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Research on Building Quality Evaluation Method Based on Association Rule Algorithm and Neural Network

Liangjun HUANG, Zuliang ZHANG, Nadan DING, Yanpeng LI*, Yirong HUANG

Abstract: Based on the fusion of association rule algorithm and neural network, a modal parameter damage detection method for building engineering structures is proposed. The frequent item sets in the historical operation data are mined through the decision tree model, and the damage identifiers are constructed by combining the vibration mode analysis as the feature input of the neural network to achieve the accurate identification of the location and degree of structural damage. A modal parameter extraction and recognition model was designed, and a collaborative correction mechanism of local substructure association rules and neural networks was proposed, significantly improving the efficiency of damage detection. Experiments show that when the amount of alarm data is small, the speedup ratio of this method differs less from that of traditional methods. With the increase of data volume, the speedup ratio under the collaborative correction mechanism has increased to 3.89/5, and the recognition error is less than 3.36%, verifying its efficiency and robustness in large-scale scenarios. However, the performance limitation problem in small data scenarios still needs to be optimized. In the future, the applicability can be expanded through transfer learning or data augmentation techniques. This research provides a technical path with high precision and high response speed for the health monitoring of building engineering structures. However, in practical applications, it is necessary to balance the data scale and computational efficiency.

Keywords: association rules; building engineering; neural network; structure inspection

1 INTRODUCTION

Since the vibration characteristics of the structure (such as the natural frequency and mode of the time-history response, etc.) are functions of the physical parameters of the structure (such as stiffness and mass), the changes in the vibration characteristics of the structure are analyzed and treated through observation [1]. With the rapid development of computer technology and the progress of signal processing technology of sensor technology, dynamic test signals can be analyzed and processed accurately and quickly. Therefore, in recent decades, damage detection of civil engineering based on structural dynamic response has become a research hotspot at home and abroad.

The core technology of structural damage detection is pattern recognition. The traditional pattern recognition technology is difficult to solve the problems of multiple damage combination explosion and pattern distortion caused by noise. The neural network itself has the ability of pattern matching and memory, and the effect of pattern recognition with certain noise is better. If a component of the covariance matrix in the pattern category is represented by a weight of the neural network, the damage detection of pattern recognition can be realized by using the neural network [2]. Neural network describes the measured data with Bayesian probability method, so PNN is applied to the damage detection of complex structures under noise conditions [3, 4], and the use of PNN requires a large number of data and feature vectors, which makes the network need to process a large number of data in pattern matching, affecting the real-time monitoring of structural health, and cannot guarantee the best recognition effect. Generally, the damage identification method based on mathematical model is as follows: construct an objective function, and obtain the minimum value of the objective function under the condition of satisfying constraints to achieve the identification of structural damage, that is, optimize the solution of structural parameters. For the state detection of civil engineering, many experts and scholars have done certain research, using the historical data and current operation data of civil engineering metrology equipment [5], and comprehensively evaluating various parameters of the equipment through deep learning model in the fault warning knowledge base, so as to obtain the condition optimization solution of civil engineering in operation with various algorithms. However, these algorithms consume time, cannot realize the real-time identification of structural damage, and the calculation results may be unstable in the case of more degrees of freedom. In recent years, artificial neural networks have been widely used in civil engineering damage identification. The relationship between structural damage and structural mechanical properties is established by using neural networks to identify structural damage. Get the main attributes of the differentiated state and improve the detection process. However, in the early stage of differentiation of civil engineering, when the alarm information is small, the performance of the detection method is not perfect. Therefore, a differentiated structure detection method of civil engineering based on association rule mining and neural network is designed.

2 RELATED WORK

At present, the international research on structural fault diagnosis mostly focuses on the level of damage identification, and damage location is the core of structural fault diagnosis, but also the difficulty of the problem. The calibration and evaluation of damage degree is usually the purpose of fault diagnosis of engineering structure, and is the basis of structural integrity assessment and maintenance decision. Traditional NDT techniques include acoustic reflection and ultrasonic method, radiography, X-ray method, eddy current method, magnetic field method, thermal field method, isotope method and visual method. The biggest shortcoming of these methods is that they require to know in advance the area where the damage occurs and are able to reach the detection area, while they are powerless to close the area that cannot be reached by human resources [7]. The method was initially developed in the fields of machinery, aviation, military and ocean engineering, and some of the research results have been successfully applied. The change information of structural vibration characteristic parameters or response parameters before and after damage can be obtained.

