Feature Extraction and Analysis of Microseismic Signal Based on Convolutional Neural Network

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Abstract. Seismic detection technology has been widely used in safety detection of engineering construction abroad. Although it has just started in the field of engineering in our country, its role is becoming more and more important. Through computer technology, micro-seismic detection can provide accurate data for the construction safety detection of large-scale projects, which has important practical significance for the rapid and effective identification of micro-seismic signals. Based on this, the purpose of this article is to study the feature extraction and classification of microseismic signals based on neural games. This article first summarizes the development status of microseismic monitoring technology. Using traditional convolutional neural networks for analysis, a multi-scale feature fusion network is proposed on the basis of convolutional neural networks and big data, the multi-scale feature fusion network is used to research and analyze microseismic feature extraction and classification. This article systematically explains The principle of microseismic signal acquisition and the construction of multi-scale feature fusion network. And use big data, comparative analysis method, observation method and other research methods to study the theme of this article. Experimental research shows that the db7 wavelet base has little effect on the Megatron signal.

Keywords: Neural Network, Microseismic Signal, Feature Extraction, Classification and Recognition, Big Data

1. Introduction

The more commonly used methods in large-scale projects are GPS detection, displacement detection, etc. Not only cannot the overall evaluation of the detected body be comprehensively evaluated, but also the results can be detected only when there is obvious instability in the damaged part. For some small cracks The production and development of serotonin can not be effectively monitored [1-2].

Microseismic monitoring technology is widely used in the distribution of rock cracks around overseas mines, tunnels and underground caves. Microseismic monitoring technology can monitor the formation and development of small cracks harmful to the project, and provide direct data basis for monitoring the safety and stability of tunnels and underground caverns. For many other engineering
monitoring projects, such as the stability of dams and bridges and other similar safety monitoring aspects, microseismic monitoring technology can also provide safety assessment standards [3-4].

The purpose of this paper is to improve the recognition of microseismic signals, using a multi-scale feature fusion network to extract and classify microseismic features. The feasibility of the research topic of this paper is carried out by studying the influence of different wavelet basis functions on the classification results.

2. Research on feature extraction and classification and recognition of microseismic signals based on neural network

2.1. Convolutional neural network

Convolutional Neural Networks (CNN), as an important class of neural networks, have many application scenarios [5-6]. Traditional artificial neural networks usually connect different levels in a fully connected manner, which is easy to cause parameter redundancy. Therefore, the network needs to rely on a very large amount of data to train these parameters [7-8]. CNN chooses a large number of local connections to reduce the parameter scale of the network. This design is similar to the sparse connections between neurons in organisms, and is more critical. However, the use of this network structure can reduce the dependence of network training on the amount of data [9-10].

2.2. The principle of feature extraction of microseismic monitoring signals

(1) Principles and methods of data preprocessing

Due to the sensor, the received pulsating seismic signal will have a certain difference [11-12]. In order to eliminate these differences, a certain amount of preprocessing was performed on the acquired data. In this article, we will first normalize the acquired pulsation signals, and then perform a zero-drift removal process on the normalized data. In other words, centralize the data.

First, normalize the obtained microseismic data, using the formula as shown in formula (1):

\[
P_l = \frac{(X - \min(X))}{(\max(X) - \min(X))}
\]

Then the data is processed centrally, as shown in formula (2).

\[
P_2 + P_1 - \text{mean}(P_l)
\]

(2) The extraction of wavelet packet coefficient Shannon entropy

Different from traditional Fourier analysis, wavelet analysis has a function equivalent to a "magnifying glass", that is, a time-frequency localization analysis method in which both time and frequency windows can be changed. Because it only decomposes the low-frequency part of the signal, the high frequency part of the signal is not processed, so that its frequency resolution decreases as the number of decompositions increases.

