Research on the Health Detection of Spatial Grid Structures Based on Deep Learning

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Abstract. With the popularization of space grid structure, the health detection of structure is an urgent problem to be solved. According to the distribution law of members and the characteristics of clear force transmission, a grid model with 29 nodes and 76 members is designed. For the model, the response time history curves of nodes are collected when the model is in good condition and some members are damaged, and the curve time history information is taken as the input vector to construct the damage information matrix. The deep learning network is established step by step by using the deep learning algorithm and trained. Through the establishment of a simplified network, the damage location and damage degree of single bar are identified. The results show that the established network can identify the health state of the structure well, and it has reference value for application.

1. Introduction

Due to the superiority of its own structure, the grid structure is widely used in various large-span building structures, but also, in the long operating time, the steel structure, bearing design loads, corrosion, and various sudden factors, will inevitably suffer damage[1]. Structural health inspection is one of the hot branches in the field of civil engineering that has emerged in recent decades. Timely and effective inspection can avoid major accidents. The dynamic fingerprint of structure[2, 3] is an inherent characteristic of the structure, in which the damage information of the structure is included. Structural health detection aims at detecting the location and extent of the damage. Combined with the development of deep learning, many universities, and research institutions at home and abroad have carried out research on this aspect[4-6].

Structural health detection was applied to aerospace in the early stage. Ibrahim et al.[7] proposed to test the modal characteristics of two systems by using the random response of the ‘generalized payload model’ and ‘space shuttle model’. This method is limited to linear structures. Brownjohn et al.[8] refined modeling of the cable-stayed bridge Safi-Link, which significantly improved the dynamic performance of the cable-stayed bridge obtained by finite element simulation. Elisa Khouri Chalouhi et al.[9] believe that it is not necessary to build a too detailed model, as long as the characteristic data in the actual structure is collected as much as possible. But for large structures, the characteristic data still needs manual screening. Pathirage et al.[10] proposed a structural damage recognition framework based on self-encoding, which defines two main components, namely dimensionality reduction and relationship learning. Pathirage conducted numerical simulation and experimental research on steel frame structures and verified the accuracy and effectiveness of the method. Xiao Shumin[11] identified the damage of the bridge structure based on the wavelet neural network method. She divided the entire bridge deck into blocks of units and then identified the coordinates of the units. With
increasingly cheap computing power, deep learning algorithms also try to build larger and more complex networks than traditional neural network algorithms to solve more complex problems. However, with the increase of the network and the amount of data used by it, it will also increase the amount of network redundancy to put the data of the entire structure in the same network, resulting in a waste of space.

In this paper, ANSYS APDL is used to analyze the transient state of the established model. Then the node displacement response time history curve is obtained, from which the corresponding node damage characteristics can be reached. Taking the node damage characteristics as indicators, the damage sample space can be established. After dividing the training sample and the test sample, the regional network training is applied. Finally, the established model will experience health detection with network pattern recognition.

2. Neural Network Algorithm

2.1. Radial basis function network algorithm
Radial basis function (RBF) network algorithm is an algorithm based on radial basis function, the characteristics of which are simple structure, fast convergence, simple input, and can approximate arbitrary nonlinear functions. RBF network structure diagram is shown in Fig. 1.

Fig. 1 RBF network structure diagram

The general RBF functions is recorded as:

\[ \Phi(x, y) = \phi(||x - y||) \]  

In the above formula, \( ||x - y|| \) refers to the Euclidean norm. Stein and Sweiss defined that the RBF network should meet:

\[ \text{If } ||x_1|| = ||x_2||, \text{ then } \Phi(x_1) = \Phi(x_2) \]  

Therefore, the change of the function value of RBF is only related to the norm of the independent variable.

