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Damage identification analysis of Cable-stayed arch-truss based on multi-node time -domain data fusion

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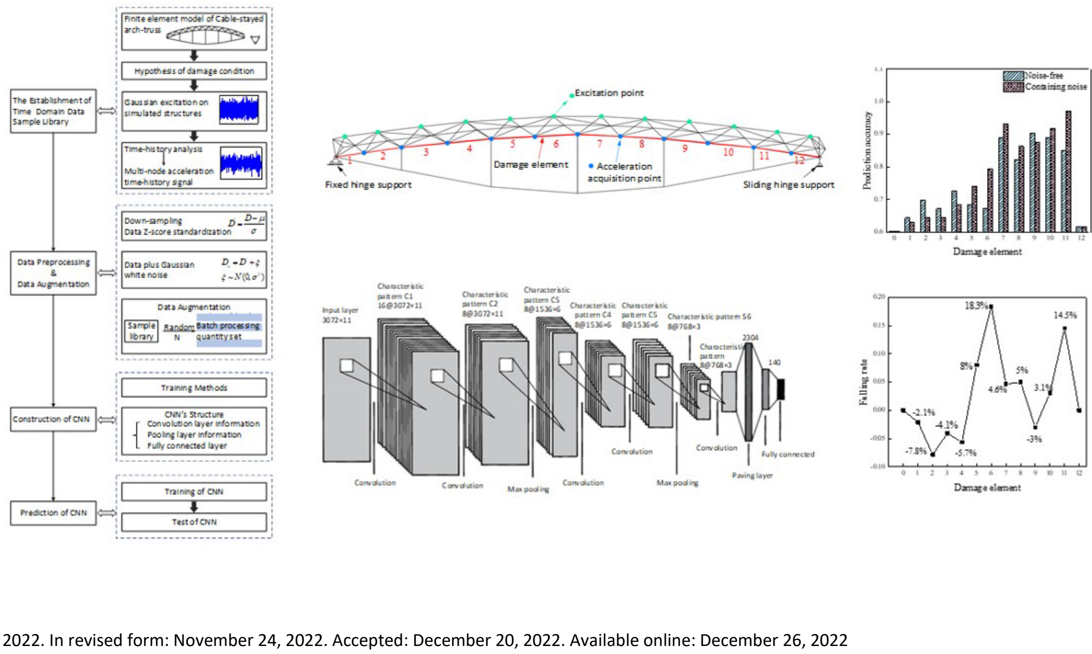
Abstract

The potential risk of cable-stayed arch-truss damage is large and the damage is undetectable. The damage identification methods based on frequency domain have limitations such as limited data and complex theoretical methods. A damage identification method based on multi-node time-domain data fusion was proposed to overcome these limitations. The time-domain data library was established by finite element analysis, and the time-domain data was preprocessed and augmented. Two CNNs models were established to identify the damage location and damage degree of cable-stayed arch-truss. The proposed method was verified by the analysis of a practical cable-stayed arch-truss scale model, and the recognition effect of the method on noisy data and noise-free data was studied respectively. The results showed that the CNN can effectively identify the damage degree and damage location of cable-stayed arch-truss structure with good robustness. CNN with Gaussian noise can accurately predict the damage degree of cable-stayed arch-truss. The prediction error of most elements is within 15%, which can meet the actual needs of engineering.

Keywords

Cable-stayed arch-truss; Damage identification; Convolutional neural networks; Time-domain data

Graphical Abstract



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1 INTRODUCTION

As a typical large-span spatial structure, cable-stayed arch-truss (CSAT) is widely used in large-span important public buildings such as convention centers and airports (Murthasmith, 1988). However, CSAT is prone to damage in the service process and the damage is difficult to detect. If the structural damage cannot be found and processed in time, it will affect the normal use of the structure and even lead to structural damage, resulting in huge casualties and property losses. Therefore, it is of great practical significance to study the damage identification of CSAT during its whole building life cycle. Nowadays, the damage identification method based on frequency domain data is widely employed for structural damage identification. But it still has the limitations such as limited structural monitoring data and complex theoretical methods. When it is applied to the damage identification of complex long-span structures such as CSAT structures, a large amount of manpower and financial resources are required to process the monitoring data.

