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# Coal-Rock Interface Recognition Method Based on Dimensionless Parameters and Support Vector Machine

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## ABSTRACT

In order to identify the coal-rock interface in the top coal caving,a new method based on dimensionless parameters and support vector machine is proposed. First the vibration signal of the hydraulic support tail beam is detected, then the feature vectors of vibration signal dimensionless parameters, such as peak factor, pulse factor, margin factor, skewness factor, kurtosis factor and waveform factor etc, are constructed, which are as support vector machine training samples to establish classifier for identifying the coal-rock interface. The experimental result shows the feature vectors constructed by the dimensionless parameters input support vector machine can automatically identify the coal-rock interface, providing a new perspective and method for the study of coal-rock interface recognition.

KEYWORDS: coal-rock interface recognition, dimensionless parameters, support vector machine, vibration signal

# INTRODUCTION

Today, fully mechanized top coal caving mining process in our country is completely controlled by the manual operation, as a result, the work quality is at random, and it is difficult to achieve the ideal control effect. Insufficient top coal caving will result in coal recovery rate decreases; excessive top coal caving will cause a decline in the quality of coal because of mixed mass rock, the increase in traffic volume and the amount of coal preparation, it leads to the raise of production cost, and drop of profits[1]. Li Chong-mao proposed the coalmine intelligent management system based on the concept of safety[2],So the study of coal-rock character recognition of fully mechanized caving working face provide basis for the top coal caving control strategy. can reduce coal mine workers labor intensity in the fully mechanized coal caving working face, ensure their personal safety and health; therefore, it has important economic and social value for coal mining safety.

In our country, the field of energy priority themes in the "national long-term science and technology development plan (2006-2020)" focus on "research and development of more efficient coal mining technology and related equipment." At the same time “national energy technology Twelfth Five Year Plan (2011-2015) "proposes to focus on coal-rock interface automatic identification technology. So the study of the coal and rock interface automatic identification theory and technology belongs to the frontier of international research, and conforms to our country's long-term planning, is one of the key technologies which call for a new breakthrough in energy technology field.

The major coal producing countries in the world attach great importance to the study of coal-rock interface recognition method, proposing cutting force detection method, r-ray detection method, image detection method, radar detection method, infrared detection method, active power monitoring method, vibration detection method, sound detection method, the dust detection method, etc[3-4].

Focusing on the vibration signal of the hydraulic support tail beam, this paper carries out the research of coal-rock interface recognition. The vibration signal produced by coal caving and rock caving impact hydraulic support tail beam contains the information of coal and rock conditions. Through testing vibration signal generated by coal caving and rock caving impact hydraulic support tail beam, and extracting the dimensionless parameters as feature vector of support vector machine, Using support vector machine classifier to classify tail beam vibration signals under two conditions, intelligent identification of coal-rock interface is to be realized.

# Support vector machine classification principle

Support vector machine (SVM) is a machine learning method specifically for small sample classification, is developed from the optimal classification plane of linearly separable case[5-7]. The basic idea is to find optimal classification line, which can not only correctly separate two types of data samples, but also make the classification interval maximum. The classification line equation is $w \cdot x - b = 0$; to normalize it, the linear separable samples $(x_i, y_i), i = 1, \cdots n, x \in R_d, y \in \{+1, -1\}$,

$$\text{meet}\quad y_i[(w\cdot x_i)+b]-1\geq 0, i=1,\cdots n \tag{1}$$

This time classification interval is equal to $2/\|w\|$, making classification interval maximum, namely, to make $\|w\|^2$ minimum. The optimal classification plane is what makes $1/2\|w\|^2$ minimum. The Lagrange optimization method can get optimal classification plane problem into its dual problem.

$$Q(\alpha)=\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i,j=1}^{n}\alpha_i\alpha_j y_i y_j(x_i\cdot x_j) \tag{2}$$

and meet the constraints $\sum_{i=1}^{n}y_i\alpha_i=0$, $\alpha_i\geq 0, i=1,\cdots,n$ ,the maximum value of $Q(\alpha)$.

