Nature Environment and Pollution Technology
An International Quarterly Scientific Journal

p-ISSN: 0972-6268
e-ISSN: 2395-3454

Vol. 18 No. 5 (Special Issue) pp. 1627-1633 2019

Original Research Paper | Open Access

Coal-Rock Interface Recognition Method Based on Image Recognition

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Nat. Env. & Poll. Tech.
Website: www.neptjournal.com

Received: 04-08-2019
Accepted: 17-10-2019

Key Words:
Coal and rock
Image recognition
Texture features
Pattern recognition
Neural network

ABSTRACT

In view of the existing problems of coal and rock recognition, the key technologies of coal and rock recognition based on image were studied. To improve the error of BP neural network, it is proposed to use wavelet transform to extract the characteristic values of coal and rock image and build a wavelet neural network with neural network to realize the recognition of coal and rock. Simulation results show that the improved wavelet neural network has a better recognition rate for coal and rock classification. When the number of hidden layer nodes is 30 and the number of iterations is 800, the recognition rate is ideal and stable, even reaching 100%. It can be widely used in specific underground coal mine conditions.

INTRODUCTION

With the development of economy, coal will be the main energy source for a long time in the future. How to effectively identify coal and rock is of great significance not only to the safe production, safe transportation and safe utilization involved in the processes of coal mining, transportation, utilization and processing and reuse, but also to the guarantee of economic and social benefits (Yunxia et al. 2018). Coal and rock identification have been the main coal-producing countries' research hotspots and a variety of around 20 recognition methods have been proposed by different scholars. However, it is difficult to explore as the methods are not mature enough, accurate, and the reliability is not high, also it is difficult to identify the method that can meet the Chinese large-scale complicated geological conditions and characteristics of coal and rock (Song et al. 2017). Therefore, a lot of research work that can use coal and rock identification technology to improve the key link of technology innovation cannot be effectively implemented. Therefore, coal and rock identification still have a strong theoretical research value and practical economic and social needs.

PAST STUDIES

With the help of image processing technology and feature extraction method, Zhang et al. (2018) proposed a coal and rock identification method based on transform domain and gaussian mixture model clustering. Discrete cosine transform and discrete wavelet transform were used to extract the content and texture information of coal and rock images respectively. Sun et al. (2017) through the selection of cutting tooth in the process of cutting vibration signals and infrared thermal image signals as the characteristics of coal and rock identification, aimed at cutting cutter tooth in the process of x, y, z three directions of vibration acceleration signal, vibration spectrum, tooth infrared flash temperature value and temperature - frequency real-time image acquisition, the cutting gear vibration signal, the infrared thermal image signals and the change rule between different proportion of coal and rock specimens. Xue et al. (2017) proposed a new coal-rock interface recognition method based on wavelet packet singular value (WPSV) and BP neural network (BPNN). WPSV was used to construct the feature vector, and then combined with BPNN to perform automatic recognition of coal-rock interface. Based on the dielectric properties of coal and rock, Li et al. (2017a) established the coal-rock boundary model based on coal content detection by using Bruggeman effective medium theory. Cheng et al. (2017) used the acoustic impedance difference between coal and rock and phased-array technology to propose the coal-rock interface recognition method based on ultrasonic phased-array. Based on the analysis of coal samples and the velocity of the rock and the ultrasonic attenuation coefficient, on the basis of parameters, such as scattering field theory based on the heterogeneity, an ultrasonic phased array coal and rock identification model is set up. A variety of frequency ultrasonic phased array of different types of scans numerical simulation research of coal and rock model are carried out, the coal rock interface echo signal and the ultrasonic phased array imaging, image of the coal rock interface recognition is realized.

In this paper, the error of BP neural network is improved, and it is proposed to use wavelet transform to extract the characteristic value of coal image and combine with BP neural network to construct the wavelet neural network to realize the recognition of coal and rock.

MATERIALS AND METHODS

Extraction of Texture Feature Values of Coal and Rock Images

Existing texture feature extraction methods have been widely used, and their advantages and disadvantages are shown in Table 1.

Considering the common defects of existing texture features, this paper extracts the texture features of coal and rock images by multi-scale decomposition on the basis of grey symbiosis matrix, so as to adapt to the classification of coal and rock textures.

