Damage Detection Method of Ancient Timber Structure Based on BP Neural Network and Total Wavelet Energy Rate

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Abstract. In order to detect the damage of beams and mortise joints of ancient buildings under environmental excitation, a damage identification method combining wavelet transform with improved BP neural network is proposed. The acceleration signal of the structure under the environment excitation is extracted and the total energy change rate of wavelet is obtained by wavelet discrete reconstruction, which is taken as the damage index. A finite element model of a timber frame of Xi’an bell tower is established to verify the proposed method. When the damage extent is less than 50%, 96% of the test samples in the neural network output the desired value; This method provides a theoretical basis for the study of damage prediction of timber structures in ancient buildings under environmental incentives.

1. Introduction

Traditional timber structure of ancient building is precious historical and cultural heritage of China. Thick columns and beams, mortise-tenon joints and Dou-gong are the typical components widely used in the traditional timber structure, which make it a unique example in the group of world architecture. While compared to modern silicate and metal construction material, timber is more susceptible to temperature and humidity, and during a long-term of service, the structure has experienced varying degrees of decay, loosening of worm and tenon-and-mortise joints, etc. Therefore, it is of great significance to carry out health monitoring and damage identification on ancient buildings.

The wavelet analysis[1] is regarded as a primary method on structure damage detection, for its extraordinary performance for adjusting the time-frequency window according to the characteristics of the signal, and amplify the signal at any scale to extract sensitive damage features, which is especially suitable for non-stationary signal processing under environmental excitation. However, the time-frequency characteristics of wavelets are not uniformly expressed, and it is inevitable to deriving the complex law of the interaction between load and structural response when Using the time-frequency distribution of wavelet to describe the damage. To solve this problem, a method to combine with wavelet and BP neural network is proposed, the powerful nonlinear fitting ability of BP neural networks is expected to avoid complex derivation processes.

In order to verify the validity of this method, natural excited technology(NeXT) is applied to Xi’an Bell Tower to acquire acceleration response as environmental excitation, and the proposed method performs well to locate damage and identify damage extent on a finite element frame of Xi’an Bell Tower.
2. Damage identification index based on wavelet transform

Structural damage is generally manifested as local stiffness reduction. Based on the principle of wavelet transform, wavelet analysis is performed on the dynamic response signals before and after the structural stiffness changes, and the signals at the local stiffness damage will be disturbed. Since the total energy\(^2\) of wavelet obtained from the reconstruction of discrete changes is not affected by the scale of wavelet decomposition, and it is robust to the types of wavelet functions, it can skip the step of selecting wavelet function and decomposition scale compared to traditional wavelet analysis method. Therefore, the total wavelet energy is selected as the index to analyze the damage location and damage degree of the beams and mortise joints of ancient buildings.

2.1. Discrete wavelet transform

For input signal \(f(t)\) with limited energy, \(f(t) \in L^2\), and its continuous wavelet transform is as follows:

\[
W_f(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} f(t) \psi^*\left(\frac{t-b}{a}\right) dt
\]

(1)

Where: \(W_f(a,b)\) represents wavelet coefficient, \(a\) represents scale factor and reflects signal frequency information, \(b\) represents the translation factor and reflects the time information of the signal; \(\psi(t)\) represents parent wavelet or basic wavelet, and \(\psi^*(t)\) is the conjugate complex of \(\psi(t)\). Discretize \(a\) and \(b\) to make \(a = a_0^j\) \((a_0 > 1, j \in Z)\), \(b = k a_0^j b_0\) \((b > 1, k \in Z)\), then transform continuous wavelet basis function into discrete wavelet function:

\[
\psi_{j,k}(t) = a_0^{-j} \psi(a_0^{-j}(t - k a_0^j b_0)), (k \in Z, b \in Z)
\]

(2)

\[
\psi_{j,k}(t) = a_0^{-j} \psi(a_0^{-j}(t - k a_0^j b_0)), (k \in Z, b \in Z)
\]

(3)

Based on the above theory, MATLAB software is used to discrete transformation process of acceleration signal. The specific steps are as follows:

1) Use statement ‘[C, l] = wavedec (X, N, \text{'wname'})’ to decompose the acceleration signal. Where \(C\) is the wavelet decomposition vector, \(l\) is the wavelet length, \(X\) is the signal to be decomposed, \(N\) is the number of decomposition layers, and \text{'wname'} is the name of the selected wavelet category;

2) Reconstruct wavelet coefficient vector \(C\) with statement ‘wrcoef’.

