Damage Identification Based on the Loaded Frequency Changes and Deep Learning for Bridge

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Abstract. Frequency is widely used in damage identification as the dynamic characteristic parameter with the simplest measurement method and the highest measurement accuracy, but the frequency changes are nonunique parameters of damage location for the symmetrical structure. To improve the method of damage location identification based on frequency changes for bridge, the bridge damage identification network based on loaded frequency changes and deep learning theory is proposed by introducing the moving vehicle detection method. A continuous beam example is used for testing, and the test results show that the identification network based on the bridge load frequency changes and the Stacked Denoising Auto-Encoder(SDAE) network can effectively locate the damage of bridge, which enables the frequency changes data to overcome the nonunique limitation of the symmetrical structure, enhances the expression ability of the parameters and improves the effectiveness and the anti-noise property of bridge damage location identification.

1. Introduction

Bridges are the key nodes and control projects of transportation infrastructure, and the safety and reliability of their structures are directly related to the safety of people's lives and properties. After the basic infrastructure has become the national will, the number of new bridges in China has exceeded the total number of bridges built in the past few thousand years. According to statistics, more than 40% of which in China are “aged” bridges that have been in use for more than 25 years [1-3], and the damage detection burden of in-service bridges is heavy. Small-span and medium-span bridges are mainly maintained by manual detection, which is restricted by the subjectivity of personnel [4]. With the expansion of the scale of bridge construction and the continuous increase of bridge inspection tasks, there is an urgent need for more active and faster damage identification methods.

The global damage identification method based on the static and dynamic characteristics of bridge can reduce the interference of human factors and can greatly improve the work efficiency and detection range of damage identification. Frequency is widely used in damage identification as the dynamic characteristic parameter with the simpler measurement method and the higher measurement accuracy among the current measurement techniques [5]. The common damage identification methods based on the frequency changes mainly refer to the frequency-based methods of signature analysis approaches. P. H. Kirkegaard [6] used the frequency changes of the bridge damage as the input of the Back Propagation Neural Network (BP-NN) to identify the damage of the steel beam; Kaminski P. C. [7] used the damage identification network to identify the damage with the natural frequency, the frequency changes and the normalized frequency changes rate respectively, and compared the effectiveness of the three parameters;
Sun Zongguang [8] used the natural frequency and vibration mode parameters as the input of the neural network to identify the location of bridge damage, and obtained good identification results. However, it is possible that the structure frequency changes the same due to the symmetry of bridge under different damage conditions, so that the parameters based on the frequency changes are nonunique. It has a certain limitation to identify the damage location only by relying on the natural frequency changes, and even the identification result is unreliable.

By combining the effect of moving vehicle loads and the damage identification parameters based on the frequency changes, a damage location identification method based on the loaded frequency changes is proposed in this paper. And the deep learning theory is introduced to study the accuracy and anti-noise property of the damage location identification method under the noisy environment. The steps and flowchart of damage identification methodology model for bridge is shown as Fig. 1.

2. Basic Theory

Bridges belong to multi-degree-of-freedom structural system. The free vibration equation of bridge structure considering the mass of moving vehicle loads is shown in (1):

\[
[K(p) - \omega_{ij}^2M(x_i)]\phi_{ij} = 0
\]  

(1)

where \([K(p)]\) is the structural stiffness matrix, \(\{p\}\) is the unknown parameters of structural stiffness; \([M(x_i)]\) is the structural mass matrix, \(x_i\) is the location of the vehicle load; \(\omega_{ij}\) is the \(j\)-th bridge loaded frequency when the vehicle load is at position \(i\); \(\{\phi_{ij}\}\) is the corresponding structural mode vector.

According to (2), the frequency is a global parameter related to the stiffness \([K]\) and the mass \([M]\) of the bridge system, and its changes can reflect the overall changes of the bridge system. For the bridge structure system, the manifestation of the local structural damage is mainly the stiffness change, and there is little change in mass of the bridge [9]. Therefore, the bridge system frequency will change with the change of structural stiffness state. As the inverse problem, the damage identification can be carried out by using the frequency changes of the bridge system.

