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Research on Defect Recognition of Acoustic Vibration Method based on Neural Network

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Abstract

Non-destructive testing technology is a new, efficient and high-precision testing technology in the field of construction engineering inspection. It plays a key role in ensuring the quality of construction engineering. Among them, the acoustic vibration method has low detection cost, high efficiency and good stability. And other advantages, it has been rapidly developed in the field of engineering inspection such as bridges and tunnels. Aiming at the problem that the acoustic vibration method cannot completely distinguish the extracted effective information in the existing traditional test analysis methods, and produces insufficiently accurate results, the acoustic method is based on the collection of multiple sets of data, the establishment of a database, and the establishment of a neural network. Research on the identification of defects by vibration method and detection and application of a tunnel project in Yunnan. The results show that the established neural network model can accurately identify defects and provide a more effective means and basis for defect detection in construction engineering.

Keywords

Non-destructive Testing Technology; Defect Recognition; Vibro-acoustic Method; Neural Network.

1. Introduction

In recent years, with the continuous expansion of the construction scale of my country's transportation infrastructure, the construction of highways and railways has developed rapidly. However, my country's geological conditions and structural forms are very complex, and both roads and railways have long construction periods and construction difficulties. Big. Therefore, it is not uncommon for diseases to be exposed during the construction process. For example, the venting under the slab in road construction and the venting between the surrounding rock of the railway tunnel and the secondary lining structure are common diseases [1]. In view of the serious harm caused by these deficiencies to the project, the quality of the project must be inspected in time after the completion of the construction in order to discover potential threats and remedy them as soon as possible.

Therefore, the use of accurate, reliable, and cost-effective methods to detect defects and diseases has become the top priority of construction safety projects. Compared with other detection methods, the vibro-acoustic method has advantages in detection cost, efficiency and stability. Peng Yongheng et al. [2] started the systematic study of the vibro-acoustic method earlier, and used the frequency drop rate and adaptive neural network technology to identify and analyze the defects of the rigid pavement

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void. However, due to the insufficient type and quantity of training samples, there was a problem. Problems such as inaccurate identification of the location and area of void defects.

Based on the existing research of vibro-acoustic method, this paper measures a nylon model with a known defect location, simulates training on the measured data, and uses the original data as parameters to construct it through a BP (Back Propagation) neural network. The predictive model of acoustic characteristics and defect morphology indicators shows the construction of neural network and the training and research process, and combined with the trained neural network, a tunnel project in Yunnan was tested and verified, which proved the feasibility of the built model in engineering applications sex. This research uses mobile phone audio equipment developed by Sichuan Shengtuo Testing Technology Co., Ltd. (Figure 1).

Fig. 1 Mobile phone audio intelligent inspection equipment

2. Vibration method

2.1 The basic working principle of the vibro-acoustic method

Vibro-acoustic testing is a fast and simple non-destructive testing technology. Its basic principle is that when hammering the surface of a concrete structure, it will induce vibration and accompanied by acoustic signals. According to the close relationship between the acoustic characteristics of sound waves and the induced structural vibration characteristics, Infer whether the structure here is empty or not.

2.2 The impact of defects on the vibration characteristics of the acousto-vibration method

According to a large number of experimental studies, generally, the vibration characteristics caused by the acousto-vibration method will undergo the following changes at the location where the defect occurs. The comparison of the sound frequency signal propagation is shown in Figure 2 and Figure 3:

(1) The bending stiffness is significantly reduced, and the cycle of excellence is increased;

(2) The dissipation of elastic wave energy becomes slower, and the duration of vibration becomes longer.

