods of damage identification [4-7]. Bridge structural damage will cause the change of dynamic characteristics accordingly. The structural damage identification can be achieved by establishing the relation between structure dynamic characteristics

and the structural damage. Early in 1969, Lifshitz and Rotem presented a structural damage identification approach on the basis of the change of structural frequency [8]. In recent years, there are a large number of studies focusing on damage identification by various approaches as reviewed by Salawu [9].

With the development of computational intelligence, artificial neural network became one of the most promising methods in the area of damage identification and location [10-13]. Venkatasubramanian and Chan conducted the structural damage identification by *BP* neural network [14], and the results showed that the accuracy rate of damage identification using *BP* neural network could reach 94 % ~ 98 %. However, the drawback of *BP* neural network is that the training time is too long and the training data is not in

real time. Lu [15] selected different input parameters of the neural network respectively, and studied the identification results of each parameter. Zhou [16] conducted the damage identification of Tsing Ma Bridge in Hong Kong using the neural network and an optimization algorithm.

However, most of the structural damage identification methods mentioned above are categorized as one-step direct method. For simple structure, these methods could identify the damage location and extent at the same time. However, for complex structures, too much structural degree of freedom will result in a large number of elements in the finite element model and hence a high dimension network in neural network model. It then requires significant computational time and computer memory to train the neural network model. Therefore, for complex structures, multi-stage identification approach is more feasible and effective.

To overcome these shortcomings, many successful applications of multi-stage identification approach based on neural network have been reported [17-21]. J. M. Ko et al., proposed a multi-stage identification scheme for detecting damage in cable-stayed Bridge. This strategy is divided into three stages: detection of damage occurrence, damage location and damage extent. However, the estimation of damage severity is not conducted in this paper [22]. V. Srinivas and K. Ramanjaneyulu developed the multi-step approach method of damage identification in 2010 by using modal strain energy and evolutionary optimization techniques. The example

of a simply supported beam model proved that the method is efficient in the exact identification and quantification of damage in structures [23]. In this paper, a multi-stage approach for damage identification based on *RBF* neural network is presented in terms of numerical simulation. According to different identifying purpose of each stage, appropriate damage indexes are selected as the input of neural network in order to realize the detection, localization and assessment of structural damage.

2. Methodology

The multi-stage approach of structural damage identification proposed in this paper is comprised of three steps: damage detection, damage localization and damage assessment. Firstly, the frequency is adopted as the input of network to identify whether the structural damage occurs. Then, the training and testing samples of neural network are formed by the index of damage location to identify the damage elements. Finally, according to the suspected damage elements identified in the previous step, the training and testing samples of neural network are established by the index of damage assessment to determine the damage severity of these elements.

The whole procedure of the proposed strategy for structural damage identification is shown in Fig. 1.

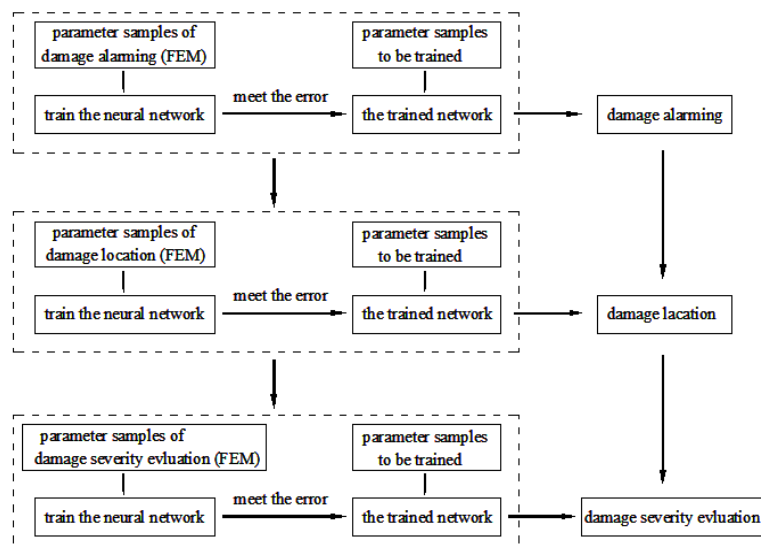


Fig. 1. The process of multi-stage identification based on neural network.