Crack detection was carried out on concrete surfaces with strong light spots and shadows [9]. VGG deep learning network is used to detect and identify building cracks [10, 11]. A feature pyramid and a hierarchical propulsion module are designed to extract the rich semantic information of road pictures. The model was evaluated on multiple crack data sets, and the results of the most advanced crack detection, edge detection and semantic segmentation methods at that time were compared [12], which proved that the convolutional neural network technology could effectively segment road cracks. A two-stage model based on deep convolutional neural network (DCNN) was developed to automatically identify the crack length of asphalt pavement [13]. Since tunnel images are very challenging due to the presence of a lot of noise, automated and accurate methods for monitoring tunnel surfaces can effectively improve safety and reduce potential costs [14]. A dataset of 60,000 tunnel crack images was established, and a deep learning algorithm U-CliqueNet based on U-Net and CliqueNet convolutional neural network was proposed for tunnel crack segmentation [15]. The MIoU obtained through testing on the constructed dataset was 86.96%, which was higher than that of classical networks such as fully convolutional networks, UNet, encoder and decoder networks, and the multi-scale fusion crack detection (MFCD) algorithm [16]. The Faster R-CNN (Region-based Convolutional Neural Network) target detection method is used to automatically cut out the crack region, and UNet network is used for crack segmentation to realize the location and segmentation of tunnel cracks [17]. An end-to-end model based on SSENets was proposed to detect bridge cracks, and the detection accuracy rate reached 97.77% [18]. The UAV is used to approach the bridge to collect the image of the bridge crack [19], and the bridge crack detection is carried out based on the Mask-RCNN algorithm, with an accuracy of 92.5%. Fatigue crack of steel structure is a type of damage caused by repeated load and deformation effect [20]. Effective and timely fatigue crack detection can support the condition assessment of existing structures, asset maintenance and management, and improve the life cycle. Unet semantic segmentation network is combined with post-image processing technology [21] to realize the identification and segmentation of fatigue cracks of steel structures.

At present, data mining has been widely used in various fields, and the direction of mining methods is also very wide. The research on knowledge discovery methods has been further developed, for example, Bayes method and decision tree method have become mainstream data mining technologies [22]. The development of statistical regression method and the combined application of association rules is a new attempt, and has obtained good results. At the same time, the close combination of association rule algorithm and database model makes the research of data mining technology more precise and targeted. In terms of application and tool use: the types and functions of association rule software and tools used in the market continue to increase [23]. If each parameter to be identified is changed and combined directly, the following consequences will be caused [24]. The number of training samples is huge, and the formation of training samples requires a large number of forward problem analyses and a huge amount of calculation. There are many input and output nodes in the network, the network structure is complex, and the convergence is difficult. Therefore, for complex structures, the two-stage method is adopted for damage identification [25]: in the first stage, the damage index is used to identify the possible damage unit, and in the second stage, the neural network is used to identify the damage degree of the damage unit. Then, the substructure method is used to reduce the number of parameters to be identified [26]: The whole structure is divided into substructures, the substructure that may be damaged is prejudged, and then the substructure is identified for damage. Or it directly identifies the damage of each substructure. The structure to be identified is divided into sub-regions [27].

3 RESEARCH ON BUILDING STRUCTURE INSPECTION ALGORITHM BASED ON ASSOCIATION RULES ALGORITHM

3.1 Structural Damage Identification Method Based on Association Rule Modification

The change of structural stiffness parameters before and after damage is identified by association rule model modification method. The damage identification process based on association rule model modification is divided into two stages, and the specific process is shown in Fig. 1.

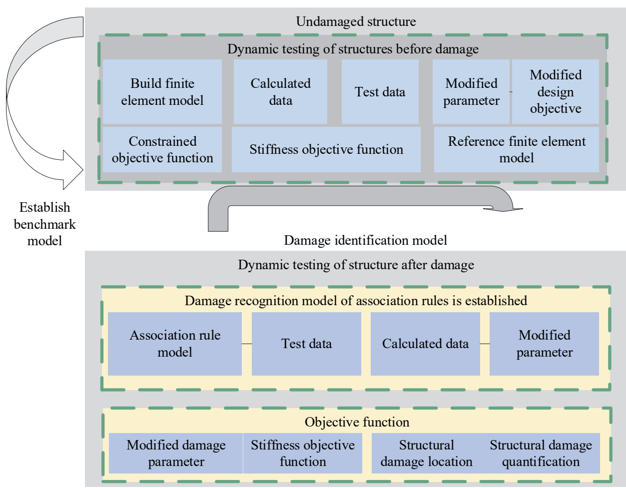

Figure 1 Damage identification process based on association rule model modification

The first process is to establish the association rule model in the undamaged state, that is, the benchmark model. The initial association rule model could not accurately reflect the characteristics of the real structure, so it is necessary to modify the material parameters, section size and constraint conditions to avoid the impact of the initial modeling error on the damage identification results in the second process. When the association rule model of the first process is corrected, the corrected model is used as the accurate association rule model of undamaged state structure. In the second process, since the structural mass constraints have been corrected in the first process, it is believed that only damage causes stiffness changes, and other factors remain unchanged. Therefore, the element stiffness is taken as the parameter to be modified.

