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Research article

Distributed sensors and neural network driven building earthquake resistance mechanism

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Abstract: The anti-seismic support and hanger are firmly connected to the building structure and are anti-seismic support equipment with seismic force as the main load. Real-time and accurate acquisition of the service status of the seismic support and hanger to check and judge whether the seismic support and hanger are in a normal working state is of great significance for practical engineering applications. In this paper, based on distributed sensor technology, a set of intelligent monitoring systems for seismic support and hanger of buildings is established. The sensing equipment installed on the seismic support and hanger senses the signal, and then the data collection, storage and processing are used to accurately judge the seismic support and hanger. Service performance status. To effectively fuse multi-source data in distributed sensor environment, an improved method based on wavelet and neural network data fusion is proposed. Compared with the existing methods, the experimental results show that the proposed method has good robustness. Besides, it has better performance in building seismic multi-source monitoring data fusion and is less affected by the data overlap ratio.

Keywords: building aseismicity; distributed sensors; data fusion; neural network

1. Introduction

Earthquakes have always been one of the most dangerous natural disasters affecting people's survival. Throughout history, the earthquake may be able to bring great losses to people and greatly hinder the progress and development of society. Therefore, for the development of the domestic construction industry, the reinforcement of buildings and the enhancement of earthquake resistance of buildings. It becomes a particularly important point in building design research, and strives to minimize the threat to people's life, health and property safety.

With the development of science and technology, China has formed relatively advanced technology in building masonry structure reinforcement. For example, widely used technologies include measures to increase the construction of buttress columns, increase the structure of the steel mesh -mortar layer on the outer layer of the building, wrap reinforced concrete, and increase the cross-sectional area of the masonry structure. The addition of buttress columns increases the column of stable building material, composed of reinforced concrete based on the original building, and to increase its cross-sectional area, so as to obtain a relatively large bearing capacity. This reinforcement method is simple and convenient, and the cost is also very cheap, which can further improve the bearing capacity on the original basis. But the degree of lifting is not high, so it is usually difficult to use in earthquake-prone areas. A reinforcement mesh-mortar layer is added to the outer layer of the building. This is by adding a mixed soil layer containing reinforced cement to the outside of the original building's masonry structure, making it more ductile than the original structure. At the same time, it can also strengthen its lateral stiffness.

With the increasing development of structural intelligence monitoring technology, distributed sensor technology has been applied to the field of structural health monitoring [1]. Distributed sensor technology integrates information collection, transmission and processing. Through the collected monitoring signals, it realizes signal analysis, data conversion and transmission, and automatically organizes and stores the data. Combining distributed sensor technology for structural monitoring can not only save a lot of manual detection costs, but also realize continuous and real-time monitoring, early warning and evaluation of the health status of multiple structures [2].

The function of the electromechanical anti-seismic support and hanger system is to connect the main body of the building structure with various pipelines, equipment and grooves in the building with anti-seismic design, and use the reaction force generated by the earthquake to provide support.

In view of the current application requirements of seismic support and hanger safety monitoring, this paper establishes a set of seismic support and hanger intelligent monitoring systems based on the combination of distributed sensor technology and support and hanger monitoring and early warning technology. Through the integrated application of intelligent perception, wireless and wired transmission, and identification technology, the system greatly improves the intelligence of the monitoring system, which is convenient for users to obtain the on-site performance status of the seismic support and hanger in real-time and better manage the monitoring data. Real-time monitoring, timely early warning and reasonable evaluation of the working conditions of the anti-seismic support and hanger system are realized. In order to achieve more accurate damage identification and timely early warning of the intelligent monitoring system, considering the complexity of the real environment and the actual engineering structure, this paper proposes to use a multi-sensor data fusion algorithm to fuse various index data. Specifically, an improved method based on wavelet and neural network data fusion is proposed. First, the sensor data is preprocessed. Then, the data is optimized by a combination of wavelet and BP neural networks. Finally, the data is fused using computational sensor confidence. The experimental results show that the method in this paper has better algorithm robustness and better data fusion performance on multiple indicators due to the three comparison methods.