2.2. Damage index

After the signal is processed by \(j\)-level discrete transformation, the signal energy \(E_J\) is defined as:

\[
E_J = |A_j|^2 + \sum_{j=1}^{J} |D_j|^2 = \sum_{j=1}^{J} |C_j(k)|^2
\]

(4)

Total wavelet energy at each scale:

\[
E_{tot} = \sum_{j=1}^{J} \sum_{k=1}^{N} |C_j(k)|^2
\]

(5)

Where: \(C_j\) is the coefficient of each subband of the wavelet decomposition vector on the \(J\)-scale.

On the premise that the environmental excitation before and after the structural damage is consistent, one or more damages are assumed, and the change of stiffness before and after the structural damage will inevitably lead to the change of wavelet energy. In this paper, the total energy change rate of wavelet is selected as the basic damage identification index, and the total energy change rate of wavelet is defined as:

\[
\varepsilon = \frac{E_d - E_{ud}}{E_{ud}}
\]

(6)

Where: \(E_{ud}\) is the total wavelet energy of the undamaged state; \(E_d\) is the total energy of the damaged state.
3. Damage identification index based on wavelet transform

3.1. standard BP neural network

BP neural network is a kind of feed forward neural network with mentor learning. It has the characteristics of stable working state, smooth algorithm, simple and clear structure and so on. In practical engineering applications, most artificial neural network models use BP networks or their variations.

The simplest three-layer BP neural network structure includes an input layer, an output layer, and a hidden layer, the signal is transmitted from the input layer to the hidden layer, and then from the hidden layer to the output layer. Each layer of the three-layer BP neural network is connected by the weight, and the information is processed by changing the size of the connection weight. The number of neurons in the input and output layers of the neural network, that is, the number of nodes, is determined by the number of corresponding parameters in each layer. The number of neurons in the middle hidden layer affects the accuracy of the calculation results to a certain extent. It can be determined by trial algorithms or combined with the empirical formula (7).

\[ n = \sqrt{n_i + n_o + a} \]  

where: \( n \) is the number of hidden neurons, \( n_i \) and \( n_o \) are the number of input and output neurons, \( a \) is a constant between 0 and 10. The number of hidden neurons affects the accuracy of the calculation results to a certain extent. The BP neural network model algorithms in this paper all use the L-M algorithm, and the corresponding activation function is \text{trainlm}.

3.2. Improved BP neural network

The standard BP neural network has the defect of slow convergence speed and easy to fall into local extremum, so the data normalization and additional momentum method are used to adjust the weight or threshold value to improve the BP neural network, and the model is improved without increasing the calculation amount of the algorithm. The principle is as follows:

\[ \Delta \omega_j(k+1) = (1-mc)\eta \delta_j p_j + mc\Delta \omega_j(k) \]  
\[ \Delta b_l(k+1) = (1-mc)\eta \delta_l + mc\Delta b_l(k) \]

Where, \( k \) is the training times of Pb neural network and \( mc \) is the momentum adjusting factor.

4. numerical example

4.1. ambient excitation and damage distribution

Set 6 measuring points and 11 sensors for Xi'an bell tower, as shown in Figure 1. Obtain the vertical acceleration signal of Xi'an bell tower under the excitation of natural traffic environment and apply it to the model as the excitation.

In terms of the characteristics of the damage distribution of ancient building timber structure, two types of damage are considered: beam damage and mortise joint damage. Single damage condition and multiple damage condition are set respectively to identify the damage location and damage extent. According to the neural network segmentation recognition theory \cite{3}, the damage is located in the first stage, and the damage degree of the damage element is determined in the second stage.
4.2. Finite element model and load

Figure 1. 11 sensors on Xi’an bell tower

Because it is impractical to carry out destructive damage experiments on ancient buildings, a timber frame finite element model is established with Xi’an bell tower as the background.

As shown in Figure 2, the finite element model of the timber structure is a timber beam with a length of 4m and a section size of 0.3m × 0.7m; a wooden pillar with a height of 6m and a section diameter of 0.5m. The beam element of ANSYS is used to simulate the timber beam and wooden column, and the six joint spring elements are used to simulate the tenon-and-tenon connection of the column and the beam, corresponding to six degrees of freedom. The stiffness of the tenon-and-mortise joint is 2х108kN.m / rad⁴. The wood properties are shown in Table 1. The viscous proportional damping defined by Rayleigh is used, and 20 elements are divided on each beam.

