# Coal-rock Interface Recognition Based on MFCC and Neural Network

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***Abstract***

*To solve the difficulty in recognition coal-rock interface for the top coal caving process, we proposed a new method based on Mel-frequency cepstrum coefficient (MFCC) and neural network. In this paper, we conducted the noise separation by Independent Component Analysis (ICA) for acoustic signal. Then we extracted MFCC as the feature and recognized the coal-rock interface via BP neural network. The result shows that MFCC reflect the voice features of coal-rock more effectively, comparing to other features (frame energy and kurtosis), it provides average relative reductions of 12% and 19% in error rate, which recognition rate is 83%. We conclude that the method based on MFCC and neural network is an effectively and automatically detection for the coal-rock interface recognitions.*

***Keyword****: MFCC, neural network, coal-rock interface recognition, top coal caving*

## 1. Introduction

Coal-rock interface recognition has been a subject of active research for years, and a lot of researches have been done. The method base on the responses of cutting force is applied to the coal mining by shearer, unable work in the top coal caving process [1]: The method base on gamma ray needs a natural gamma ray coal-rock interface sensor, which is worth more than 50000 dollars. There are about 100 hydraulic supports in a working face, so it is too expensive to apply in a large scale [2]; The method base on image identification often be influenced by working condition such as coal ash, miner light, which affect the accuracy of recognize results greatly [3]; The method base on the vibration of tail beam of hydraulic needs to remake hydraulic support [4], which is difficult to installation and repair. In actual production, most of top coals caving processes are accomplish by manual work. Not only the work efficiency is very low, but also increases the miner's life risk.

In order to make up the above shortcomings, researches now pay attention to acoustical signals. It is easy to collect, and the sensor is much cheaper than others. The coal-rock interface recognition issue is mainly divided into two stages: feature extraction and identification. MA Rui using wavelet package to analysis the acoustical signal in top coal caving [5], but it don't give a complete algorithm to recognize coal-rock interface. Zhang Yanli give a method based on independent component analysis and have a good performance [6], but it needs to improve the stability.

This paper developed a method based on MFCC and neural network, we collected acoustical signals using sound transducer, which install on the tail beam of hydraulic support. Then we conducted the noise separation by Independent Component Analysis (ICA) and extract MFCC features from the signals. Finally we recognized coal-rock interface via neural network.

## 2. Noise Separate

There are multiple sources of noise in the acoustical signal, among which chute is the noisiest one. In consideration of the noise of chute is periodic signal, while the sound of coal and rock isn't, we use ICA separate them.

The instantaneous time-invariant noiseless ICA model is described by the equation [7]

$$X = F(S) \tag{1}$$

Where $S = [s_1, s_2, ..., s_M]^T$ denotes the unknown mutually independent non-degenerate signal sources, $X = [x_1, x_2, ..., x_N]^T$ denotes the signals collected by independent sensors, $F(\cdot)$ is an unknown mixing function. In a conventional ICA problem, the mixing function $F(\cdot)$ in Eq. (1) is assumed to be linear [8].

$$X = A \times S \tag{2}$$

Where A is unknown mixing matrix $(N \times M)$. ICA algorithm work out the best inverse of the mixing matrix $W$ using the characteristic of statistic independence of signal sources, such that the recovered signals

$$\hat{S} = W \times X \tag{3}$$

The key of ICA algorithm is to estimate the independence between signals. FastICA algorithm using negentropy as judge standard

$$J(y) = H(Y_{Gauss}) - H(y) \tag{4}$$

Where $y$ is the signal need to be estimated, $Y_{Gauss}$ is Gaussian random variables with the same variance of $y$, $H(\cdot)$ is the negentropy function

$$H(y) = -\int p(y) \lg p(y) dy \tag{5}$$

Where $p(\cdot)$ is the probability distribution function. Because it is difficult to get the probability distribution function, we use Eq.(6) instead

$$Ng(y) = \{E[G(y)] - E[G(y_{Gauss})]\}^2 \tag{6}$$

Where $E[\cdot]$ is mean function, $G(\cdot)$ is given by $G(y) = -e^{-\frac{y^2}{2}}$.