2.1. The Structure of the Neural Network

RBF neural network is a three-layered forward network composed of input layer, hidden layer and output layer. The input layer composed of perception

units is used to connect the network with the external environment; the function of hidden layer is to transform the input data in order to realize the classification or regression of the data; the output layer is to provide a response to the activation pattern of the input, as shown in Fig. 2.

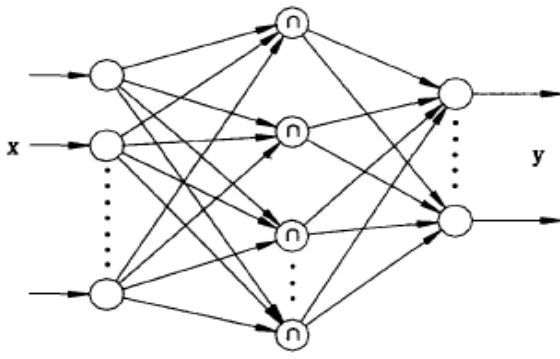


Fig. 2. The structure of the neural network.

The mapping relationship of *RBF* neural network consists of two parts. The first part is the space conversion of input data by radial basis function. The j^{th} hidden output is:

$$h_j(x) = \phi(\|x - c_j\|, \sigma_j) = e^{-\frac{\|x - c_j\|^2}{2\sigma_j^2}}, \quad (1)$$

where $\phi(*)$ denotes the radial basis function of hidden unit; $\|*\|$ denotes the norm, usually is the second norm; x is the n -dimensional input vector $x = [x_1, x_2, x_3, \dots, x_n]^T$; c_j is the central vector of j^{th} nonlinear transformation unit; σ_j is the width of j^{th} nonlinear transformation unit.

The second part is the weighted summation of the transformed data of hidden layer, the output is:

$$f(x) = \sum_{j=1}^n h_j(x) \omega_j, \quad (2)$$

where ω_j is the weight of the j^{th} hidden unit and the output, n is the number of hidden units.

The objective function (error of quadratic sum) is defined as:

$$E(t) = \sum_p \|y_p - y_p(t)\|^2 = \sum_p \sum_k (y_{kp} - y_{kp}(t))^2 = \sum_p \varepsilon_p^2(t), \quad (3)$$

where $y_p(t)$ is the actual output of p^{th} input sample after t times weight adjustment, ε is the predetermined target error.

E is an important index of the identification results of the *RBF* neural network, and the learning aim of the network is to make $E \leq \varepsilon$.

At the stage of damage detection, the output vector of neural network is abnormal index. If the abnormal index is separated obviously from that of health structure, the structure is identified to be damaged. At the stage of damage location, the value of each output vector represents the damage probability of corresponding element. The aim output

is set to be one when the neural network is trained, and the element whose corresponding output is greater than 0.7 will be determined as damaged. At the stage of damage assessment, the value of output vector represents the damage severity of corresponding element, whose range is $[0, 1]$.

2.2. Procedure of Damage Identification

2.2.1. Damage Detection

The modal characteristics of a health structure are first extracted to calculate the health index. Then the modal characteristics of the tested structure are extracted to identify the corresponding damage index. When the index of a health structure and the tested structure is different, the neural network will give the warning signal.

In the training stage of neural network, the input of the network is $X = \{x_1, x_2, \dots, x_n\}^T$, and the output of the network is $Y = \{y_1, y_2, \dots, y_n\}^T$. For the convenience of calculation and observation, the output Y is transformed to a value including input information of X expressed as:

$$y_i = c(x_i - m_i) + m_i \quad (i=1, 2, \dots, n), \quad (4)$$

where c denotes the constant greater than zero and m_i denotes the average of the i^{th} element in training sample set.