3.2 Association Rules Mining Algorithm and its Improvement

1) Support degree of association rules in:

$$\sup(X-Y)=\text{count}(X\cup Y)/\|T\| \tag{1}$$

count(X) represents the number of occurrences of item set X in T, and $\|T\|$ is the total number of transaction database records. The minimum support is the user-set support threshold, referred to as Minsupport. Ievery element in the K-order item set has a support greater than the minimum support, then the set is the frequent item set L_k.

2) Confidence C of association rules in: C is the ratio of the number of association rules X-Y in T to the number of association rules Y, that is:

$$C\%=\text{confidence}(X-Y)=P(X\cup Y)/P(X) \tag{2}$$

When the association rule algorithm checks whether the candidate item set is frequent item set, it needs to scan the entire database. When the amount of data is too large, the database is scanned too many times. The algorithm of association rules is improved. In the process of generating L_k from candidate set C_k, the transaction set is compressed. Transactions that do not contain frequent items in the last iteration are skipped in this iteration. The improved association rule model algorithm is shown in Fig. 2.

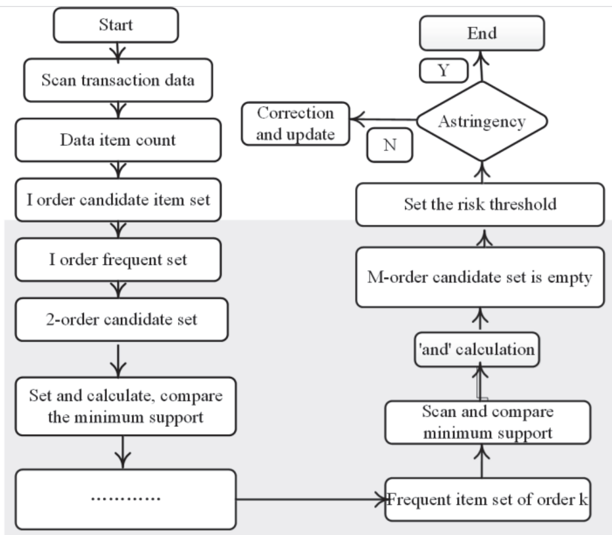

Figure 2 Mining steps of association rules civil structure detection algorithm

Starting from scanning the transaction data, count the occurrence times of individual items and generate the first-order candidate item set, and screen out the first-order frequent item set by comparing the minimum support degree. Subsequently, high-order candidate item sets (such as 2nd order and M order) are generated layer by layer based on low-order frequent item sets. The support degree is calculated and screened in a loop until no new candidate item sets can be generated and the process is terminated. During the process, branch judgment (Y/N) is used to determine whether to continue the iteration or enter optimization steps such as modifying parameters (such as adjusting support, setting risk thresholds), and finally output frequent item sets of each order, laying the foundation for association rule mining. Its core logic is to efficiently mine frequent patterns that meet the conditions through layer-by-layer iteration and pruning.

The Notations used in this article are shown in Tab. 1 as follows:

Table 1 Notations

Notation	Meaning
l	particle label
C_1	learning factors
p, X	motion vector
V	particle velocity
I	data set
D	Transaction inventory
T	time step size
RC	number of transaction

This model mainly compresses the information related to alarm database and association rule mining. Frequent alarm sets in different data are of different importance to fault analysis. Therefore, some correlation exists among alarm sets. When one alarm set is detected, you can troubleshoot the other alarm set. The optimized decision tree is used to parallelize the end of multiple branches to obtain the frequent alarm set. The mined data set based on the operation of civil structure equipment is in a dynamic equilibrium state with a large amount of data, so it is necessary to carry out recursive calculation of particles in the decision tree model in the association process:

$$V_i^{k+1}=V_i^k+c_1\times r_1(p_i^k-X_i^k) \tag{3}$$

In the Eq. (l) is the particle label in the decision tree model. After k iterations, the current particle velocity can be obtained through the particle state and learning factors c1 and r in the previous period. p and X are motion vectors in the particle motion process and exist:

$$X_i^{k+1}=X_i^k+V_i^{k+1} \tag{4}$$

Since there are a lot of project status data during the operation of the equipment, the data set of all projects is represented as:

$$I=\{I_1,I_2....I_k\} \tag{5}$$

Transaction inventory at:

$$D=\{T_1,T_2....T_n\} \tag{6}$$

All items in the transaction library form a data set, and any item in the transaction library can be written as:

$$T_i=\{I_{i1},I_{i2}....I_{ik}\} \tag{7}$$

I represents the number of iterations, the dimension of hidden layers, the intensity of regularization, etc. T may represent the time step size, temperature parameters (such as simulated annealing), the learning rate decay coefficient, etc. By traversing different parameter combinations and cross-validation, the optimal value is selected. In the mining process, the number of transaction repeats RC in the transaction database is calculated, and its value is defined as:

$$RC = \begin{cases} RC+1, T_{sj} = T_{tj} \\ 1, T_{sj} \neq T_{tj} \end{cases} \tag{8}$$

According to the above mining algorithm, abnormal data in the target transaction database can be detected, differentiated data can be screened, and the results of differentiated state detection of excavated wooden structures can be further displayed.