Based on the theory of vehicle-bridge interaction, the variable of moving mass load position is introduced to amplify the effect of structure damage on frequency. The vehicle amplification effect at different positions will be different, which can solve the nonuniqueness and symmetry problem of damage identification parameter based on frequency changes in the process of identifying the damage location. The general steps of the moving vehicle detection method are as follows: Firstly, sensors are arranged at appropriate locations on the bridge to collect the bridge frequency data; Secondly, the bridge beam is divided into \(N\) sections (elements), which will produce \(N+1\) nodes; Then, the first to \(m\)-th loaded frequencies of the vehicle-bridge system are measured when the vehicle load is in the \(i\)-th position; Similarly, the first to \(m\)-th loaded frequencies data of the vehicle-bridge in the undamaged state are

\[
[K(p) - \omega_{ij}^2M(x_i)]\phi_{ij} = 0
\]  

(2)

Figure 1. The process of bridge damage identification model
measured; Finally, the damage location of bridge can be identified by the monotonicity and mutation of the parameters that are constructed with the loaded frequencies data before and after the bridge damage.

The change rate of the squared loaded frequencies ($SFFc$) is defined by using the loaded frequencies data before and after the bridge damage in this paper. The expression of the $j$-th $SFFc$ when the vehicle is located at the $i$-th position is illustrated in (3), where $\omega_{i,j,0}$ is the loaded frequencies data of the vehicle-bridge in the undamaged state; $\omega_{i,j}$ is the loaded frequencies data of the vehicle-bridge in the unknown state.

$$SFFc_{i,j} = \frac{\Delta \omega_{i,j}^2}{\omega_{i,j,0}^2} = \frac{\omega_{i,j}^2 - \omega_{i,j,0}^2}{\omega_{i,j,0}^2}$$  \hspace{1cm} (3)

The influence of vehicle on the frequency is small when the vehicle is at the nodal positions of each modal shapes. Given that the bridge damage may be located at the nodal positions of modal shapes, the first to $n$-th $SFFc$ are summed up to prevent the occurrence of damage missed detection, which is named the summed change rate of the squared loaded frequencies ($SFCR$). The expression of $SFCR$ is illustrated in (4):

$$SFCR = \sum_{j=1}^{n} SFFc_{i,j}$$  \hspace{1cm} (4)

3. The FEA Model Example

A three-span continuous box girder bridge(30+40+30m) is selected for analysis in this paper as shown in Fig. 2. The Euler-Bernoulli beam elements are used in the finite element analysis (FEA) model. The main beam is divided into 100 elements, which are numbered with E1~E100 from left to right. And the element nodes are numbered with N1~N101.

![Figure 2](image-url)  \hspace{1cm} Figure 2 The diagram of the FEA model

The FEA model is established by ANSYS. The beam element is BEAM3, the local damage of which is simulated by adjusting the elastic modulus of the material according to the theory of Saint-Venant’s Principle. The moving MASS21 element of ANSYS is used to simulate the moving vehicle load, and the combination of mass element and beam element is realized by binding. The loaded frequency is calculated by the Block-Lanczos modal solver of ANSYS when the vehicle is in different positions of the FEA vehicle-bridge system modal. The calculation is carried out in the X-Z surface, and the influence of damping force and temperature is not considered. Given the difficulty of measuring high-order frequencies in practical engineering, the first to 4-th vertical loaded frequencies data of beam are selected for analysis of damage identification parameters.

In order to verify the effectiveness of the proposed parameters for structural damage location identification, four beam damage conditions are set up for analysis in this section:

| Condition | Location | Degree |
|-----------|----------|--------|
| 1         | E40#, E41# (in 1/4L of the second span) | 20%    |
| 2         | E60#, E61# (in 3/4 L of the second span) | 20%    |
| 3         | E15#, E16# + E50#, E51# | 20% + 20% |
| 4         | E40#, E41# + E50#, E51# | 10% + 40% |
In accordance with the moving vehicle detection method, the values of damage identification parameters \( SFCR \) are calculated and normalized as shown in Fig. 3:

![Figure 3](image)

**Figure 3** The values of damage identification parameters \( SFCR \)

Fig. 3(a) and Fig. 3(b) show the identification results of the single damage location condition, from which we can see that the curves of parameters \( SFCR \) have a good mutation that the curve fluctuates slightly at the undamaged position while there is an obvious mutation at the damaged point. The parameters \( SFCR \) can identify the specific damage position of the symmetric structure and overcome the nonunique limitation of the frequency changes of the symmetric structure. Fig. 3(c) and Fig. 3(d) show the identification results under two damage location condition, from which we can see that the \( SFCR \) curve has obvious mutations at both the damage location and each damage location can be identified accurately. When the degrees of damage are different, the peak values of the curves are significantly different. The location with a large degree is easy to identify, while the position mutation of the lower one is easy to be covered by the higher one. The parameters \( SFCR \) can identify the damage location of the bridge effectively.