Deep learning (Zhang, Cheng, Qiu, Ji, & Ji, 2019; Mu & Zeng, 2019) is based on big data and analyzed by computers, which has strong learning ability, good convergence and better stability. It provides a feasible way for feature location extraction in damage identification. Won et al (2021) proposed an automatic detection method of structural damage based on data normalization and CNN. The numerical simulation of simply supported beam model under random and traffic load excitations was carried out, showing that the damage location of the beam can be successfully detected. Fu et al (2021) took advantage of the CNN high-dimensional feature extraction and the time series modeling ability of long-short memory networks to identify the damage of long-span bridges. Taking a long-span suspension bridge as an example, the feasibility of its application in practical engineering was verified. Yang & Huang (2021) combined the flexibility curvature method and CNN, which can well identify the damage location and damage degree of the prestressed concrete beam bridge structure. Duan et al (2019) proposed an automated damage identification method of hanger cables in a tied-arch bridge using a CNN and simulated the multiple damage detection in the hangers. The results showed that the current CNN performed better under various damage states than the traditional neural network. Wang et al (2021) proposed a structural damage identification method based on IASC-ASCE SHM benchmark, which adaptively optimized the structural parameters of CNN model to ensure better performance and robustness of CNN. At present, the application scope of deep learning in structural damage is mainly concentrated in the damage monitoring of bridges, while less used in the damage identification of string truss structures. However, the application of deep learning in bridge damage monitoring also proves the feasibility of applying deep learning to structural damage identification.

Therefore, a CSAT damage identification method based on multi-node time-domain data fusion is proposed in this paper. Two CNN models are established to identify the CSAT damage location and damage degree. The influence of noise on the accuracy of CSAT damage identification by CNN is studied. A CSAT model is selected to illustrate the establishment process of the method in detail to prove the damage identification effect and robustness of the method.

2 Overview of the steps for damage identification

Convolutional Neural Networks (CNN), also known as convolutional networks, is a multi-layer neural networks based on deep supervised learning framework (Cha, Choi, & Buyukozturk, 2017; He, Zheng, Liao, & Chen, 2021) When the CNN is used to identify the damage, the acceleration time history signal measured by multiple sensors is input, and the final recognition result is obtained after data fusion and multi-layer convolution kernel pooling feature extraction. Essentially, this method is a data layer fusion method (Krizhevsky, Sutskever, & Hinton, 2017; Zhan, Lu, Xiang, & Wei, 2021). According to the fact that CSAT damage identification is essentially the same as deep learning, the flow chart of CSAT damage identification based on CNN is shown in Figure 1, which includes the following steps:

(1) Establishment of time-domain database;

(2) Data preprocessing and data augmentation ;

(3) Construction of CNN ;

(4) Training and testing of CNN.

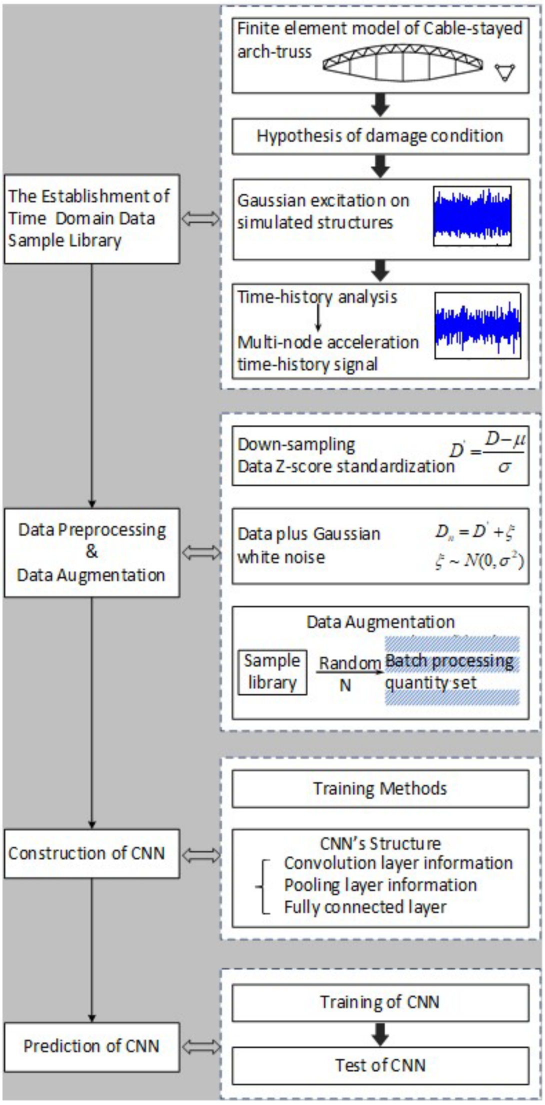


Figure 1 Flow chart of damage identification method based on CNN.

3 Time-domain database and data processing

3.1 CSAT finite element model

The CSAT model shown in Figure 2 is selected for finite element analysis. The model is obtained by simplifying the actual roof structure of a railway station (Luo & Yu, 2013) by scaling. The total length of the model is 6 m, the rise height is 0.4 m, and the sag is 0.4 m. Only the three representative components of the upper rigid truss, the middle rigid brace member and the bottom flexible cable member in the CSAT structure are retained (Zeng, Zhou, Zhao, & Xu, 2016). Among them, the upper part of the structure is an inverted triangle three-dimensional truss, five symmetrical circular steel pipe struts are evenly arranged in the middle part, the bottom part is arranged with wire rope cables, and 2 KN prestress is applied to the cables.