$\alpha_i$ is Lagrange multiplier corresponding to each constraint condition. This is a quadratic function optimization problems under inequality constraints, where there is a unique solution. The solution will be only a part (usually a small part) $\alpha_i$ is not zero; the corresponding sample is support vector. The solution of these problems leads to get the optimal classification function

$$f(x)=\operatorname{sgn}\{(w\cdot x)+b\}=\operatorname{sgn}\{\sum_{i=1}^{n}\alpha_i^* y_i(x_i\cdot x)+b^*\} \tag{3}$$

In the formula, $\operatorname{sgn}\{\}$ is the symbol function, the summation is actually only the support vectors. $\alpha_i^*$ is the optimal solution of $\alpha_i$, $b^*$,the classification threshold, can be obtained by any support vector, or can be obtained through any pair support vector of two types by taking the median. According to the unclassified sample $x$, can determine the category of $x$ by positive and negative of the classification function $f(x)$.

In solving linear inseparable problems, a non-negative slack variables $\xi_i$ can join and introduce errors punishment component C which control the degree of punishing wrong samples. The greater C is the more severe punishment is for the error.

The use of properly inner product function $K(x_i\cdot x_j)$ in the optimal classification plane can realize a linear classification after nonlinear transform, In this case the objective function equation becomes

$$Q(\alpha)=\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i,j=1}^{n}\alpha_i\alpha_j y_i y_j K(x_i\cdot x_j) \tag{4}$$

And the corresponding classification function equation is also changed to

$$f(x)=\operatorname{sgn}\{\sum_{i=1}^{n}\alpha_i^* y_i K(x_i\cdot x)+b^*\} \tag{5}$$

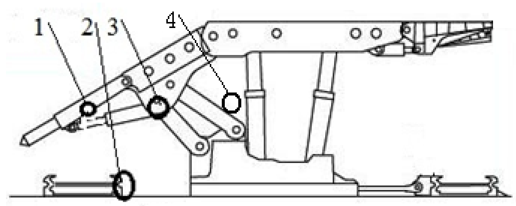
# Experiment Settings

In this paper, the analysis of the hydraulic support tail beam vibration signal is used to study the coal-rock interface recognition problem in the process of fully mechanized coal caving working face.

Vibration signal acquisition is simple; it directly reflect the caving situation. The acquisition equipment is of low cost, and easy to promote. In the process of caving, coal or rock falling impacts hydraulic tail beam, causes the vibration of tail beam. The caused vibration has distinction because of different coal and rock mechanical properties. We can reach the desired purpose of coal-rock interface recognition by detecting the tail beam vibration signal[8].

The experiment was carried out in a coal mine 9103 fully mechanized coal caving working face. Due to the high gas, coal dust, damp, poor working environment in the coal mine, data recording instrument used on the ground is difficult to use in underground. China University of Mining and Technology (Beijing) developed YHJ(D) Portable Vibration Measurement Data Recorder for the collection and storage of vibration and sound pressure signal[9]. The recorder which has obtained coal mine security certification has the characteristics of explosion-proof, waterproof, moisture-proof, anti-corrosion, high temperature resistance, anti-vibration. The intrinsic safe mine acceleration sensor developed by our research group was used to measure the vibration signal. INV9206 type ICP sound pressure sensor was used to measure sound pressure signal, and the image signal is collected by the high definition camera. The experiment collected vibration signal, sound pressure signal and image signal. This paper is an analysis of the vibration signal of tail beam.

In order to obtain accurate the vibration, sound pressure and image signal of coal and rock, the hydraulic support tail beam, and the rear scraper conveyor are selected as the testing object. The sensor mounting position is shown in Figure 1.




1,2- acceleration sensor 3- sound pressure sensor 4-Image acquisition device

**Figure 1:** Sensor mounting location

The acceleration sensor of 1# measuring point picks up the hydraulic support tail beam vibration signal; the acceleration sensor of 2# measuring point picks up the rear scraper conveyor vibration signal.The sound pressure sensor of 3# measuring point picks up sound pressure signal of the rear scraper conveyor and hydraulic support tail beam. Image acquisition device of 4# measuring point picks up the coal caving export image signal.