2. Related work

2.1. Seismic resistance of anti-seismic supports and hangers and suspended pipelines

Buildings using the anti-seismic support and hanger system are less affected by earthquakes, which can effectively reduce earthquake damage, prevent secondary disasters, try to avoid casualties, reduce economic losses, and improve the safety of buildings. In recent years, some achievements have been made in the research on the seismic performance of seismic supports and hangers and suspended pipelines under earthquakes. Goodwin et al. [3,4] found through shaking table tests that setting seismic supports can effectively reduce the displacement response of the pipeline system. Hoehler et al. [5] studied the seismic performance of the seismic support and hanger under different seismic excitations, and the results showed that the load on the load-bearing hanger during the earthquake was much greater than the anchoring force of the seismic hanger. Tian et al. [6] studied the seismic performance of the pipeline system by setting different forms of supports and verified the necessity of seismic design of supports in the code.

2.2. Multi-sensor data fusion algorithm

Reference [7] proposes a privacy-preserving protocol for outlier detection by using support vector machines. Reference [8] proposes a fusion method based on the weighted fusion method to calculate node weights with the feedback trust model. Reference [9] uses the Kalman Filtering algorithm, and a new fusion scheme is proposed based on the TEEN (threshold-sensitive energy efficient sensor network protocol) routing protocol. Reference [10] considers the multivariate space-time relationship and proposes a data fusion algorithm based on multiple regression equations. References [11–13] use the Kalman filter algorithm to filter and fuse the monitoring data. Reference [14] combined the distance evaluation technology and the coupled feature selection scheme of maximum correlation and minimum redundancy to obtain the optimal feature set and proposed a scheme based on deep structure fusion of multi-sensor data. References [15,16] use the self-organizing learning ability and fuzzy logic reasoning ability of neural networks for data fusion, which improves the data accuracy. Reference [17] proposes an integrated diagnostic model based on improved evidence theory that integrates learning vectorized neural network and decision tree to solve the problem of the inability to effectively deal with evidence conflict. Through further decision fusion, bearing fault diagnosis can be achieved. Reference [18] uses rough sets and back-propagation networks to improve the precision and accuracy of multi-sensor processing data. Reference [19] proposed an adaptive fuzzy Kalman fusion algorithm to improve the accuracy of GPS (global position system) positioning data. Reference [20] proposes a multi-sensor data fusion method based on evidence-based belief divergence measure and belief entropy, which overcomes the possibility of unconventional results when fusing highly conflicting data. Reference [21] uses fuzzy sets to fuse multi-sensor data to reduce the uncertainty of sensor data. Reference [22] designs a fusion algorithm for motion control and somatosensory sensor data based on the continuous hidden Markov model. The experimental results show that the algorithm can effectively reduce the uncertainty of sensor data. On this basis, a sign language recognition framework is proposed. Reference [23] uses random finite sets to fuse multi-sensor data while predicting subsequent sensor data. The above single data fusion methods can partially achieve the purpose of fusion, but the robustness is low, and the fusion results lack stability and accuracy.

3. System design

3.1. The structure of the proposed system

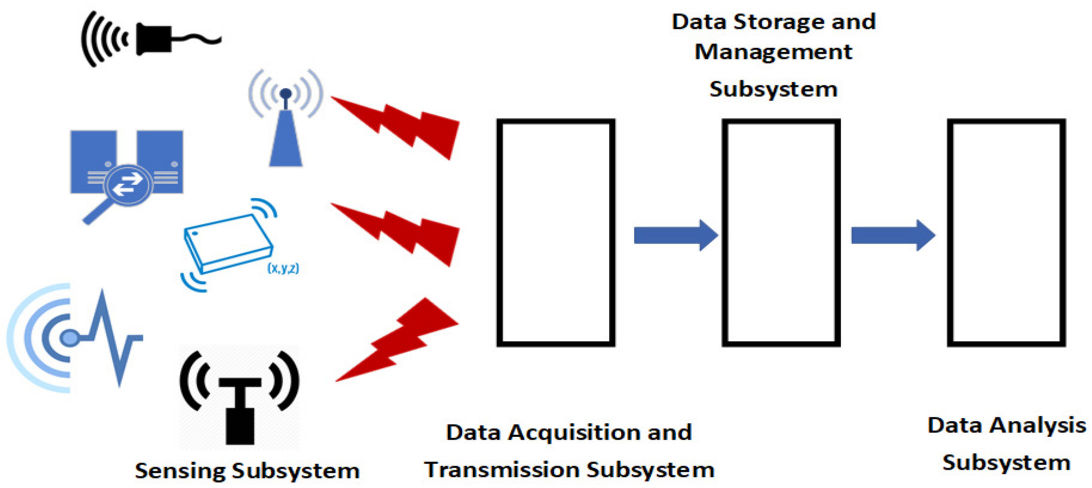

Figure 1. The Structure of The Proposed System.