2.2. Regularization of radial basis function networks
The RBF network is generally a regularized network. The general representation of the basis function is shown in Fig. 2. For a regularization problem, the solution is generally given as:

\[ F(x) = \sum_{i=1}^{N} \omega_i G(x, x_i) \]
In the above formula, \( G \) represents the Green function, and \( \omega_i \) represents the weight. The number of the input vectors \( X_\) of the sample is named as \( M \); The number of neurons \( \Phi \) is \( N \); \( X_k \) is the \( k \)-th input vector; \( X_i = [x_{i1}, x_{i2}, ..., x_{im}] \) denotes the center of the basis function; \( j \) is the number of output units, and the actual output vector \( y \) is set as \( Y_k = [y_{k1}, y_{k2}, ..., y_{kj}, ... y_{kJ}] \). Under these suppositions, when the training sample \( X_k \) is input, the \( y_{kj} \)-th result of the RBF network is:

\[
y_{kj} = \sum_{i=1}^{N} w_{ij} \phi(X_k, X_i), j = 1, 2, ..., J
\]

(4)

Generally, the Green function is selected as the basis function of RBF. The Gaussian function is a special Green function, that is, \( \phi(X_k, X_i) \) can be expressed as:

\[
\phi(X_k, X_i) = G(X_k, X_i) = G(||X_k - X_i||) = \exp \left( -\frac{1}{2\sigma^2} ||X_k - X_i|| \right)
\]

(5)

Fig. 2 shows the basic function curve of \( y = e^{-x^2} \), where the interval of \( x \) is \([-10, 10]\). It can be seen that the closer to the center, the steeper the curve. When the input \( x \) is farther away from the center, its influence on the curve will decrease rapidly.

![Fig. 2 Basis function curve](image)

2.3. Establishment of radial basis function network

This article uses the Newrbe function in the Matlab toolbox as the core to train the network. Assuming the number of poles is \( N \), \( X_i \) represents the \( i \)-th pole, and the stiffness is divided into \( K \) types by itself. In this paper, the \( K \) types of stiffness under the \( X_i \)-th pole is separately trained as a network, denoted as \( \text{net}_i \). So, the \( \text{net} \) of each pole obtained are isolated from each other. In other words, a total of \( N \) networks can be obtained in a single-pole training. Due to a large number of networks but a small number of \( P \) in a single network, the newrbe function is selected to establish the network after considering the cost of time and space.

3. The establishment of grid structure model and acquisition of time history curve

3.1. The establishment of grid structure model

ANSYS APDL was used for numerical simulation analysis. The poles are steel pipes with an outer diameter of 48mm and a wall thickness of 5mm and the stiffness loss is controlled by section loss. The material parameters of the steel pipe are: elastic modulus \( E = 210Gpa \), poisson's ratio \( \mu = 0.3 \), with the density of \( 7850 \text{ kg/m}^3 \). The model is shown in Fig. 3, and the node number is shown in Fig. 4.
3.2. The acquisition of time history curve

Steady-state sinusoidal excitation (Fig. 5) is used for the Y direction of node 2. The exciting force frequency is 20Hz and the sampling frequency is 200Hz. In addition, 3% Gaussian white noise conforming to the normal distribution is added as interference. The added noise is treated as follows:

\[ \bar{x}_i = x_i (1 + \varepsilon \beta) \]  

In which, \( \bar{x}_i \) is the displacement response time history of the node after adding noise; \( x_i \) is the time history of node displacement response without adding noise; \( \varepsilon \) is the white noise; \( \beta \) is the size of the added white noise.

4. Network training

4.1. The working condition setting

Assuming that the stiffness of the four columns does not change, a damage condition is set every 10% from 0% to 100%. There are \( 72 \times 11 = 792 \) working conditions. The damage state is represented by 0 and 1, in which 0 is the complete damage state, and 1 is the undamaged state.
4.2. The identification results
Table 1 represents the damage detection error of some poles, and the box font shows the poles which are far away from the applied load.

