Research on Deep Convolutional Neural Network in Damage Identification of Truss Structure

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Abstract. Aiming at the problem of damage identification inside the truss, through the convolutional neural network, after a large amount of data simulation, the deep learning convolutional neural network can effectively identify the internal damage of the truss and accurately determine the damage location as well as the damage recognition and effective prediction of other large roof trusses. First, we import the existing data into the convolutional neural network for identification, and calculate the damage identification process belonging to the truss. Then, we import another part of the data to verify the practicability and accuracy of the convolutional neural network, and obtain a series of data streams.

1. Introduction

Structural monitoring and damage identification are the future development direction and have been extensively studied. Research on different methods: Weng Shun[1] summarized the advantages of the finite element model in improving the efficiency of calculation and compared the application results of two different finite element methods, opening up the application of finite element in large-scale structural damage identification. Precedent. Zhang Feng[2] et al. used the ARCH model to identify the nonlinear damage problem of steel frame structures, and concluded that the nonlinear index should not be directly used for the damage identification of steel frame structure, but the residual offset distance index and Euclidean distance can be used. It can better identify the nonlinear damage of the steel frame structure.

After entering the era of big data, the method of studying damage identification problems through big data methods has also been studied in many aspects. As an application in the field of deep learning, Convolutional Neural Networks can also be trained on big data obtained in the test process to derive models. The convolutional neural network is most used in the fault diagnosis of rolling bearings in damage identification. Li Yibing[3] and others combined the hybrid leapfrog and convolutional neural network in the fault diagnosis of rolling bearings, and obtained the results of the new algorithm with higher accuracy and better training times. Li Shujin [4] and others have studied and improved convolutional neural networks in depth, and constructed one-dimensional and two-dimensional convolutional neural networks. The results have greater advantages than traditional diagnostic methods. Guo Mingjun[5] et al. used convolutional neural networks to solve the problem of axis trajectory recognition, and obtained a model with better recognition effect and higher recognition rate. Ding Chengjun[6] et al. combined VMD and deep convolutional neural network for feature extraction for the problem of rolling bearing faults, and their judgment results were more accurate.
2. Experiments and methods

In order to obtain the acceleration response data of the truss, a force hammer was used to conduct a force hammer-induced vibration mechanics experiment. The non-destructive truss and the destructive truss are respectively subjected to hammer-induced vibration mechanics experiments. Among them, the non-destructive truss includes various damages, and the treatment of beams under statically determinate conditions and the drop of screws at different positions.

2.1. Convolutional Neural Network

As a deep learning model, CNN has obvious advantages in accuracy and applicability compared with shallow models, and it is an efficient feature recognition method. It has developed rapidly in recent years and has been widely used. Convolutional neural networks are mainly used to process network structure data. The three major characteristics are weight sharing, downsampling and local receptive fields. The input of the latter layer is the output of the previous layer, and the filter is constructed in this way to extract data step by step. Convolutional neural network includes input layer, convolution layer, pooling layer, fully connected layer and output layer.

![Convolutional Neural Network](image)

Convolutional layer

The role of the convolutional layer is feature extraction, which can be divided into two processes, activation and convolution. First, multiple convolution kernels are used to convolve the input image. Then, the offset is added to the output. Finally, select an activation function and perform a nonlinear transformation on it to obtain a feature map. The more convolutional layers, the stronger the convolution ability and the more specific the expression of features. The process of convolution calculation is expressed by a formula:

$$C_n = \sum_{x,y,z=1}^{m} C_{x,y,z} o_{x,y,z}^n + \beta^n$$

Where: n is the serial number of the convolution kernel, Cn is the n-th layer decomposition machine model of the convolutional neural network, C is the input of the convolution layer, \( \beta \) is the bias of the convolution kernel, x, y, and z are the input data respectively Different dimensions.