After the training of neural network is completed, X is imported into the trained network to yield the output value Y^* of the network model. The abnormal index in the training stage λ_1 can be expressed by the Euclidean distance function as:

$$\lambda_1 = \|Y^* - Y\| \quad (5)$$

In the testing stage of neural network, X_t (the modal parameters to be tested) is input into the trained neural network to yield the output Y_t^* of the network. The abnormal index in the testing stage λ_2 can then be represented as:

$$\lambda_2 = \|Y_t^* - Y_t\| \quad (6)$$

The input of network in testing stage is $X_t = \{x_{1t}, x_{2t}, \dots, x_{nt}\}^T$, and the expected output of the network is $Y_t = \{y_{1t}, y_{2t}, \dots, y_{nt}\}^T$, where the i^{th} element is:

$$y_{it} = c(x_{it} - m_i) + m_i \quad (i=1, 2, \dots, n) \quad (7)$$

The index λ_1 (the abnormal index in training stage) is then compared with λ_2 (the abnormal index in testing stage). If λ_2 deviates from λ_1 significantly, the structure can be regarded as damaged; otherwise the structure is regarded as undamaged.

2.1.2. Damage Localization

In this paper, a composite indicator X_1 is established by combining the natural frequency and vertical component of the first-order mode of a small number of test points, which is expressed as:

$$X_1 = \{NFRN_1, NFRN_2, \dots, NFRN_m, DS_1(1), DS_1(2), \dots, DS_1(n)\}, \quad (8)$$

where $NFRN_m$ denotes the normalized frequency changing ratio of the m^{th} mode, which can be expressed as:

$$NFRN_i = \frac{FFC_i}{\sum_{j=1}^m FFC_j} \quad (i=1,2,3,\dots,m), \quad (9)$$

where m denotes the first m -order frequencies used in damage identification; FFC_i denotes the natural frequency changing ratio which is represented as

$$FFC_i = \frac{\omega_{ui} - \omega_{di}}{\omega_{ui}} \quad (i=1,2,3,\dots,m), \quad (10)$$

where ω_{ui} denotes the i^{th} order natural frequencies of the health structure, ω_{di} denotes the i^{th} order natural frequencies of the damaged structure [24].

$DS_1(n)$ denotes the DS value of n^{th} test point calculated by the data of first mode [25].

$$DS_i = \frac{\{\Delta\phi_i\}}{\Delta\omega_i^2}, \quad (11)$$

where ϕ_i denotes the i^{th} order normalized vibration mode, $\Delta\omega_i^2 = \omega_s^2 - \omega_i^2$ is square difference between any two frequencies.

The damage location index X_1 is calculated through Eq. (9~11), and the training samples of the neural network are formed. Then the neural network is trained and tested by feeding the testing samples into the neural network to detect its error of identification. When the error meets a specified criterion, the neural network can be applied.

2.1.3. Damage Assessment

At the stage of damage assessment, the damage index RNF (changing ratio of squared frequencies) is adopted as the input samples of neural network training. RNF_i is a function of the damage severity:

$$RNF_i = \frac{\omega_{ui}^2 - \omega_{di}^2}{\omega_{ui}^2} = \frac{\Delta\omega_i^2}{\omega_i^2} \approx \frac{\{\phi_i\}^T [\Delta K] \{\phi_i\}}{\{\phi_i\}^T [K] \{\phi_i\}}, \quad (12)$$

where $[K]$ denotes the stiffness matrix of the structure, $[\Delta K]$ denotes the change of the stiffness matrix.

Based on the damage elements identified in the second step, the index RNF_i under different damage conditions is calculated to form the samples of neural network. The samples are then used to train the neural network and to test the identify errors. When the error meets a specified criterion, the neural network can be applied.

3. Numerical Simulation and Noise Influence

In order to validate the feasibility and effectiveness of the method proposed in this paper, a three-span pre-stressed concrete continuous girder bridge is taken as an example. The span of this bridge is 20 m + 30 m + 20 m. The main beam is T section with inertia moment of 0.725 m⁴. C30 concrete is adopted whose density, elasticity modulus and Poisson ratio is 2500 kg/m³, 30 GPa and 0.167 respectively.

