Shearer Cutting Pattern Recognition Based on Multi-scale Fuzzy Entropy and Support Vector Machine

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Abstract. Aiming at the problem of low intelligent level of shearer, a shearer cutting pattern recognition method is proposed based on the combination of multi-scale fuzzy entropy, Laplace score and support vector machine. By extracting the multi-scale fuzzy entropy of the vibration signal under different cutting modes, the feature vector representing the cutting pattern is mastered. At the same time, the Laplace score is used to select the feature vectors with possessing rich cutting pattern information. The selected features are produced as the learning samples of support vector machine. The experimental system of shearer cutting coal-rock is built, and the vibration signals of rocker arm under different cutting patterns are extracted. The experimental analysis is carried out and the results indicate that the cutting pattern recognition method proposed in this paper has high recognition accuracy, and the correct rate can reach to 98.86%. The research results provide technical support for the intelligent and rapid development of fully mechanized mining face.

Keywords: shearer, cutting pattern, vibration signal, multi-scale fuzzy entropy.

1. Introduction
In February 2020, eight ministries including the National Development and Reform Commission and the National Energy Administration jointly issued the “Guiding Opinions on Accelerating the Development of Intelligent Coal Mines” which clearly stated that there will be basically a small or unmanned operation in a fully-mechanized face by 2021. As the key equipment for comprehensive mechanized coal mining, shearers are of great significance to the safe and efficient production of coal mines. Its degree of intelligence is an important factor in the realization of "less people" or "unmanned" in fully-mechanized face. One of the key factors to improve the intelligence of the shearer is to realize the accurate recognition of the cutting mode of the shearer [1].

At present, scholars have conducted certain research on the method of shearer cutting pattern recognition. Liu Yiwen and other authors [2] took advantage of the change of coal wall temperature pre-and post-the shearer cutting to establish a shearer cutting pattern recognition model based on BP neural network. Asfahani and other authors [3] proposed a method that identifies the coal-rock interface with gamma rays, and then judges the cutting mode of the shearer drum. However, due to the harsh downhole environment and complex geological structure, the recognition status of infrared temperature sensors...
and gamma rays is not good enough, so other people indirectly judge its cutting mode through changes in some state parameters of the shearer itself: Ma Zhenglan and other authors[4] indirectly identify the cutting resistance based on the cutting load of the shearer, and then judge the cutting status of the shearer; Chen Chen [5], Zhang Tianci[6], Xu Zhipeng [7], Yan Zhongliang[8] and other authors analyzed the load and judged the shearer cutting mode by combining the relevant current data of the shearer with the characteristic values extracted by wavelet decomposition. Xu Jing [9], Zhang Qizhi [10], Jiang Gan [11] and other authors obtained the characteristics of the shearer's corresponding cutting mode by analyzing the shearer's cutting sound signal and rocker vibration signal. But, the complexity of the spatial distribution of the shearsers' pick makes the characteristics of the rocker vibration signal very different under different time scales. Therefore, the shearer cutting mode discrimination method based on the single-scale characteristic signal established by the above-mentioned scholars has certain limitations.

Therefore, the author of this paper put forward a new method of shearer cutting pattern recognition based on multi-scale fuzzy entropy and support vector machine. First, we can obtain the feature vector characterizing the cutting mode of the shearer by extracting the multi-scale fuzzy entropy of the rocker arm vibration signal under different cutting modes, and then select the vectors that have high correlation through the Laplace score as the learning samples of the support vector machine to determine the cutting mode of the shearer.

