Vibration Signal-based Structural Damage Detection through Deep Learning and Digital Image Correlation

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Abstract. The methods that structural damage detection (SDD) based on vibration signal can effectively detect invisible structural damages. This paper presents a progressive SDD method using a deep learning algorithm and the digital image correlation (DIC) measurement technique. As structural damage will affect the structural mass, damping and stiffness, and then leads to changes in dynamic response, thus the vibration signal may be able to effectively reflect structural defects. A vibration signal database was established from the experimental tests of a steel frame under random excitations, a camera used to record the vibration responses of the structure. The DIC method was employed to obtain the dynamic displacements of the points of interest (POIs). The obtained POI displacement signal was employed as the training and testing data for a convolutional neural network (CNN) which was designed to classify vibration signals. The results confirm that it was feasible to employ a CNN to detect structural damage, the accuracy was nearly 100%, the computational performance and accuracy exceed back-propagation neural networks (BPNN); its uptime was only about 12% that of the BPNN. It has been demonstrated that: (1) the CNN was sensitive to the structural damage detection; (2) the computational performance of the CNN was superior to that of the BPNN.

1. Introduction
SDD is a hot subject for real and long service structure, which damage is accumulating and endangering life. Up to now, structural safety is assessed mainly by visual experience assessment; nevertheless, the effectiveness of this method is limited due to heavy personnel costs, damage location accessibility, and huge time consumption. Many studies have proved more effective methods for SDD [1]. Structural damage will affect the structural mass; damping and stiffness, resulting in changes in vibration information (i.e., the natural frequencies and mode shapes), so vibration-based SDD methods become a hot research topic.

Vibration-based SDD are a state-of-the-art method due to high sensitivity. Vibration-based SDD methods can be classified into the model information-based and signal-based. In model information-based methods, the correlations between the modal information (frequency, mode shape, and their derivatives) and structural damage state have been explored. On the other hand, signal-based approaches need a lot of data statistics and analysis, in order to detect damage from these signals. However, these vibration-based SDD methods in practical engineering is limited, e.g., (1) Low order frequencies are susceptible to environmental noise and the frequency change does not reflect location information of structural damage; (2) A few damage detection methods (e.g., based on flexibility [2-5], modal strain energy [6-7], and mode curvature [8] etc.) relied on the accurate identification of mode shapes which is impossible for engineering structures; (3) Signal-based methods relied on a large
number of statistical data and expert skills in relevant fields; this will be time-consuming and results are subjective. Hence, there is an urgent need for a powerful data processing tool to integrate multiple information.

The application of artificial neural networks (ANNs) provides a new SDD method. Though the traditional BPNN has achieved ideal results, however it has some inherent shortcomings (e.g., convergence is low, high time cost, etc.). To overcome the limitations of the BPNN, the convolutional neural network (CNN) has been developed to extract structural damage feature and been proven successful. The latest research results confirm that the CNN can automatically detect damage from the fully utilize acceleration data [9]. Several papers have studied the problems of bolt loosening [10], mass changes before and after damage [11], damage detection of a 3-D steel frame [12]. The result of latest vibration-based SDD is encouraging. Usually, the vibration signals of structures are obtained by sensors, which have disadvantages such as deployment difficulty in signal acquisition.

Image-based vibration measurement has been proposed as a flexible and effective tool, and the related literature has proved that it was comparable with traditional methods (e.g., sensor methods). New research demonstrates that the digital image correlation (DIC) algorithm may be more accurate in displacement measurement. Furthermore, measure the displacement of multiple points using a master system [13]. In this paper, the vibration signal was measured by the DIC and then the CNN and the vibration signals were used to detect the structural damage.

2. Method

2.1. Vibration Experiment

The experimental model in this paper is a steel frame (figure 1). Its length, width and height are 10.62 m, 0.354 m and 0.354 m, it consists of 381 rods and 120 steel balls, and the rods are connected by steel balls. Vibration signal is measured by a high-speed camera. The experimental facilities includes: A high-speed camera (FASTCAMS A3, PHOTRON Inc., Tokyo, Japan), an instrumented hammer (JML-03, Jing-Ming Technology Inc., Yangzhou, China), and a laptop and a dynamic data acquisition instrument (JM3840, Jing-Ming Technology Inc., Yangzhou, China), and cables.

Figure 1. Experimental model with 381 rods.

The model is excited by the hammer manually; a laptop and the dynamic data acquisition instrument are utilized to collect the force signal; the camera records the image of the structural vibration process. The following equation [14] can be used to track the displacement of moving POI:

\[
C(\Delta x, \Delta y) = \frac{\int \int I_0(x, y) I_1(x + \Delta x, y + \Delta y) \, dx \, dy}{\sqrt{\int \int I_0^2(x, y) \, dx \, dy \, g(\int \int I_1^2(x + \Delta x, y + \Delta y) \, dx \, dy)}}
\] (1)
where $I_0(x,y)$ and $I_1(x,y)$ are the gray-scale distributions of two images, and $S$ is the area of the subset surrounding the POI; the actual displacement, $(\Delta x, \Delta y)$, of the POI ($S$) maximizes the function $C(\Delta x, \Delta y)$.

This paper considers four structural damage cases. Case 1: No-damage; Case 2: Rod 2 damage; Case 3: Rod 11 damage; Case 4: Rods 2 and 11 damage (simultaneous damage on the two rods).

2.2. CNN Samples

The steel frame is excited 3 times (the excitation point is shown in figure 1). 1,024 images are collected for each excitation, so a total of 3,072 images are collected throughout the process. The displacement of 10 points (the red crosses in figure 1) is tracked by DIC technology.