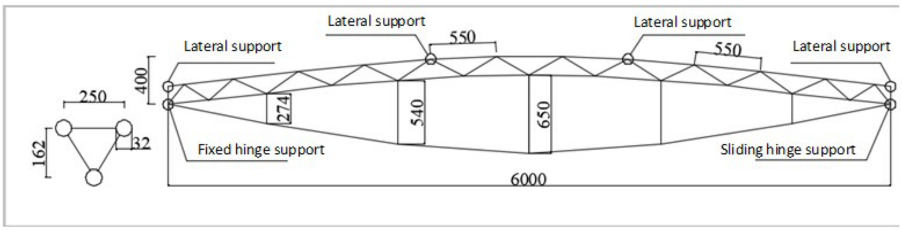


Figure 2 CSAT finite element model.

3.2 Construction of multi-node time-domain database

In this paper, the structural damage is simulated by reducing the elastic modulus of the section. In real life, the degree of damage greater than 50% is easier to be identified, so this paper only considers the degree of damage within 50%. Four degrees of damage 0%, 30%, 40% and 50% were selected for parametric analysis. The external load acting on the structure is simulated by Gaussian random excitation. In order to simulate the limited environmental load acting on the actual project, the low-pass filter is selected to further deal with Gaussian random excitation. In the time-history analysis, the Newmark method is selected to calculate the time-history response of the structure without considering the effect of constant load. The load step is 2 – 11 s, and the load is 3 s. The number of acceleration time histories of each node is 1 × 6144. In this paper, the vertical acceleration time-history data of 11 nodes in the bottom chord shown in Figure 3 are extracted to a sample database. Finally, the data amount obtained by each time-history analysis of the structure is 11 × 6144.

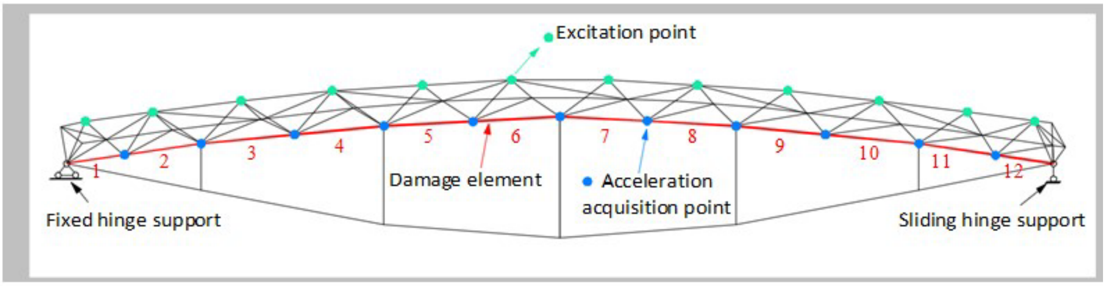


Figure 3 CSAT damage location.

To obtain higher prediction accuracy, a large amount of time-domain data is required to train CNN. Therefore, a large of time history analysis and calculations are carried out in this paper. Considering single damage each time, only one node of the upper chord is excited, so there are 48 calculated damage conditions under each Gaussian excitation (12 non-destructive and 36 damage at each position). In order to ensure the same number of samples for the four damage degrees, 15 different Gaussian excitations are used for time history analysis and calculation for each element under non-destructive working conditions, while 5 different Gaussian excitations are used for time history analysis and calculation for each element under the other three damage working conditions. Table 1 shows the consideration factors of damage conditions. Finally, the CSAT time-domain database with 2340 data sets and 1 × 6144 sample dimensions is obtained.

Table1. Damage conditions considerations

Factor	Damage degree	Damage location	Position of excitation
Detail	Non-destructive + 3 damage degrees	Bottom chords 1-12 elements	Upper chord 2-14 nodes
Quantity	4	12	12

3.3 Data Preprocessing and data augmentation

The selected 2-11s load step in time history analysis leads to a large characteristic diagram, which affects the calculation efficiency and accuracy of convolution. In other words, it is detrimental to the overall training of the structure. Therefore, each group of data is downsampled by numerical analysis. After the raw data was down-sampled, the sample size of each data changed from 11 × 6144 to 11 × 3072 in two dimensions and the size of time-domain data sample library was twice the original size. The downsampling operation reduces the sample size of each data while improves the sample size of the time domain database, which indirectly improves the training efficiency and training accuracy of CNN from two aspects.

