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Damage warning of suspension bridges based on neural networks under changing temperature conditions

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Abstract: This paper aims at successive structural damage detection of long-span bridges under changing temperature conditions. First, the frequency-temperature correlation models of bridges are formulated by means of artificial neural network techniques to eliminate the temperature effects on the measured modal frequencies. Then, the measured modal frequencies under various temperatures are normalized to a reference temperature, based on which the auto-associative network is trained to monitor signal damage occurrences by means of neural-network-based novelty detection techniques. The effectiveness of the proposed approach is examined in the Runyang Suspension Bridge using 236-day health monitoring data. The results reveal that the seasonal change of environmental temperature accounts for variations in the measured modal frequencies with averaged variances of 2. 0%. And the approach exhibits good capability for detecting the damage-induced 0. 1% variance of modal frequencies and it is suitable for online condition monitoring of suspension bridges.

Key words: structural damage detection; modal frequency; temperature; neural network; suspension bridge

Over the past several decades, a significant research effort has focused on the health monitoring and condition assessment of long-span bridges[1-2]. How to explain the health condition of the bridge structure according to the collected structural responses remains a great challenge in the civil engineering community. It is well known that bridge structures are subject to varying environmental conditions such as traffic load and environmental temperature. These environmental effects will cause changes in the structural damage detection parameters which may mask the changes caused by structural damage. Therefore, for reliable performance of structural health monitoring techniques for long-span bridges, it is paramount to characterize normal variabilities of damage detection parameters due to environmental effects and discriminate such normal variabilities from abnormal changes in damage detection parameters caused by structural damage[3].

Considerable research efforts have been devoted to investigating the influences of environmental conditions on modal frequencies of bridges[3-8]. Most of these investigations indicate that temperature is the most significant environmental effect affecting bridge modal properties. For instance, Abdel Wahab and De Roeck[4] conducted two dynamic tests for a prestressed concrete bridge in the spring and in the winter, respectively, and observed an increase of 4% to 5% in modal frequencies with the decrease in temperature. Cornwell et al. [5] observed the variability of modal frequencies by up to 6% over a 24-hour period on the Alamosa Canyon Bridge. Ni et al. [3] observed that the normal environmental change of the Ting Kau Bridge accounted for variations in modal frequencies with variances from 0. 2% to 1. 52% for the first ten modes. Therefore, it is necessary to develop an effective scheme for online health monitoring of long-span bridges which should account for the temperature influence on modal frequencies efficiently.

In this paper, a novel damage detection technique based on neural networks is proposed for long-span suspension bridges using long-term monitoring data. The proposed method includes three steps: 1) Construction of the seasonal relationship of frequency-temperature; 2) Neural-network-based modeling of the seasonal relationship of frequency-temperature; 3) Neural-network-based classification of the measured changes of modal frequencies due to environmental conditions and structural damage. The feasibility of the proposed method is demonstrated using 236-day health monitoring data of the Runyang Suspension Bridge.

1 Measurement of Modal Frequencies of Runyang Suspension Bridge

The subject of this study is the Runyang Suspension Bridge, which is a single-span steel suspension bridge that crosses the Yangtse River, along the highway between Zhenjiang and Yangzhou in China. The main span of the bridge is 1 490 m. The health monitoring system for the Runyang Suspension Bridge has been established to real-time monitor the responses of the bridge under various kinds of environment actions and mobile loads by application of modern techniques in sensing, testing, computing and network communication[9-10]. A total of 27 uni-axial servo type accelerometers have been installed at the nine sections of the bridge deck to measure the dynamic characteristics of the bridge. The nine sections are equidistantly located in the main span. Likewise, a total of 27 temperature sensors have been installed at the sections of the bridge deck to measure the temperature of steel box girders. The sampling rates for acceleration and temperature are 20 and 1 Hz, respectively.

The 236-day monitoring data (from January to October of the year 2006) are used in this study. With the acceleration measurement data, the modal frequencies of the six vibra-

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tion modes are identified at 10-min intervals. Fig. 1 shows the identified frequency sequences of the 5th mode on a typical day for the Runyang Suspension Bridge. On the whole, the measured modal frequencies have the minimum at approximately 14:00 and reach the maximum at approximately 6:00. Therefore, the measured modal frequencies can effectively reflect the fluctuation characteristics of ambient temperature in one day. In addition, it can be observed from Fig. 1 that the influences of ambient load on the measured frequencies cause instantaneous changes because of vehicle loading and wind loading.