The original data with alarm content about the differentiation of civil structure is selected from the historical database of civil structure. After processing, partial samples of alarm data about the differentiation of civil structure are obtained, as shown in Tab. 2.

Table 2 Pre-processing results of differentiated data of civil structure

Alarm content	Alarm severity	weight
Temperature anomaly	importance	0.096
Connection exception	exigency	0.088
Speed anomaly	importance	0.162
Communication error	exigency	0.161
The signalling point is unreachable	importance	0.187
Forbid transmission	importance	0.081
Overpower	exigency	0.138

The differentiated state detection method of civil structure based on association rules mining T and the traditional detection method are used respectively. Since association rule mining C is used in the detection method designed in this paper, it belongs to parallel mining method and is a linear variable, and the linear acceleration ratio is:

$$R = \frac{T_q + c_1}{T_s + c_2} \tag{9}$$

The test results of the acceleration ratio of the two methods are shown in Tab. 3.

Table 3 Acceleration ratio of the two detection methods

Number of civil structure equipment	Ideal acceleration ratio	Alarm quantity	Acceleration ratio of the method in this paper	Differential state detection method acceleration ratio
30	3	5000	1.89	1.14
		10000	1.88	1.45
		50000	1.78	1.57
		80000	1.95	1.78
40	4	5000	2.76	1.87
		10000	2.78	2.24
		50000	2.87	2.65
		80000	2.89	2.87
50	5	5000	3.78	2.76
		10000	3.87	3.34
		50000	3.82	3.65
		80000	3.89	3.87

As can be seen from the detection results in Tab. 2, when the amount of alarm data is relatively small, the acceleration ratio of the differentiated status detection method has a large deviation from the ideal value, and the system overhead has little difference with the running time of the differentiated status detection method, resulting in a low acceleration ratio. As the amount of alarm data increases, the proportion of system overhead decreases. The acceleration ratio can be approximately regarded as the ratio of the running time of the detection method in a networked experimental environment to the running time of a single machine. However, the differentiated state detection method of civil structure based on association rule mining designed in this paper can be used without restriction and interference when the number of alarms is small, and it is closer to the ideal acceleration ratio.

4 STUDY ON ASSOCIATION RULES AND NEURAL NETWORK COLLABORATION IN CIVIL ENGINEERING STRUCTURE INSPECTION MODEL

4.1 Damage Identification of Civil Structures Based on Natural Frequency Variation

The basic motion equation of civil structure can be expressed as:

$$(K - wM)\theta = 0 \tag{10}$$

where M is the mass matrix of the structure, K is the sum stiffness matrix, and w is the frequency.

$$(K + \Delta K) - (w^2 + \Delta w^2)(M + \Delta M) = 0 \tag{11}$$

When the structural damage occurs, the change of the first order frequency Δw is related to the change of the structural stiffness matrix K ΔK and the position parameter r where the damage occurs. The formula is as follows:

$$\Delta w_i = f_i(\Delta K, \theta) \tag{12}$$

Under the condition of no damage, it can be considered that the change of stiffness is zero, and when the structure is without damage, it can be considered that the structure is without damage, and it can be obtained:

$$\Delta w = f_i(0, \theta) + \Delta K \frac{\partial f_i}{\partial \Delta K} \tag{13}$$

Damage identification of structures is a process of using mathematical models to establish and describe physical systems. Some characteristics of structures that suffer different degrees of damage often change. The occurrence of damage at a certain location leads to changes in certain characteristics of the structure, which can be used as specific damage indicators. The finite element method can be used to calculate the change of damage index caused by different damage and save it in the database system. The damage can be identified by comparing and matching the change of measured damage index with the change of possible damage index stored in the database. The training stage is the process of establishing the damage pattern database, and the inspection stage is the process of matching the damage pattern.

Firstly, the global structure association rules and neural network are divided into several independent substructure models, and the vibration characteristics of the substructure models are calculated. Then, the physical parameters of the substructure were adjusted through the optimization process to make the vibration characteristics of the overall structure consistent with the measured structure test data, so as to achieve damage identification (as shown in Fig. 3). The vibration characteristics used to modify the association rules and neural networks include frequency domain characteristics (frequency, mode, frequency response function, etc.) and time domain characteristics (acceleration, displacement, etc.).