The intelligent monitoring system for seismic supports and hangers of buildings should adhere to the principle of long-term planning. It should be able to provide support combined with the specific characteristics of the engineering structure for the verification of seismic performance after the installation, the early warning of damage during long-term maintenance, and the status assessment after an earthquake. The entire monitoring system should be safe and reliable, technologically advanced, economical and reasonable, and easy to maintain. The intelligent monitoring system of building anti-seismic supports and hangers based on distributed sensors is composed of four subsystems: sensor perception subsystem, data acquisition and transmission subsystem, data storage and management subsystem, and data analysis subsystem. The workflow and system architecture of this system can be shown in Figure 1. The state of the anti-seismic support and hanger will be sensed and acquired in real-time by the sensing and sensing sub-system. The acquired signals will be collected by the data acquisition and transmission subsystem and transmitted to the data center. The data center will store the data through the data storage and management subsystem. Storage management, and finally the perception information is analyzed by the data analysis subsystem. In this way, for the seismic support and hanger cluster of a certain building or building group, the information collection and interaction of real-time sensing, monitoring, connection, and interaction process are realized, and a huge distributed sensor network is formed by combining with the Internet to realize the seismic support of the building. Diagnosis and maintenance decisions for the health of the hanger.

3.2. Sensing subsystem

The sensing subsystem is primarily set up to realize the state perception of the anti-seismic support and hanger. The real-time state of the anti-seismic support and hanger can be acquired by sensing one or more sensors installed on the support and hanger. The intelligent monitoring of building anti-seismic supports and hangers should be based on specific project requirements and actual application conditions and should be based on the main principle of "complete monitoring, stable performance and optimal cost performance". The mechanical analysis results determine the necessary and reasonable monitoring location, quantity and installation method, and have good stability and anti-interference ability during the monitoring period, and the signal-to-noise ratio of the collected signal should meet the actual engineering needs. At present, for the intelligent monitoring of building anti-seismic supports and hangers, acceleration sensors and strain sensors that reflect the vibration and deformation characteristics of supports and hangers can generally be used.

3.3. Data acquisition and transmission subsystem

The data acquisition and transmission subsystem mainly use the acquisition equipment to collect the structural information felt by the sensor perception subsystem. There should be a clear topological relationship between the acquisition equipment and the sensor. According to the engineering characteristics and specific conditions of the site, two modes of centralized data acquisition and decentralized data acquisition can be selected. At the same time, the acquisition equipment should perform preprocessing such as amplifying, filtering, denoising, and isolating the signal. For different signals with large differences in the magnitude of the signal strength, the signal isolation before the acquisition should be strictly performed. Data transmission can adopt different methods such as signal-based synchronization technology, time-based synchronization technology, wired transmission, wireless transmission, etc. At the same time, the reliability, efficiency and data transmission quality of data transmission should be guaranteed.

3.4. Data storage and management subsystem

The data storage and management subsystem mainly stores and manages the data collected and transmitted by the data acquisition and transmission subsystem, and the core part of the data storage and management subsystem is the database. The database can be divided into a monitoring equipment database, monitoring information database, structural model information database, evaluation and analysis information database and user database according to the theme. The design of the database should follow the basic principles of reliability, advancement, openness, scalability, standardization and economy. At the same time, it should also ensure the sharing of data, the integrity of data structure, the unity of the database system and application system. The database system should support online real-time data processing and analysis, offline data processing and analysis, and a hybrid mode of the two working modes when used. The database functions involved in the monitoring system should include: monitoring equipment management, monitoring information management, structural model information management, evaluation and analysis information management, data dump management, user management, security management and early warning information management.