2. Multi-scale fuzzy entropy

2.1. Fuzzy entropy

Fuzzy entropy uses the concept of fuzzy function to introduce the characteristics of exponential function in the process of solving the similarity degree of two time series which includes continuity and non-mutation, ensuring that the time series has the greatest similarity to itself. It is defined as follows [12]:

(1) Transform n-point time series \(\{u(i) : 1 \leq i \leq N\}\) ; construct m-dimension vector:

\[
X^m_i = \{u(i), u(i+1), \ldots, u(i+m-1)\} - u_0(i)
\]

\[
u_0(i) = \frac{1}{m} \sum_{j=0}^{m-1} u(i + j)
\]

(2) Define \(d[X^m_i, X^m_j]\) as the maximum distance corresponding to the element value of the \(X^m_i\) and \(X^m_j\). It can be expressed as follows:

\[
d^m_{ij} = d[X^m_i, X^m_j] = \max_{k \in (0, m-1)} \{ \| (u(i+k) - u_0(i)) - (u(j+k) - u_0(j)) \| \}
\]

In the above formula, \(i, j = 1, 2, \ldots, N-m, i \neq j\).

(3) Define \(D^m_{ij}\) as the similarity between the vector \(X^m_i\) and \(X^m_j\) according to the fuzzy function \(\mu(d^m_{ij}, n, r)\):
\[ D_{ij}^m = \mu(d_{ij}^m, n, r) = e^{-(d_{ij}^m / r)^n} \] (4)

In the above formula, \( n \) and \( r \) are the gradient and width of the fuzzy function boundary respectively.

(4) defining function:

\[ \phi^m(n, r) = \frac{1}{N - m} \sum_{i=1}^{N-m} \left( \frac{1}{N - m - 1} \sum_{j=1 \atop j \neq i}^{N-m} D_{ij}^m \right) \] (5)

(5) Repeat step (1) to step (4) and construct \((m+1)\)-dimension vector:

\[ \phi^{m+1}(n, r) = \frac{1}{N - m} \sum_{i=1}^{N-m} \left( \frac{1}{N - m - 1} \sum_{j=1 \atop j \neq i}^{N-m} D_{ij}^{m+1} \right) \] (6)

(6) According to the above deduction, the fuzzy entropy can be defined as the following:

\[ \text{FuzzyEn}(m, n, r) = \lim_{N \to \infty} [\ln \phi^m(n, r) - \ln \phi^{m+1}(n, r)] \] (7)

When \( N \) is not infinite, the above formula can be expressed as:

\[ \text{FuzzyEn}(m, n, r, N) = \ln \phi^m(n, r) - \ln \phi^{m+1}(n, r) \] (8)

2.2. Multi-scale fuzzy entropy

In different cutting modes, there are certain differences in the frequency band characteristics and complexity characteristics of the vibration signal of the shearer rocker arm cutting source in terms of different time scales. It is feasible to improve the accuracy of the result by extracting the fuzzy entropy value of the vibration signal of the shearer rocker arm in terms of different time scales. The main function of multi-scale entropy is to calculate the complexity of a certain time series under various scale factors, which is defined as follow [13]:

(a) Time series coarse graining. For \( n \)-point time series \( X_i = \{x_1, x_2, \ldots, x_n\} \), Combine the original time series into a new vector through suitable similarity tolerance \( r \) and embedding dimension \( m \) [14]:

\[ y_j(\tau) = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i \quad 1 \leq j \leq \frac{N}{\tau} \] (9)

In the above formula, the scale factor is \( \tau = 1, 2, \ldots, n \). when \( \tau = 1, \{y_1(1), y_2(1), \ldots, y_n(1)\} = X_i \) is original time series. Therefore, The meaning of the new vector is to divide the \( n \)-point time series \( X_i \) into \( \tau \) time series \( y_j(\tau) \). The specific process is shown as Figure 1.

(b) Fuzzy entropy solution for each time series \( y_j(\tau) \) and describe it as the corresponding scale factor function.
Multi-scale fuzzy entropy is defined as obtaining the corresponding fuzzy entropy value of the same time series under different scale factors, which reflects the complexity of vibration signal in terms of different time scale and overcomes the defect of single fuzzy entropy. The results of fuzzy entropy are related to data length N, similarity tolerance r, embedding dimension m and fuzzy function gradient n. After a lot of simulation analyses, the parameters are selected as follows: \( m = 2, \ r = 0.15SD \) (SD represents the standard deviation of the original data), \( n = 2, \ \tau = 15 \).