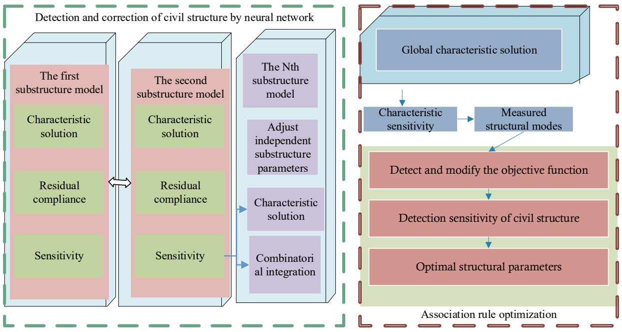

Figure 3 Flow chart of civil structure model revision by neural network

4.2 Neural Network Model Weight Correction for Civil Structure Inspection

As shown in Fig. 4, the neural network is trained by using known structural damage samples to establish a functional mapping relationship between input (damage index) and output (structural damage), so that it has the ability to identify structural damage. Using trained neural network for damage recognition is the process of pattern matching.

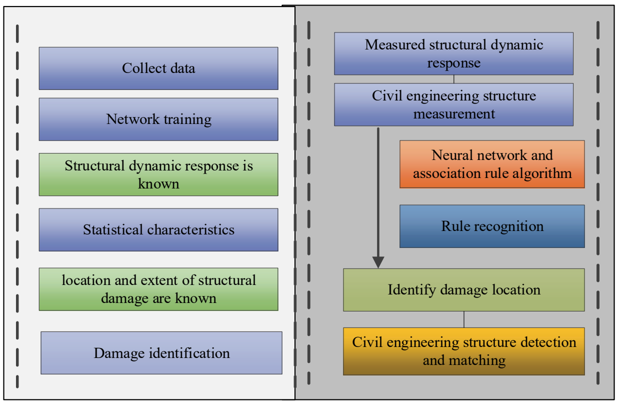

Figure 4 Structural damage identification neural network method based on statistical characteristics of structural dynamic response

For the output node:

$$\frac{\partial E}{\partial T_n}=\sum_i \frac{\partial E}{\partial O_k}\frac{\partial O_i}{\partial T_i} \tag{14}$$

E is multiple functions of O_k:

$$\frac{\partial E}{\partial O_i}=\sum(t_k-O_k)\frac{\partial O_k}{\partial O_i} \tag{15}$$

Set output node error:

$$\delta_i=(t_i-O_i)\times f(\theta) \tag{16}$$

The weight is corrected to:

$$w_{ij}(k+1)=w_{ij}(k)+\Delta w_{ij} \tag{17}$$

Firstly, the location of the damage in the continuous beam is identified, that is, on which unit of the beam the damage occurs. Then the damage degree of the damaged unit is identified. In this example, the structural damage is simulated by reducing the element stiffness, 0.1 represents a 10% reduction in the element stiffness, and so on. The structural damage degree considered in damage identification, that is, the reduction degree of element stiffness, is obtained from the following analysis. Fig. 5 shows the relationship between the change of structural dynamic response variance (normalized) and the damage degree. It can be seen from Fig. 5 that when the degree of damage is small, with the increase of the degree of damage, the input vector of the neural network does not change much. When the damage degree exceeds 0.6, with the increase of the damage degree, the input vector changes significantly. When the damage degree reaches 0.9, the amplitude of the input vector is several times that of the input vector when the damage degree is lower than 0.6. The above phenomenon will lead to the change of the input vector being covered by the change of the input vector when the damage degree is small, thereby causing the difficulty for the neural network to identify small damages and making the artificial neural network method ineffective for structural damage identification. On the other hand, the identification of minor damage in a structure is more important than that of major damage. The structure is often formed by the continuous accumulation of minor damage, and the major damage will cause significant changes in the structural properties and is easy to be found, so the identification of major damage in a structure is of little significance. Therefore, only the cases in which the damage degree of the structure is below 1.2 are considered in this example.

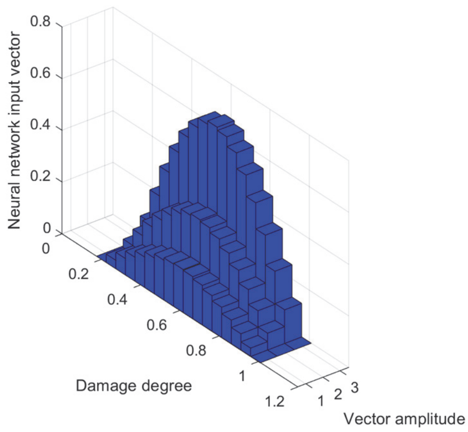

Figure 5 Relationship between variation of structural dynamic response variance and damage degree

5 SIMULATION VERIFICATION

The relevant data used in this example are shown in Tab. 4. Modal damage identification indexes and neural networks are used to identify, locate and calibrate structural damage.