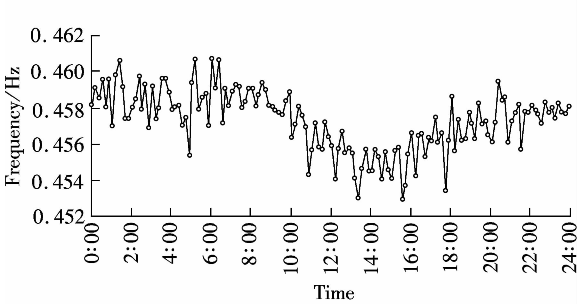

Fig. 1 Measured frequency sequences of the 5th symmetric vertical mode

The seasonal correlation analysis is further applied to eliminate the random variations due to ambient load, namely, using the daily averaged values to construct the seasonal relationship between frequency and temperature. The daily averaged frequency-temperature scatter diagrams of vibration modes 1, 2, 5 and 6 are presented in Fig. 2. It can be seen that the measured modal frequencies of higher vibration modes have remarkable seasonal correlations with the temperature. Tab. 1 summarizes the statistical information of modal frequencies from the 236-day data in 2006. It is observed that the minimum variance, maximum variance and mean variance are 0.649%, 2.186% and 1.403%, respectively.

Tab. 1 Seasonal change of modal frequencies

Mode	Nature of mode	Maximum/Hz	Minimum/Hz	Variance/%
1	1st symmetric vertical mode	0.124 1	0.123 3	0.649
2	2nd anti-symmetric vertical mode	0.181 2	0.179 2	1.116
3	3rd anti-symmetric vertical mode	0.281 2	0.278 0	1.151
4	4th symmetric vertical mode	0.344 4	0.339 1	1.563
5	4th anti-symmetric vertical mode	0.383 3	0.375 1	2.186
6	5th symmetric vertical mode	0.458 9	0.451 0	1.752

2 Modeling of Frequency-Temperature Correlations

2.1 Neural network topology

As temperature is the critical source causing the variability in measured modal frequencies, it is necessary to remove the temperature effects on modal frequencies before the measurement data are utilized for structural damage detection.

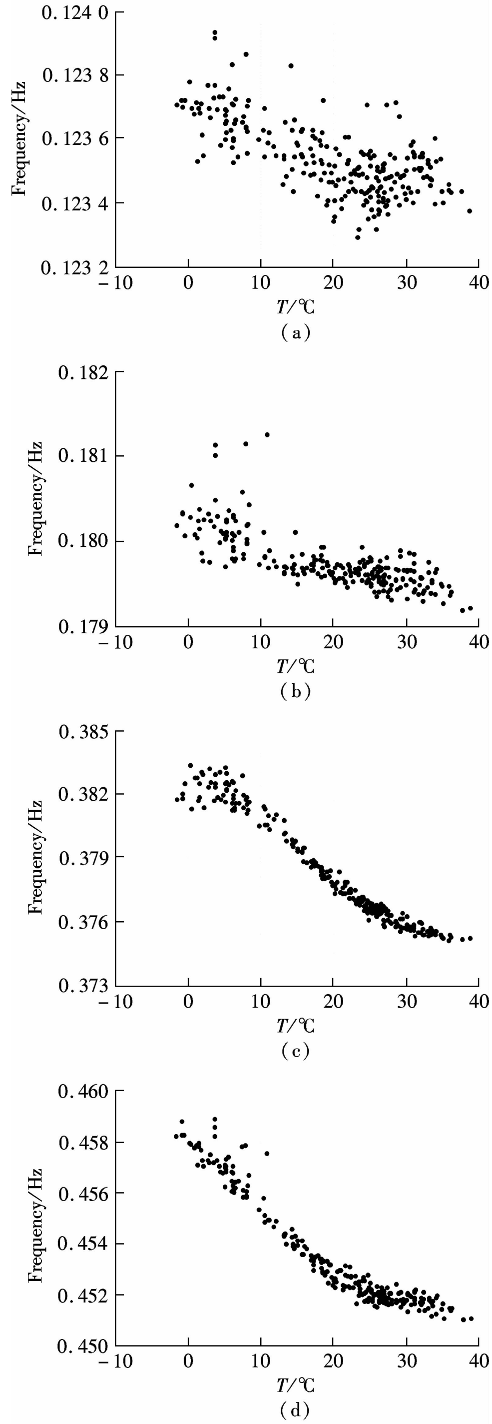

Fig. 2 Seasonal correlations of temperature and frequency. (a) Mode 1; (b) Mode 2; (c) Mode 5; (d) Mode 6