This method firstly extracted the features of the initial images of coal and rock, then analysed the characteristics of coal and rock images after multi-scale decomposition, and finally extracted the features of the decomposed coal and rock images. After multi-scale decomposition of coal and rock images, it will be better than the existing methods of texture feature extraction in terms of accuracy and calculation.

An Improved Wavelet Neural Network

BP neural network is generally multi-layer. Multi-layer perceptive network includes input layer, output layer and several hidden layers (Liu et al. 2017). The multi-layer perception network emphasizes that the structure is composed of multiple layers, and the core of BP neural network is a learning algorithm using error back-propagation (Yiming et al. 2017). In most cases, the multi-layer perceptive network adopts error back propagation to carry out weight adjustment, so it is generally considered that they are the same kind of network.

BP network is used in many fields. However, BP neural network also has shortcomings in the recognition of coal-rock interface, such as easy access to local minimum points, leading to paralysis of the system, etc. We propose to combine BP neural network with wavelet analysis, namely wavelet neural network. At the same time, the image is decomposed at multiple scales and the corresponding feature vectors are extracted and then input into the wavelet neural network for processing (Li et al. 2017b). At present, wavelet neural networks can be summarized into two categories:

(1) Loose combination: Feature vectors are provided for the neural network through wavelet analysis. The two are related to each other and independent of each other. Its structure is shown in Fig. 1.

(2) Close combination: the wavelet function is used to replace the hidden node function of the conventional single hidden layer neural network, the weight from the input layer to the hidden layer is replaced by the scale of the wavelet function, and the hidden layer threshold is replaced by the translation parameter, as shown in Fig. 2. The reason why wavelet neural network can complete pattern recognition is that it can well realize nonlinear transformation and transform the input signal space into a new space to solve the classification problem.

The linear output multilayer perceptron with the minimum mean square error criterion is composed of two parts, the first part is that the input layer and the hidden layer complete the nonlinear feature extraction of the input signal, and transform the input space into the output space of the hidden layer to maximize the function, so that the sample has the best separability in the new space; The second part is that the output node completes the linear classification decision. The traditional method is to extract the features first and then design the classifier, while the wavelet neural network is carried out simultaneously. The performance of neural network is determined by topology, node characteristics and training rules. The wavelet neural network transforms the input signal into a new feature space and the mapping relation can automatically adapt to the change of input to achieve the approximation of input and output. Fig. 3 is the flow chart of wavelet neural network algorithm.

Table 1: Advantages and disadvantages of common feature extraction methods.

Method type	Advantages	Disadvantages
Texture features based on greyscale co-occurrence matrix	It better reflects the relationship between pixels	Calculation amount is large and there are many relevant features
Texture features based on local greyscale statistics	Implementation is simple	Spatial relationship between pixels is not reflected and the discrimination performance is general
Texture features based on fractal models	Texture discrimination performance is better	Heavy computation
Texture features based on CDTM matrix	Feature correlation is not significant	Heavy computation
Texture features based on Gabor filter Banks	Simple feature extraction	Heavy computation

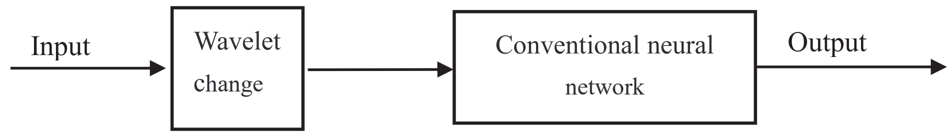

Fig. 1: Loosely coupled wavelet neural network.

