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RESEARCH ARTICLE

Performance Analysis of Coal Gangue Recognition Based on Hierarchical Filtering and Coupled Wrapper Feature Selection Method

HE LI[1], YAO ZHANG[1], YANG YANG[1,2,3], (Member, IEEE), AND QINGLIANG ZENG[1,4]

[1]College of Mechanical and Electrical Engineering, Shandong University of Science and Technology, Qingdao 266590, China
[2]Shandong Provincial Key Laboratory of Mining Mechanical Engineering, Qingdao 266590, China
[3]Coal Mine Safety Mining Equipment Innovation Center of Anhui Province, Huainan 232001, China
[4]College of Information Science and Engineering, Shandong Normal University, Jinan 250358, China

Corresponding author: Yang Yang (yang.yang@sdust.edu.cn)

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ABSTRACT Coal gangue recognition of top coal caving is one of the important links in the process of intelligent coal mine construction. However, the recognition accuracy of this technology in practical application is still challenging, because the recognition model is not perfect in the following aspects: 1) the filtering scale is not suitable for signal noise reduction;, 2) the selected features have no obvious difference in vibration signals of coal and gangue; and 3) the overall relevance of the model input data to the target classification is insufficient. The purpose of this paper is to establish a coal gangue recognition model with effective filtering, feature extraction and classification capabilities, which can adaptively carry out purposive feature extraction while retaining relevant information to improve the recognition accuracy. Firstly, hierarchical filtering (HF) method was proposed. Secondly, an effective information correlation fusion based coal gangue recognition model (EICF-coal gangue recognition model) was established by coupling wrapper feature selection method and recognition algorithm. Then, 2223 groups of vibration impact tests were carried out on the coal gangue mixture with gangue content of 0 to 50%, and two kinds of coal gangue recognition sample sets of ''caving category'' and ''shutdown category'' were established. Finally, coal gangue recognition experiments were carried out on 9 hierarchical filter sample sets by coupling wrapper and 5 recognition algorithms. Under the combined effect of the HF method, wrapper feature selection method and Stacking, coal gangue recognition accuracy reaches 99%. This paper demonstrates the effectiveness of the EICF-coal gangue recognition model.

INDEX TERMS Hierarchical filtering (HF) method, wrapper feature selection, effective information correlation fusion (EICF), coal gangue recognition, recognition accuracy.

I. INTRODUCTION

Coal is the cornerstone of China's energy security [1], and top coal caving is one of the most important mining methods for thick and extra-thick coal seams in the process of coal production. At present, completion of most top coal caving operations requires the participation of workers, which not only produce low efficiency, but also cause great harm to the physical and mental health of workers. The development of coal mine intelligent process has promoted the exploration of automatic recognition method of coal gangue interface.

In recent years, many experts and scholars have studied the characteristics and methods of coal gangue recognition. Among these recognition methods, images and

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image features are used as the main recognition medium. Wang et al. [2] conducted a precise recognition study on mining dirt in the process of coal caving through the intelligent image recognition technology that could accurately and quickly recognize the mixed gangue rate and adapted to the harsh environment. However, this technology cannot be used in practice at present. According to the principle of increasing the temperature difference between coal and gangue caused by liquid intervention, Zhang et al. [3], [4], [5], [6] improved the efficiency of coal gangue recognition through the significant difference of infrared images. One issue that needs to be raised is that liquid intervention may degrade the quality of the coal. Shan et al. [7] studied the recognition of coal gangue static images in dusty environment based on improved Faster Region based Convolutional Neural Network (Faster R-CNN). Yang et al. [8] used an adaptive optimization learning method to recognize the infrared spectra of coal and gangue. Guo et al. [9] studied the multi-dimensional analysis and recognition method of coal and gangue by using R-value image features and high energy image features. Yan et al. [10] carried out coal gangue detection based on the embedded scSE module of improved YOLOv5.1 to accurately recognize images. Dou et al. [11] used relief Support Vector Machine (relief-SVM) and machine vision methods to identify the optimal features and construct the optimal classifier. For various forms of image recognition, the actual production environment of the mine is far from the experimental condition, and the process of applying theoretical research to the mine is also a great challenge.

The study based on auditory signals simulates workers listening to hydraulic support sound to distinguish coal and gangue. Pang et al. [12] established a response model to convert vibration acceleration signals into sound pressure signals for feature extraction according to the functional principle of human auditory nervous system, so as to improve the recognition accuracy. Chen et al. [13] combined auditory spectrogram with convolutional neural network to realize automatic coal gangue recognition. However, the composition of acoustic signals in the mine production environment is extremely complex and unstable, so it is difficult to perform multiple blind source separation of noise.

In addition, laser radar, with its accurate three dimensional information acquisition ability, has become an emerging method of coal gangue recognition with unique advantages. Zhang et al. [14] used different measurement methods such as laser radar to monitor the coal seam conditions at different coal caving stages, so as to realize real-time feedback control and precise coal caving. However, current recognition technical problems caused by the sensitivity of lidar itself to dust and light environment changes are difficult to overcome. Studies on coal gangue recognition based on other medium [15], [16], [17], [18] cannot completely simulate the mine environment, and the corresponding technology is not yet mature.

The components of the tail beam vibration signal are simple and easy to extract, and the mixed noise components in the actual production are relatively fixed. Therefore, results of coal gangue recognition experiments with vibration signals are reliable. In recent years, many studies have been carried out based on vibration signals. Dou et al. [19] used SVM to recognize the features of several Intrinsic Mode Function (IMF) components obtained by EEMD decomposition of vibration signals. Li et al. [20] used the methods of EEMD-Kernel Principal Component Analysis (KPCA) and Kullback-Leibler (KL) divergence to process vibration signals, so as to realize real-time recognition of collapsing coal and improve the efficiency of fully mechanized caving mining. Some of our previous studies [21], [22] based on vibration signals have also achieved good results. However, previous methods lack of research on the filtering scale of vibration signal and signal features adaptive selection.