Before using CNN for data analysis and processing, it is necessary to standardize the data. The standardized data is used as the input data of the network for feature extraction and classification. In this paper, the value range of acceleration sensor is unknown, so Z-score standardization method is selected to standardize the data.

$$D' = \frac{D-\mu}{\sigma} \tag{1}$$

Where D is the input sample data of the network, D' is the input sample data after standardization, μ is the mean value of the input sample data, σ is the standard deviation of the input sample data.

Noise is inevitable in the actual monitoring of CSAT structures. At present, the noise level of practical engineering is about 1% -2%. In order to analyze the CNN robustness, this paper adds 1% Gaussian noise to the standardized time-domain data (Lin, Nie, & Ma, 2017). The specific formula of Gaussian noise is as follows:

$$\begin{aligned} &D_n = D' + \xi \\ &\xi \sim N(0, \sigma^2) \end{aligned} \tag{2}$$

After the down-sampling and data standardization steps, the size of data in the time-domain database is 4680. The size still belongs to the category of small data sets, so the data augmentation method is introduced (Lin, Nie, & Ma, 2017). 128 samples are randomly selected from the time-domain library to form a batch dataset for subsequent CNN training.

The data processing is completed through the steps of down-sampling, data standardization, Gaussian noise introduction and data augmentation. The data samples are divided into 3263 training samples (about 70%), 949 test samples (about 20%) and 468 validation samples (about 10%). The test set, validation set, and training set data are completely independent without duplicate samples.

4 CNN Implementation

4.1 Construction of CNN

CSAT is a complex structure, so it is necessary to identify the CSAT damage location and the CSAT damage degree separately when studying the CSAT damage identification. The damage location is essentially a classification problem by analyzing the monitoring data, while the damage degree identification is essentially a data fitting problem by obtaining the damage degree of the damage interval according to the monitoring data. Due to the different characteristics of CSAT damage location recognition and damage degree recognition, two corresponding CNN models of damage location recognition and damage degree recognition were constructed respectively.

The learning curve was used to determine the value intervals of each parameter during the parameter adjustment process. Each parameter was adjusted one by one until the prediction model achieved the highest accuracy, and the specific values were shown in Table 2 and Table 3. Besides, in the final layer design of the fully connected layer, Softmax was selected by the damage location prediction model to predict the damage location (Table 2 and Figure 4). While the damage degree prediction model uses nonlinear activation functions to obtain the damage degree at different locations (Table 3).