During the testing process, the data testers and the coal caving workers cooperate with each other, making the recording data corresponding to coal caving and rock caving working condition; the coal caving workers are responsible for coal caving or rock caving, and tell the condition information to the data tester; the data testers timely record the condition data and the condition duration time.

# Feature vector extraction of dimensionless parameter of coal and rock

The essence of coal-rock interface recognition is pattern recognition, including feature extraction and state recognition. The feature extraction is extracting dimensionless parameter as feature vector. State recognition is using SVM to complete the classification of coal caving and rock caving.

The dimensionless parameter acquisition does not need to use various signal processing and transformation, directly use detected vibration signal, so does not cause the signal distortion and leakage and other defects, easy to field implementation. The dimensionless parameters are peak factor C, pulse factor I, margin factor L, skewness factor P, kurtosis factor K and waveform factor S[10-11]. Different vibration signals, the nature and size of the vibration is different, the dimensionless parameters will have significant differences. This paper analyses vibration signal dimensionless parameters size and changes of the coal-rock impacting hydraulic tail beam, study the relationship between coal-rock characteristics and dimensionless parameters, combines with SVM intelligent classification method and carries out coal-rock interface classification, provides an effective method for the coal-rock interface recognition.

$$C = \max(|x_n|) / \sqrt{\frac{1}{T}\sum_{n=1}^{N} |x_n|^2 \Delta t} \tag{6}$$

$$I = \max(|x_n|) / (\frac{1}{T}\sum_{n=1}^{N} |x_n| \Delta t) \tag{7}$$

$$L = \max(|x_n|) / (\frac{1}{T}\sum_{n=1}^{N} \sqrt{|x_n|}\Delta t)^2 \tag{8}$$

$$P = \sqrt{N}\sum_{n=1}^{N}(x_n - \frac{1}{T}\sum_{n=1}^{N}|x_n|\Delta t)^3) / (\sum_{n=1}^{N}(x_n - \frac{1}{T}\sum_{n=1}^{N}|x_n|\Delta t)^2)^{3/2} \tag{9}$$

$$K = (N\sum_{n=1}^{N}(x_n - \frac{1}{T}\sum_{n=1}^{N}|x_n|\Delta t)^4) / (\sum_{n=1}^{N}(x_n - \frac{1}{T}\sum_{n=1}^{N}|x_n|\Delta t)^2)^2 \tag{10}$$

$$S = (\sqrt{\frac{1}{T}\sum_{n=1}^{N}|x_n|^2 \Delta t}) / (\frac{1}{T}\sum_{n=1}^{N}|x_n| \Delta t) \tag{11}$$

In the formula, $x_n$ —recording signal vibration amplitude, $n$ —sequence element number, $\Delta t$ —sample interval, $T$ —signal sampling time, $N$—discrete signal points.

The vibration signal of the tail beam is obtained by acceleration sensor, and the sampling frequency is 10000Hz.Figure 2 and Figure 3 are time domain waveform of the tail beam vibration signal when coal caving and rock caving.