The element numbers of the model are shown in Fig. 3 and the first eight natural frequencies are listed in Table 1.

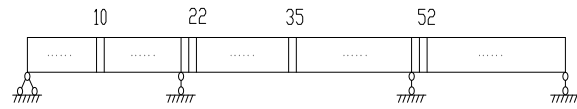


Fig. 3. Element numbers of the model.

3.1. Structural Damage Alarming

The damage is simulated by reducing the elastic modulus of the elements which is assumed to be damaged. The first eight natural frequencies before and after the structural damage are adopted as the input parameter of *RBF* neural network. The ten damage conditions are listed in Table 2. Accounting for the influence of measurement noise, the simulation formula of noise is expressed as follows:

$$PN = P(1 + \varepsilon \cdot r), \quad (13)$$

where PN denotes the modal parameters after noise pollution; P denotes the calculated modal parameters; ε denotes the level of measurement noise; r is the random number normally distributed with the mean 0 and variance 1, which is generated by using the function *randn* in MATLAB.

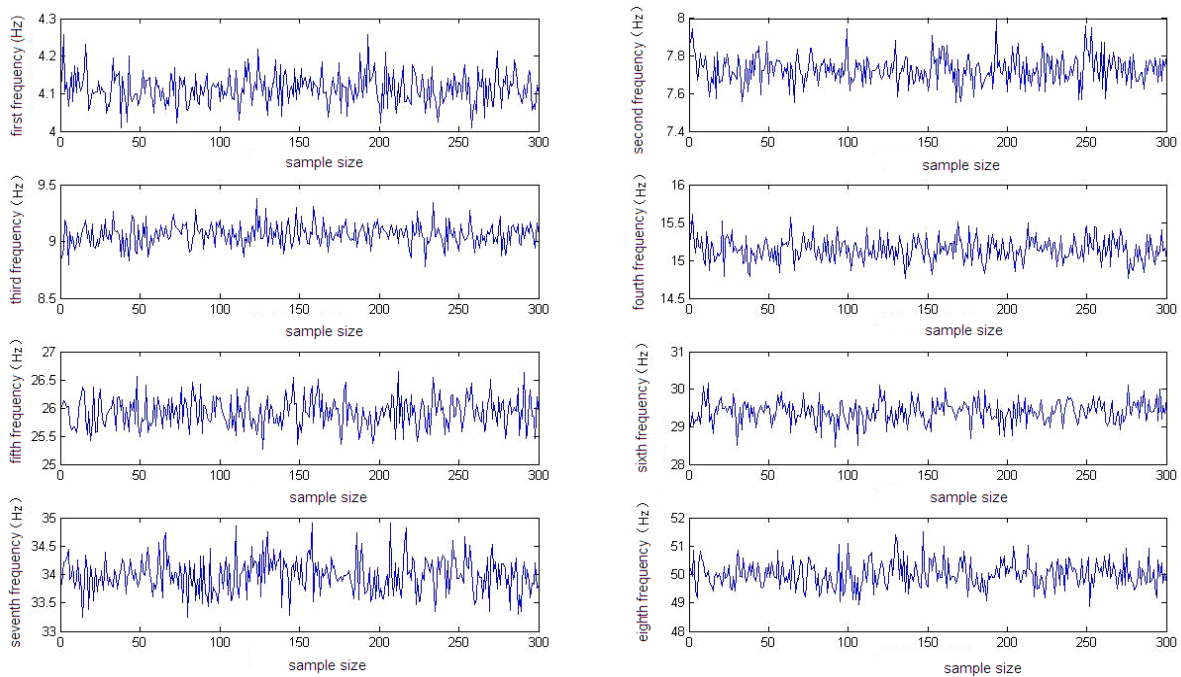
The sample length of each health and damage condition is 300. Sample data sets under health condition are used in the training stage of neural network, while the sample data sets of ten different damage conditions are used in the testing stage. The training sample data containing 1 % measurement noise is shown in Fig. 4.