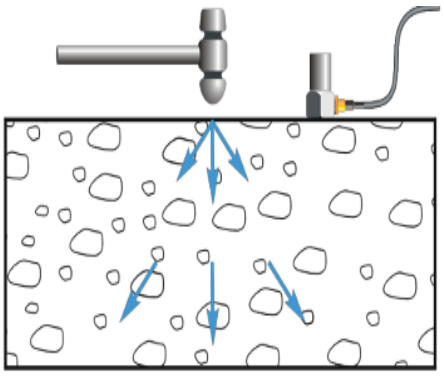

Fig. 2 No voiding defect

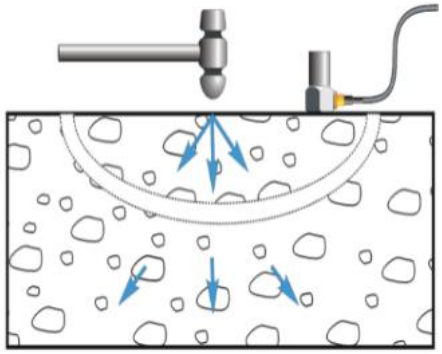

Fig. 3 Void defect

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When a defect occurs in a concrete structure, the vibration duration and period of excellence will be longer compared to normal components. Therefore, in view of the above characteristics, we can judge the internal defects of the concrete structure under the existing acoustic-vibration method.

2.3 Disadvantages of the existing technology of the vibro-acoustic method

Although the vibro-acoustic method has the advantages of being fast, simple, effective and easy to operate compared with other defect detection methods, it still has the following shortcomings:

(1) The environmental impact of noise

In actual detection, if the surrounding environment is noisy, it will have a greater impact on the detection and result judgment.

(2) The detection range is limited

The existing vibro-acoustic technique cannot effectively detect the defects at a deeper level.

(3) Human error

The inevitable influence of human error caused by the subjective judgment of the tester will lead to the error of the tester's threshold and benchmark judgment of the defect, which will reduce the detection accuracy.

(4) Parameter selection and extraction

According to parameters such as thickness and void area, the remarkable frequency of concrete can be estimated as follows (take the voided circular plate model as an example) [3].

$$f_k = \frac{h}{2\pi D^2} \cdot {R_k}^2 \sqrt{\frac{E}{3\rho(1-\mu^2)}} \tag{1}$$

In the formula, h represents the thickness of the disc, D represents the diameter of the disc, and Rk represents the characteristic value of each model. From formula (1), it can be seen that different excitation hammers will induce different modes, and the corresponding excellent frequency will also change greatly, and the change of the void thickness and void area also has a certain impact on the excellent frequency. Therefore, in the existing traditional test analysis methods, if only characteristic parameters such as the remarkable period or the remarkable frequency are extracted as the basis for defect identification, the detection results will have certain limitations due to insufficient extraction of effective information.

Therefore, the innovation of this research lies in: with the good prediction accuracy and nonlinear generalization ability of BP neural network, it does not extract the characteristic parameters of the collected data, but uses the original number itself as the input layer variable, and establishes the defects based on the BP neural network. Recognize the model, thereby improving the accuracy of defect recognition of the vibro-acoustic method.

3. BP neural network

BP (Back Propagation) neural network is a multi-layer feedforward network trained by error back propagation (abbreviated as error back propagation). Its algorithm is called BP algorithm and consists of input layer, hidden layer and output layer (Figure 4). The learning process includes two stages of forward calculation and error back propagation [4]. Its essence is to use the sum of squared errors as the objective function, and the gradient descent method is used to continuously correct the weight of the network according to the error value calculated in the forward direction of the signal. And threshold [5], so that the actual output of the network is closer to the expected output.

BP neural network has received extensive attention because of its features such as the least-mean-square algorithm as a multilayer forward neural network and back propagation learning to simulate neuron work [6]. Its powerful independent learning ability can transform the process of learning and acquiring knowledge into a process of network self-regulation, which greatly facilitates the processing of information feature extraction and memory storage. At present, BP neural network technology has been combined with traditional non-destructive testing technology to identify defects in structures such as tires, bolts, and composite materials [7-9].