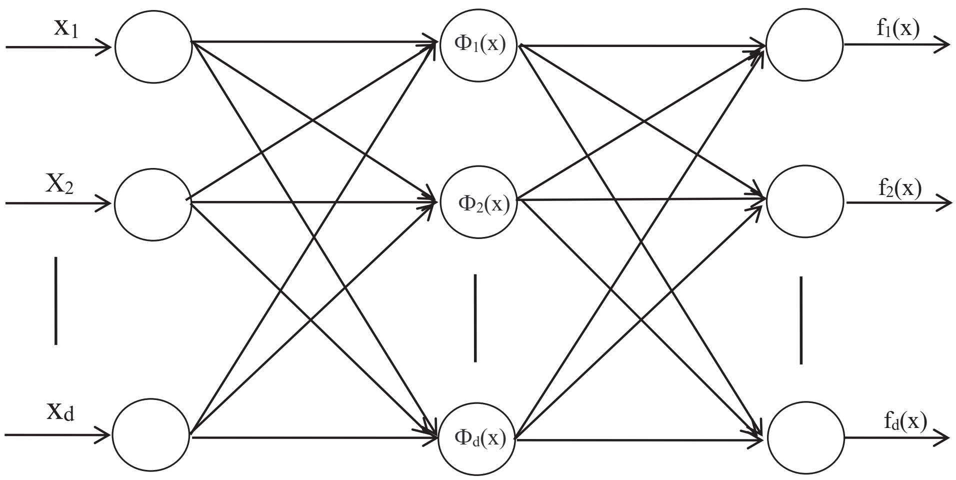

Fig. 2: Closely combines the wavelet neural network.

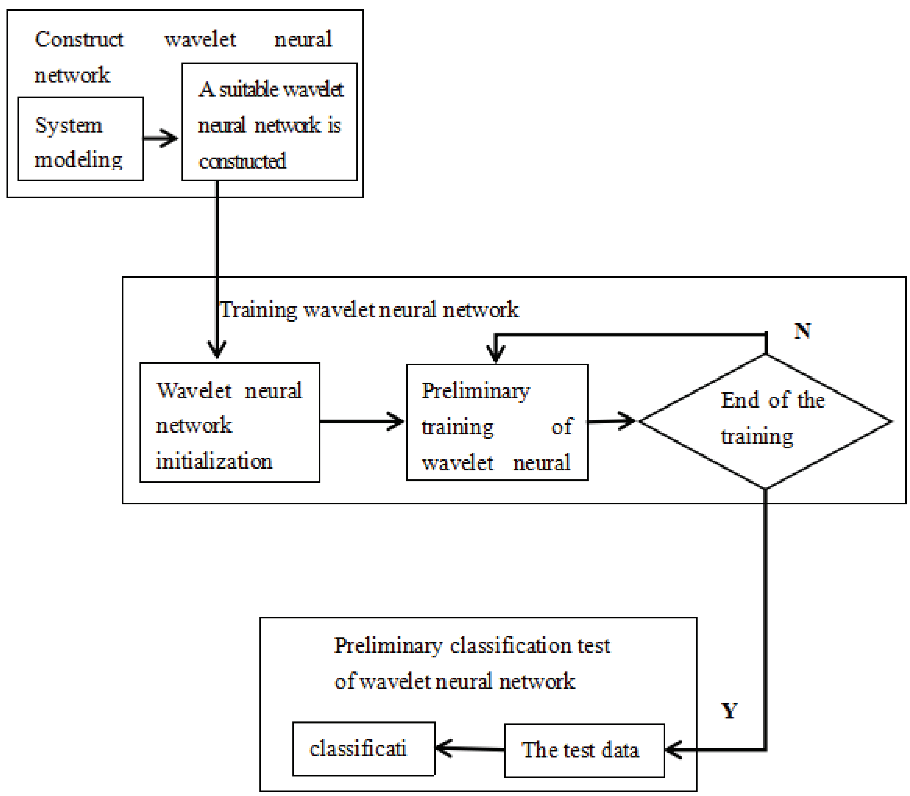

Fig. 3: Flow chart of wavelet neural network algorithm.

Classification and Recognition of Coal and Rock Iimages Based on Neural Network

The wavelet neural network is selected to determine the number of neurons in the input layer according to the dimension of characteristic input, while the number of neurons in the output layer is determined by the number of coal and rock types. In this experiment, the number of neurons in the input layer was 27. When the output layer is of four types of coal-rock images, the number of neurons in the output layer is divided into 4. At this time, the expected output of the network is set as 1 represents bituminous coal, 2 represents anthracite, 3 represents sandstone and 4 represents shale. When the output layer type is coal (bituminous coal and anthracite are classified into one category) and rock (sandstone and shale are classified into one category), the number of neurons in the output layer is 2. At this time, the expected output of the network can be set as 1 to represent coal and 2 to represent rock. The number of nodes in the hidden layer will be tested by experiments.