The artificial neural network (ANN) technique is applied herein for the modeling of frequency-temperature correlations. In this work, feed-forward back-propagation (BP) neural networks are configured for modeling the seasonal correlations of the frequency-temperature. The input to the network is daily-averaged temperature and the output is daily-averaged modal frequency for each vibration mode. Since 27 temperature sensors have been selected to provide measurement data, the number of input nodes is set as 27. The output layer has only one node which represents the frequency at a specific vibration mode. Through trial-and-error, three-layer neural networks with a node structure of 27-15-1 are found to be able to achieve satisfactory prediction performance and are therefore adopted in this study. The activation function is taken as the sigmoid function between the input and the hidden layers and as a linear function between the hidden and output layers.

2.2 Modeling and results

In order to evaluate both the reproduction and generalization capabilities of the configured neural networks, the 196-day monitoring data (training samples) are discontinuously extracted from the total 236-day data to train the neural network model, and the other 40-day monitoring data (validation samples) are used to test the prediction capability of the neural network model. In this study, four vibration modes (mode 3 to mode 6 in Tab. 1) are employed in the seasonal correlation modeling. For each vibration mode, the training samples of both daily-averaged temperature and frequency are used to train the neural network. Then the training temperature samples are again presented as input into the trained network to generate frequency outputs which are compared with the target outputs (training frequency samples) to evaluate the reproduction (simulation) capability. Similarly, the validation temperature samples that are not used in the training are fed into the trained network to generate frequency outputs which are compared with the expected outputs (validation frequency samples) to evaluate the generalization (prediction) capability of the neural network model.

Fig. 3 and Fig. 4 show comparisons between the measured modal frequencies and those generated by the neural network models for training and validation data, respectively. Both the reproduction and generalization capabilities of the formulated neural network models are validated. Tab. 2 summarizes the means and standard deviations of residuals of the reproduced frequencies associated with the training samples and the predicted frequencies corresponding to the testing samples. It is observed that the neural networks exhibit better reproduction (simulation) capability than the generalization (prediction) capability, but the discrepancy is insignificant. On the whole, the developed neural network models exhibit good capabilities for modeling the seasonal correlations of frequency-temperature so that the temperature-caused variability of the modal frequencies can be effectively quantified.

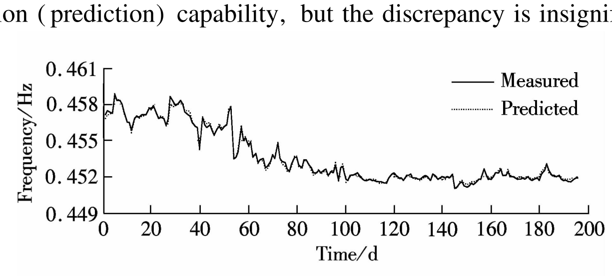

Fig. 3 Comparison of measured and ANN reproduction results of the 6th vibration mode

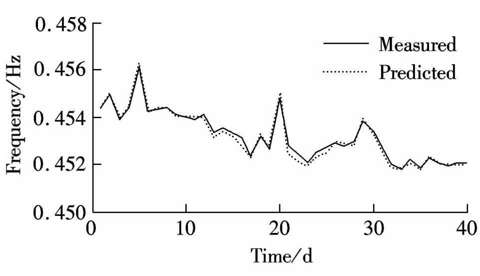

Fig. 4 Comparison of measured and ANN prediction results of the 6th vibration mode

Tab. 2 Statistics of residuals of ANN-generated modal frequencies Hz

Mode	Reproduced frequencies		Predicted frequencies	
	Mean	Standard deviation	Mean	Standard deviation
3	-3.9084×10^{-10}	8.5533×10^{-5}	3.0188×10^{-5}	8.7331×10^{-5}
4	-3.1721×10^{-10}	1.1645×10^{-4}	5.0389×10^{-5}	1.2882×10^{-4}
5	-4.2766×10^{-10}	1.2445×10^{-4}	2.7282×10^{-5}	1.6784×10^{-4}
6	-5.6078×10^{-10}	1.4599×10^{-4}	5.0357×10^{-5}	1.4938×10^{-4}