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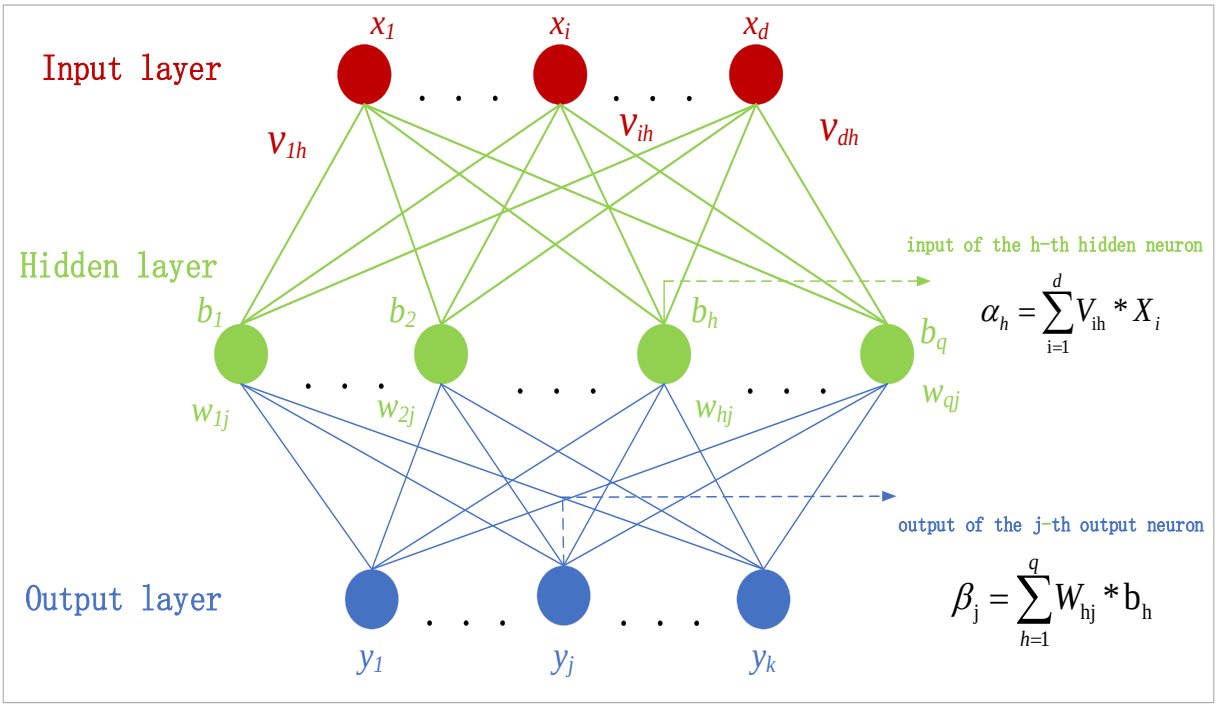

Fig. 4 Propagation structure of BP neural network

4. Defect Recognition of Acoustic Vibration Method Based on Neural Network

4.1 Indoor model test

4.1.1 Data Collection

In order to obtain the training input vector of the neural network, combined with the existing acoustic vibration method in the room, the free fall of the vibrating hammer is used to excite the test block, the data collection is completed through the corresponding mobile phone audio device, and the professional audio analysis software is used to perform the data handle. In this experiment, a nylon block with a size of 30cm×20cm×20cm with known defect locations (Figure 5 and Figure 6) was used as a model, and data was collected in the dense and defect range. A total of 1000 sets of data are collected. Figure 7 and Figure 8 are the waveform diagrams of the tested model under defect and compact state respectively.

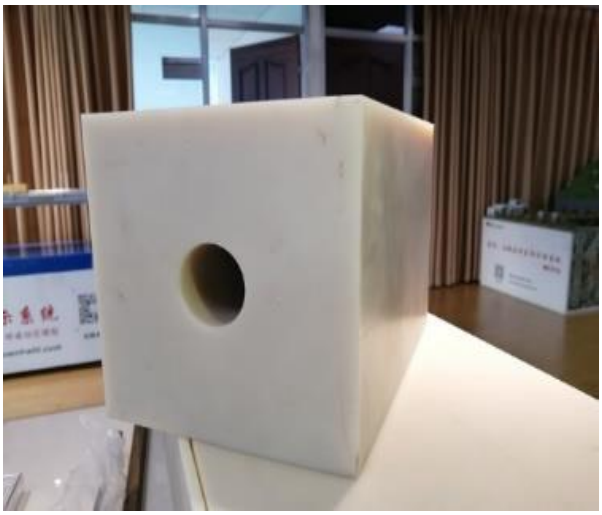

Fig. 5 Model sound surface

Fig. 6 Model defect surface

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Fig. 7 Waveform of sound signal