Table 1. Natural frequencies of the continuous girder bridge.

Order	1	2	3	4	5	6	7
Frequency (Hz)	4.1110	7.7318	9.0590	15.143	25.935	29.396	33.973

Table 2. Damage conditions of the structure.

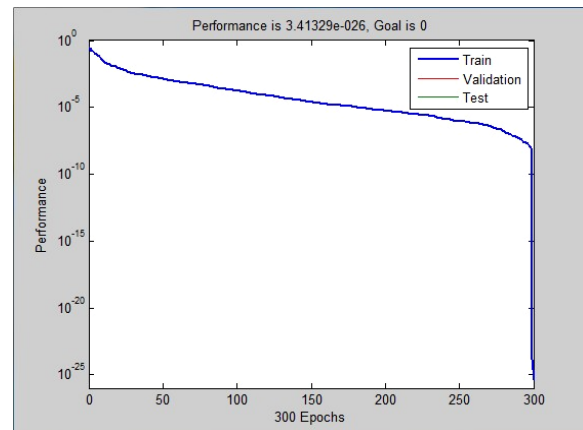
No.	Damage condition
G1	30 % damage of element 10
G2	30 % damage of element 22
G3	30 % damage of element 35
G4	30 % damage of element 52
G5	30 % damage of element 10 & 30 % damage of element 22
G6	30 % damage of element 10 & 30 % damage of element 35
G7	30 % damage of element 10 & 30 % damage of element 52
G8	30 % damage of element 22 & 30 % damage of element 35
G9	30 % damage of element 22 & 30 % damage of element 52
G10	30 % damage of element 35 & 30 % damage of element 52

**Fig. 4.** Training sample data containing measurement noise.

The final training result is shown in Fig. 5.

After the training of the neural network is completed, ten damage conditions are selected to test the neural network. The test results are shown in Fig. 6.

In Fig. 6, the first 300 sample data are the abnormal index of the health structure, while last 300 sample data are the abnormal index of structure in different damage conditions. For the health structure, because the error of neural network training is closed to zero, the abnormal index is also close to zero. For the structure under different damage conditions, the abnormal index is mostly estimated as between 0.15 ~ 0.50. The abnormal index of the health structure is separated obviously from the damaged structure. Therefore, the abnormal index method with *RBF* neural network could identify the damage occurrence of structure accurately.