3 Damage Detection by Novelty Detection Technique

3.1 Removal of temperature effect

Before the measurement modal frequencies are used for structural damage detection, the temperature effect on the measured modal frequencies should be removed. It is achieved by normalizing all the measured frequencies to a set of fixed reference temperatures based on the established neural models. In this study, the reference temperature for each temperature measurement point is taken as the average of the 236-day measured temperatures. By feeding the set of reference temperatures into the neural networks, a nominal frequency f_r is obtained for each vibration mode. Likewise, by feeding the temperature measurement data into the neural network, a temperature induced frequency f_t is predicted. Then the normalized frequency after removing the temperature effect can be obtained by

$$f=f_m-(f_t-f_r) \tag{1}$$

where f is the normalized modal frequency; f_m is the measured modal frequency. It should be noted that for a specific temperature measurement point, a fixed value of the reference temperature should be used to normalize the measured modal frequencies obtained at different seasons.

3.2 Definition of novelty index

A neural-network-based novel detection technique is further employed for damage detection. A novel detector can be realized by using an auto-associative memory neural network that is configured as a multi-layer perceptron with a bottleneck hidden layer[11]. The auto-associative network is trained using a series of measurement data from the healthy structure as both the input and the output. After the network is trained, the input data presented on training is fed again into the trained network to yield a set of output data. A novelty index can be defined as the difference between the input and output vectors using some form of distance function. In the testing phase, a new series of measurement data obtained from an unknown structure (damaged or undamaged) is passed into the above network to form a novelty index sequence of the testing phase. The structural abnormal condition can be indicated if this sequence deviates from the novelty index sequence of the training phase.

The normalized modal frequencies are used to construct the novelty index. In the training phase, a series of measured modal frequencies of the healthy structure is used as input fed into the auto-associative neural network. The input vectors are four vibration modes (mode 3 to mode 6 in Tab. 1) as follows:

$$\boldsymbol{f} = \{f_1, f_2, f_3, f_4\}^{\mathrm{T}} \tag{2}$$

The output of the network is set as

$$y_i = (f_i - m_i)\alpha + m_i \qquad i = 1, 2, 3, 4 \tag{3}$$

where α is a given positive constant and is taken as 3 in the present study; m_i is the mean of the i-th element f_i of the input vector $\boldsymbol{f}$ over the training data. With the input training vector $\boldsymbol{f}$ and the output vector $\boldsymbol{y}$, the neural network is trained using the back-propagation algorithm.

After performing the training, the input vector $\boldsymbol{f}$ presented on training is fed again into the trained network to yield output vector $\hat{\boldsymbol{y}}$, and the novelty index sequence for the training phase is obtained using the Euclidean distance as

$$\lambda(\boldsymbol{y}) = \| \boldsymbol{y} - \hat{\boldsymbol{y}} \| \tag{4}$$

In the testing phase, a new series of data ($\boldsymbol{f}_{\mathrm{t}} = \{f_{1\mathrm{t}}, f_{2\mathrm{t}}, f_{3\mathrm{t}}, f_{4\mathrm{t}}\}^{\mathrm{T}}$) collected from the same structure (damaged or undamaged) is fed in to the above trained network to yield output $\hat{\boldsymbol{y}}_{\mathrm{t}}$. The corresponding novelty index for the test set is then obtained by

$$\lambda(\boldsymbol{y}_{\mathrm{t}}) = \| \boldsymbol{y}_{\mathrm{t}} - \hat{\boldsymbol{y}}_{\mathrm{t}} \| \tag{5}$$

where $\boldsymbol{y}_{\mathrm{t}}$ is the vector. Its i-th element can be written as

$$y_{i\mathrm{t}} = (f_{i\mathrm{t}} - m_i)\alpha + m_i \qquad i = 1, 2, 3, 4 \tag{6}$$

If the testing novelty index sequence deviates from the training novelty index sequence, the occurrence of structural damage can be indicated; if the two sequences are indistinguishable, no damage is signaled.

3.3 Damage cases and identification results

Auto-associative neural networks are developed with their input vectors being the measured modal frequencies. The 196-day monitoring data and the 40-day monitoring data used in section 2 are also employed to train and test the auto-associative neural networks. Neural networks are four-layer feed-forward perceptrons with two "bottleneck" internal layers. The activation functions are taken as the tan-sigmoid function between the second layer and the third layer, and the linear transfer function between the input layer and the second layer and between the third layer and the output layer. Fig. 5 shows the novelty indices in both training and testing phases for modal frequency. It can be seen that the novelty index sequence in the testing and training phases are indistinguishable.