The following is the weight correction process of the wavelet neural network:

$$e = \sum_{k=1}^{m} yn(k) - y(k) \quad \dots(1)$$

Where, e is network prediction error, yn(k) and y(k) are expected output and predicted output respectively. The correlation weights and coefficients were corrected by the prediction error e.

$$\omega_{n,k}^{(i+1)} = \omega_{n,k}^{i} + \Delta\omega_{n,k}^{(i+1)} \quad \dots(2)$$

$$a_k^{(i+1)} = a_k^i + \Delta a_k^{(i+1)} \quad \dots(3)$$

$$b_k^{(i+1)} = b_k^i + \Delta b_k^{(i+1)} \quad \dots(4)$$

Where $\Delta\omega_{n,k}^{(i+1)}$, $\Delta a_k^{(i+1)}$, $\Delta b_k^{(i+1)}$ can be obtained from the following formula:

$$\Delta\omega_{n,k}^{(i+1)} = -\eta \frac{\partial e}{\partial w_{n,k}^{(i)}} \quad \dots(5)$$

$$\Delta a_k^{(i+1)} = -\eta \frac{\partial e}{\partial a_k^{(i)}} \quad \dots(6)$$

$$\Delta b_k^{(i+1)} = -\eta \frac{\partial e}{\partial b_k^{(i)}} \quad \dots(7)$$

(3) The training samples are used to train the neural network to determine the network model and make the actual output as close as possible to the ideal output.

The training steps of the wavelet neural network algorithm are as follows:

Step 1: Random initialization of a_k, b_k, ω_{ij}, ω_{jk}, η, where a_k and b_k are the scaling and translation factors of wavelet function respectively, ω_{ij}, ω_{jk} are the weight of network connection, and η is the learning rate.

Step 2: Training samples and test samples are used to train the network and test the network classification performance, respectively.

Step 3: Input the training sample and calculate the error e between its output and the expected output.

Step 4: Modify the network weight according to e.

Step 5: Determine whether the algorithm is finished or return to step 3.

(4) Input the test samples into the final trained neural network to test the classification performance of the network.

A total of 180 coal and rock images (bituminous coal, anthracite, sandstone and shale) were collected, including 45 bituminous coal, anthracite, sandstone and shale respectively. The image size was 247×215, and the grey scale was 256, which was in BMP format. The software environment is MATLAB2010 software simulation experiment system.

ANALYSIS OF EXPERIMENTAL RESULTS

This experiment is also divided into two groups. The first group is divided into coal and rock. Bituminous coal and anthracite are classified as coal, while sandstone and shale are classified as rocks. The second group is subdivided into four categories namely bituminous coal, anthracite, sandstone and shale. Coal and rock images (bituminous coal, anthracite, sandstone and shale) were decomposed at multiple scales and corresponding feature vectors were extracted. They were randomly divided into training samples and test samples, respectively, for the training of neural network to determine the threshold and network weight and the classification performance of test network.

Table 2 shows the recognition rate of wavelet neural network in classifying four coal rocks when the node number of hidden layers is 30 and the number of iterations is 100.

Table 3 shows the recognition rate of wavelet neural network in classifying four coal rocks when the node number of hidden layers is 30 and the iteration number is 160.

Table 4 shows the recognition rate of wavelet neural network in classifying four coal rocks when the node number of hidden layers is 30 and the iteration number is 210.

Table 5 shows the recognition rate of wavelet neural network in classifying four coal rocks when the node number of hidden layers is 30 and the number of iterations is 320.

Table 6 shows the recognition rate of wavelet neural network in classifying four coal rocks when the node number of hidden layers is 30 and the number of iterations is 500.

Table 2: Coal and rock classification recognition rate (1).

Coal and rock image category	Sandstone	Anthracite coal	Bituminous coal	Shale
Number of samples	15	15	15	15
Correct identification number	7	0	2	0
Correct rate	46.67%	0	13.33%	0

Table 3: Coal and rock classification recognition rate (2).

Coal and rock image category	Sandstone	Anthracite coal	Bituminous coal	Shale
Number of samples	15	15	15	15
Correct identification number	6	0	15	9
Correct rate	40%	0	100%	60%

Table 4: Coal and rock classification recognition rate (3).