3.5. Data analysis subsystem

The data analysis subsystem is to reasonably analyze the data after sensing, acquisition, transmission and storage, and make appropriate judgments and evaluations. The data analysis subsystem is primarily aimed at three aspects: multi-source data fusion, modal parameter identification, damage identification and seismic performance evaluation of seismic support and hanger. Through the vibration monitoring data of building anti-seismic supports and hangers, structural dynamic characteristic parameters such as natural vibration frequency, mode shape and damping ratio can be obtained, which can provide basic data for damage identification and seismic performance evaluation of building anti-seismic supports and hangers. The identification of the modal parameters of the seismic support and hanger of the building can use the frequency domain identification method [24], such as the component estimation method, the Levy method and other artificial excitation methods. And random excitation methods such as peak picking method, frequency domain decomposition method, enhanced frequency domain decomposition method, etc. Or use time domain identification methods such as the random subspace method and characteristic system realization method. Time-frequency domain identification methods such as short-time Fourier transform, wavelet analysis, and HHT transform can also be used. The damage identification not only needs to qualitatively judge whether there is damage but also needs to quantitatively judge and evaluate the damage. For the seismic performance evaluation, the actual bearing load and lateral stiffness of the seismic support and hanger should be accurately identified, and the seismic check should be carried out considering the maximum rated load.

Multi-sensor data fusion technology is the basis and premise of other data analysis technologies. Multi-sensor data fusion technology can improve the accuracy and reliability of processed data. Aiming at the diversity of collected equipment data, an improved method based on wavelet and neural network data fusion is proposed to realize effective fusion analysis of multi-sensor data and provide a basis for system decision-making.

3.5.1. Wavelet threshold denoising

The wavelet transform decomposes the signal-containing noise into high-frequency components and low-frequency components, and the low-frequency components are also called approximate components [25]. Because the wavelet coefficients obtained by the soft threshold have good continuity and have the advantage of not generating additional oscillations in the estimated signal, the algorithm in this paper selects the soft threshold for threshold processing. If $|s| \le \lambda$, then s=0, otherwise $s = s - \lambda$, where: s is the decomposition coefficient obtained after layering; λ is the set threshold. The soft threshold processing formula is:

$$s = \begin{cases} 0, & |s| \le \lambda \\ s - \lambda, & |s| > \lambda \end{cases} \tag{1}$$

The steps of wavelet threshold denoising are as follows: 1) Wavelet transform is performed on the signal containing noise, and a series of wavelet decomposition coefficients are obtained by layer decomposition of the signal; 2) Thresholding the wavelet decomposition coefficients through the soft threshold function to obtain the estimated wavelet coefficients; 3) Use the estimated wavelet coefficients for wavelet reconstruction, and the reconstructed signal is the signal after denoising.

3.5.2. Neural networks

The learning process of BP neural network [26] is as follows: 1) Initialization of BP neural network: give initial value to each connection weight, determine error function e, calculation accuracy ε and maximum learning times M, and use Sigmoid function as excitation function. 2) Calculate the input u_j and output h_j of each neuron in the hidden layer.

$$u_j = \sum_{i=1}^{n} w_{ij}\, x_i + \theta_j \tag{2}$$

$$h_j = \mathrm{f}(u_j) = \frac{1}{1 + \exp\{-u_j\}} \tag{3}$$

Among them: θ_j is the threshold of the jth neuron in the hidden layer; w_{ij} is the weight.

3) Calculate the input v_k and output y_k of the kth neuron in the output layer:

$$v_k = \sum_{j=1}^{l} w_{jk} h_j + \gamma_k \tag{4}$$

$$y_k = \frac{1}{1 + \exp\{-v_k\}} \tag{5}$$

where γ_k is the threshold of the kth neuron in the output layer.

4) Calculate the global mean squared error:

$$\begin{cases} \left|\sum_{k=1}^{z} E_k\right| \le \varepsilon \\ E_k = \dfrac{1}{2}\sum_{k=1}^{m} (c_k - y_k)^2 \end{cases} \tag{6}$$

where: E_k is the mean square error; ε is the preset precision.

