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Coal-Gangue Interface Detection Based on Ensemble Empirical Mode Decomposition Energy Entropy

WEI LIU[1,2], PEIYAO LI[1], KEYU WANG[1], LU LU[1], MANYU ZHAO[1], AND WENBO YANG[1]

[1]School of Information and Electronic Engineering, Shandong Technology and Business University, Yantai 264005, China
[2]Key Laboratory of Sensing Technology and Control in Universities of Shandong, Yantai 264005, China

Corresponding author: Wei Liu (liuwei@sdtbu.edu.cn)

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ABSTRACT To realize the unmanned automation of the full mechanized caving, the bottleneck problem of coal-gangue interface detection in top coal caving must be solved first. Targeting coal-gangue interface detection on fully mechanized mining face, an alternative scheme to detect coal-gangue interface based on vibration signal analysis of the tail boom support of the longwall mining machine. It is found that when coal and gangue fall, the characteristics of vibration signals generated by coal and gangue shocking the tail boom are different. First, EEMD algorithm is used to decompose the original vibration signals into intrinsic mode functions (IMFs). Each IMF represents the distribution of energy from high to low. EEMD algorithm can restrain the mode mixing phenomenon caused by empirical mode decomposition (EMD). The energy of vibration signals will change in different frequency bands when the top-coal fall down or the coal-gangue fall down. According the information theory, we define EEMD energy entropy to describe this change. Experimental results show that EEMD energy entropy of top-coal caving is always greater than that of coal-gangue caving. Thus, the Mahalanobis distance metric method based on EEMD energy entropy is proposed for coal-gangue interface detection. The results show the proposed method can be used as a robust empirical method for coal-gangue interface detection.

INDEX TERMS Coal-gangue interface detection, vibration signals, ensemble empirical mode decomposition, energy entropy, Mahalanobis distance.

I. INTRODUCTION

Top-coal caving on a fully mechanized mining face is a coal mining method for gently inclined extra-thick coal seams or steeply inclined extra-thick coal seams [1], [2]. In the process of fully mechanized top-coal caving, the difficult problem to be solved urgently is how to control the caving time according to the caving degree of top-coal. At present, as all of the coal caving processes are completed by manual operation of the electro-hydraulic valve controller, the length of coal caving time, the level of top-coal recovery, and the amount of gangue contained depend on manual experience. The realization of unmanned technology on full mechanized top coal mining can release manpower, reduce coal mining cost, and improve production safety and efficiency. Thus, coal-gangue interface detection is significant for controlling the ratio of coal to gangue accurately and realizing the fully mechanized mining automation.

In recent years, many methods have been proposed for detecting the coal-gangue interface. Zhang *et al.* proposed to detect the instantaneous refuse content of drawn coal and gangue mixture during top-coal caving by using natural gamma-ray technology and set up the connection between radiation intensity and refuse content [3]. Hobson *et al.* analyzed several coal and gangue materials through a process of image acquisition and digital processing and used intensity values and surface texture properties to find possible differentiation between varieties of bituminous coal and associated gangue [4]. Yu *et al.* proposed an expanded-order GLCM algorithm to recognize coal and coal-gangue image [5]. Based on the noise separation by Independent Component Analysis (ICA) for acoustic signal, Xu *et al.* proposed

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a new coal-rock interface detection method by extracting Mel-frequency cepstrum coefficients [6]. Zhang *et al*. carried out Hilbert spectrum analysis for coal and gangue acoustic signals and proved that the acoustic signal characteristics could be used to the recognition of coal-gangue interface [7]. Song *et al.* proposed a new multi-class characteristic selection method based on vibration and acoustic signal and designed an effective minimum enclosing ball algorithm for rapid detection of coal-gangue in the caving process [8]–[10]. Liu *et al.* found the distribution of the Hilbert spectrum of top-coal caving to be more uniform than that of coal-gangue caving and proposed a new method to detect coal gangue interface based on the information entropy of the Hilbert spectrum [11].

However, the method based on gamma-ray requires that the coal or gangue must contain a large number of radioactive elements, which is easily disturbed by inclusions in coal and limited by geological conditions. The frequency-domain characteristics of acoustic signals of coal and gangue are also used to identify the coal-gangue interface, but it is difficult to extract the real acoustic signal from the strong complicated noise environment. The coal gangue identification method based on image recognition remains at the stage of static image analysis. Under the adverse mine production environment and complex lighting conditions, it is difficult to denoise and reconstruct the dynamic image of coal and gangue caving. According to the different physical and mechanical parameters of coal and gangue, the empirical mode decomposition (EMD) method is utilized to analyze the vibration signal while coal-gangue fall down, and performs well [11]–[14]. EMD is an adaptive method of signal analysis proposed by Huang *et al.*, which has been widely used in the fields of fluid mechanics and geophysics [15]–[18]. However, the EMD method still has some shortcomings such as end-point divergence effects, stopping criteria, and mode mixing [19]–[23]. To solve this problem, Wu *et al.* proposed an ensemble empirical mode decomposition (EEMD) method, which superimposed the finite amplitude white noise many times in the original signal [24]. This method makes the signal continuous on different scales and eliminates modal aliasing phenomenon to a great extent. Recently, Liu *et al.* developed a hybrid model combining EEMD and support vector regression (SVR) to predict vibration of the gearbox in high-speed trains [25]. Jiang *et al.* proposed a novel detection method for rolling bearing based on EEMD, which can extract fault feature information of rolling bearing more effectively [26]. Considering the real-time recognition of caving coal-rock, Li *et al.* employed a new method based on EEMD and kernel principal component analysis (KPCA) to realize the real-time recognition of caving coal-rock [27].