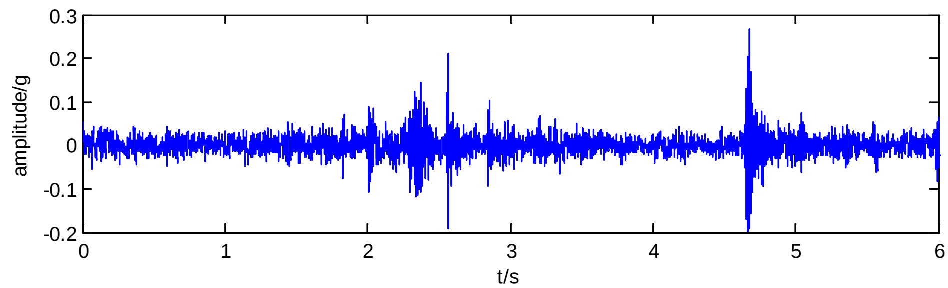



**Figure 2:** Time-domain waveform of hydraulic support tail beam vibration signal when coal caving

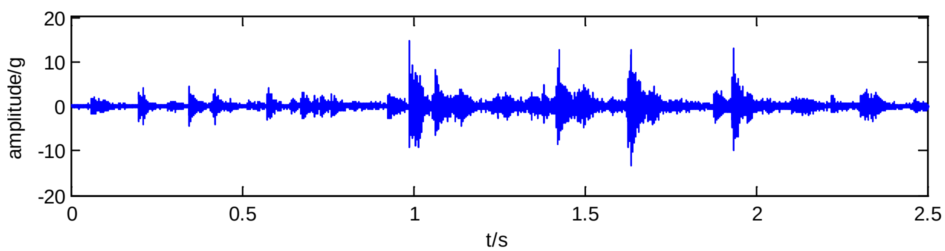



**Figure 3:** Time-domain waveform of hydraulic support tail beam vibration signal when rock caving

In order to facilitate pattern recognition of SVM, feature extracting with dimensionless parameters is used. The dimensionless parameter values of the two samples of coal caving and rock caving are shown in Table 1.

**Table 1:** Two samples dimensionless parameters of coal caving and rock caving

| working condition | skewness factor | kurtosis factor | waveform factor | pulse factor | peak factor | margin factor |
|---|---|---|---|---|---|---|
| coal caving | 0. 0925 | 12. 4674 | 1. 55949 | 17. 7326 | 11. 3707 | 23. 097 |
| rock caving | −0. 81901 | 45. 8465 | 2. 30526 | 34. 0959 | 14. 7904 | 51. 9838 |

Table 1 shows that, each dimensionless parameter value has variation when coal caving and rock caving; rock caving dimensionless parameters have greater growth, compared to coal caving, which kurtosis factor, pulse factor, margin factor change most significantly. That is because the different mechanical properties of coal and rock cause different vibration signal generated by the tail beam, illustrating that different coal caving and rock caving conditions lead to different dimensionless parameter values, and dimensionless parameter variation feature value can be used as the basis to recognize coal caving and rock caving. The dimensionless parameters are constructed as a feature vector Q; the feature vector Q can be described as: Q=[skewness factor, kurtosis factor, waveform factor, pulse factor, peak factor, margin factor],the feature vector is as the SVM sample for coal-rock interface automatic identification.

# Coal-rock recognition experiment

Sixteen groups of experimental data are collected, including eight groups of coal caving data, eight groups of rock caving data. After calculating sixteen groups of data dimensionless parameters, 16 feature vectors are constructed. eight samples of each working condition of coal caving and rock caving are selected in the experiment process, in which five samples are used as the training samples to build SVM classifier; three samples are used as testing samples to verify whether the established SVM classifier can accurately realize classification and identification of coal and rock. Five coal caving samples are used as a class; the category label is 1. The five rock caving samples are used as a class; the category label is -1. The feature vector of each sample IS calculated and ten groups of six dimensional feature vectors are obtained. This is used as the training samples of SVM pattern recognition, the training samples are shown in table 2.