Fig. 8 Waveform of defect signal

4.1.2 Data preprocessing

In order to facilitate data extraction and network training, the collected data is sequentially converted through the conversion code, and finally the csv format is obtained, and the collected data is differentiated by 0 (defect)/1 (compact). In order to eliminate the dimensional influence between different evaluation indicators, data normalization processing is required before network training. The normalization of data is to scale the data to a small specific interval, and the processed raw data is in the same order of magnitude, which is more suitable for comprehensive comparative evaluation [10]. In this study, we use max-min standardization to normalize the data.

4.1.3 BP neural network training

(1) Model construction

Construct a BP neural network to identify model defects. The relevant parameters of the model are:

1) The number of layers of the neural network: According to Kolmogoro's theorem [11], it can be known that a three-layer BP neural network with a hidden layer (sufficient number of nodes) can approximate any nonlinear continuous function with arbitrary precision. Therefore, the three-layer BP neural network model is constructed in this study.

2) The number of hidden layer nodes: In neural networks, hidden layer nodes play the role of extracting and storing internal laws from sample data. There is currently no sufficient theoretical basis to determine the optimal number of hidden layer nodes. Based on design experience and many experiments, this research finally determined the number of hidden layer nodes as 13.

3) Learning rate: The amount of weight change after each cycle is affected by the learning rate. In order to avoid the error function from falling into local convergence, and ultimately make the network tend to the minimum mean square error, the learning rate is generally set to be small Value. In this study, adaptive learning rate and additional momentum algorithms are used to determine that the initial learning rate is 0.015 and the momentum factor is 0.85.

4) Excitation function. The activation function is generally used between the layers of the neural network. After the output of the previous layer is converted by the activation function, it is input to the next layer in a non-linear form. After the non-linear activation function, the neural network has More expressiveness [12]. Commonly used activation functions are Sigmoid function, tanh function, and Relu function. In this study, tanh function is used.

(2) Training results

In the training model, the number of hidden layers is two, the first layer is 22 dimensions, and the second layer is 12 dimensions. For the sample data of the 80th to 400th column intercepted in the csv file, the separator function is used to divide the entire sample set Randomly divided into two parts, namely the training set used for model training and the test set for judging whether the model is valid, and the two parts do not overlap.

This training iteration is 300 times. It can be seen from the training results in Figure 9that when the number of iterations reaches about 100 times, the accuracy of the training set and the test set are respectively 95% and 92%, and the loss function also approaches 0.05. It shows that the neural network designed by directly using data features is reasonable.

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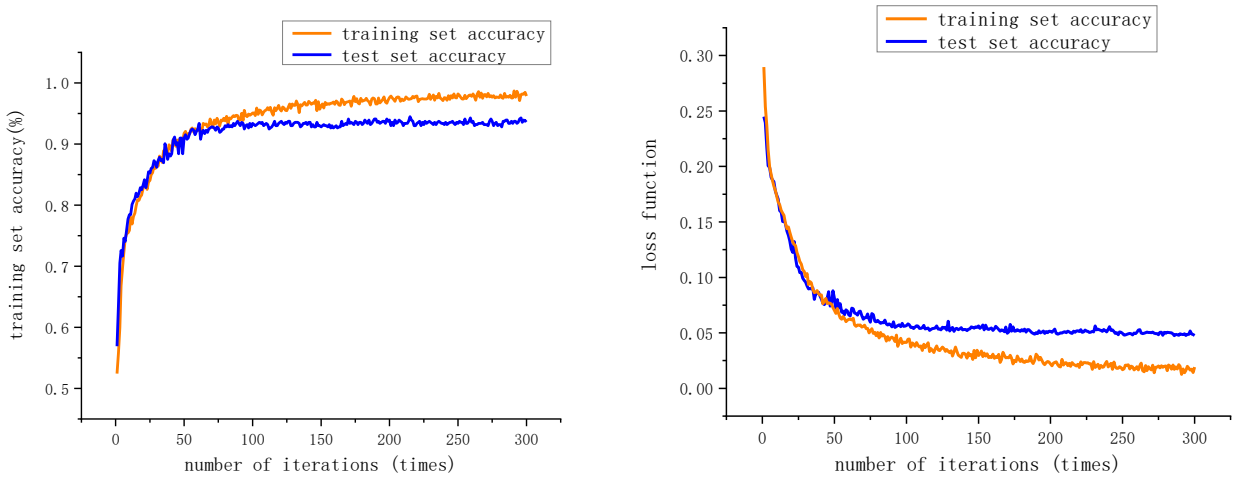