3.5.3. Credibility Fusion

The absolute value of the difference between the sampling data s_i and s_j of sensors i and j is defined as the absolute distance dis_{ij}, and the calculation formula is: $dis_{ij} = |s_i - s_j|$

Definition 1 When the time is t, the fusion degree c_{ij} of the sampled data s_i and s_j of the sensors i and j is: $c_{ij} = \exp\{-\frac{1}{2} \cdot dis_{ij}\}$

Definition 2 When the time is t, the fusion degree matrix of the sample data is:

$$\mathbf{C} = \begin{bmatrix} 1 & c_{12} & \cdots & c_{1n} \\ c_{21} & 1 & \cdots & c_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n1} & c_{n2} & \cdots & 1 \end{bmatrix} \tag{7}$$

Definition 3 When the time is t, the calculation formula of the consistent fusion degree $u_i(t)$ of sensor i is: $u_i(t) = \sum_{j=1}^{m} \frac{c_{ij}(t)}{m}$

Definition 4 When the time is t, the calculation formula of the distribution equilibrium degree $\tau_i(t)$ of the sensor i is: $\tau_i(t) = [\sum_{j=1}^{m} \frac{(u_i(t)-c_{ij}(t))^2}{m}]^{-1}$

Definition 5 When the time is t, the calculation formula of the reliability coefficient $\omega_i(t)$ of sensor i is: $\omega_i(t) = u_i(t) \times \tau_i(t)$. After normalization, $w_i(t) = \frac{\omega_i(t)}{\sum_{i=1}^{m} \omega_i(t)}$ is obtained.

So, at time t, the final fusion result expression is expressed by credibility as:

$$y = \sum_{i=1}^{m} w_i(t)s_i(t) = \sum_{i=1}^{m} \frac{w_i(t)s_i(t)}{\sum_{i=1}^{m} \omega_i(t)} \tag{8}$$

3.5.4. Improved fusion method

The fusion process steps of the improved fusion method are as follows: 1) The data collected by the sensor is preprocessed by PauTa Criterion, etc., including data cleaning, replacement of outliers, and so on. 2) Use wavelet threshold denoising to denoise the preprocessed data, perform threshold processing on the high frequency coefficients after wavelet layering, and use neural network to optimize the obtained low frequency coefficients. 3) Perform neural network optimization on the transformed and reduced data. 4) Perform data fusion through the reliability of the sensor to obtain the final fusion result.

Data preprocessing. The PauTa criterion refers to the assumption that a set of test data only contains random errors, and the standard deviation is obtained by calculating and processing them. An interval is determined according to a certain probability, and it is considered that any error exceeding this interval is not a random error but a gross error, and the data containing this error should be eliminated.

Data preprocessing mainly includes outlier detection, missing value filling, and data transformation. The steps are as follows: 1) Use PauTa criteria to detect abnormal data in the collected data and use interpolation to fill in outliers or missing values. 2) Normalize the changed data values, and the normalization relationship of the original data is $y = (y_{max} - y_{min}) \times \frac{x - x_{min}}{x_{max} - x_{min}} + y_{min}$. Where: x is the sample original data value; x_{max}, x_{min} are the maximum and minimum values in the sample original data, respectively. y is the result value mapped in $[y_{min}, y_{max}]$ after normalization. 3) After obtaining the normalized sample data, reduce the amount of data by replacing or estimating the original data with smaller data.

Credibility-based fusion of wavelets and neural networks. The steps of wavelet and neural network fusion based on sensor credibility are as follows: 1) use wavelet technology to perform hierarchical processing on the sample data to obtain the low-frequency coefficients and high-frequency coefficients of each layer; 2) first, perform threshold processing on the obtained high-frequency coefficients, and then use neural networks to optimize the low-frequency coefficients to obtain the optimized low-frequency coefficients; 3) reconstruct the optimized low-frequency coefficients with the high-frequency coefficients processed by the wavelet technology; 4) use the sample data to calculate the fusion degree matrix of the data at each moment and the consistent fusion degree of the sensor, and use the two calculate the credibility of the sensor; 5) use the neural network to optimize the data of each sensor, and finally obtain the fusion result through the credibility of the sensor.

4. Experimental results

To achieve more accurate damage identification and timely early warning of the intelligent monitoring system, considering the complexity of the real environment and the actual engineering structure, this paper proposes to use a multi-sensor data fusion algorithm to fuse various index data, and obtain a fusion index to monitor the health of the system. In this paper, experimental data acquisition and data fusion experiments are carried out on a small steel frame system equipped with anti-seismic supports and hangers. The experimental data includes multi-sensor data such as humidity, temperature, uniaxial acceleration sensor, tri-axial acceleration sensor, lateral support force, longitudinal support force, and relative displacement of components. The collected data is analyzed in a group of 40960 points, and 500 groups of data are extracted sequentially from front to back.

