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Characteristic Analysis and Recognition of Coal-Rock Interface Based on Visual Technology

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Abstract

To research coal-rock interface automatic recognition technology, a method of characteristic analysis and recognition of coal-rock interface based on visual technology is proposed. Firstly according to the coal and rock image, we analyze the texture difference between coal and rock. Secondly we calculate four texture feature values based on spatial gray co-occurrence matrix method. Thirdly the coal-rock is recognized using neural network trained by texture feature. The result shows that there is a great difference of texture feature between coal and rock. Coal and rock can be recognized use Energy, contrast, correlation, entropy as feature vector. In addition, entropy has a better effect in recognition.

Keywords*: Visual technology; Texture characteristic; Network; Coal and rock recognition*

1. Introduction

In China, Automatic identification of coal and rock is mainly depends on artificial visual method. Due to poor environment of coal working conditions, it may bring security issues to the site operation workers [1-3]. Automatic identification of coal and rock is one of the key technologies to realize the comprehensive mechanized coal mining [4-5]. So the world's major coal-producing countries have attached great importance to the key technology and successively put forward a variety of coal and rock automatic identification method, such as: artificial gamma ray method [6-7], radar detection method [8-9], response based on cutting force [10-11] and passive infrared detection method [12-13]. The above several ways have their own characteristics which are shown in Table 1.

Table 1. Characteristics of Coal-Rock Interface Automatic Recognition Technology

Method	Characteristics
Artificial gamma ray method	Radioactive, unsafe
Radar detection method	Non-radioactive
Response based on cutting force	Not apply to the top coal caving
Passive infrared detection method	Strong penetrating power, but immature

With the rapid development of computer technology, Image processing and pattern recognition is applied to various fields gradually. So we propose a method of characteristic analysis and recognition of coal-rock interface based on visual technology. Firstly according to the coal and rock image, we analyze the texture difference between coal and rock. Secondly we calculate four texture feature values based on spatial gray co-occurrence matrix method. Thirdly the coal-rock is recognized using neural network trained by texture feature.

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2. The Principle of Coal-Rock Interface Recognition

From a visual perspective, coal and rock have the different texture which is shown in figure 1.

(a) Coal (b) Rock

Figure 1. Images of Coal and Rock

Texture characteristic is the basic nature in object surface that is used to describe and distinguish different objects. Texture analysis is to extract and analyze texture characteristic of different objects through image operation. The basic idea is to find some model which can describe texture space distribution and give some parameters to constitute feature vector and meet discrete of different texture. R. Haralick etc have proposed spatial gray co-occurrence matrix method which is an effective method based on statistics. Any gray surface of image can be thought as a surface in three-dimensional space. Assume that in an image, i is gray value of $f(x, y)$ and j is gray value of $f(x+\Delta x, y+\Delta y)$, δ is interval distance, $p(i, j, \delta, \theta)$ is probability of $f(x+\Delta x, y+\Delta y)$ appearing. So,

$$p(i, j, \delta, \theta) = \{[(x, y), (x+\Delta x, y+\Delta y)] I(x, y) = i, I(x+\Delta x, y+\Delta y) = j, \\ x = 0,1,\cdots, N_x - 1; y = 0,1,\cdots N_y - 1\} \quad (1)$$

Where, $i, j = 0,1,\cdots, L-1$; L is gray series; (x,y) is pixel coordinate; N_x and N_y are the number of rows and columns. In paper, θ is respectively 0°, 45 °, 90 ° and 135 °; δ=1.

Because the gray series is 256 levels containing a large amount of data, it is necessary to compress series before solving gray symbiotic matrix. Generally, the compression level is 16. And then image is normalized, as Eq. 3 indicates.

$$\tilde{p}(i, j) = \frac{p(i, j)}{R} \quad (2)$$

Where, R is normalization coefficient.

3. Texture Feature Calculation

Generally we do not directly calculate gray symbiotic matrix, but extract texture feature in texture analysis process. There are some texture feature vectors such as energy, contrast, correlation and entropy. For example, energy is defined as:

$$a_1 = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} \tilde{p}^2(i, j) \quad (3)$$

Energy mainly reflects image gray distribution and texture roughness. If a_1 is bigger, texture is more rough. Compared with rock, coal has smoother surface, so the energy of coal is lower.

Contrast is defined as:

$$a_2 = \sum_{n=0}^{L-1} n^2 \left\{ \sum_{\substack{i=0 \\ n=|i-j|}}^{L-1} \sum_{j=0}^{L-1} \tilde{p}^2(i, j) \right\} \tag{4}$$

If a_2 is bigger, texture characteristics is deeper. For coal having smoother surface, the brightness value and contrast is higher.