**Table 2:** Training samples of SVM

| sample number | feature vector of training sample | | | | | | category label | Working condition |
|---|---|---|---|---|---|---|---|---|
| 1 | 0.0925 | 12.4674 | 1.55949 | 17.7326 | 11.3707 | 23.097 | 1 | coal caving |
| 2 | 0.09961 | 3.88708 | 1.36499 | 10.9544 | 8.0253 | 13.4142 | 1 | coal caving |
| 3 | −0.12058 | 5.26518 | 1.38839 | 11.1805 | 8.05284 | 13.7545 | 1 | coal caving |
| 4 | −0.0519 | 8.36026 | 1.57693 | 14.3499 | 9.09991 | 18.9839 | 1 | coal caving |
| 5 | 0.08076 | 3.42621 | 1.36247 | 9.97657 | 7.3224 | 12.223 | 1 | coal caving |
| 6 | −0.70376 | 28.9391 | 1.70511 | 28.6754 | 16.8173 | 38.8098 | -1 | rock caving |
| 7 | −0.81901 | 45.8465 | 2.30526 | 34.0959 | 14.7904 | 51.9838 | -1 | rock caving |
| 8 | −0.18498 | 58.1049 | 1.92932 | 33.6949 | 17.4646 | 45.8297 | -1 | rock caving |
| 9 | 0.10999 | 58.2535 | 3.11115 | 49.6643 | 15.9633 | 97.9247 | -1 | rock caving |
| 10 | −0.98889 | 55.6888 | 1.90472 | 30.0552 | 15.7792 | 41.122 | -1 | rock caving |

In this paper, the established SVM classifier selects the radial basis kernel function[12-13].

$$K(x,y)=\exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right) \tag{12}$$

In the formula, $\sigma$ >0 is the width of the radial basis function. Then the error punishment parameter C and kernel parameter $\sigma$ are determined. With determined radial basis kernel function, after test analysis and comparison, when the error punishment parameter C is 1000 and the kernel parameter $\sigma$ is 1, the training and test accuracy of SVM is higher, and the classifier promotion ability is best.

**Table 3:** Testing samples of SVM

| sample number | working condition | feature vector of testing sample | | | | | | output label |
|---|---|---|---|---|---|---|---|---|
| 1 | coal caving | 0. 23539 | 14. 0382 | 1. 65221 | 17. 3302 | 10. 4891 | 22. 9537 | 1 |
| 2 | coal caving | 0. 051004 | 8. 803624 | 1. 50840 | 14. 3095 | 29. 40757 | 18. 44066 | 1 |
| 3 | coal caving | 0. 11618 | 3. 8399 | 1. 37255 | 10. 6882 | 7. 78714 | 13. 1372 | 1 |
| 4 | rock caving | −0. 31007 | 49. 9859 | 2. 6660 | 41. 7934 | 15. 6764 | 73. 1775 | -1 |
| 5 | rock caving | −0. 38157 | 48. 22598 | 2. 34336 | 37. 58478 | 16. 1424 | 61. 5451 | -1 |
| 6 | rock caving | −0. 50924 | 55. 4761 | 2. 70954 | 39. 1282 | 14. 4409 | 65. 9652 | -1 |

Verifying the above established SVM classifier with test samples shown in Table 3, the three coal caving samples feature vector are input in SVM classifier and all output category labels are 1, namely, the three feature vectors classification result is coal caving by SVM classifier, consistent with the actual working condition. The three rock caving samples feature vector are input in SVM classifier and all output category labels are -1, namely, the three feature vector classification result is rock caving by SVM classifier, consistent with the actual working condition. From the test results, it can be seen that established SVM classifier by training samples can classify the constructed feature vectors of dimensionless parameters, namely to classify and identify coal caving and rock caving in fully mechanized coal caving face, and the coal-rock condition classification results are correct. It shows that it is feasible to use dimensionless parameters of the vibration signal as feature vector to identify the coal and rock.

## CONCLUSION

In order to extract coal and rock state information contained in the tail beam vibration signal, this paper proposes using dimensionless parameters to construct feature vector, and applying it to coal and rock feature extraction, using SVM for coal and rock classification and recognition. The experimental analysis shows that:

(1) By detecting hydraulic support tail beam vibration signal, after dimensionless parameter feature vector extraction, feature information of coal and rock has been fully expressed, can recognize coal-rock interface in fully mechanized coal caving face.

(2) The feature vector constructed by tail beam vibration signal dimensionless parameters which are input in SVM classifier can realize coal caving and rock caving classification, and provide a new idea and method for coal-rock interface recognition. It lays a foundation for fully mechanized coal caving mining automation and intelligent control, and less humanized and then unmanned coal caving working face.

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