In order to investigate the damage detectability, the modal frequencies of the damaged structure are simulated by subtracting a value from the measured modal frequencies of the latter 40 testing samples:

$$f_i = f_i^{\mathrm{a}} - \varepsilon \bar{f}_i^{\mathrm{a}} \tag{7}$$

where f_i^{a} is the measured modal frequency of the i-th vibration mode; f_i is the simulated modal frequency of the damaged structure; ε denotes the damage extent; in the latter examples ε is chosen to be 0.1%; $\bar{f}_i^{\mathrm{a}}$ is the annual average of the measured modal frequency of the i-th vibration mode.

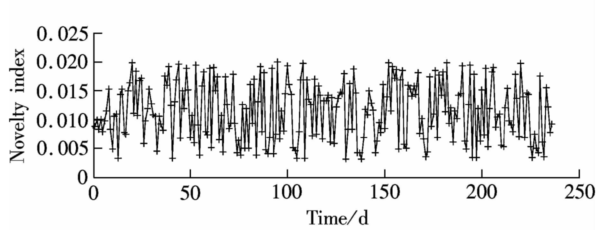

Fig. 5 Novelty index sequences of healthy structure

Fig. 6 shows the novelty index sequences with respect to the former 196 samples of the intact structure and the latter 40 samples of the damaged structure. It can be seen that the latter 40 samples have an obvious shift with regards to the centerline, which indicates the existence of the damage. It is found that the seasonal change of environmental temperature accounts for the variation in modal frequencies with an averaged variance of 2.0%, while the novelty detection method can detect the damage-induced 0.1% variances of the modal frequencies.

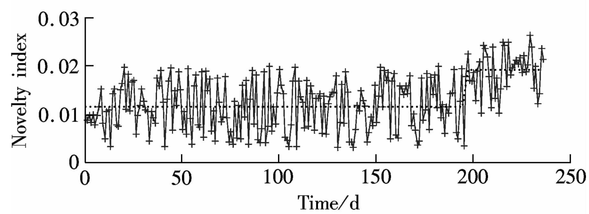

Fig. 6 Novelty index sequences of damaged structure

4 Conclusion

This paper focuses on the successive detection of the occurrence of structural damage in the Runyang Suspension Bridge using neural network techniques. The modal frequencies of the Runyang Suspension Bridge are identified from the measured dynamic responses under ambient excitations. The seasonal correlation analysis is further applied to eliminate the random variations of measured modal frequencies due to ambient loadings, namely using the daily averaged values to construct the seasonal relationship of frequency-temperature. Results reveal that measured modal frequencies have remarkable seasonal correlations with the temperature. The seasonal change of environmental temperature accounts for variations in the measured modal frequencies with an averaged variance of 2.0%. Then the seasonal correlation models of frequency-temperatures are formulated using artificial neural network techniques. Making use of the developed models, the measured modal frequencies at different temperatures are then normalized to a reference temperature to remove the temperature effects.

The normalized modal frequencies are utilized for structural damage detection using a neural-network-based novel detection technique. The auto-associative network is trained as a novel detector to signal damage occurrence. Results reveal that the proposed method can effectively eliminate temperature complications from the time series of modal frequencies and exhibit good capability for detecting the damage-induced 0.1% variance of modal frequencies.

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温度变化影响下基于神经网络的悬索桥损伤预警方法

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摘要:提出了考虑温度变化影响的悬索桥结构损伤预警方法. 首先,采用神经网络技术建立桥梁实测模态频率与温度的相关性模型,用以消除温度变化对模态频率的影响. 然后,将不同温度下的实测模态频率进行“温度归一化”,在此基础上利用神经网络新奇检测技术建立自联想神经网络进一步识别模态频率的异常变化. 通过润扬大桥悬索桥 236 d 的实测数据分析验证了该方法的可行性. 分析结果表明,不同季节下模态频率的相对变化平均约为 2.0%,采用所提方法可以识别出悬索桥模态频率 0.1% 的异常变化,适用于悬索桥结构的在线整体状态监测.

关键词:结构损伤预警;模态频率;温度;神经网络;悬索桥
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