3. Multi-scale fuzzy entropy screening based on Laplace score
Pattern recognition requires related feature vectors, but many feature vectors will be obtained and the degree of correlation between each eigenvector and the cutting mode varies when the scale factor \( \tau = 15 \). Therefore, it is necessary to select n feature vectors with the highest correlation with the mode from the m eigenvectors, that is, eigenvector screening. This not only allows better pattern recognition, but also reduces the calculation time and avoids dimensionality disasters and information redundancy. Dash and other authors use distance entropy to sort and filter sample data. This method has a good clustering effect and removes irrelevant feature vectors effectively [15-16]. The feature vector screening has better discrimination through the Laplacian score algorithm that combines the clustering characteristics of the sample and the variance information.

1) Construct adjacency graph
Suppose \( X = \{x_1, x_2, \ldots, x_n\} \) is sample data, \( n \) is the number of samples, and \( m \) is the feature dimension. Take any two-sample data \( x_i, x_j \). The adjacency graph G has only one edge \( x_i \) \( x_j \), that is \( G = 1 \), if the k neighboring points of \( x_i \) include \( x_j \). If the k neighboring points of \( x_i \) do not include \( x_j \), then \( G = 0 \). The neighbor relationship of different points in the sample data can be judged by constructing the adjacency graph G.

2) Calculate adjacency weight
When \( x_i, x_j \) is connected, the weight of the edge can be determined by the heat kernel method.

\[
S_{ij} = \begin{cases} \
\frac{e^{-\|x_i-x_j\|^2}}{t} & G = 1 \\
0 & G = 0 
\end{cases}
\]

(10)

In the above formula, \( t \) is a constant. The adjacent weight \( S_{ij} \) represents the closeness of two points, and the size of \( S_{ij} \) is positively correlated with the distance between the two points; The adjacency weight
$S_0=0$, when $G=0$. In order to make the difference between the sample data points more obvious, the adjacent weight method is used as a penalty factor to assign a larger value to the points that are closer and a smaller value to the points that are far away.

3. The index of feature evaluation

If the points in the adjacency graph $G$ are clustered within a certain range, the points in the sample data will have local characteristics. It can be achieved by the following objective function:

$$L_r = \frac{\sum_y (f_{ri} - f_{rj})^2 S_y}{\text{Var}(f_r)}$$  \hspace{1cm} (11)

Where $\text{Var}(f_r)$ is called the feature variance, which represents the degree of correlation of the r-th feature vector in all sample data; $\sum_y (f_{ri} - f_{rj})^2 S_y$ represents the distribution of sample data in the r-th eigenvector, where $f_{ri}$ and $f_{rj}$ respectively represent the distribution of sample data i and j in the r-th eigenvector. The smaller difference between the two is, the closer the distance between sample data is.

4. Standardized feature evaluation index [17]

Standardized solution to the $f_r$ of the above formula:

$$\tilde{f}_r = f_r - \frac{f_r^T D I}{I^T D I} I$$  \hspace{1cm} (12)

The characteristic value of the r-th Laplacian is as follows:

$$L_r = \frac{\tilde{f}_r^T L \tilde{f}_r}{\tilde{f}_r^T D \tilde{f}_r}$$  \hspace{1cm} (13)

The larger the Laplacian score is, the greater the contribution of the feature vector to cutting pattern recognition, on the contrary, the smaller the contribution is. According to the final Laplace score, the first n values are selected as the final pattern recognition vector.

4. The method and process of shearer cutting pattern recognition

According to the actual working conditions, the shearer cutting modes set in this article mainly include no-load, cutting the roof, cutting the floor, cutting F1 hardness coal-rock, and cutting F2 hardness coal-rock. Extract multi-scale fuzzy entropy features as training samples from vibration signals in different cutting modes. The structure of multi-class support vector machine is shown in Figure 2.