Coal and rock image category	Sandstone	Anthracite coal	Bituminous coal	Shale
Number of samples	15	15	15	15
Correct identification number	9	0	0	1
Correct rate	60%	0	0	6.67%

Table 5: Coal and rock classification recognition rate (4).

Coal and rock image category	Sandstone	Anthracite coal	Bituminous coal	Shale
Number of samples	15	15	15	15
Correct identification number	6	0	6	9
Correct rate	40%	0	40%	60%

Table 6: Coal and rock classification recognition rate (5).

Coal and rock image category	Sandstone	Anthracite coal	Bituminous coal	Shale
Number of samples	15	15	15	15
Correct identification number	4	0	1	0
Correct rate	26.67%	0	6.67%	0

Table 7 shows the recognition rate of wavelet neural network in classifying four coal rocks when the nodal number of hidden layers is 10 and the number of iterations is 60.

Table 8 shows the recognition rate of wavelet neural network in classifying four coal rocks when the nodal number of hidden layers is 10 and the number of iterations is 500.

Table 9 shows the recognition rate of wavelet neural network in classifying four coal rocks when the node number of hidden layers is 10 and the number of iterations is 800.

Table 10 shows the recognition rate of the wavelet neural network in classifying four coal rocks when the nodal number of hidden layers is 10 and the number of iterations is 1000.

Table 11 shows the recognition rate of wavelet neural network in classifying four coal rocks when the node number of hidden layers is 15 and the iteration number is 900.

Table 12 shows the recognition rate of wavelet neural network in classifying four coal rocks when the node number of hidden layers is 15 and the iteration number is 900.

Table 13 shows the recognition rate of wavelet neural network in classifying four coal rocks when the node number of hidden layers is 30 and the iteration number is 800.

Table 14 shows the recognition rate of wavelet neural network in classifying four coal rocks when the node number of hidden layers is 30 and the iteration number is 800.

Table 7: Coal and rock classification recognition rate (6).

Coal and rock image category	Rock	Coal
Number of samples	30	30
Correct identification number	15	17
Correct rate	50%	56.67%

Table 8: Coal and rock classification recognition rate (7).

Coal and rock image category	Rock	Coal
Number of samples	30	30
Correct identification number	28	29
Correct rate	93.33%	96.67%

Table 9: Coal and rock classification recognition rate (8).

Coal and rock image category	Rock	Coal
Number of samples	30	30
Correct identification number	30	27
Correct rate	100%	90%

Table 10: Coal and rock classification recognition rate (9).

Coal and rock image category	Rock	Coal
Number of samples	30	30
Correct identification number	30	29
Correct rate	100%	96.67%

Table 11: Coal and rock classification recognition rate (10).

Coal and rock image category	Rock	Coal
Number of samples	30	30
Correct identification number	30	28
Correct rate	100%	93.33%

Table 12: Coal and rock classification recognition rate (11).

Coal and rock image category	Rock	Coal
Number of samples	30	30
Correct identification number	30	27
Correct rate	100%	90%

Table 13: coal and rock classification recognition rate (12).

Coal and rock image category	Rock	Coal
Number of samples	30	30
Correct identification number	30	26
Correct rate	100%	86.67%

Table 14: Coal and rock classification recognition rate (13).

Coal and rock image category	Rock	Coal
Number of samples	30	30
Correct identification number	30	30
Correct rate	100%	100%

It can be seen from the above simulation results that the improved wavelet neural network has an ideal recognition rate for bituminous coal, but a low recognition rate for sandstone, anthracite and shale. After the improvement, the wavelet neural network has an ideal and stable recognition rate when it classifies coal and rock, and even reaches 100% recognition rate when the node number of hidden layers is 30 and the number of iterations is 800. Compared with other recognition methods, the wavelet neural network has a more perfect recognition rate. In general, the improved wavelet neural network proposed in this paper achieves an ideal effect in coal and rock classification.

CONCLUSION

The paper puts forward using wavelet transform to extract characteristic values of coal and rock image wavelet neural network combined with BP neural network theory, using MATLAB software to simulation experiment. The results show that the improved wavelet neural network used to identify the two classification of coal and rock, compared with other identification method has better recognition rate. When the number of hidden layer nodes is 30 and the number of iterations is 800, the recognition rate is ideal and stable, even reaching 100%. Therefore, in a specific underground coal mine, the coal and rock image classification and recognition method can be widely used.

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