The above research provides a reference and foundation for coal-gangue interface detection in top coal caving. However, due to the complex working conditions underground, different distribution of coal seams, and the existence of particle disturbance and other conditions, there is still a big gap between the various detection methods and the actual application of the coal gangue identification in the top coal caving.

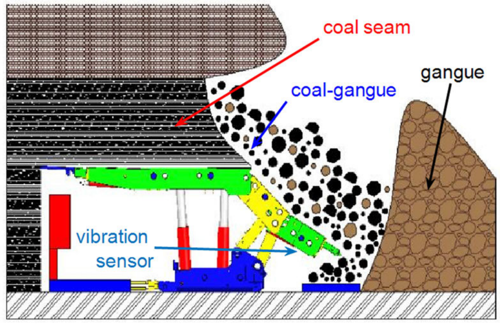

FIGURE 1. Hydraulic support and position of sensors(1. coal seam 2. coal-gangue 3. gangue 4. sensors).

In this paper, EEMD is applied to the feature extraction of vibration signals of coal and gangue. The vibration signals produced under two typical caving states of top-coal and coal-gangue are decomposed by EEMD, and the natural IMFs with frequencies arranged from high to low are obtained, which effectively suppresses the mode mixing in these IMFs. Since the energy of the vibration signal in different coal caving states varies with the frequency distribution, a new coal-gangue interface detection method combining the EEMD energy entropy feature and Mahalanobis Distance is proposed to describe this change quantitatively according to the information entropy theory.

This paper is organized as follows: in the next section, the basic principles and experimental device of coal-gangue interface detection are introduced. Then, the EEMD algorithm and its implementation are given, and the definition of EEMD energy entropy is also given. EMD and EEMD of the simulated signal are presented in the section ''Simulation signals analysis''. The application of EEMD energy entropy characteristics to classify the caving states is then discussed, and the detailed experimental results are reported. The conclusions are provided in the last section.

II. BASIC PRINCIPLE OF THE COAL-GANGUE INTERFACE DETECTION

The experimental site is located at the No.2303 fully mechanized caving face of Zhangcun Coal Mine of Lu'an Mining Group, Shanxi, China. The geological structure of the coal mine is complex with a length of 220m, an average coal thickness of 6.45m, a roadway length of 1600m, and the average dip angle is 5°. Coal caving equipment adopts MGTY250/600-1.1D shearer, ZZP4800-17/33 low-level hydraulic support, and SGZ-830/800 double-chain scraper conveyor.

The process of coal caving is sequential single-wheel, then the top-coal falls into the rear chute through the tail beam. When the top-coal is caved, the coal seam collapses under the pressure of mine, then the top-coal is released under the action of tail beam and flapper. The time of

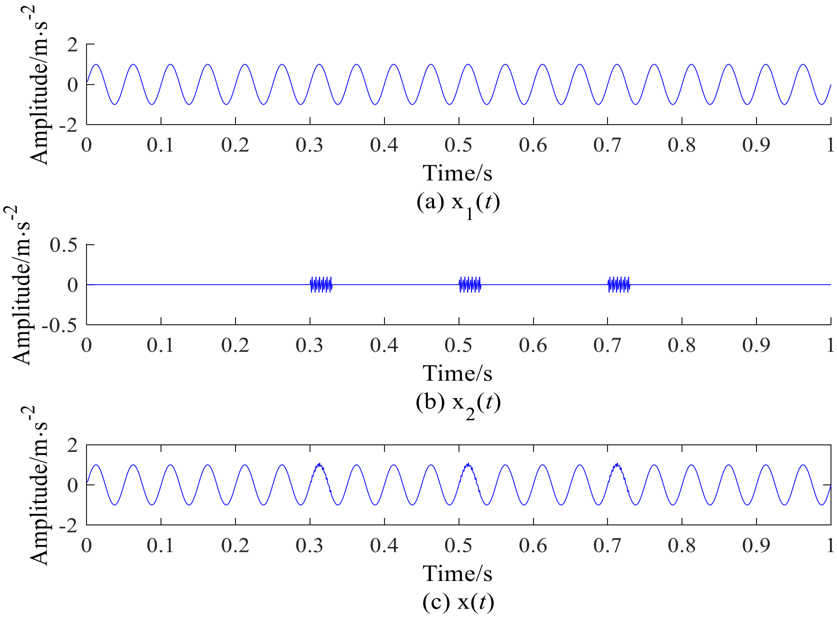

FIGURE 2. The simulation signal (a) sinusoidal signal with 50Hz (b) high frequency oscillation signal (c) superimposed signal.