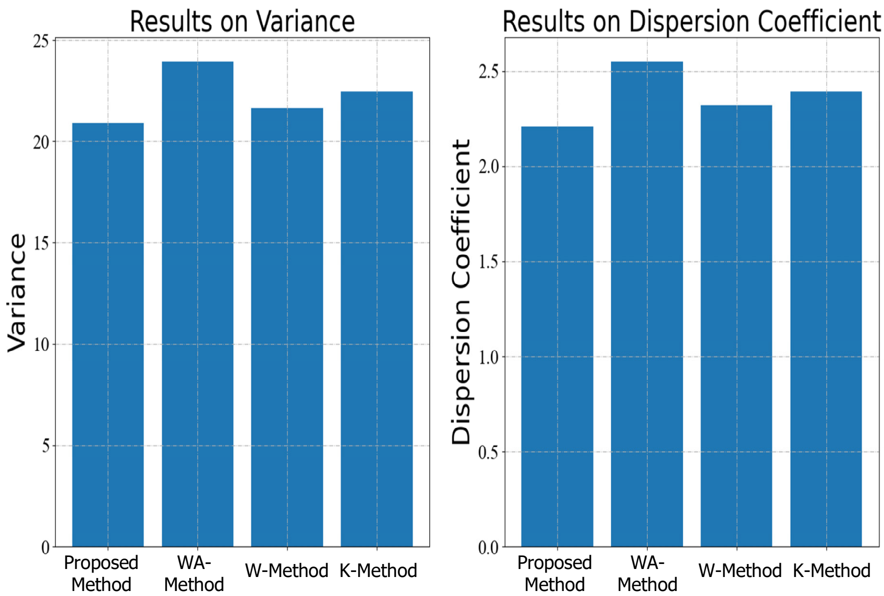

Figure 2. Experimental Results on Variance and Dispersion Coefficient.

To verify the effectiveness of the proposed data fusion algorithm, this paper selects three methods for comparison: the weighted average-based data fusion method (WA-Method), the Kalman-based data fusion method (K-Method), and the wavelet-based data fusion method (W-Method). Variance and dispersion coefficient are selected as evaluation indicators. Variance is a measure of the degree of dispersion of a set of data, and the coefficient of dispersion is a relative statistic that measures the degree of dispersion of data. The larger the values of these two evaluation indicators, the worse the robustness of the fusion algorithm; on the contrary, the smaller the value of the evaluation indicators, the better the robustness of the fusion algorithm. The experimental results are shown in Figure 2. As we can see, in both the variance and the dispersion coefficient, the value of the method proposed in this paper is the smallest. The second is the data fusion method based on wavelet. The Kalman-based data fusion method and the weighted average-based data fusion method have the largest values of the two methods. This illustrates the algorithmic robustness of the proposed method due to the other three methods.

Table 1. Experimental Results on Precision.

Overlap Ratio	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Proposed Method	0.82433	0.85241	0.84077	0.86097	0.88459	0.82261	0.78817	0.81518	0.82215	0.79420
K-Method	0.73962	0.72972	0.73380	0.71505	0.72795	0.72185	0.71857	0.73729	0.76222	0.72860
WA-Method	0.59713	0.56987	0.56258	0.57376	0.59975	0.60387	0.56702	0.61774	0.63367	0.64702
W-Method	0.65642	0.67640	0.65493	0.67881	0.67636	0.67422	0.64214	0.66042	0.67455	0.68889

Table 2. Experimental Results on Recall.

Overlap Ratio	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Proposed Method	0.78795	0.83325	0.80103	0.83836	0.86358	0.81241	0.75289	0.77732	0.81632	0.77669
K-Method	0.71217	0.71770	0.69482	0.68191	0.67343	0.69277	0.66672	0.71576	0.72009	0.69087
WA-Method	0.57315	0.53800	0.53260	0.53225	0.57265	0.58971	0.55234	0.58361	0.61612	0.62032
W-Method	0.62412	0.65937	0.62997	0.66417	0.66277	0.66592	0.63048	0.64027	0.66129	0.67295