The concrete processes of FastICA are

Step1 White signal $X$ and get signal $\tilde{X} = BX$ , where $B$ denotes the whitening matrix, so the vectors of $\tilde{X}$ are orthogonal each other.

Step2 Find the best inverse of the mixing matrix $W$ via iterative method

$$\hat{S}_i^{(n)} = \tilde{w}_i^T(n)\tilde{X} \tag{7}$$

Where $\hat{S}_i^{(n)}$ denotes the $i$ component of signals after n times iteration. The iterative formula as shown in Eq.(8) and Eq.(9)

$$\tilde{v}_i^T(n+1) = E[\tilde{X}G'(\hat{S}_i^{(n)}) - E[\tilde{X}G''(\hat{S}_i^{(n)})]\tilde{w}_i^T(n) \tag{8}$$

$$\tilde{w}_i^T(n+1) = \tilde{v}_i^T(n+1) / \left\|\tilde{v}_i^T(n+1)\right\| \tag{9}$$

The iteration ended when $\tilde{w}_i^T(n) < \varepsilon$, where $\varepsilon$ is a small number.

Step3 The resultant signal $\tilde{X}_{i-1}$ minus the signal component $\hat{S}_i$, and repeat step2, then we can get all the signal components and the best inverse of the mixing matrix $W$.

## 3. Feature Extraction

Sound features are many and varied, and some of them are commonly used [9], including MEL cepstrum coefficient, kurtosis, frame energy, formant frequency and bandwidth *etc*. This paper analysis the MEL cepstrum coefficient, kurtosis and frame energy to find the best sound features.

### 3.1. Mel Cepstrum Coefficient

Mel-frequency cepstrum (MFC) is a Short-term energy spectrum, which aims at computing the speech parameters similar to the way how a human hears and perceives sounds [10]. It reflects the characteristic of sound very well and has gained widespread adoption.

At first, the sound sample, which is about 2 seconds, is segmented into 100 frames via Hamming window. As a result, one frame is about 20 milliseconds. Then get the power spectral density via FFT (Fast Fourier Transformation). After that, we filtering the signal using 12 Triangular filters and calculate with Eq.(10). Finally, we can get the Mel cepstrum coefficient after discrete cosine transform (DCT).

$$Mel(f) = 2595\log_{10}(1 + f / 700) \tag{10}$$

### 3.2. Kurtosis

Kurtosis is the fourth-order cumulant of signal variable. It is a dimensionless feature that signifies the gaussianity of signal. The more non-gaussian signal is, the bigger kurtosis we get, and vice versa. The kurtosis will be zero when the signal is exactly the gaussian distribution. The method of calculation is

$$Kurtosis = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^4}{\left(\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2}\right)^4} \tag{11}$$

Where $x$ denotes the variable of signal and $\bar{x}$ denotes the mean value of the variable.

### 3.3. Frame Energy

As we know, there is a big difference about the density and the hardness between coal and rock. It makes the energy of sound different, which is made by collision when they fall. Here is the formula as Eq. (12)

$$E_i = \int_0^T |x_i(t)|^2 \, dt \tag{12}$$

## 4. Coal-rock Interface Recognition based on the Neural Network

Artificial Neural Network (ANN) is a mathematical model inspired by biological neural networks [11]. Artificial neuron is the basal information processing unit of ANN, and the principle of it as shown in Figure 1. We can set up a parallel computing architecture by organize the mass of artificial neuron via an assuming topology.