4. Anti-Noise Property

Considering that the measured bridge loaded frequencies contain a certain amount of noise, it is of practical significance to identify the damage location with the damage identification model effectively in a noisy environment. The application of the deep learning theory to bridge damage identification can improve the accuracy [10-11], so this section introduces the stacked denoising auto-encoder network to identify bridge damage. The loaded frequencies with noise are used as the input of the SDAE-Softmax for noise reduction and damage identification so as to study the anti-noise property of the bridge damage identification methodology model. The bridge damage identification network that has three hidden layers and one output layer (Softmax) is constructed by the Tensorflow platform.

This section only conducts damage identification and noise resistance research for single location damage by using the parameters \( SFCR \). A training set of 600 samples generated randomly of the single damage location is used for the unsupervised training of the identification model. The supervised training of the model is trained by the corresponding parameters \( SFCR \) of the damage at the quarter of each span, and the supervised training samples contain 9 damage conditions, and each condition contains 9 damage degrees ranging from 7% to 50%. The random noises (10%~80%) which obey Guass distribution are added to form the independent training set data and test data during training process. One-Hot coding is used to mark the damage location. The configuration of bridge damage identification network is [101,200,100,50,9]. Taking 50% noise level as an example, the trained identification model is used to reconstruct the data with noise in the test set. The bridge loaded frequency parameters \( SFCR \) without noise, with noise and reconstructed are shown in Fig.4:
Comparing the three parameter curves, it can be seen that the SDAE can denoise parameters, and the denoised parameter curves can identify the damage location effectively. The SDAE-Softmax model is constructed for comparative analysis with the BP-NN at the same time. In terms of accuracy and confidence, the anti-noise property of the trained identification model in the test data is studied in the following sections.

The Curves that correlate the test accuracy with the noise level is shown in Fig. 5. The test accuracy curve trend of the SDAE-Softmax is generally consistent with BP-NN when the noise level is less than 50%, while the reduction in accuracy rate of the SDAE-Softmax is smaller than that of the BP-NN. When the noise level is 80%, the test accuracy rate of SDAE-Softmax model is 56.17%, which is 22.21% higher than that of BP-NN. The SDAE-Softmax identification model has a certain advantage in higher noise environment.

The output confidence degrees of the SDAE-Softmax model and the BP-NN model are compared to verify the anti-noise property. A test data set of parameters \( SFCR \) with the noise level of 0%~50% is selected for analysis under the damage conditions of each midspan. The average confidence degrees of 10 times independent noise-addition tests are shown in Fig. 6:

It can be seen from the figure above: The SDAE-Softmax has a higher confidence degree than the BP-NN in bridge damage identification; the confidence degrees of the two kinds of networks decrease with the increase of noise level, while the decrease of the SDAE-Softmax is smaller than that of the BP-
NN. The results show that the noise reduction method introduced by the SDAE-Softmax network has a certain effect, which can improve the anti-noise property of the damage identification network.

5. Conclusion
The damage identification model based on the loaded frequency changes and the theory of deep learning for bridge in this paper is a new attempt from two aspects of signal analysis technology and damage identification technology. The summary is as follows:

1) Due to the introduction of the variable of moving vehicle load position, the identification parameters based on the loaded frequency changes of the bridge make the frequency data be of "time-frequency-domain" characteristic, which overcomes the nonunique limitation of the frequency changes of the symmetric structure and improves the effectiveness of bridge damage location identification.

2) Taking the loaded frequency changes parameters as input, the bridge damage identification model based on the stacked denoising auto-encoder network is constructed, which enhances the expression ability of parameters and improves the accuracy of damage identification and anti-noise property.

3) The damage identification parameters based on the loaded frequency changes have high requirements for frequency measurement accuracy, and the high-precision frequency measurement in the actual test environment still needs to be further studied.

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