The activation function can be linearly transformed. The ReLu activation function has unilateral suppression characteristics, and the excitation boundary is relatively wide. It can sparse the deep learning model and mine its characteristics, improve the model's convergence accuracy and accelerate the model's convergence speed, and is widely used. Therefore, ReLu is used as the activation function.

Pooling layer

The pooling layer is mainly used to compress the features and reduce the dimensionality to prevent over-fitting. The feature dimensionality reduction can reduce the number of data output points and control the amount of calculation. Pooling strategies include maximum pooling, average pooling and
norm pooling. This article adopts maximum pooling, that is, select the maximum value among nodes within a fixed window length and output. The key information can be enlarged during the enlargement process, and useless information can be discarded. At the same time, the position of the data before and after the pooling layer can be kept unchanged, which ensures the originality of the data.

Fully connected layer
After the input image passes through multiple convolutional layers and pooling layers, it enters the fully connected layer, connects all the features and classifies all the extracted features. The calculation process is:

\[ a^n = f(Q^n \cdot a^{n-1} + b^n) \]

(2)

Where: \( a^n \) is the output of the current layer; \( a^{n-1} \) is the output of the previous layer; \( f(\cdot) \) is the activation function; \( Q^n \) is the weight; \( b_n \) is the bias.

2.2. Vibration test of steel truss hammer
The boundary conditions are fixed at one end and hinged at one end. The artificial truss damage test is shown in the table.

The truss was subjected to a hammer-excited vibration test, and a series of data were collected using Donghua's data collector. The specific operation is to change the tightness of the bolts to cause damage, select different nodes on the truss, apply pulse excitation, and measure the impulse response at other nodes. The sampling frequency is 2kHz and the sampling time is 1s. Among them, the excitation points are A1-A6 in the figure, and the measurement points are B1-B6. Under different damage levels, select 1 excitation point and 1 measurement point, and repeat the experiment three times to reduce the experimental error. The data obtained in the experiment are time (s) and acceleration of different channels (m/s²). The different degrees of damage are the loosening of screws at the nodes of A1-A3 and B1-B5. The destructive and non-destructive experiments are numbered: the non-destructive experiment is 0, and the destructive experiment changes from A1-A3, B1-B5 to 1-8. The non-destructive test and the destructive test are carried out in sequence. Each experiment stimulates different nodes and measures the data of different nodes. The excitation direction is the xyz direction, and the measurement position is the z direction.

In order to verify the effectiveness of the convolutional neural network for this experiment, the data was preprocessed, and the principal component analysis method was used to transform the damage identification problem of the truss into a binary classification problem for research. Use a large portion of the data to derive the model, and use the remaining data to train the model.

3. Test results and analysis
The development environment is the pycharm platform, and the macro package used is TensorFlow to identify damage to the truss and obtain a damage identification model suitable for the truss structure. The data obtained is exported as a TXT file, and then it is transformed into Excel. There are 5041 pieces of acceleration response data obtained in each test. In order to make the model more accurate,
more data is needed to train and validate the model. Select 2/3 of the data to train the model, select 1/6 to verify the model, and select 1/6 to test the model.

Put the training set into the convolutional neural network model shown in Figure 1 for training, and the learning rate is 0.001. After verification, the accuracy curve shown in the figure is obtained. It can be seen that the accuracy is high, the highest is 97.36%. This is the final model, the test set is selected for testing and the summary shows that the convolutional neural network model is suitable for the truss test.

From this accuracy curve, it can be seen that the convolutional neural network curve is suitable for this experiment and has a good simulation effect, which can evaluate the structural state.

4. Conclusions
This paper uses convolutional neural networks to study the structural damage of steel trusses through experiments, and the conclusions are as follows:

1. The convolutional neural network method is used to establish a model through the relationship between acceleration recognition and damage location and verify this model, which is suitable for truss structures.

2. Multiple convolutions and pooling are used to improve the model, which greatly improves the applicability of this model.

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