Wavelet packet coefficient Shannon entropy (E_{\text{Shannon}}): Entropy is a concept used to measure the law of information. If S is assumed to be the original signal, S_i is the i-th coefficient of the signal S on a set of orthogonal basis. If you use letters E represents information entropy, then E represents a value added by a certain transformation of the coefficients on each different orthogonal basis, which is the following formula:

\[
E = \sum E(S_i)
\]

And it satisfies E(0)=0.

If S is the original signal and S_i is the i-th wavelet coefficient of the signal s decomposition, its length is n. Then define the Shannon degree entropy of the wavelet packet coefficient as:
\[ E_{\text{shannon}}(i) = - \sum_{j=1}^{n} S(i, j)^2 \log_2(S(i, j)^2) \] (4)

Substitute the 16 wavelet coefficients of the fourth layer to obtain a 16-dimensional feature vector.

(3) Extraction of coefficient energy ratio

If \( S \) is the original signal, its length is \( m \), and \( S_j \) is the \( j \)-th wavelet coefficient after the signal \( S \) is decomposed. If it is decomposed with the wavelet, the coefficients of the last layer of decomposition are organized in the order of the wavelet tree node number, and its length is \( n \), Define the energy ratio of wavelet packet coefficient (Ewt) as:

\[ E_{\text{wt}}(j) = 100 \times \frac{\sum_{k=1}^{n} S(j, k)^2}{\sum_{i=1}^{m} s_i^2} \] (5)

2.3. Micro-seismic signal recognition method based on multi-scale feature fusion network

Assuming that \( s(t) \) represents a piece of data in the post-stack seismic signal, its CWT is as follows:

\[ W_s(a, b) = \frac{1}{\sqrt{a}} \int s(t) \psi^*(\frac{t-b}{a})dt \] (6)

Among them, \( \psi^* \) represents the complex conjugate of the mother wavelet, \( b \) is the practical translation factor of the mother wavelet, and \( a \) is the scale factor of the mother wavelet. The wavelet transform can be understood as the cross-correlation between the signal \( s(t) \) and the new wavelet after the original mother wavelet is compressed or expanded on the time axis and translated on the time axis.

(1) Calculate the instantaneous frequency of the seismic signal

If the unclear lines around the time axis are ignored, the instantaneous frequency can be obtained by calculating the partial derivative of the wavelet transform at any point \((a, b)\). For the wavelet coefficients satisfying \( W_s(a, b) \neq 0 \), we can get:

\[ \omega_s(a, b) = \frac{\partial W_s(a, b)}{\partial b} \] (7)

(2) Calculate the SST value of the post-stack seismic signal \( T_s(\omega, b) \)

By formula (8), the signal coefficients are mapped from the time-scale plane to the new time-frequency plane. This step is called synchronous compression. In this way, a new time-frequency distribution based on continuous wavelet transform can be obtained, and the scale discretization is used to calculate \( W_s(a, b) \), and the scale interval is \( \Delta a_k = a_{k+1} - a_k \). When the signal is mapped from the time-scale plane to the time-frequency plane, the \( T_s(\omega, b) \) value of SST is determined by the range \( [\omega_l - \Delta \omega / 2, \omega_l + \Delta \omega / 2] \) centered on \( \omega_l \):

\[ T_s(\omega_l, b) = \frac{1}{\Delta \omega} \sum_{|a_k-b| \leq \Delta \omega / 2} W_s(a_k, b)a^{-3/2} \] (8)

Through the above formulas and constraint conditions, the fuzzy area of the CWT value of each data in the post-stack seismic signal can be squeezed to a range that is very close to the true frequency value in the scale (frequency) direction, which greatly improves the signal in time and frequency. The directional concentration ability can clearly and accurately describe seismic signals, thereby improving the efficiency and accuracy of post-stack seismic signal feature extraction.
3. Experimental research on feature extraction and classification of microseismic signals based on neural network

3.1. Experimental protocol
The use of different wavelet basis functions will have a certain impact on the classification results, so the choice of wavelet basis is very important. This article has passed different choices of db7, db3, and rbio1.5 three wavelet basis using C support vector machine classifier (C -Support Vector Classifier, C-SVC) plus RBF kernel function for classification experiments to test the impact of different basis functions on the classification results.