Table 4 First three natural frequencies of intact plane unit

Rank	Plane element
1	244.083
2	856.572
3	1338.426

The dynamic calculation of the rectangular beam was carried out, and the damage was simulated by sawing the notch of 5, 10, 15, 20, 25, 30 mm in depth and 12 mm in width at 100 mm, 200 mm, 300 mm and 400 mm of the rectangular beam respectively. The data in Tab. 5 are the first 5 natural frequencies w of the simply-supported beam at different damage locations and different damage degrees.

Table 5 Damage condition table

Damage location	Damage size	Phase one w_1	Stage two w_2	Stage three, w_3	Stage four w_4	Stage five w_5
		234.1	855.23	1348.4	2133.1	3409.5
100	5	233.97	852.34	1345	2133.1	3407.9
100	10	233.07	842.48	1337.9	2131.9	3397.6
100	15	232.9	847.52	1351.8	2127.5	3372.5
100	20	231.43	829.94	1301.2	2123.9	3349.7
100	25	234.55	785.3	1378.9	2121.5	3332.1
100	30	223.75	791.65	1232	2102.7	3225 .5
200	5	233.69	851.62	1349.3	2133.4	3409.4
200	10	232.45	844.07	1349.7	2123.3	3407.1
200	15	234.56	528.62	1349.5	2126.9	3402 .8
200	20	226.34	841.98	1345.7	2117.4	3394.3
200	25	224.97	770.37	1346.4	2149.2	3383.3
200	30	216.57	744.42	1342.1	2113.7	3357.5
300	5	233.63	854.28	1349.3	2130.9	3399.1
300	10	232.34	852.17	1349.9	2127.1	3314.4
300	15	229.47	847.57	1350.2	2117.5	3321.7
300	20	225.44	744.42	1345.1	2143.9	3254.4
400	25	216.17	555.33	1349.3	2113.7	3357.5
400	30	233.4	555.5	1349.6	2123.1	3409.5
400	5	230.4	555.72	1351.1	2233.5	3448.5
400	10	217.85	855.86	1351.4	2123.7	3445.5
400	15	223.83	856.64	1351.7	1993.6	3399.8
400	20	212.16	855.87	1352.3	1846.3	3391.2

The dynamic response of the structure is obtained by three vibration pickers. In this example, the vibration pickers obtain the dynamic displacement response of the structure.

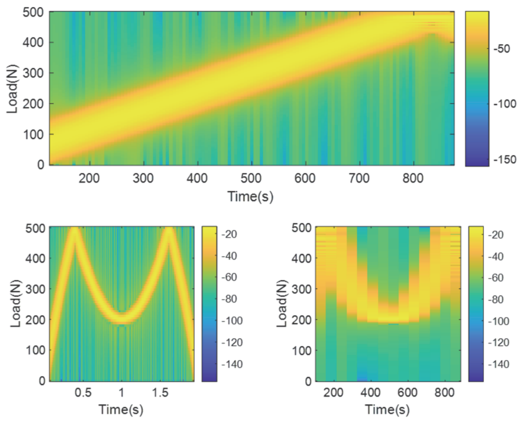

Figure 6 Random excitation of white noise input in civil structure

Fig. 6 shows the random excitation of white noise input to the structure, and Fig. 7, Fig. 8 to Fig. 9 respectively show the dynamic displacement response of the structure before and after damage obtained by the three vibration pickers.

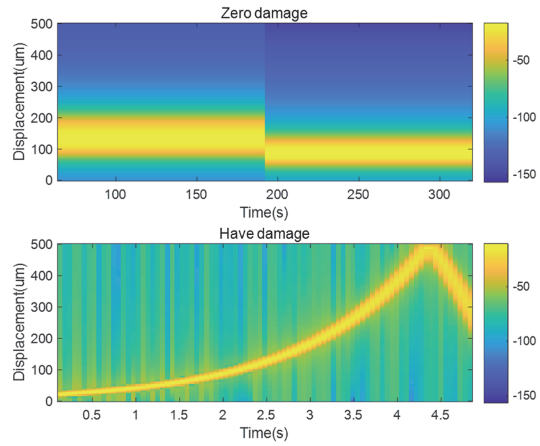

Figure 7 Dynamic displacement response of the left quarter point of the consolidated beam of civil structure