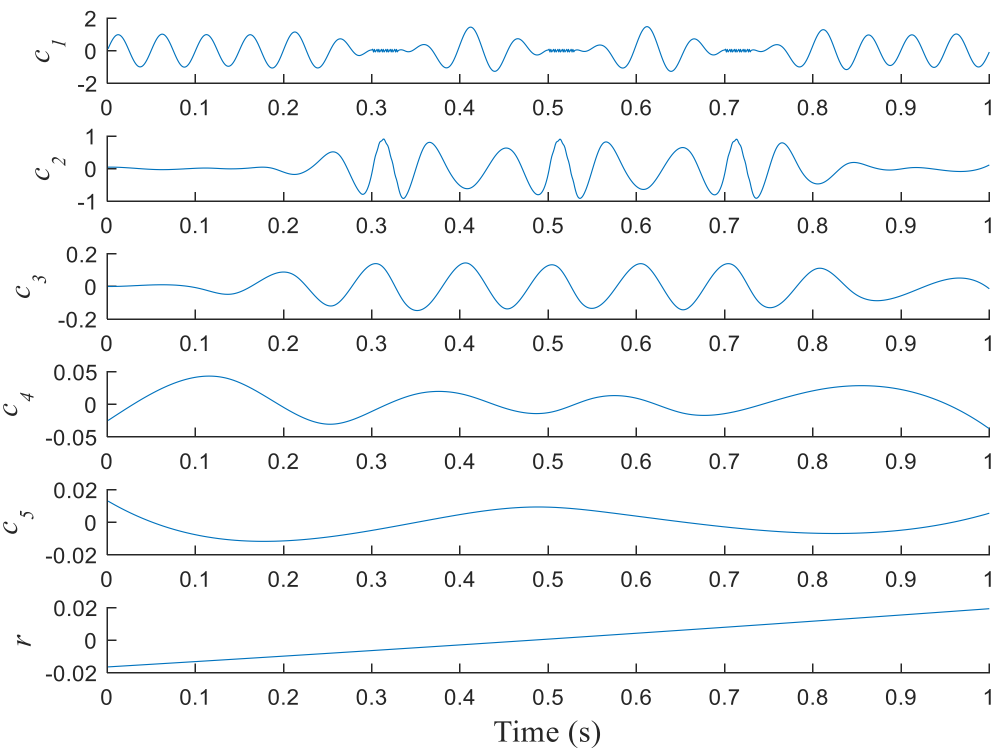

FIGURE 3. EMD decomposes the simulation signal into five IMFs and one residual.

top-coal caving is not strictly limited. Generally, the coal caving outlet is closed immediately when a large amount of gangue is released. We found that when coal and gangue fall down, the characteristics of vibration signals generated by coal and gangue shocking the tail boom are different [11]. Zhou *et al.* proved that the crushing probability of coal and gangue increases with the increase of impact velocity through the impact crushing test of coal-gangue, but the crushing probability of the gangue in the same condition is far less than that of coal, which provides a research foundation for coal gangue recognition based on impact [28]. The coal-gangue interface detection system is to identify coal caving states by analyzing the difference of vibration signals of coal and gangue. The entire system consists of a portable vibration