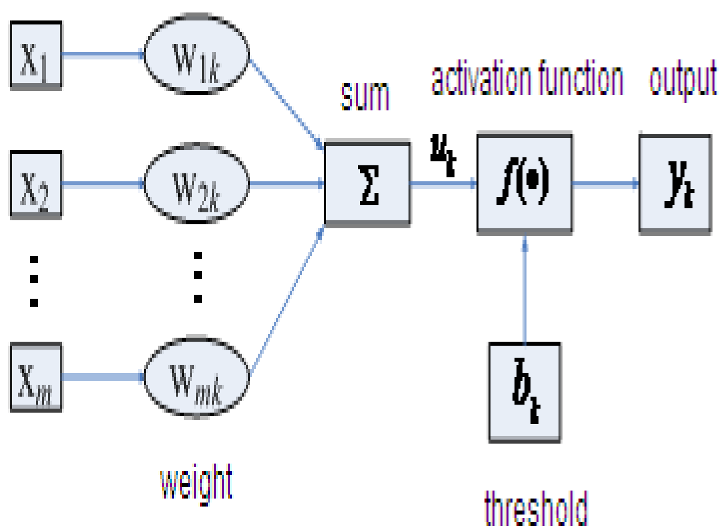


**Figure 1. The Principle of Artificial Neuron**

This paper analysis using back propagation neural network [12-14] that contains input layer, hidden layer and output layer. There is no activation function in input layer. At the same time, we use tansig function in hidden layer as shown in Eq. (13) and use purelin function in output layer as shown in Eq. (14).

$$f(x) = \frac{2}{1+e^{-2x}} - 1 \tag{13}$$

$$f(x) = x \tag{14}$$

Where $x$ is the weighted sum of neural inputs and $f(x)$ is the output of an individual neuron.

Then we train the neural network by back propagation neural learning algorithm to optimize the weights, so as to recognize the coal-rock interface efficiently. This paper learning with 350 coal samples and 50 rock samples, and setting the training times are 10000, the error goal is 0.0001, and the learning rate is 0.05.

## 5. Experimental Result

In order to validate the performance of recognition, we installed the binaural PCM linear acoustic transducer under hydraulic support, and collected the acoustic signal, about 60 seconds and the sample frequency is 44 KHz, when it was drawing. After that, we cut the large sample into small one, which is about 2 seconds. Due to the bad working condition, we could only collect the sample of pure coal but couldn't collect the sample of pure rock, so we used the coal-rock mixed samples instead, and the rock in the coal-rock mixed sample is about 30%. Finally, we got 400 coal small samples and 100 coal-rock mixed small samples collected in five different hydraulic supports. There is a frame coal sample and a frame coal-rock sample as shown in Figure 2 and Figure 3.