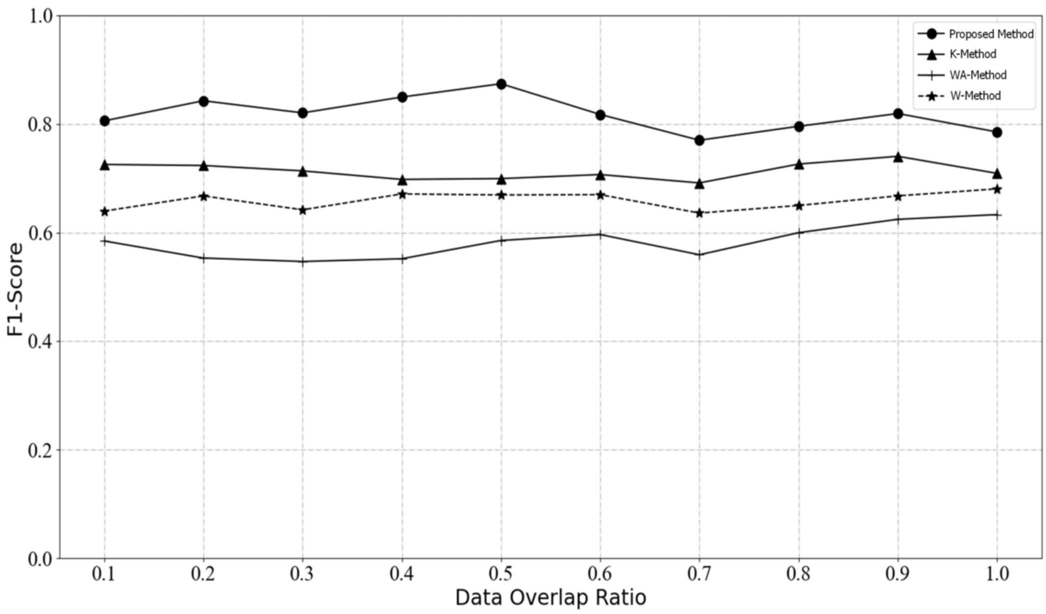

Figure 3. Experimental Results on F1-Score.

To further evaluate the performance of the proposed multi-source monitoring data fusion method for building environment, the experimental results are presented using Precision, Recall and F1 value as metrics. As shown in Table 1 and Table 2, Precision and Recall values are shown, respectively. Whether it is Precision or Recall, the method in this paper is significantly better than other comparison methods on each data overlap ratio. The F1 value is the harmonic mean of Precision and Recall, which can more accurately and comprehensively evaluate the method in this paper. The higher the F1 value, the better the fusion performance. The experimental results of the F1 value are shown in Figure 3. Among them, the vertical axis is the F1 value, and the horizontal axis represents the data overlap ratio. Compared with other methods, the fusion F1 value of this method is the highest, and the minimum value is also more than 77%. It is less affected by the data overlap ratio. The above results show that the method in this paper has better performance of building seismic multi-source monitoring data fusion and is less affected by the data overlap ratio.

5. Conclusion

The frequent occurrence of natural disasters such as earthquakes has brought significant harm and loss to people's lives and property. Therefore, it is necessary to use distributed sensor technology for seismic monitoring of buildings to improve the seismic level of the building itself. Based on distributed sensor technology and structural monitoring and early warning technology, this paper establishes a set of intelligent monitoring systems for building seismic support and hanger. The system realizes real-time monitoring, damage identification, state assessment and early warning of the seismic support and hanger of the building, which can provide a decision-making basis for the maintenance of the seismic support and hanger during the operation period and reduce secondary disasters during earthquakes. Considering the diversity of sensor data, in order to effectively fuse data, this paper proposes a fusion algorithm of wavelet neural network based on credibility, which combines the advantages of wavelet and neural network, and uses the credibility of sensors to fuse data. The experimental results show that the fusion results of the algorithm in this paper are better than other comparison algorithms in the evaluation indicators such as variance, range and dispersion coefficient, and have better stability and feasibility in data processing and fusion. Specifically, for precision, recall and F1 value, the method in this paper is significantly better than other comparison methods on each data overlap ratio. However, the method in this paper is only validated on a small steel frame system with anti-seismic supports and hangers and has not been further evaluated and validated on large-scale datasets and large-scale real building systems. In addition, how to evaluate and improve the robustness of this method is also a research problem that needs to be solved in the future.

Conflict of interest

All authors declare no conflicts of interest in this paper.

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