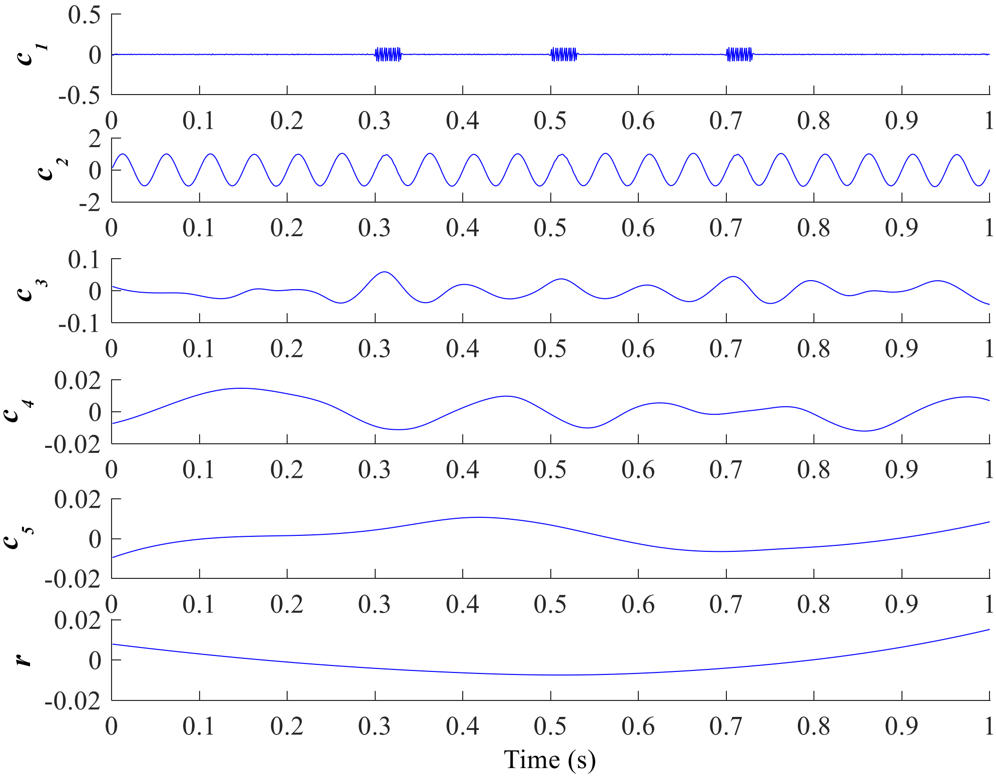

FIGURE 4. EEMD decomposes the simulation signal into five IMFs and one residual.

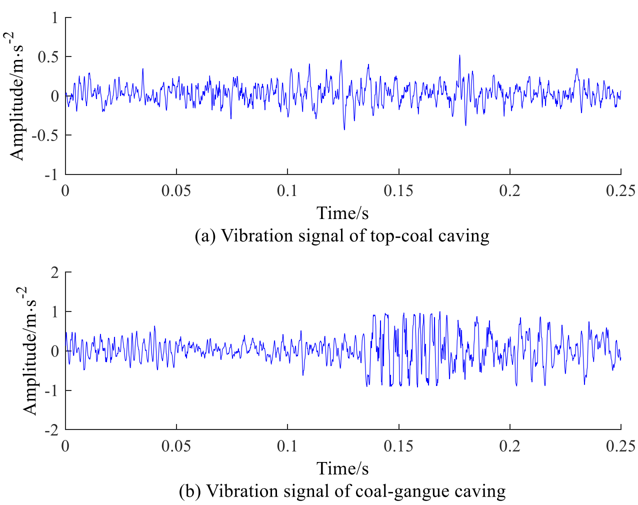

FIGURE 5. The original vibration signals.

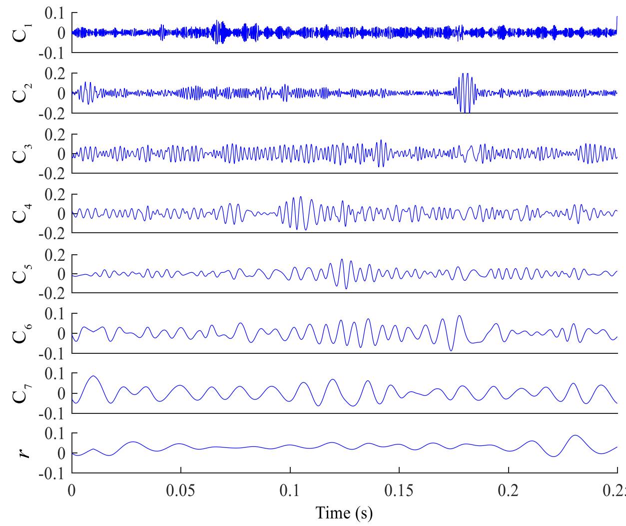

FIGURE 6. EEMD results of vibration signal for top-coal caving.

data acquisition terminal and a real-time signal processing platform. As shown in Figure 1, the acceleration sensors are fixed on the hydraulic support, acquiring vibration signals from the steel plate when coal and gangue fall down and shock the tail boom. The level of sensitivity of the vibration sensor is 5mV/g, and the maximum measuring range is 1000g. The frequency range of the sensor is from 1Hz to 15KHz. The axial front-end of the sensor is equipped with a powerful magnet which can be firmly attached to the steel plate.

III. EEMD ALGORITHM AND ENERGY ENTROPY

A. EEMD ALGORITHM

EMD is a time series analysis method proposed by Huang *et al.*, which can analyze both linear stationary signals and nonlinear and non-stationary signals. Its key idea is to decompose the complex signal into several IMFs, which contain different time scales reflecting the local physical characteristics of signals. However, the mode mixing of EMD will