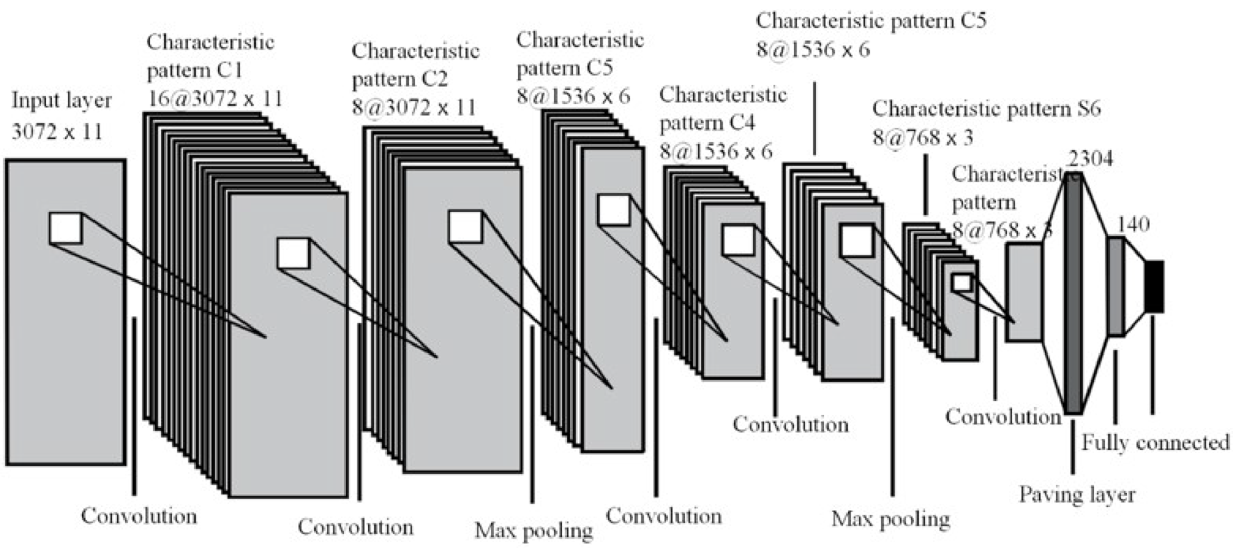


Figure 4 Schematic diagram of damage location convolution structure

Table 2. CNN Structure—damage location recognition

Number	Network layer type	Network input size	Network output size	Kernel size	Stride	Filling	Excitation function
1	convolution layer+BN	[3072,11,1]	[-1,3072,11,16]	[3, 3, 1, 16]	[1,1,1,1]	same	—
2	convolution layer+BN	[-1,3072,11,16]	[-1,3072,11,8]	[3, 3, 16, 8]	[1,1,1,1]	same	—
3	maxpool layer	[-1,3072,11,8]	[-1,3072,6,8]	[1, 2, 2, 1]	[1, 1, 2, 1]	valid	—
4	convolution layer+BN	[-1,3072,6,8]	[-1,1536,6,8]	[3, 3, 8, 8]	[2,1,1,1]	same	—
5	convolution layer+BN	[-1,1536,6,8]	[-1,1536,6,8]	[3, 3, 8, 8]	[1,1,1,1]	same	—
6	maxpool layer	[-1,1536,6,8]	[-1,768,3,8]	[1, 2, 2, 1]	[1, 2, 2, 1]	valid	—
7	convolution layer+ BN	[-1,768,3,8]	[-1,768,3,1]	[1, 1, 8, 1]	[1,1,1,1]	same	—
8	Paving layer	[-1,768,3,1]	[-1,2304]	[-1, 2304]	—	—	—
9	fully connected layer	[-1,2304]	[-1,140]	[2304, 140]	—	—	Elu
10	fully connected layer (Softmax)	[-1,140]	[1,13]	[140, 13]	—	—	—

Table 3. CNN Structure—damage degree recognition

Number	Network layer type	Network input size	Network output size	Kernel size	Stride	Filling	Excitation function
1	convolution layer	[1024,9,1]	[1024,9,32]	[16, 1, 1, 32]	[1,1,1,1]	same	Leaky Relu
2	convolution layer +BN	[-1,1024,9,32]	[-1,1024,9,32]	[16, 1, 32, 32]	[1,1,1,1]	same	Leaky Relu
3	maxpool layer	[-1,1024,9,32]	[-1,256,9,32]	[1, 4, 1, 1]	[1, 4, 1, 1]	valid	—
4	convolution layer	[-1,256,9,32]	[-1,256,9,64]	[16, 1, 32, 64]	[1,1,1,1]	same	Leaky Relu
5	convolution layer +BN	[-1,256,9,64]	[-1,256,9,64]	[16, 1, 64, 64]	[1,1,1,1]	same	Leaky Relu
6	maxpool layer	[-1,256,9,64]	[-1,64,4,64]	[1, 4, 2, 1]	[1, 4, 2, 1]	valid	—
7	convolution layer	[-1,64,4,64]	[-1,64,4,128]	[16, 1, 64, 128]	[1,1,1,1]	same	Leaky Relu
8	convolution layer +BN	[-1,64,4,128]	[16, 1, 128, 128]	[16, 1, 128, 128]	[1,1,1,1]	same	Leaky Relu
9	maxpool layer	[16, 1, 128, 128]	[-1,16,1,128]	[1, 4, 4, 1]	[1, 4, 4, 1]	valid	—
10	Paving layer	[-1,16,1,128]	[-1,2048]	[-1, 2038]	—	—	—
11	fully connected layer	[-1,2048]	[-1,256]	[2048, 256]	—	—	Leaky Relu
12	fully connected layer	[-1,256]	[-1,128]	[256, 128]	—	—	Leaky Relu
13	fully connected layer	[-1,128]	[1,12]	[128, 12]	—	—	Leaky Relu

4.2 Training and testing of CNN

The supervised learning algorithm is selected to train the CNN. Parameters such as learning rate and batch size are preset firstly during the training of CNN. Then appropriate parameters are selected for training through multiple debugging. The network training parameters selected in this paper are shown in Table 4.

Table 4. Training parameters of CNN

Training parameters	Parameter definition	Parameters interpretation
Batch size	128	Sample size of data read in each training
Frequency of training	2000	Total training times of CNN
Moving average decay	0.99	To control the update speed of the model
η	0.0001	Initial learning rate of Adam algorithm
β_1	0.9	The weight of momentum term of Adam algorithm
β_2	0.999	Controlling the decay rate of learning rate in Adam algorithm

In order to enhance the reliability of the prediction model, 10-fold cross-validation was performed during the training. The training process is divided into two stages, as shown in Figure 5. The input data are transmitted from low level to high level in turn to the forward propagation stage. The data enters the backward propagation stage when the prediction accuracy error is not within the allowable range. The error in the propagation is propagated from high level to low level. The training will not stop until the prediction accuracy meets the requirements and the confidence interval is [0.95,1].