(a) BP neural network training/test accuracy (b) BP neural network training/testing loss value

Fig. 9 BP neural network training results

(3) Model verification

At a certain construction site, for a concrete test block with a size of 30cm×30cm×40cm, the BP neural network established in this paper is used for defect identification verification. After the test, the feedback value will be uniformly mapped in the interval [-1,1], The feedback value 0.5 is the limit, the verification feedback value greater than 0.5 is regarded as a compact judgment, and the verification feedback value less than 0.5 is regarded as a defect judgment. The verification results of 50 sets of data collected in the case of compactness and defects are shown in Figure 10. The correct rate of defect judgment is 90%, and the correct rate of compact judgment is 76%.

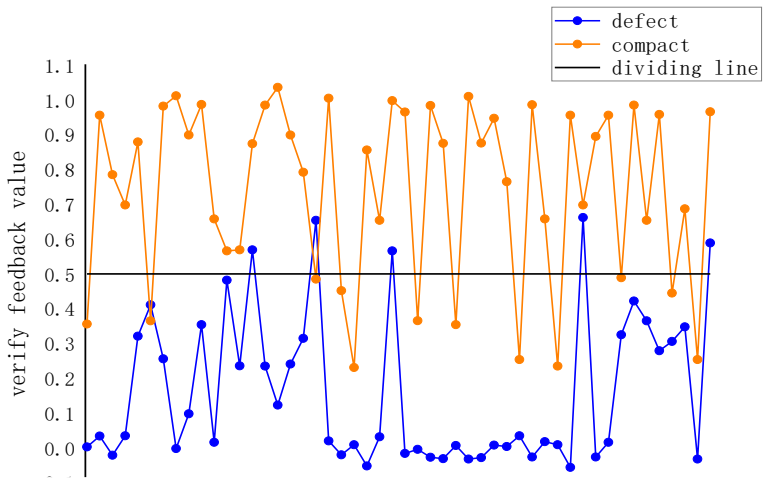

Fig. 10 BP neural network verification results

4.2 Detection and application of railway tunnel lining defects

In railway tunnel engineering, there are often quality problems such as voids caused by excessive deformation, cracking, spalling of the lining, and the thickness of the secondary lining concrete that does not meet the related requirements. The "Red Line Management Regulations on the Quality and Safety of Railway Construction Projects" It is clearly pointed out that the initial support of the tunnel, insufficient lining thickness and concrete strength are strictly prohibited. In TB10223-2004 "Railway Tunnel Lining Quality Non-destructive Inspection Regulations" and TB10753-2018 "High-speed

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Railway Tunnel Engineering Construction Quality Acceptance Standards", it is also pointed out that during the acceptance of the project, the surface of the concrete structure is required to be dense, free of laitance, exposed tendons, Quality defects such as honeycombs and holes. For tunnel lining quality problems, the main detection methods currently used are ground penetrating radar method, percussion method and sonic method. In addition, Jiang Yong et al. [13] also proposed Impact Acoustic Echo, a new type of non-destructive testing method. In order to verify the accuracy of the neural network and research ideas built in this article, and to provide a reference for the non-destructive detection method of railway tunnel lining defects, after collecting data on the site of a tunnel project in Yunnan, the neural network model built in this article was used to identify lining defects verify.