**Fig. 5.** Result of neural network training.

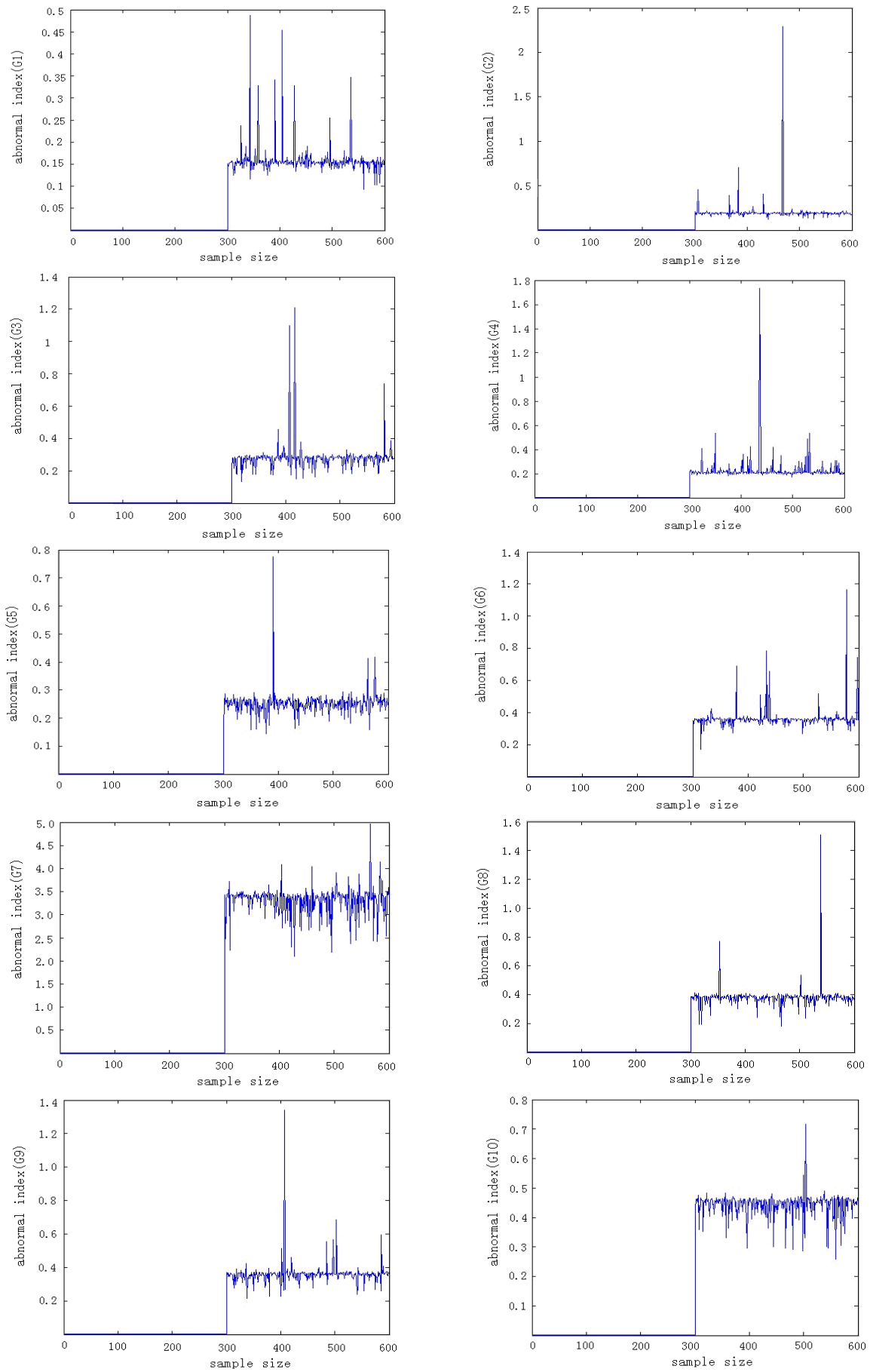


Fig. 6. Test results under 10 damage conditions.

3.2.1. Training and Testing of Neural Network

Sixteen damage conditions in Table 3 are selected as the training samples. The *FCC* of the first eight order frequency under these damage conditions and the vertical components of displacement of the first mode at eight test points (node 4, node 8, node 12, node 16, node 24, node 28, node 32 and node 35) are calculated to establish the input indicator X_I of the neural network.

3.2. Structural Damage Location

The ideal output of the network should be binary-encoded where 1 means damage occurs and 0 means no damage occurs. The output is coded according to the order of element 10, 22, 35, 52. For example, 0 1 0 0 represents that the damage occurs only in element 22, while 1 0 1 0 means damage occurs in both element10 and 35, and so on.

When the neural network is tested, the element whose corresponding output is greater than 0.7 is identified as damage element. The training error curve of the network is shown in Fig. 7.

After the training of neural network, four damage conditions listed in Table 3 (G2, G4, G6, G9) are introduced as the test samples into neural network. The results of structural damage location are as shown in Table 4.

The elements corresponding to the values in bold are identified as the damaged elements. The identification results of G2, G4, G6 and G9 indicate that single damage occurs in element 22 and 52 and

double damages occur in element10 and 35 and in element 22 and 52.

The identification results of four damage conditions are entirely consistent with the damage conditions.