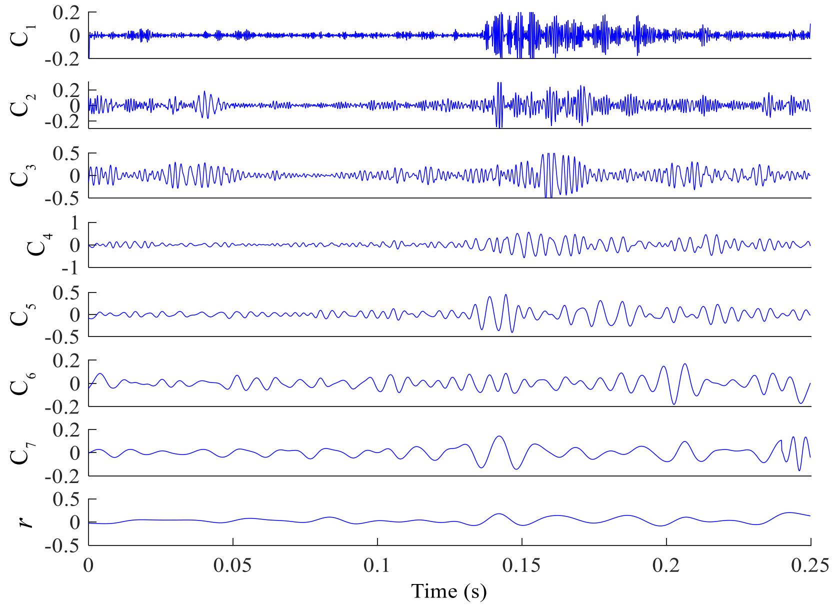

FIGURE 7. EEMD results of vibration signal for coal-gangue caving.

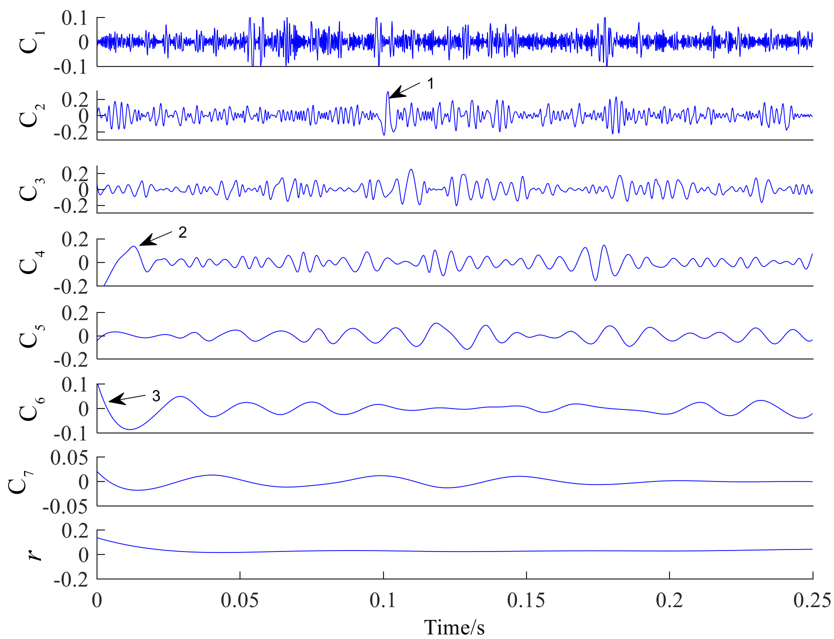

FIGURE 8. EMD results of vibration signal for top-coal caving.

make IMF lose its physical meaning [29]–[31]. Huang considers that mode mixing is an intermittent phenomenon and is related to the selection of extreme points during decomposition. To address this problem, Wu *et al.* proposed the EEMD algorithm. In this algorithm, the Gauss white noise is superimposed on the original signal, and then EMD decomposition is carried out many times. The total mean value of each IMF component is taken as the final decomposition result. EEMD algorithm takes full advantage of the statistical characteristic of uniform frequency distribution of Gauss white noise, which makes the signal with noise continuous at different scales and significantly reduces the mode mixing [32]–[35].

EEMD algorithm is described as follows:

Step (1): Let the original signal is $x(t)$, and superimpose random Gauss white noise $g_m(t)$ with an amplitude coefficient k on $x(t)$ to get the noise signal $x_m(t)$, namely

$$x_m(t) = x(t) + kg_m(t) \tag{1}$$

Step (2): Perform EMD on $x_m(t)$ to get p IMFs c_{mn}(t) ($n = 1, 2, 3 \ldots\ldots p$), where c_{mn}(t) represents the nth IMF got from the mth EMD.

Step (3): Repeat steps (1) and (2) N times. Perform the total average operation of the IMF got by N times EMD to eliminate the influence of adding Gauss white noise on the

TABLE 1. Comparison of EEMD energy entropy.