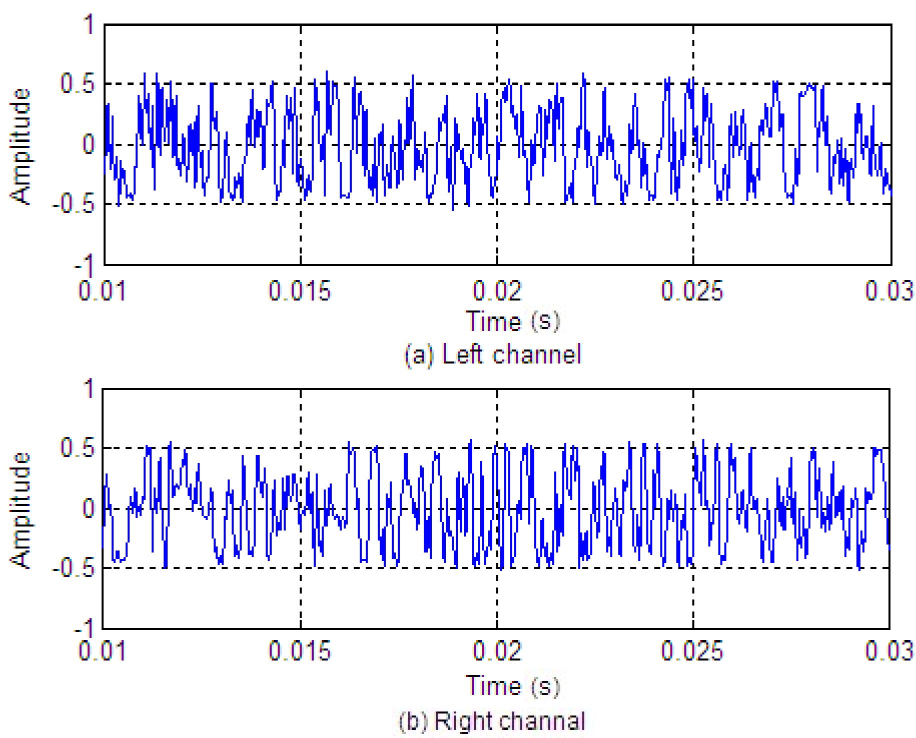


**Figure 2. A Frame of Coal Sample**

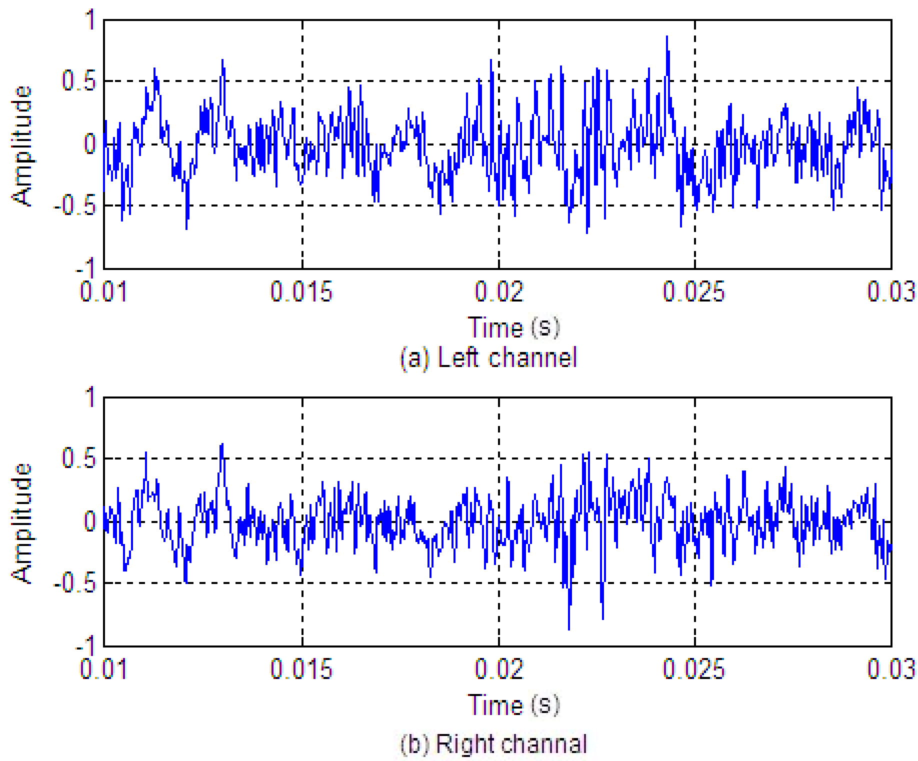


**Figure 3. A Frame of Coal-rock Mixed Sample**

Calculate the frequency spectrum of the samples above. As we can see from Figure 4, the high frequency part of coal-rock mixed sample is obviously higher than the coal sample. It gives the opportunity that recognition using frequency characteristic.