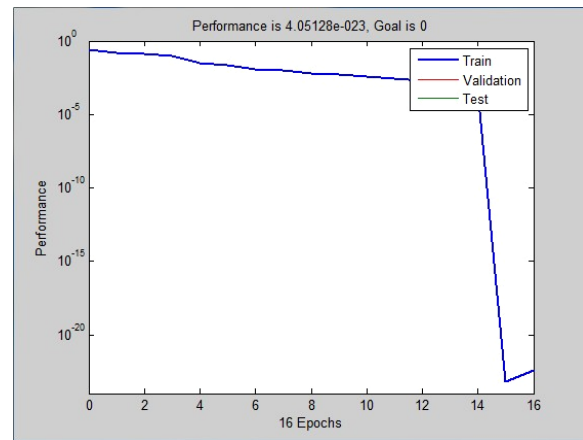


Fig. 7. Training error curve of network.

3.2.2. Influence of Noise Levels

Four measurement noise levels are selected: $\varepsilon_1=0.5\%$, $\varepsilon_2=1\%$; $\varepsilon_1=0.1\%$, $\varepsilon_2=0.5\%$; $\varepsilon_1=0.1\%$, $\varepsilon_2=1\%$, where ε_1 is the noise level of the frequency and ε_2 is the noise level of the vibration mode. For each level of assumed measurement noise, twenty data sets are generated randomly and then added to frequency and vibration mode. The identification results of damage location containing noise samples are shown in Table 5.

Table 3. Structural damage location and damage condition.

No.	Damage condition
G1	30% and 50% damage of element 10
G2	30% and 50% damage of element 22
G3	30% and 50% damage of element 35
G4	30% and 50% damage of element 52
G5	30% (30%) damage of element 10 & 30% (50%) damage of element 22
G6	30% (30%) damage of element 10 & 30% (50%) damage of element 35
G7	30% (30%) damage of element 10 & 30% (50%) damage of element 52
G8	30% (30%) damage of element 22 & 30% (50%) damage of element 35
G9	30% (30%) damage of element 22 & 30% (50%) damage of element 52
G10	30% (30%) damage of element 35 & 30% (50%) damage of element 52

Table 4. Results of structural damage location.

Damage condition	Element 10	Element 22	Element 35	Element 52
G2	0.0535	0.8741	-0.0974	-0.0057
G4	0.0663	0.0515	0.0365	0.9143
G6	0.8053	0.0369	1.0510	-0.0491
G9	-0.0389	1.3139	-0.0254	0.9785

Table 5. Identification results of structural damage location under four noise levels.

Damage condition	Sample size	Correct identification number of the neural network under 4 noise levels			
		$\varepsilon_2=0.5\%$	$\varepsilon_2=1\%$	$\varepsilon_1=0.1\%$ $\varepsilon_2=0.5\%$	$\varepsilon_1=0.1\%$ $\varepsilon_2=1\%$
G2	20	18	12	14	7
G4	20	17	9	11	4
G6	20	19	13	18	10
G9	20	17	9	14	5

According to the number of successful identification under different noise levels, the average identification accuracy of the network is 88.75 % when $\varepsilon_2=0.5\%$, 53.75 % when $\varepsilon_2=1\%$, 71.25 % when $\varepsilon_1=0.1\%$, $\varepsilon_2=0.5\%$ and 32.5 % when $\varepsilon_1=0.1\%$, $\varepsilon_2=1\%$. It indicates that with the increase of noise level, the identification accuracy of the network decrease. When the measurement noise is less than 0.5 %, the identification result of neural network is reliable.

3.3. Evaluation of Damage Severity

3.3.1. Training and Testing of Neural Network

The damage severities under the ten damage conditions listed in Table 2 are evaluated. The training samples for element damage identification are: single damage 0 %-70 % and the damage combination of each two.

According to the damage combinations above, the neural network is trained accordingly. When the training of neural network is completed, the test samples are inputted into the neural network. The results of damage identification are as shown in Table 6.

The errors of identification results under these ten damage conditions are analyzed, and the results are shown in Fig. 8. Some conclusions could be found from the results: 1) The identification errors of structural damage severity using the first eight order *RNF* are within 4 %, and the largest one is 3.91 %. 2) The maximum error of identification results appears in the G10 condition, which is caused by the calculation method of neural network. The interpolation capability of neural network is strong, thus the input data could be interpolated better. However, the extrapolating ability of neural network is relatively weak, and thus the calculation error is large.