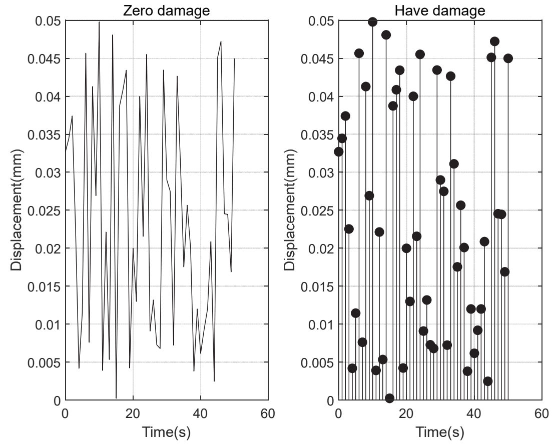

Figure 8 Mid-span dynamic displacement response of consolidated beams in civil structures

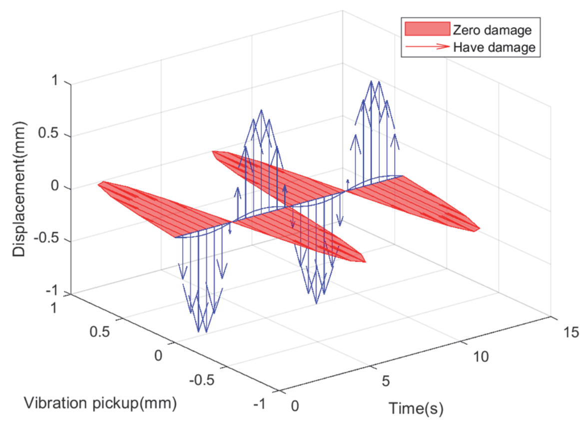

Figure 9 Dynamic displacement response of the right quarter point of the consolidated beam of civil structure

From Fig. 7 to Fig. 9, it can be seen that the dynamic response of the structure before and after damage is obviously different, which also indicates that the dynamic response of the structure is very sensitive to structural damage.

By comparing the frequencies of each order of the intact beam with those of the lossless beam, only the modal frequency changes of the beam before and after the damage at 200 mm and 400 mm are given, as shown in Fig. 10.

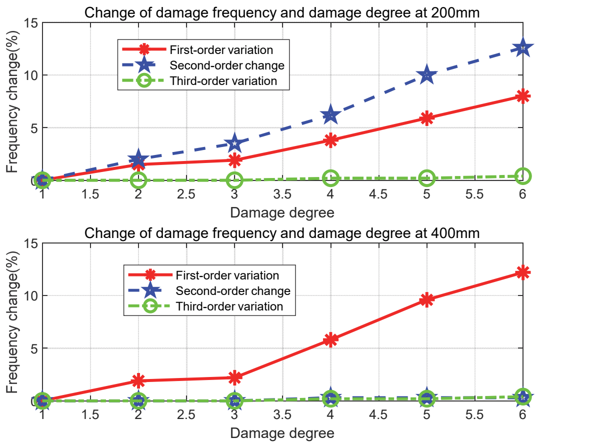

Figure 10 Relationship between damage frequency change and damage degree at 200-400 mm of civil structure

It can be clearly seen from Fig. 10 that the modal frequency changes to low frequency after structural damage, indicating that the stiffness of the structure deteriorates after damage. It can be seen from the absolute change value of modal frequency that the sensitivity of modal frequency to damage is not equal in each order. From the relative change value of modal frequency, it can be seen that the frequency change caused by damage increases nonlinearly with the amount of damage, that is, the frequency is more sensitive to large damage.

As can be seen from Tab. 6 and Tab. 7, in the recognition results, if the output is greater than 0.8, it is considered that the output value is 1. If the output value is less than 0.2, the output value is considered to be 0. Obviously, the recognition of structural damage by neural network is satisfactory. We can also see that our trained network can not only "recall" previously trained damage states, but also associate damage states that were never present in the training sample.

Table 6 Comparison of neural network training at injury sites

Association rules neural network input				Ideal output				Actual output of association rules neural network			
$\frac{\Delta w_1}{\Delta w_2}$	$\frac{\Delta w_1}{\Delta w_3}$	$\frac{\Delta w_4}{\Delta w_3}$	$\left(\frac{\Delta w_1}{\Delta w_5}\right)^2$								
0.049	0.042	0.115	740.346	1	0	0	0	0.887	0	0.112	0
0.048	0.046	0.208	950.687	1	0	0	0	0.887	0	0.112	0
0.05	0.048	0.187	708.743	1	0	0	0	0.887	0	0.112	0
0.051	0.051	0.168	500.276	1	0	0	0	0.887	0	0.112	0
0.053	0.086	0.256	194.578	1	0	0	0	0.887	0	0.112	0
0.063	−0.465	0.335	0.058	1	1	0	0	0.887	0	0.112	0
0.118	−1.612	−4.462	1.328	1	1	0	0	0.887	0	0.112	1
0.138	−2.578	−4.428	3.438	0	1	0	0	0.887	0	0.112	1
0.139	−26.76	−52.34	3.869	0	1	0	0	0.887	0	0	1
0.137	6.57	11.967	3.986	0	1	0	0	0.887	0	0	1
0.145	2.856	3.078	8.439	0	1	0	0	0.887	1	0	1
0.156	−0.543	−2.453	487.638	0	1	1	0	0.887	1	1	1
0.164	−1.18	−4.285	398.657	0	0	1	0	0	1	1	0
0.604	−2.587	−8.668	320.768	0	0	1	0	0	1	1	0
0.608	−4.134	−13.987	289.564	0	0	1	0	0	1	0	0
−2.586	−4.576	−15.39	8.453	0	0	1	1	0	1	0	0
−7.709	2.867	−15.83	0.432	0	0	1	1	0	1	0.114	0
−9.48	−3.086	3.087	0.546	0	0	1	1	0	1	0	0
−16.28	−6.674	−34.65	0.687	0	0	1	1	0	1	0	1