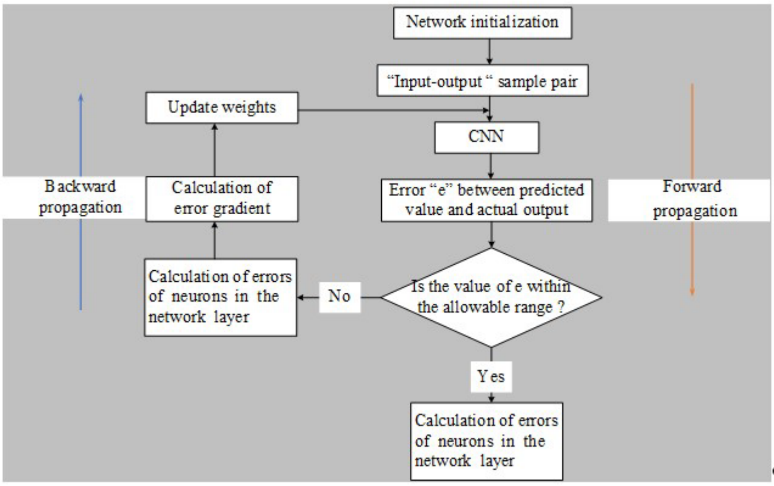


Figure 5 Training process of CNN.

The test process of CNN are as follows: After the network training is completed, the CNN training accuracy is tested with test samples without output value. If the prediction results of test samples do not meet the requirements, the CNN training parameters need to be adjusted and retrained.

5 Analysis of Damage Location Identification Results

In this section, 949 noise-free test samples and 949 noisy test samples are employed for damage location prediction model, which are trained by noise-free samples and noisy samples respectively. Then, their respective prediction results are obtained. Compared with the actual output, the convolution test accuracy is shown in Figure 6. It can be seen in Figure 6:

(1) The noise-free CNN prediction accuracy is 74.4%, which means that CNN can accurately identify the CSAT damage location.

(2) The noise-free CNN prediction accuracy is 74.4%, while the noisy CNN prediction accuracy is 77.6%. The noisy CNN prediction accuracy is slightly higher than that of the noise-free CNN. Adding noise in CNN is equivalent to increasing the number of training samples, so the accuracy is improved accordingly. The higher prediction accuracy exactly shows that CNN has good anti-noise ability.

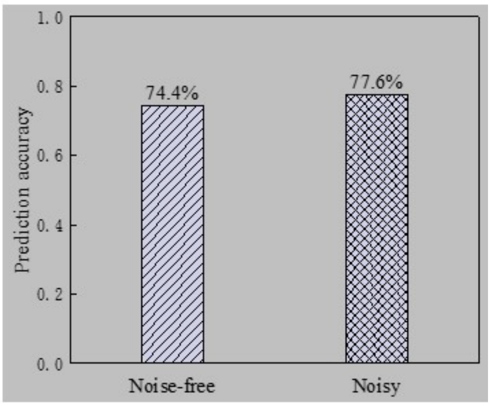
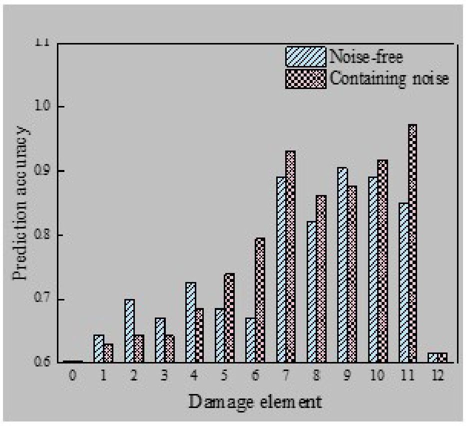
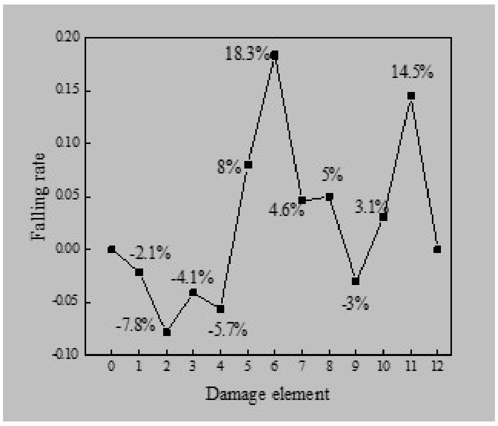


Figure 6 Test accuracy of CNN.

Figure 7(a) shows the prediction accuracy of noise-free CNN and noisy CNN for different position elements. From Figure 7(a), it can be seen that CNN has better damage prediction accuracy for each element of the bottom chord, which is more than 60%, and the noise-free CNN has the highest damage prediction accuracy for Element 9 of the bottom chord, which is 90.4%. The CNN with noise has the highest damage prediction accuracy of 97.3% for Element 11 of the bottom chord.