Caving state	EEMD energy entropy of 10 samples									
	1	2	3	4	5	6	7	8	9	10
Top-coal caving	**0.9661**	**0.9058**	**0.9134**	**0.9575**	**0.8762**	**0.9340**	**0.9502**	**0.8909**	**0.9293**	**0.9172**
Coal-gangue caving	**0.7375**	**0.8147**	**0.6324**	**0.7922**	**0.8491**	**0.7577**	**0.7431**	**0.7952**	**0.7547**	**0.8308**

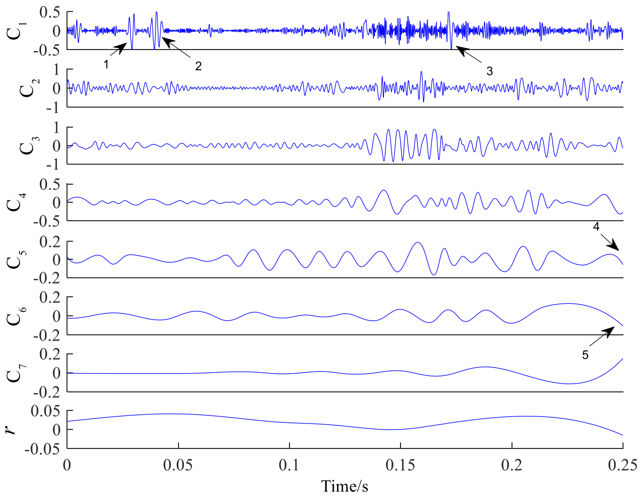

FIGURE 9. EMD results of vibration signal for coal-gangue caving.

TABLE 2. EEMD Energy entropy eigenvalue.

Caving state	Template mean $\bar{S}_i$	variance σ_i
Top coal caving	**0.8702**	**0.0014**
Coal-gangue caving	**0.7112**	**0.0089**

actual IMF. Thus, the final IMF is as follows:

$$c_n(t) = \frac{1}{N}\sum_{m=1}^{N} c_{mn} \tag{2}$$

where $c_n(t)$ is the nth IMF after EEMD, $n = 1, 2, 3 \ldots p$.

B. EEMD ENERGY ENTROPY

Information entropy can describe the average uncertainty of probabilistic systems [36]–[38]. If the probability distribution $p(x_i)$, $i = 1, 2, \ldots, n$, denoted by $p_1, p_2, \ldots, p_n$, then the information entropy $H(S)$ can be defined as:

$$H(S) = -\sum_{i=1}^{n} p_i \lg p_i \tag{3}$$

The probability distributions satisfy the following equation because of the completeness of probability space:

$$\sum_{i=1}^{n} p_i = 1 \tag{4}$$

According to the extreme principle of information entropy, if the probability distribution is uniform while the probability of each event in the system is equal, the value of information entropy, that is, the degree of uncertainty is the largest [39]–[43].

After EEMD of the original input signal $x(t)$, n IMFs can be obtained to calculate the energy of each IMF, denoted by $E_1, E_2, \ldots, E_n$.

$$E_i = \int_{-\infty}^{+\infty} |c_i(t)|^2 dt, \quad (i = 1, 2, \ldots, n) \tag{5}$$

Due to the orthogonality of EEMD, the sum of the energy of n IMFs should be equal to the total energy of the input signal if the residual is ignored. Since each IMF component contains different frequency components, $E = \{E_1, E_2, \ldots, E_n\}$ automatically forms an energy distribution of the input signal in the frequency domain. The energy of each IMF is normalized, that is, $p_i = E_i/E$. Then, similar to the information entropy, energy entropy based on EEMD can be defined as:

$$H(p) = -\sum_{i=1}^{N} p_i \log_{10} p_i \tag{6}$$

The formula (6) also satisfies the complete property of information entropy. According to the extreme principle of information entropy, the more uniform the p_i distribution is, the larger the value of EEMD energy entropy is.

IV. SIMULATION SIGNAL ANALYSIS

To verify the EEMD method, a simulation signal $x(t)$ is constructed by a frequency of sinusoidal signal $x_1(t)$ with a frequency of 50Hz and the high-frequency oscillation signal $x_2(t)$. The sampling frequency is 1KHz and the number of sampling points is 1000, as shown in Figure 2.

Firstly, the signal $x(t)$ is decomposed by EMD, and the result is shown in Figure 3. It can be seen that five IMFs and one residue are obtained by EMD, but the two constituent signals $x_1(t)$ and $x_2(t)$ are not completely separated. Serious mode mixing occurs at 0.3s, 0.5s, and 0.7s of the C_1 component. In this case, the IMFs obtained by EMD are meaningless.

In order to overcome mode mixing, the EEMD is further used to decompose the simulation signal above. The amplitude coefficient k of the added white noise is 0.04, and the number of times m of EMD is 100. Figure 4 shows the decomposition result of EEMD. It can be seen that the C_1 component

TABLE 3. Experimental results for EEMD energy entropy.

Sample No.	Caving state	Test sample S_t	d_1	d_2	Results
1	Top-coal caving	0.8842	**10.00**	19.44	Right
2	Top-coal caving	0.8572	**9.286**	16.40	Right
3	Top-coal caving	0.8903	**14.35**	20.12	Right
4	Top-coal caving	0.8655	**3.357**	17.34	Right
5	Top-coal caving	0.8736	**2.429**	18.25	Right
6	Coal-gangue caving	0.7434	90.57	**3.618**	Right
7	Coal-gangue caving	0.7668	73.86	**6.247**	Right
8	Coal-gangue caving	0.7573	80.64	**5.179**	Right
9	Coal-gangue caving	0.8009	49.50	**10.08**	Right
10	Coal-gangue caving	0.7938	54.57	**9.281**	Right

TABLE 4. EMD energy entropy eigenvalue.