![Figure 2. The structure of multi-class support vector machine](image-url)
5. Experimental verification
In order to verify the correctness of the feature extraction of the vibration signal of the shearer rocker arm and the recognition of the cutting pattern proposed in the previous article, this paper built a coal-rock cutting experiment system for the shearer at the National Energy Mining Equipment research and development Experimental Center of Zhangjiakou Coal Mining Machinery Limited Company and carried out ground tests. The experimental site and equipment are shown in Figure 3.

![Experimental site of coal-rock cutting](image1)

![Vibration signal acquisition unit](image2)

**Figure 3.** Vibration signal acquisition system of shearer rocker arm

The vibration signal collected by the above system from five cutting modes including shearer no-load, cutting the roof, cutting the floor, cutting F1 hardness coal seam, and cutting F2 hardness coal seam are called Signal1, Signal2, Signal3, Signal4, Signal5. Traction speed of the shearer is 2.5m/min and the sampling frequency is 15kHz in the experiment. Collect 60 groups of data for each operating condition, randomly select 25 groups of them for support vector machine training and the remaining 35 groups for testing. There are 7500 sampling points in each group of vibration signals. The time-domain waveform as shown in Figure 4 that is drawn according to a set of data selected from each cutting mode vibration signal.

![Rocker arm vibration signal waveforms in different cutting modes](image3)

**Figure 4.** Rocker arm vibration signal waveforms in different cutting modes
According to the signal processing method proposed above, we can obtain the multi-scale fuzzy entropy value of the vibration signal in the five cutting modes and the result is shown in Figure 5. Filter the fuzzy entropy of different scales based on the Laplacian score to get the final feature vector.

![Figure 5](image1.png)

**Figure 5.** The value of multi-scale entropy of rocker vibration signal

Input the characteristic signals of the preset 5 cutting modes into the support vector machine, randomly select 25 groups of data for training according to the rules and use the remaining 35 groups of data for testing. The final result is shown in Figure 6.

![Figure 6](image2.png)

**Figure 6.** Support vector machine recognition result

The statistical results of the accuracy of the test samples of various cutting mode in the improved support vector machine pattern recognition are listed in Table 1. Through the table, we can see that the overall accuracy rate of shearer cutting pattern data recognition reached 98.86%. Among them, the data recognition accuracy rate of no-load mode, cutting the floor mode, and cutting F1 hardness coal seam mode is all 100%; One data sample of the cutting the roof mode is identified as the cutting the floor mode; One data sample of cutting F2 hardness coal seam pattern was identified as cutting F1 hardness coal seam pattern. The specific reasons for misjudgment are as follows: The data is selected when the shearer is in the transition phase between two cutting modes. As a result, the signal is unstable or overlapped, and the extracted feature vector is biased to the wrong cutting mode.
Table 1. Statistics of test results based on improved support vector machine

| Pattern category | No load | Cutting the roof | Cutting the floor | F1 hardness coal seam | F2 hardness coal seam | recognition rate |
|------------------|---------|-----------------|-------------------|-----------------------|-----------------------|------------------|
| No load          | 35      | 0               | 0                 | 0                     | 0                     | 100%             |
| Cutting the roof | 0       | 34              | 1                 | 0                     | 0                     | 97.14%           |
| Cutting the floor| 0       | 0               | 35                | 0                     | 0                     | 100%             |
| F1 hardness coal seam | 0 | 0 | 0 | 35 | 0 | 100% |
| F2 hardness coal seam | 0 | 0 | 0 | 1 | 34 | 97.14% |

6. Conclusion
In order to improve the intelligent level of the shearer, this paper proposes a shearer cutting pattern recognition method based on multi-scale fuzzy entropy and support vector machine. The characteristic fuzzy entropy of the vibration signal when the shearer cutting in terms of different time scales is extracted based on the Laplacian score algorithm, and then streamline the extracted data. This paper verifies the feasibility of the proposed method by building the coal-rock cutting experiment system. The final result shows that the overall accuracy rate of coal machine cutting pattern recognition is 98.86%, which proves that the method is feasible.

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