| Pole position | Node | result | Degree | Error value | Pole position | Node | result | Degree | Error value |
|---------------|------|--------|--------|-------------|---------------|------|--------|--------|-------------|
| 25% stiffness loss | 1 | 1 | 0.7483 | 0.17% | 18 | 2 | 2 | 0.7512 | 0.12% | 24 | 24 | 0.7536 | 0.36% |
| | 15 | 15 | 0.7468 | 0.32% | 25 | 25 | 0.7566 | 0.66% | F |
| | 16 | 16 | 0.7361 | 1.39% | 46 | 17 | 17 | 0.7522 | 0.22% | |
| | 17 | 17 | 0.7516 | 0.16% | 15 | 15 | 0.7438 | 0.62% | 63 | |
| | 18 | 18 | 0.7510 | 0.10% | 25 | 25 | 0.7528 | 0.28% | |
| 55% stiffness loss | 1 | 1 | 0.4504 | 0.04% | 18 | 2 | 2 | 0.4505 | 0.05% | 24 | 24 | 0.4509 | 0.09% |
| | 15 | 15 | 0.4373 | 1.27% | 25 | 25 | 0.4514 | 0.14% | 2 | 2 | 0.4505 | 0.05% |
| | 16 | 16 | 0.4254 | 2.46% | 46 | 17 | 17 | 0.4574 | 0.74% | |
| | 17 | 17 | 0.4490 | 0.10% | 15 | 15 | 0.4412 | 0.88% | 63 | |
| | 18 | 18 | 0.4468 | 0.32% | 25 | 25 | 0.4475 | 0.28% | |
| 85% stiffness loss | 1 | 1 | 0.1546 | 0.46% | 18 | 2 | 2 | 0.1514 | 0.14% | 24 | 24 | 0.1377 | 1.23% |
| | 15 | 15 | 0.4042 | 25.42% | 25 | 25 | 0.1457 | 0.43% | 2 | 2 | 0.1112 | 3.88% |
| | 16 | 16 | 0.3835 | 23.35% | 46 | 17 | 17 | 0.1397 | 1.03% | |
| | 17 | 17 | 0.1230 | 2.70% | 15 | 15 | 0.1788 | 2.88% | 63 | |
| | 18 | 18 | 0.1140 | 3.60% | 25 | 25 | 0.1664 | 1.64% | |

There are prediction deviations in the prediction of pole 12. When 85% of the stiffness is lost, the prediction of pole 12 is always inaccurate. In the process of neural network debugging, the deviation of pole 12 is large all the time. However, pole 1, which is center-symmetrical with pole 12, can have multiple neural networks by changing the position of the load applied to it to eliminate the influence of error.

5. Conclusion
This article, based on deep learning, analyzes a common grid structure. We simulate the response time history signals under different damage conditions and establish the damage feature matrix. The conclusions are as follows after constructing the input vectors and training the deep learning network.

- The simulation results of the grid structure show that it is feasible and effective to collect node response time history curves for in-depth training based on a dynamic test, which can solve the health detection problem of space grid structures.
- The results show that there is a positive correlation between the damage degree and the detection results: the more serious the damage, the better the detection results.
- For the low sensitivity of some poles, especially when the grid structure becomes larger and the number of poles increases geometrically, multi-point load can be applied to reduce the negative impact.
References

[1] Su Xin, (2015) Analysis of current situation and development trend of Civil Engineering. Urban construction theory research, 5: 505-507.

[2] Guo Xongjun, Wei Xiansheng, (2015) Analysis of steel structure detection and reinforcement measures. Urban construction theory research, 5: 1652-1655.

[3] Papaleo Elena, Renzetti Giulia, (2013) Dynamics fingerprint and inherent asymmetric flexibility of a cold-adapted homodimeric enzyme. Biochim Biophys Acta, 1830: 2970-2980.

[4] Yang, E.C., Li,Y.H., Zhao, X., (2014) Vibration characteristics analysis of cracked beams based on energy method. Water resources research. 50: 8845-8867.

[5] Liu Peng, Liu Hongjun, Lin Kun. (2016) Free transverse vibration analysis of tapered Bernoulli-Euler beams based on spline finite point method. Journal of vibration and shock. 35: 66-73.

[6] Ma Aimin, Zhang Zhijun, Li Qun, (2018) Dynamic fingerprint damage identification method for cracked beams based on the continuous bending stiffness model. Chinese journal of applied mechanics. 36: 18-25.

[7] Ibrahim, S.R., (2012) Random Decrement Technique for Modal Identification of Structures. Journal of Spacecraft & Rockets. 14: 696-670.

[8] Brownjohn, J. M. W., Xia, P.Q., (2000) Dynamic Assessment of Curved Cable-Stayed Bridge by Model Updating. Journal of Structural Engineering. 126: 252-260.

[9] Chalouhi, E.K., Gonzalez. (2017) Damage detection in railway bridges using Machine Learning: application to a historic structure. Procedia Engineering. 199: 1931-1936.

[10] Nadith, P.C.S., Li, J., (2018) Structural damage identification based on autoencoder neural networks and deep learning. Engineering Structures. 172: 13-28.

[11] Xiao Shu min, Yan Yun ju, Jiang Bo lan, (2016) Damage Identification for Bridge Structures Based on the Wavelet Neural Network Method. Applied Mathematics and Mechanics. 037: 149-159.