Table 1 Parameters for ancient timber⁵

| timber     | Density (kg/m³) | Modulus of elasticity (Pa) | Poisson’s ratioµ | age   | Modulus of elasticity reduction |
|------------|-----------------|-----------------------------|------------------|-------|---------------------------------|
| ancient    | 410             | 83073×10⁵                   | 0.25             | >500years | 0.75                            |

4.3. beam damage identification

4.3.1. Single damage identification of beams

In the identification of single damage of beam, 1-9 element of half span beam (regardless of the element of mortise and tenon joint) is taken to simulate the damage, and the node numbers of corresponding elements are 1-10. The modulus of elasticity of unit 1-9 was reduced by 5%, 10%, 15%, 20%, 25%, 30%, 35%, 40%, 45% and 50% respectively. 90 groups of data were obtained, including 70 training samples and 20 test samples.

The results of location and damage degree identification for single damage condition of beam are shown in Figure. 3 (a) and Figure. 3 (b). The two lines in each figure represent the expected output value and the actual output value respectively. It can be seen from the figure that the change trend of the two lines is basically the same, indicating that the expected output of each sample is basically consistent with the actual output. Therefore, the improved BP neural network with wavelet energy change rate as the main characteristic parameter can accurately locate and identify the damage degree of single beam.
4.3.2. Multi damage identification of beam

For the damage of the beam mostly occurs in the middle of the beam span, 6-14 units in the middle of the span are selected for double damage combination, and the damage extent of the two units is set to be the same. Eight damage levels, including 5%, 10%, 15%, 20%, 25%, 30%, 35% and 40%, are set. 160 samples are obtained, including 130 for training and 30 for testing.

The results of location and damage degree identification for multi damage condition of beam are shown in Figure 3 (c) and Figure 3 (d). In each figure, the trend of the broken line between the desired output value and the actual output value is basically the same, indicating that the expected output of each sample is very consistent with the actual output, and showing extraordinary performance of BP neural network combined with wavelet transform on damage detection.

4.4. Damage identification of tenon-and-mortise joints

To locate the damage of 8 tenon-and-mortise joints of the model shown in Figure 1, the stiffness of damaged tenon joints are reduce by 5%, 10%, 15%, 20%, 25%, 30%, 35%, 40%, 45%, 50% when simulating single damage, 80 samples are acquired, including 60 training samples and 20 testing samples. In the case of double damage occurs, 280 samples are obtained, including 230 training samples and 30 testing samples.

The results of damage location identification of mortise and tenon joints under single and double working conditions are shown in Figure 3(e) and Figure 3(f). The desired output value in the figures is close to the actual output value. All 50 test samples under single damage and multiple damage conditions are accurately identified. Therefore, the proposed method is feasible for the damage location identification of mortise joint.

Figure 3. Results for damage detection

Figure 4. Results for accuracy analysis
4.5. accuracy analysis
The sensitivity of the damage index is analyzed by the error of the beam extent identification result. The damage extent of the single damage and double damage of the beam is identified, and the results are shown in Figure. 4 (a) and 4 (b). Under single damage conditions, the absolute error of 20 test samples does not exceed 3%; under double damage conditions, the maximum error of 30 test samples does not exceed 0.4%. Therefore, it is accurate to use the wavelet energy change rate as an improved BP neural network characteristic parameter to identify the damage of ancient buildings.

5. Conclusion
A method combining the total energy change rate of wavelet with improved BP neural network is proposed to identify the damage of beams and mortise joints of ancient buildings. The effectiveness of the method is verified by numerical examples, and the conclusions are as follows:

1) taking the total energy change rate of wavelet as the damage index, there is no need to construct wavelet function and decomposition level selection standard;

2) the damage identification method proposed in this paper is used to identify the damage location and damage degree of the beams and mortise joints of ancient buildings, and the single damage and multiple damage conditions are considered. The feasibility of this method is verified by practical engineering. The results provide a theoretical basis for the study of damage early warning of Xi’an bell tower under environmental excitation.

3) The method is accurate. Under the condition of single damage index and small learning samples, 96% of the test samples get the expected value, and with the increase of damage samples, the accuracy of damage identification increases.

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