Table 7 Comparison of neural network tests at damage locations

Association rules neural network input				Ideal output				Actual output of association rules neural network			
$\frac{\Delta w_1}{\Delta w_2}$	$\frac{\Delta w_1}{\Delta w_3}$	$\frac{\Delta w_4}{\Delta w_3}$	$\left(\frac{\Delta w_1}{\Delta w_5}\right)^2$								
−0.265	0.048	0.045	0.076	1	0	0	0	0.883	0	0.114	0
−0.364	0.049	0.048	0.106	1	0	0	0	0.883	0	0.114	0
−25.87	−22.765	−7.347	−72.897	0	0	0	1	0.883	0	0	1

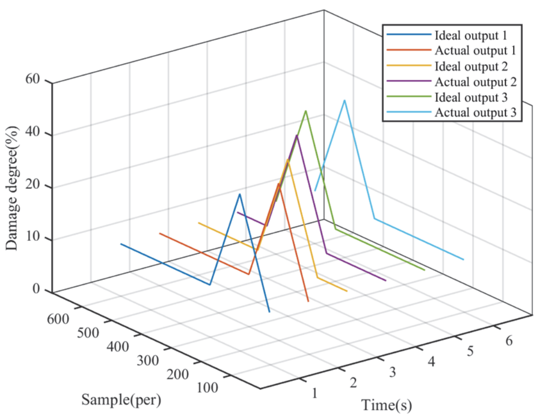

Figure 11 Comparison of association rule neural network test

Comparison of the identification of damage degree of test samples. Fig. 11 shows the comparison of neural network test. The maximum error (3.36%) occurs at the boundary of the sample space, indicating that the network has a good ability of interpolation generalization for new data in the sample space. However, for the data outside the sample space, the recognition result is not very ideal, so the training sample should contain as many damage cases as possible when applying the neural network for damage recognition.

6 CONCLUSION

This study, by integrating the association rule algorithm and neural network technology, proposes a damage detection method for civil engineering structures based on modal parameter recognition. The frequent item sets in historical data were mined by using the decision tree model, and the damage identifiers were constructed by combining the vibration mode analysis as the input of the neural network, achieving the accurate identification of the location and degree of structural damage. Experiments show that when the amount of alarm data is small, the speedup ratio of the proposed method deviates greatly from the ideal value (for example, the speedup ratio is only 1.89/3 under 30 devices and 5000 pieces of data), and the system overhead is not significantly different from the traditional method. With the increase of data volume (such as 50 devices and 80,000 pieces of data), through the collaborative correction of local substructure association rules and neural networks, the speedup ratio was significantly improved to 3.89/5, and the recognition error was less than 3.36%, verifying the efficiency and robustness of this method in big data scenarios. However, the performance limitation problem under small sample data still needs to be optimized. In the future, its applicability can be expanded by introducing transfer learning or data augmentation techniques. This research provides a technical path with high precision and high response speed for the health monitoring of civil engineering structures. However, in practical applications, it is necessary to balance the data scale and computational efficiency in combination with specific scenarios. This paper still has insufficient performance in small data scenarios. When the amount of alarm data is small, the speedup ratio of the detection method deviates greatly from the ideal value, and the system overhead is not significantly different from the traditional method, which may lead to limitations in practical applications.

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Contact information:

Liangjun HUANG
Jiangxi College of Applied Technology,
Ganzhou, 341000, China

Zuliang ZHANG
Jiangxi College of Applied Technology,
Ganzhou, 341000, China

Nadan DING
Jiangxi College of Applied Technology,
Ganzhou, 341000, China

Yanpeng LI
(Corresponding author)
Jiangxi College of Applied Technology,
Ganzhou, 341000, China
E-mail: huangliangjun_2025@163.com

Yirong HUANG
Ganzhou City Land and Spatial Planning Research Center,
Ganzhou, 341000, China