(a) Comparison of prediction accuracy



(b) Decrease rate of training accuracy of CNN with noise

Figure 7 Comparison of prediction accuracy of noisy and noise-free CNN

Figure 7 (b) shows the decline rate of the noisy CNN training accuracy compared with that of the noise-free CNN. When the noisy CNN is used to predict from Element 1 to Element 4, the accuracy is reduced and the maximum decline is 7.8%; the prediction accuracy of Element 5 to Element 12 is generally improved. The prediction accuracy of Element 6 is the largest, which is 18.3%. Although the structure is symmetrical, the accuracy of damage identification is different due to the difference in the constraint conditions of the left span and the right span. In general, the recognition effect of CNN with noise is ideal, and the CNN has good robustness.

Meanwhile, the t-sne dimension reduction algorithm is used to classify 130 training data. Figure 8 intuitively shows that the data with the same feature are concentrated together while the data with different features are scattered, which reflects the strong feature extraction ability of CNN.

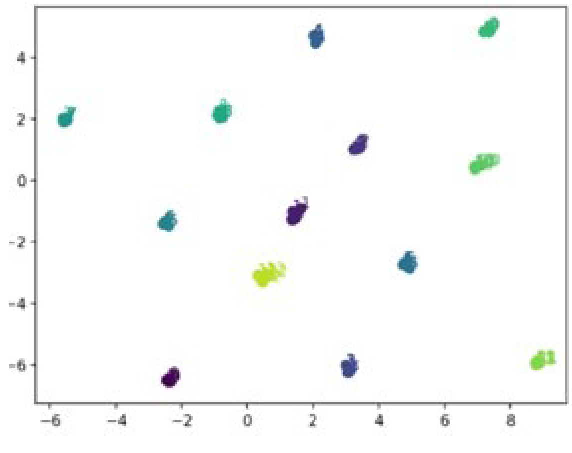
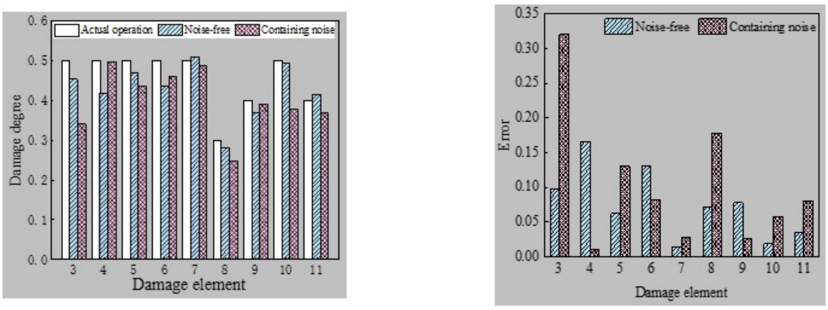


Figure 8 Result of t-sne dimensionality reduction

6 Analysis of Damage Degree Identification Results

Considering the randomness of the prediction of CNN, this paper takes the average value of the prediction results with the same actual damage location and damage degree to obtain the average accuracy of the CNN degree prediction. Figure9(a) compares the noisy CNN damage prediction results with the noise-free CNN damage prediction results under four damage conditions (0%, 30%, 40%, 50%) mentioned above, and Figure9(b) compares the CNN prediction errors based on two different kinds of data.