Caving state	Template mean $\overline{S}_i$	variance σ_i
Top coal caving	**0.8143**	**0.0042**
Coal-gangue caving	**0.7802**	**0.0076**

is approximate to a high-frequency oscillation signal, and the C_2 component is approximate to a low-frequency sinusoidal signal with a frequency of 50Hz. Therefore, the simulation results prove EEMD to be an effective method that can separate the components of the original signal reflecting the physical meaning of the signal accurately. The mode mixing phenomenon is effectively suppressed.

V. COAL-GANGUE INTERFACE DETECTION BASED ON EEMD ENERGY ENTROPY

A. EEMD FOR COAL-GANGUE VIBRATION SIGNAL

In this paper, EEMD is applied to coal-gangue interface detection. The experimental data is from No.2303 fully mechanized caving face of Zhangcun Coal Mine. The total time of coal caving usually lasts about 90s. Generally, the whole process of coal caving can be divided into two stages. The stage in the first 60s is considered as the state of top-coal caving without gangue. The next stage in the last 30s is considered as the state of coal mixed with gangue caving. The vibration signals acquired from these two stages are used as experimental samples. Figure 5 shows the acquired two-stage vibration signals in the coal caving face, in which Figure 5(a) is the time-domain signal of top-coal caving, and Figure 5(b) is the time-domain signal of coal-gangue caving. The sampling frequency is 8KHz and the sampling time is 250ms.

In this research, EEMD is applied to the analysis of separate vibration signals of top-coal and coal-gangue. The number of decomposition is set to 200, and the standard deviation of white noise is 0.4 times that of the original signals. The decomposition results are shown in Figures 6-7. And the signals are also decomposed by EMD for comparison, as shown in Figures 8-9.

As shown in Figures 6-7, EEMD decomposes the two original vibration signals into 7 IMFs and residual r. The 7 IMFs contain different frequency components from high to low. The original vibration signals are also decomposed by EMD into 7 IMFs and residual r, in which each IMF contains different time scales.

However, it is found that there is an obvious mode mixing in EMD results. In the case of the top-coal caving, low-frequency signals appear in the high- frequency sequence in IMFs from C_2, as shown by arrow 1 in Figure 8. When coal-gangue fall down, the same phenomenon also appears in IMF C_1, as shown by the arrows 1-3 in Figure 9. There are even end-point divergence effects in IMF C_4 and IMF C_6 shown by the arrows 2-3 in Figure 8. Arrows 4 and 5 in Figure 9 also show serious end-point divergence effects. Comparatively, the result of EEMD is relatively stable with good orthogonality, which can better explore the essence of signals.

B. COAL-GANGUE INTERFACE DETECTION BASED ON EEMD ENERGY ENTROPY

In the state of top-coal caving, the frequency of each IMF forms the uniform distribution automatically after EEMD. When goal-gangue fall down, the frequency distribution of each IMF will change. At the same time, the energy distribution of the coal-gangue vibration signal will change accordingly. To verify this change, EEMD energy entropy is then calculated respectively according to Section 3. Table 1 lists the value of energy entropy under the two caving states.

As shown in Table 1, the EEMD energy entropy of top-coal caving is greater than that of coal-gangue caving. Because when top-coal fall down, the coal flow is relatively uniform, and the energy distribution of the vibration signal is close to

TABLE 5. Experimental results for EMD energy entropy.

Sample No.	Caving state	Test sample S_t	d_1	d_2	Results
1	Top-coal caving	0.8728	**13.929**	16.536	Right
2	Top-coal caving	0.7923	5.238	**2.161**	**Error**
3	Top-coal caving	0.9254	26.452	**25.929**	**Error**
4	Top-coal caving	0.8512	**8.786**	12.679	Right
5	Top-coal caving	0.8696	**13.167**	15.964	Right
6	Coal-gangue caving	0.7632	12.167	**3.036**	Right
7	Coal-gangue caving	0.7533	14.524	**4.804**	Right
8	Coal-gangue caving	0.7126	24.214	**12.071**	Right
9	Coal-gangue caving	0.6948	28.452	**15.250**	Right
10	Coal-gangue caving	0.7448	16.548	**6.321**	Right

random distribution, so the entropy value is relatively higher. However, when gangue mixed with coal fall, the energy of the vibration signal will be concentrated in certain frequency bands. The less uniform energy distribution causes the value of energy entropy to be smaller. If a large amount of gangue is mixed in top-coal, the energy of IMFs is more concentrated. If appropriate analysis time is selected, the coal-gangue interface can be detected by the value of EEMD energy entropy.