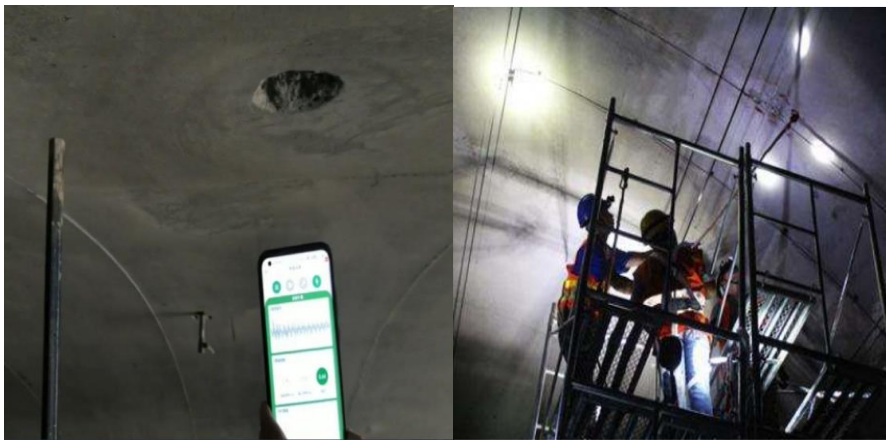

Fig. 11 Data collection site

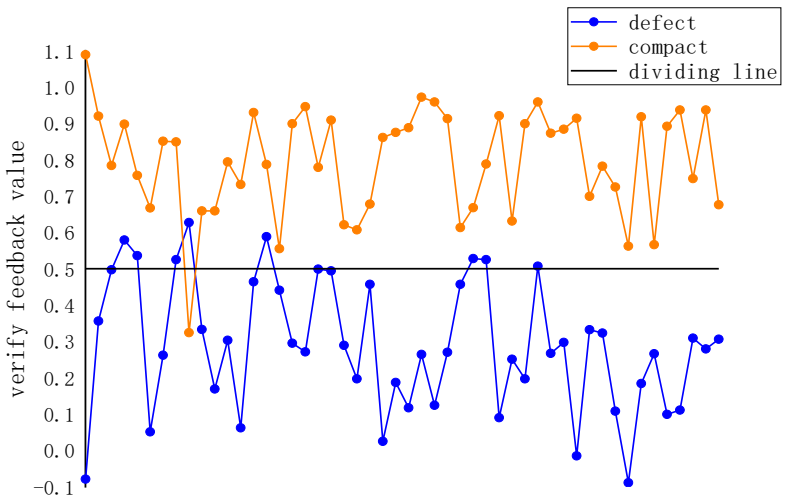

Fig. 12 Validation data feedback form

For the collected data, the BP neural network model in this paper is used for training, and the known defects are densely verified at 50 locations. The live data collection photos and training results are shown in Figure 12. The training results are also divided by the feedback value of 0.5. 50 sets of data collected in the case of compactness and defect. It can be seen from the verification feedback value that the 50 groups of data in the defect group were identified and judged through the network model constructed in this paper, and 42 groups were accurately judged with an accuracy rate of 84%. For the dense group, 49 groups were accurately judged from the 50 groups of data. , The accuracy rate is as high as 98%, and the verification results show that the neural network defect recognition model established in this paper is feasible and practical in practice.

5. Summary

Aiming at the low precision and low efficiency of the traditional concrete defect recognition technology, this paper proposes a neural network-based acousto-vibration method for defect recognition.

(1) This method uses the high self-organization, self-adaptation and self-learning capabilities of the BP neural network, and on the basis of overcoming the influence of randomness caused by manual evaluation, it not only guarantees the objectivity and accuracy of the evaluation results, but also With strong dynamics, as time progresses and the number of participating samples increases, further learning and dynamic tracking can be achieved.

(2) The non-linear function used in this research is closer to the complex non-linear dynamic economic system, and can more accurately synthesize information, so it is more practical than traditional methods.

(3) The neural network trap recognition model in this paper can be used to describe the concrete void defects. This method reduces labor costs, increases detection efficiency, and makes defects visible. It can be used to judge the availability and safety of concrete used in construction.

(4) This article also provides a technical reference for the detection of railway tunnel lining defects. Using this paper to establish a neural network model, the recognition accuracy can reach 98%, which proves the feasibility of the model in practical engineering applications.

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