3.2. Parameter setting
Classifier mode: C-SVC; kernel function: radial basis function Rbf (Radial Basis Function); parameters c and: determined by cross-validation K-CV; data type: wavelet packet coefficient Shannon entropy; wavelet basis: db7, db3, rbio1.5; v=0.5.

4. Experimental analysis of feature extraction and classification and recognition of microseismic signals based on neural network

4.1. The impact of the choice of different wavelet basis functions on classification
In order to make this experiment more scientific and effective, this research uses C support vector machine classification machine to perform classification experiments on different wavelet bases. The data obtained are shown in Table 1.

Table 1. The influence of the choice of different wavelet basis functions on classification

| Wavelet Basis | The most in K-CV verification Large correct classification rate(%) | Support vector Nsv number | Boundary support Number of Bsv | The test set is correct Classification rate(%) | Wrong test set Number of points |
|---------------|--------------------------------------------------|---------------------------|-------------------------------|---------------------------------|--------------------------------|
| Db7           | 86.7                                              | 30                        | 28                            | 80                              | 4                              |
| Db3           | 83.3                                              | 23                        | 16                            | 85                              | 3                              |
| Rbilo.5       | 83.3                                              | 30                        | 30                            | 60                              | 8                              |

Figure 1. The influence of the choice of different wavelet basis functions on classification
It can be seen from Figure 1 that the best classification effect is 85% under the db3 wavelet base, followed by 80% under the db7 wavelet base, and the adaptability of the rbio1.5 wavelet base is relatively poor, with the worst classification effect being only 60%.

4.2. The impact of the choice of different classifiers on classification

The classifiers selected in this article are C-SVC and V-SVC. The difference between the two is that the penalty value of C-SVC is in the range of 1 to positive infinity, and V-SVC replaces the penalty value C in C-SVC with V, where the value of V generally ranges from 0 to 1. The larger the V, the smoother the decision interval. The influence of the choice of different classifiers on classification is shown in Table 2.

| Category            | Large correct classification rate(%) | Support vector Nsv number | Boundary support Number of Bsv | The test set is correct Classification rate(%) | Wrong test set Number of points |
|---------------------|--------------------------------------|---------------------------|-------------------------------|-----------------------------------------------|-------------------------------|
| Db7(V-SVC)          | 86.67                                | 18                        | 18                            | 80                                            | 4                             |
| Db3(V-SVC)          | 83.33                                | 28                        | 20                            | 60                                            | 8                             |
| Rbio.5(V-SVC)       | 86.67                                | 30                        | 30                            | 50                                            | 10                            |

Table 2. The impact of the choice of different classifiers on classification

It can be seen from Figure 2 that under the C support vector machine classifier, the db3 wavelet base has the best classification effect of 85%, followed by the db7 wavelet base with 80%, while the adaptability of the rbio1.5 wavelet base is relatively poor. The worst classification effect is only 60%. In general, it seems that the db7 wavelet basis classifies the three kernel functions well. Generally speaking, various kernel functions have little influence on the classification of such microseismic signals.

5. Conclusion

This paper uses big data technology to fully study the microseismic signal recognition and feature extraction technology in machine learning, and proposes a pre-stack seismic reflection pattern
recognition method based on multi-scale feature fusion of convolutional neural network. Firstly, the theoretical basis of related networks is introduced, and on this basis, a multi-scale feature fusion network is proposed through computer technology, which contains two sub-networks, a fusion network and a generation network. The fusion network is used to extract the fusion features of pre-stack seismic signals, and the generation network is used to assist the training of the entire multi-scale feature fusion network.

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