Correlation is defined as:

$$a_3 = \frac{\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} ij\, \tilde{p}^2(i, j) - u_1 u_2}{\sigma_1^2 \sigma_2^2} \tag{5}$$

Where,

$$u_1 = \sum_{i=0}^{L-1} i \sum_{j=0}^{L-1} \tilde{p}(i, j) \tag{6}$$

$$u_2 = \sum_{i=0}^{L-1} j \sum_{j=0}^{L-1} \tilde{p}(i, j) \tag{7}$$

$$\sigma_1^2 = \sum_{i=0}^{L-1} (i - u_1)^2 \sum_{j=0}^{L-1} \tilde{p}(i, j) \tag{8}$$

$$\sigma_2^2 = \sum_{j=0}^{L-1} (j - u_2)^2 \sum_{i=0}^{L-1} \tilde{p}(i, j) \tag{9}$$

For homogeneous surface, rock has higher correlation.

Entropy is defined as:

$$a_4 = -\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} \tilde{p}(i, j) \,\mathrm{lb}\, \tilde{p}(i, j) \tag{10}$$

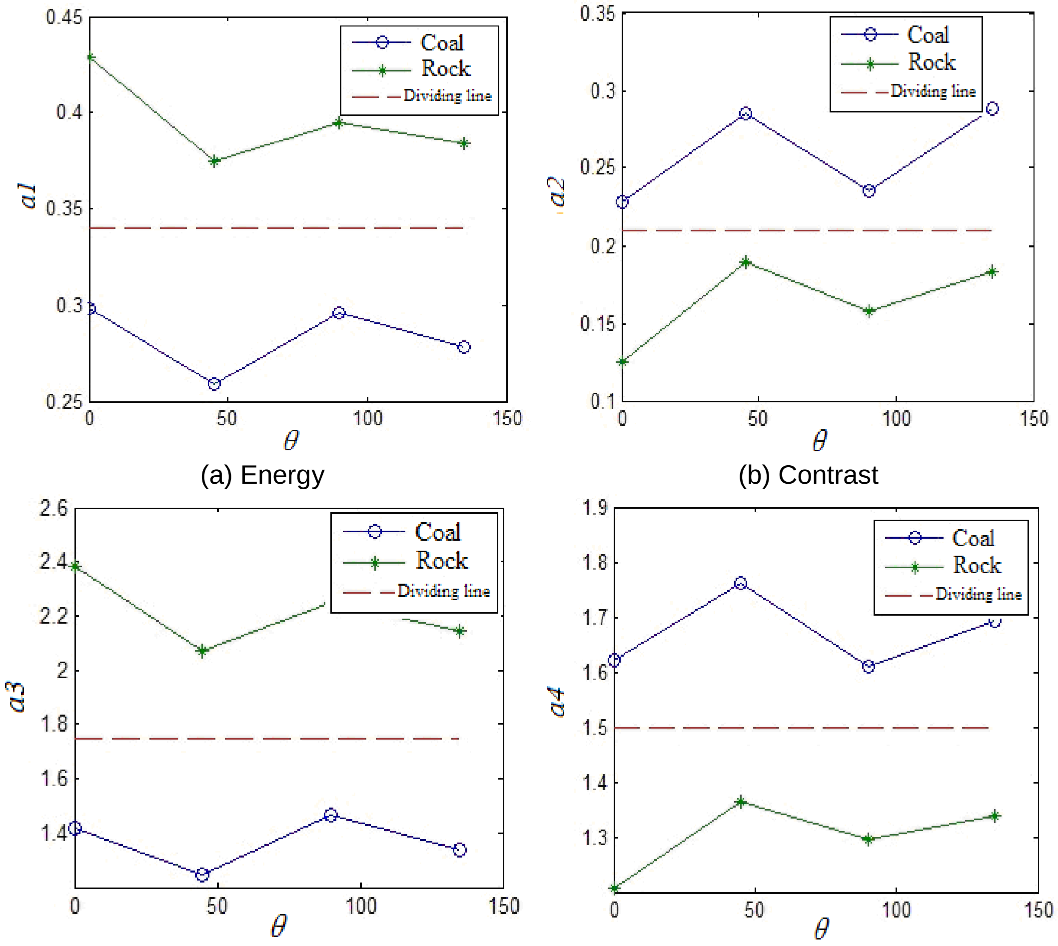
If the image grayscale change without rules, the entropy is higher.

Finally, we can conclude the differences of texture features between coal and rock that are shown in table 2.

Table 2. The Differences of Texture Features Between Coal and Rock

Texture features	Coal	Rock
Energy	smaller	higher
Contrast	higher	smaller
Correlation	smaller	higher
Entropy	higher	smaller

The results of 4 texture feature vectors calculation in Figure 1 are shown in Figure 2. We conclude that coal and rock have the obvious dividing line.



(a) Energy (b) Contrast

(c) Correlation (d) Entropy

Figure 2. 4 Texture Feature Vectors Calculation

4. The Method of Coal-Rock Interface Recognition Based on Neural Network

Artificial neural network is a mathematical method which simulates the biological neural network to process information. The main work is to determine the layer number, node number, transfer function, the initial weights and bias, learning algorithm. BP neural network is a widely used method which usually includes an input layer, one hidden layer and one output layer. The number of input layer neurons is determined by the input feature vector. System chooses 4 input layer neurons. According to the approximate relationship between input layer and hidden layer, the number of hidden layer neurons is 9. The transfer function of hidden layer is s-shaped tansig. According to results of coal-rock recognition, the number of output layer is 2. [1-0] represents coal and [0-1] represents rock. The transfer function of output layer is linear purelin. The weight and bias of each node is based on the results of sample data training. The structure of BP neural network model is shown in figure 3. $IW\{1,1\}$ represents the weight of hidden layer; $b\{1\}$ represents the bias of hidden layer. $LW\{2,1\}$ represents the weight of output layer; $b\{2\}$ represents the bias of output layer.