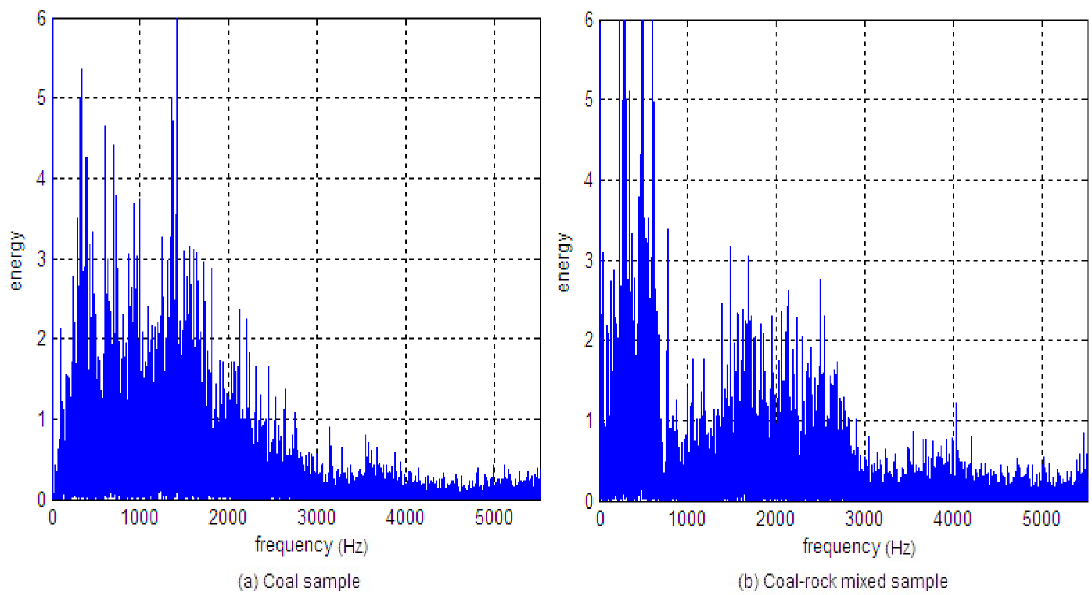


**Figure 4. Frequency Spectrum of Samples**

In the field situation, the sound created by rock over the sound created by coal in the coal-rock mixed sample. As a result, we assume that it will be identified as the coal-rock mixed sample if there are 30% frames of sample are recognized as the rock signal. The partial recognize result as shown in Table 1. It shows that some frames of coal sample may be recognized as the rock signal falsely, but there is nothing to worry about as the occurrence probability is very low.

**Table 1. Partial Recognize Result**

| data code | type | MFCC | Kurtosis | Frame Energy |
|---|---|---|---|---|
| 1 | coal | 0.05 | 0.07 | 0.17 |
| 2 | coal | 0.17 | 0.10 | 0.26 |
| 3 | coal | 0.01 | 0.05 | 0.12 |
| 4 | coal | 0.22 | 0.23 | 0.29 |
| 5 | coal | 0.37 | 0.40 | 0.44 |
| 6 | coal-rock mixed | 0.54 | 0.40 | 0.43 |
| 7 | coal-rock mixed | 0.47 | 0.29 | 0.40 |
| 8 | coal-rock mixed | 0.36 | 0.34 | 0.42 |
| 9 | coal-rock mixed | 0.33 | 0.23 | 0.36 |
| 10 | coal-rock mixed | 0.39 | 0.22 | 0.34 |

The overall recognize result as shown in Table 2. As we can see, the recognition capability of frame energy is not enough, there is only 64% samples recognize properly. The recognition result of kurtosis is tending to the coal. The recognition rate of coal-rock mixed sample is 56%, although the overall recognition rate is about 71%. The MFCC can reflect the characteristic of both two type sample very well, the overall recognition rate is up to 83%.

**Table 2. Overall Recognize Result**

| Sample type | amount | identification number | | |
|---|---|---|---|---|
| | | MFCC | kurtosis | frame energy |
| coal | 50 | 46 | 43 | 31 |
| coal-rock mixed | 50 | 37 | 28 | 33 |
| total | 100 | 83 | 71 | 64 |

## 6. Conclusion

Sound recognition is a cost-effective convenient method that others cannot be matched. With the development of sound recognition technology, not only the recognition rate but also the stability has a significant improvement. This paper compared three different Sound features and recognized coal-rock interface using back propagation neural network. Find that the MFCC have a better performance compares with the other two. Finally get the coal-rock interface recognition method based on MFCC and neural network. The experiment proofs that it has good accuracy and stability.

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