The CNN samples are divided into training data and testing data:

For training data: e.g., the displacement signals collected from the first two excitations can get a 10×2,048 matrix (figure 2). The first sample is 1-10 columns of the matrix (i.e. 10×10 matrix, in the black dotted box of figure 2), the second sample (in the red dotted box) is obtained by moving the red box down one step, this operation can obtain 2,039 samples; for the 4 structural states considered in this paper, the total number of the training samples is 2,039×4 =8,125.

For testing data: the vibration signals of the third excitation are used to generate the samples (1,015 samples) in the method of training data acquisition. The total number of the testing samples of the four structural states is 1,015×4=4,060.

![Figure 2. Sample acquisition method with intact structure.](image)

2.3. Structural State Detection

The CNN includes the convolution layer, pooling layer, activation layer and fully connected layer. For classification problems, the softmax layer is used to classify damage states. The structural parameters of the CNN are shown in table 1.

| Layer num. | Operation process | Kernel num. | Size | Stride | Activation function |
|------------|-------------------|-------------|------|--------|--------------------|
| 1          | Input             | Non         | Non  | Non    | Non                |
| 2          | Convolution       | 100         | 5    | 1      | Leaky ReLU         |
| 3          | Max pooling       | Non         | 2    | 1      | Non                |
| 4          | Convolution       | 200         | 3    | 1      | Leaky ReLU         |
| 5          | FC                | Non         | Non  | Non    | Non                |
| 6          | Softmax           | Non         | Non  | Non    | Non                |
| 7          | Classification (Output) | Non         | Non  | Non    | Non                |

Table 1. Structural parameters of the CNN.
The network input is the matrix described in Section 2.2, i.e., the displacement information in the process of structural vibration. The output of the network is categorized into different structural states, i.e., the No-damage is set to 1, Rod 2 damage is set to 2, Rod 11 damage is set to 3, Rod 2 and 11 damage is set to 4.

The whole detection process including: training and testing process. The training process is participated by training data package (Section 2.2). The testing process is implemented after training. The testing data package is shown in Section 2.2. The same data and methods by using the BPNN to compare the detection effect of the BPNN and CNN.

This paper uses a three-layer BPNN with only one hidden layer. The number of input neurons was 100 and the output has 4 neurons. The calculation equation of hidden neurons is:

\[ n_1 = \sqrt{n + m + a} \]  

where \( n \) and \( m \) are the numbers of input and output neurons, and \( a \) is a constant between 1 and 10. So the number of hidden neurons ranges from 11 to 20 in this paper.

3. Results

3.1. Experimental Results

Figure 3(a) is the force-time history curve (State 2) of 3 times of excitation. Figure 3(b) and figure 3(c) are the displacement-time history curves (of Node 1 and Node 2) obtained by the DIC method.

![Figure 3](image)

**Figure 3.** The force and displacement signals. (a): The force signal; (b) and (c): the displacement signal of Node 1 and Node 2, respectively.

3.2. Experimental Results

The training samples (section 2.2) participate in training the network. The network converges in 2 epochs using 4 s, the accuracy of testing samples is 100%. Then a BPNN was designed, its basic principle and topology have been illustrated in related research [15], the accuracy is also 100% (table 2 and table 3).
The accuracy of the detection result by the CNN.

| Count | Predicted structural state | 1  | 2  | 3  | 4  | Total | %  |
|-------|-----------------------------|----|----|----|----|-------|----|
| Actual structural state | 1   | 1015 | 0  | 0  | 0  | 1015 | 100|
| 2     | 0   | 1015 | 0  | 0  | 0  | 1015 | 100|
| 3     | 0   | 0    | 1015 | 0 | 0  | 1015 | 100|
| 4     | 0   | 0    | 0   | 1015 | 0 | 1015 | 100|
| Total | 1015 | 1015 | 1015 | 1015 | 4060 | 100|

Detection result of the BPNN.

| Nodes of hidden layer | Epoch | Uptime | Termination reason | Accuracy (%) |
|-----------------------|-------|--------|--------------------|--------------|
| 11                    | 28    | 122 s  | Validation         | 100          |
| 12                    | 41    | 173 s  | Validation         | 100          |
| 13                    | 41    | 216 s  | Validation         | 100          |
| 14                    | 22    | 126 s  | Validation         | 100          |
| 15                    | 29    | 201 s  | Validation         | 100          |
| 16                    | 30    | 225 s  | Validation         | 100          |
| 17                    | 27    | 237 s  | Validation         | 100          |
| 18                    | 38    | 361 s  | Validation         | 100          |
| 19                    | 49    | 545 s  | Validation         | 100          |
| 20                    | 43    | 499 s  | Validation         | 100          |

The computing speed of the CNN and BPNN.

| Network type | Epoch | Uptime | Computation speed (uptime/epoch) |
|--------------|-------|--------|----------------------------------|
| CNN          | 2     | 4 s    | 2                                |
| BPNN         | 28    | 122 s  | 4                                |

4. Discussion and Conclusion

Section 3.2 demonstrates that the CNN is effective for SDD and performs better than the BPNN. For the BPNN, when the beat performance is when the hidden layer has 11 nodes, its uptime is still 30 times longer than that of the CNN (table 4).

| Network type | Epoch | Uptime | Computation speed (uptime/epoch) |
|--------------|-------|--------|----------------------------------|
| CNN          | 2     | 4 s    | 2                                |
| BPNN         | 28    | 122 s  | 4                                |

Based on the above detection results, the conclusions are as follows:

1. The CNN is sensitive to the structural damage detection.
2. The computational performance of the CNN is superior to that of the BPNN.

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