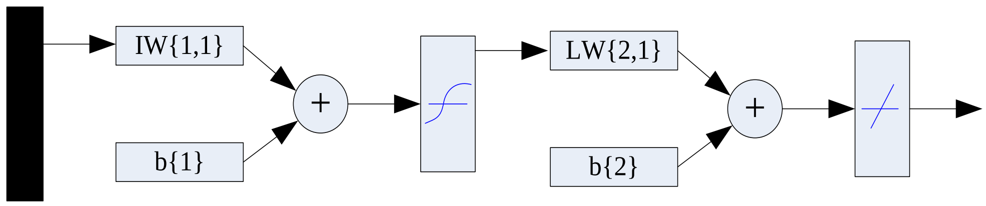


Figure 3. The Structure of BP Neural Network Model

5. Experiments and Analysis

To train the neural network model accurately, we have collected a large number of coal and rock images. After data being discretized and normalized, we have chosen 200 samples of coal and rock respectively. We have randomly selected 150 samples of coal and rock respectively to train the neural network model. Neural network's learning rate is 0.1; the training target is 0.01; the initial weight and bias are the random values between 0~1. [1-0] represents coal and [0-1] represents rock. The rest of 50 samples are used to test the trained neural network and the results are shown in table 3. The whole results are shown in table 4. We can conclude that entropy has a better effect in recognition and the recognition rate of coal is 96.2% and the recognition rate of rock is 95.4%.

Table 3. The Part Results of Coal-Rock Interface Recognition

Number	Samples	Energy		Contrast		Correlation		Entropy	
1	Coal	1.0125	0.0032	1.0563	0.0002	1.0012	0.0064	1.0001	0.0002
2	Coal	1.0042	0.0019	1.0564	0.0021	1.0000	0.0000	1.0001	0.0001
3	Coal	0.9865	0.0189	1.0002	0.1135	1.0001	0.0000	1.0000	0.0000
4	Coal	0.9683	0.0223	1.0096	0.0013	1.0003	0.0001	1.0000	0.0005
5	Coal	1.0425	0.0631	0.9952	0.0147	1.0000	0.0022	1.0003	0.0000
6	Coal	1.0085	0.0072	1.0077	0.2305	1.0001	0.0001	1.0002	0.0000
7	Coal	1.0125	0.2386	1.0129	0.0105	1.0003	0.0000	1.0000	0.0000
8	Coal	1.0002	0.0039	1.0084	0.0414	1.0001	0.0005	1.0001	0.0001
9	Coal	1.0124	0.0523	0.0426	0.0516	1.0000	0.0000	1.0001	0.0001
10	Coal	1.0254	0.0846	1.0105	0.0206	1.0001	0.0000	1.0009	0.0011
11	Rock	0.0052	1.0145	0.0009	1.0063	0.0000	1.0000	0.0000	1.0000
12	Rock	0.0011	1.0142	0.0087	1.0104	0.0000	1.0001	0.0000	1.0000
13	Rock	0.0102	0.9999	0.0035	1.0112	0.0000	1.0002	0.0000	1.0000
14	Rock	0.0210	0.9789	0.0042	1.0006	0.0001	1.0003	0.0000	1.0000
15	Rock	0.0412	1.0004	0.0007	0.9992	0.0002	1.0000	0.0000	1.0001
16	Rock	0.0062	1.0081	0.1005	1.0004	0.0001	1.0000	0.0000	1.0000
17	Rock	0.0376	1.0005	0.1205	1.0009	0.0000	1.0004	0.0000	1.0000
18	Rock	0.0031	1.0033	0.0304	1.0004	0.0003	1.0005	0.0000	1.0000
19	Rock	0.0003	1.0024	0.0006	1.0006	0.0000	1.0000	0.0000	1.0000
20	Rock	0.0006	1.0004	0.0116	1.0005	0.0000	1.0000	0.000	1.0000

Table 4. The Whole Results of Coal-Rock Interface Recognition

Samples	Recognition rate /%			
	Energy	Contrast	Correlation	Entropy
50(Coal)	87.5	90.6	95.7	96.2
50(Rock)	86.9	89.7	94.6	95.4

6. Conclusions

We propose a method of characteristic analysis and recognition of coal-rock interface based on visual technology. Firstly according to the coal and rock image, we analyze the texture difference between coal and rock. Secondly we calculate four texture feature values based on spatial gray co-occurrence matrix method. Thirdly the coal-rock is recognized using neural network trained by texture feature. The result shows that there is a great difference of texture feature between coal and rock. Coal and rock can be recognized use Energy, contrast, correlation, entropy as feature vector. In addition, entropy has a better effect in recognition.

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