3.2.2. Influence of Noise Level

Three noise levels of the structural natural frequencies are selected as $\varepsilon=0.1\%$, $\varepsilon=0.3\%$, $\varepsilon=0.5\%$. The measurement noise is then added into the frequencies of training samples and testing samples. The first eight order *RNF* of the structure are then calculated and inputted into the program of element damage severity identification. The identification results of damage severity under different noise levels are shown in Table 7.

Table 6. Actual and identified damage severity.

Damage condition	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
Actual	0.35	0.65	0.25	0.55	0.65	0.70	0.35	0.40	0.45	0.75
					0.65	0.45	0.35	0.35	0.40	0.35
Identificated	0.357	0.638	0.261	0.558	0.649	0.705	0.332	0.388	0.460	0.789
					0.659	0.440	0.331	0.337	0.403	0.340

Table 7. Identification results of damage severity under different noise levels.

Damage condition	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
Sample size	20	20	20	20	20	20	20	20	20	20
Correct number	$\varepsilon=0.1\%$	14(19)	15(16)	18(20)	18(20)	16(19)	18(20)	18(20)	17(19)	17(20)
	$\varepsilon=0.3\%$	8(16)	7(13)	13(19)	11(16)	8(15)	10(17)	11(16)	9(15)	7(17)
	$\varepsilon=0.5\%$	3(9)	2(7)	7(14)	4(11)	5(12)	3(10)	4(10)	3(8)	5(11)

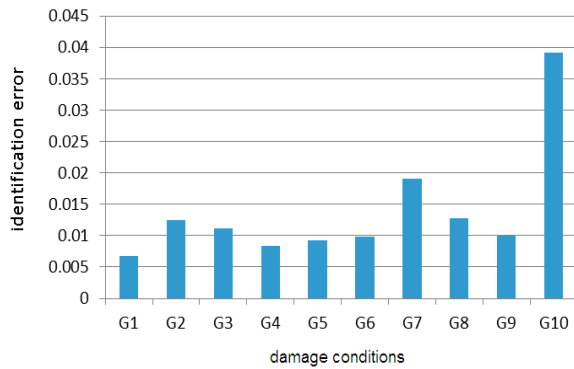


Fig. 8. Identification error of damage severity.

From the identification results, the following conclusions could be obtained. With the increasing of the noise level, the identification accuracy of the network under the same identification error decreases. When $\varepsilon=0.1\%$, the average accuracy with an identification error within 5% is 83.5%; and the average accuracy with an identification error within 10% is 96.5%. When $\varepsilon=0.3\%$, this value is 46.5% and 79.5%, and when $\varepsilon=0.5\%$, the value will be 20% and 50.5%. Therefore, the influence of measurement noise on damage severity identification is significant. The neural network has better identification results of structural damage severity when the measurement noise of frequency is less than 0.1%.

4. Conclusion

In this paper, a multi-stage approach for structural damage identification based on *RBF* neural network is proposed to remove the limitations of one-step direct identification method. Based on the simulation of a three-span continuous girder bridge, the damage alarming, damage location and damage severity evaluation is conducted, and the influence of measurement noise on damage identification is investigated. Some useful conclusions are as follows:

- i. In comparison with the one-step direct identification method, the number of training samples is reduced significantly. This method simplifies the network structure and thus improves the identification precision.
- ii. Numerical results show that the damage indexes adopted in this paper are proper and efficient. Using the index X_I as input vector, the neural network could identify structural damage location accurately, and using *RNF* as input vector of neural network could also evaluate the damage severity of structure efficiently.

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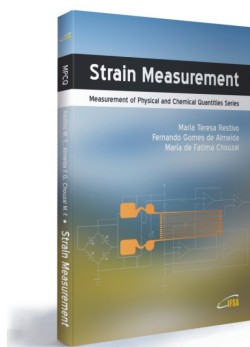


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