Hence, the Mahalanobis distance function is proposed as a quantitative method to identify the interface between coal and gangue during coal caving, based on the value of EEMD energy entropy calculated from selected IMFs. The algorithm is described as follows:

Step (1): Acquire $2N$ vibration signals with N known states of top-coal caving and known states of coal-gangue caving as a training set. The sampling frequency is 8KHz.

Step (2): Carry out EEMD for each sample in the training set and calculate energy entropy value S as the eigenvalue.

Step (3): For each state i, the mean $\bar{S}_i$ and variance σ_i of the eigenvalue S are calculated respectively (where $i = 1,2$ denotes the two caving states of top-coal caving or coal-gangue caving) and $\bar{S}_i$ is used as the feature template in each state.

Step (4): For each test signal, the eigenvalue is also obtained according to the above steps, denoted by S_t.

Step (5): Calculate the Mahalanobis distance between S_t and the template eigenvalue $\bar{S}_i$ in each state:

$$d_i = \frac{\left|S_t - \bar{S}_i\right|}{\sigma_i}, \qquad i = 1, 2 \tag{7}$$

Step (6): Compare the values of d_1 and d_2, and take the state corresponding to the minimum Mahalanobis distance as the caving state of the test sample signal. For example, if $d_1 < d_2$, it means that top-coal fall down. And if $d_1 > d_2$, the coal-gangue state is applicable. In the special condition of $d_1 = d_2$, it is unable to classify the state of the test sample signals.

C. VALIDATION STUDY

In this study, a total of 50 vibration signals are acquired by the data acquisition terminal for each state with a sampling frequency of 8KHz, among which 10 randomly selected samples for each state are taken as test samples. The remaining 40 samples, consisting of 20 samples for each state, are used for training data sets. The EEMD energy entropy mean $\bar{S}_i$ and variance σ_i for the training samples corresponding to each caving state are listed in Table 2.

Utilizing formula (7), the Mahalanobis distance between S_t and the template eigenvalue $\bar{S}_i$ is obtained. Table 3 lists the detection results of 10 sample signals. It can be seen that there is a clear difference between the Mahalanobis distances corresponding to each of the caving states, suggesting an unambiguous identification of the signals. Furthermore, the detection results are totally consistent with the real caving state. Experimental results show that the Mahalanobis distance of EMMD energy entropy of tail boom vibration signals can be used to classify the caving states.

For comparison, EMD energy entropy is also used for validation testing with the same training set and test set. The EMD energy entropy mean and variance for the training samples corresponding to each caving state are listed in Table 4. Table 5 lists the detection results of 10 sample signals. From Table 5, we found that there is error discrimination in samples No.2 and No.3. The overall accuracy rate is only 80% in this validation.

VI. CONCLUSION

Coal-gangue interface detection during top-coal caving mining is a challenging problem. In this paper, the EEMD algorithm and energy entropy theory are applied to extract the vibration signal features of the tail boom support, which can be used for top-coal and coal-gangue caving state classification. We decomposed the measured vibration signals of coal-gangue into IMFs, each of which represented the distribution of frequency from high to low. Compared with

EMD, we found that EEMD can effectively suppress the mode mixing phenomenon and reduce the degree of end-point divergence. Therefore, it can reveal the physical nature of vibration signals better. The energy of vibration signals will change in different frequency bands when the top-coal fall down or the coal-gangue fall down, so we applied EEMD energy entropy to distinguish the two caving states. Experiments show that the EEMD energy entropy of top-coal caving is considerably bigger than that of coal-gangue caving. Based on these results, we proposed the Mahalanobis distance metric applied to EEMD energy entropy as a classification tool for top-coal and coal-gangue caving states. The validation study proved that EEMD energy entropy can be used as a robust empirical method for coal-gangue interface detection.

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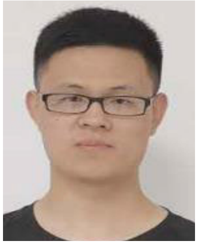
WEI LIU received the Ph.D. degree in control theory and control engineering from the China University of Mining and Technology, Beijing, in 2008. He is currently an Associate Professor with Shandong Technology and Business University. His research interests include signal processing, computer monitoring, and sensor technology.

PEIYAO LI received the B.E. degree in electrical engineering and automation from Shandong Technology and Business University, in 2019, where he is currently pursuing the master's degree.



KEYU WANG received the B.E. degree in electrical engineering and automation from Shandong Technology and Business University, in 2019, where he is currently pursuing the master's degree.

LU LU received the B.E. degree in communication engineering from Xi'an Polytechnic University, in 2016. She is currently pursuing the master's degree with Shandong Technology and Business University.

MANYU ZHAO received the B.E. degree from Shandong Technology and Business University, in 2016, where she is currently pursuing the master's degree.

WENBO YANG received the B.E. degree in optoelectronic information science and engineering from Weinan Normal University, in 2016. He is currently pursuing the master's degree with Shandong Technology and Business University.