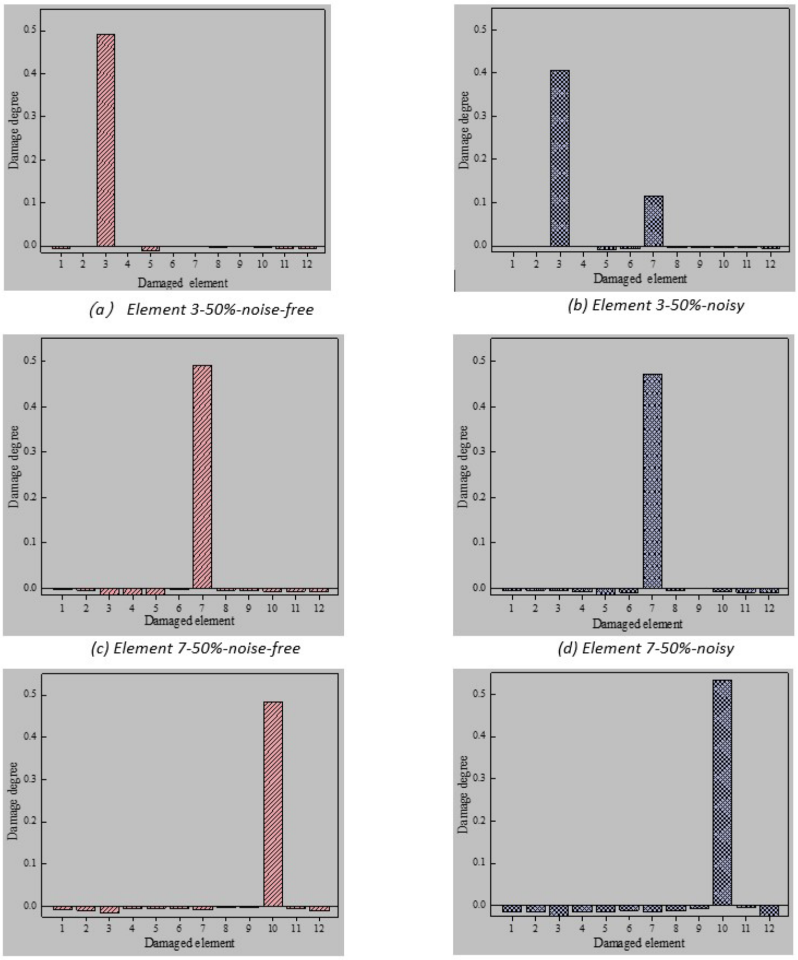


(a) Comparison of damage prediction *(b) Comparison of damage prediction errors*

Figure 9 Comparison of damage prediction and damage prediction errors

It is seen from Figure 9 that: (1) When the damage prediction is based on the CNN with noise-free data, the prediction error of the other elements is less than 15% except Element 4(16.63%). indicating that the CSAT damage identification is ideal; (2) When the CNN based on noise data is used to predict the damage, the prediction error of Element 3 and Element 8 is more than 15%, and the prediction error of other elements is less than 15%, which can also meet the actual needs in engineering; (3) The prediction effect of noise-free CNN is better than that of noisy CNN.

The average accuracy verifies the effectiveness of the CNN in identifying the damage degree. However, the average accuracy only analyzes the prediction of the damaged element by the network, which cannot reflect the prediction of the undamaged element. Therefore, this paper extracts the output layer data of the CNN, and selects three kinds of elements including the mid-span element (Element 7) and the two-side span elements (Element 3 and Element 10) to analyze the specific prediction effect of the CNN on each element under the damage condition. The prediction effect of CNN on each element of the damage condition is shown in Figure 10.



(a) Element 3-50%-noise-free *(b) Element 3-50%-noisy*

(c) Element 7-50%-noise-free *(d) Element 7-50%-noisy*

(e) Element 10-50%-noise-free *(f) Element 10-50%-noisy*

Figure10 Detailed identification result of damage degree

Figure 10 shows that: (1) CNN can better predict the damage degree of each member element. In the prediction results of the two types of CNN, the predicted damage degree of non-damage elements is far less than that of damage elements, and the damage degree predicted by most non-damage elements is close to 0, which can be judged as non-damage. (2) Since the constraints of the left span (fixed hinge support) and the right span (sliding hinge support) are different, the damage prediction results of the left span Element 3 are different from the right span Element 10 at its symmetric position. (3) CNN has different damage identification accuracy for bar elements at different positions. The noise-free CNN of Figure 10 (a) (c) (e) show that the prediction accuracy of the left-span Element 3 is the best, the prediction accuracy of the right-span Element 10 is the second, while the prediction accuracy of the mid-span Element 7 is the lowest. The noisy CNN of Figure 10 (b) (d) (f) show that the prediction accuracy of the mid-span Element 7 is the best, the prediction accuracy of the right span Element 10 is the second, and the prediction accuracy of the left span Element 3 is the lowest.

7 Conclusion

In this paper, a fusion damage identification method based on CNN is proposed to identify the CSAT damage. Based on the two identification targets of CSAT damage location and damage degree, two CNN prediction models were established to predict the noise-free time domain data and the noisy time domain data respectively. The two prediction models were applied in the following way: the damage location prediction model output the damage location identification results, and then the damage degree prediction model output the damage degree identification results. The main conclusions are as follows:

(1) The damage location prediction model can accurately identify the damage location of CSAT. Moreover, the prediction accuracy of the damage location prediction model with noise is higher than that of the prediction model without noise, which also indicates that the damage location prediction model has good robustness.

(2) The damage degree prediction model without noise can effectively identify the damage degree of CSAT. And the damage degree prediction error of damage degree prediction model with noise is less than 15% for each CSAT unit, which can meet the needs of engineering practice.

(3) The fusion damage identification method of CSAT based on CNN is effective. CNN not only has good prediction effect on bar elements, but also has different damage identification accuracy for bar elements in different positions.

This paper mainly calculated and studied the single damage of CSAT. Considering that the CSAT is a complex structure with complex forces, further research can be conducted in the future on the case of multiple damages occurring simultaneously in CSAT.

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