In previous studies, we extracted the vibration acceleration signal generated by the impact of the tail beam of coal gangue mixture with a gangue rate of [0, 100] for coal gangue recognition. However, in the actual top coal caving process, when the mixed gangue rate in the coal flow reaches a certain range, the coal caving will be stopped by swinging the tail beam. Therefore, samples with nearly pure coal or gangue composition will undoubtedly have a positive impact on the recognition accuracy, which is not the focus and difficulty of recognition research. In this study, vibration acceleration signals of 2223 groups of coal gangue mixtures with gangue rate between (0, 50%) were extracted by building a simulation test bed for top coal caving. Taking 25% gangue rate as threshold, it is divided into ''caving category'' and ''shutdown category'', and the method of improving the recognition accuracy of difficultly distinguished coal gangue mixture is studied.

The purpose of this paper is to establish a model with effective filtering, feature extraction and classification ability by optimizing each link of coal gangue recognition, so as to improve its accuracy and generalization ability and promote the application of this technology in practice.

Previous work has focussed on the comparison of different filtering methods. The filtering size of coal and gangue vibration signals is still an open problem. Coal gangue vibration acceleration signal with its nonlinear, non-stationary characteristics, has not yet determined a suitable noise band filtering method. Qiao and Shu [23] proposed an adaptive coupled neurons-based method with multi-objective optimization to overcome blind noise suppression. In this context, we aim to select the most appropriate HF method for retaining the effective information of coal gangue vibration signals by comparing the recognition accuracy of different samples. This work is also of great significance for the accurate recognition of coal gangue in top coal caving operations. EMD [24] has obvious advantages in dealing with nonlinear and nonstationary signals. EEMD [25] proposes a noise assisted data analysis method based on EMD. Wavelet [26], [27], [28] analysis is fast in calculation and meet the requirements of real-time denoising in automatic systems. EMD, EEMD and wavelet analysis realizes hierarchical filtering by reconstructing different frequency components of the signal [29], [30], [31] to explore the effective information distribution of coal gangue vibration acceleration signals, so as to achieve a balance between noise filtering and effective information retention.

In addition, feature extraction and recognition algorithms still need to be improved. Feature extraction may cause the loss of information while reducing the dimension of signal data, so some features have no differences in coal gangue vibration signals and cannot be effectively used for signal classification. Single recognition algorithm cannot achieve satisfactory matching effect for coal gangue recognition, and lacks consideration of the comprehensive impact of model input data on target classification. Previously, we used the feature selection method of cross-optimal fusion to study the recognition accuracy of different time domain features and their combinations according to the recognition accuracy from high to low, and the highest result reached 97% [32]. Although the recognition accuracy of coal gangue vibration signal is improved in this method, the interaction between features is not considered, so the selected combination cannot be guaranteed to be optimal. Cao et al. [33] proposed a new hybrid classification model, the optimal froth image feature that contributes the highest to the SSGMM classifier is screened out using MRMR, and the SSGMM classifier is used as the evaluation criterion for the features screened by MRMR. Inspired by this idea, this paper couples the principle of wrapper with several recognition algorithms, so as to focus on the most effective features for target classification, and improve the recognition accuracy by amplifying the difference of vibration acceleration signals of coal and gangue. Wrapper feature selection method solves the problem of feature correlation analysis and selection by combining various learners to optimize each feature subset [34], [35], [36], [37].

To sum up, there are still three problems in coal gangue recognition of top coal caving at present: (1) The filtering scale is not suitable for signal noise reduction. At present, the filtering method for vibration signals of coal and gangue has not been determined, so it is challenging to achieve a balance between effective filtering and retaining signal information. (2) The selected features have no obvious difference in vibration signals of coal and gangue. The information contained in the features cannot distinguish the vibration signals of coal and gangue. (3) The overall relevance of the model input data to the target classification is insufficient. When all features are taken as the whole input, the influence of their mutual influence on the classification results is unconsidered. In order to solve many problems existing in current research on coal gangue recognition, firstly, this paper proposes a HF method to filter vibration acceleration signals at different scales. Secondly, an EICF-coal gangue recognition model is established by coupling wrapper feature selection method and recognition algorithm. Then, vibration acceleration signals of multiple positions of the tail beam are extracted, and nine HF sample sets are established by using the HF method. Finally, five recognition algorithms are used to verify the performance of the coupling model and the filtering sample sets at different levels.

The main innovations of this paper are summarized as follows.

1. The hierarchical filtering (HF) method is proposed to study the frequency band distribution of noise, so as to better achieve the balance between retaining effective information and filtering noise.

2. By coupling wrapper feature selection method and recognition algorithm, an EICF-coal gangue recognition model is established, which daptively retains effective information and improve the recognition accuracy and generalization ability.

3. The overall effect of the interaction among features on target classification is studied, and the recognition model can automatically find the maximum correlation feature combination to improve the recognition accuracy.

4. The vibration acceleration signal simulation test bed is built, and difficultly distinguished coal gangue recognition sample sets are established when the gangue content is around the threshold of the top coal caving, which has practical application significance.

The rest of this paper is organized as follows. Section II studies the principle of the filtering algorithm and proposes a HF method. Section III establishes an EICF-coal gangue recognition model by coupling wrapper feature selection method and recognition algorithm. Section IV builds difficultly distinguished coal gangue recognition sample sets through experiments. Section V verify the performance of the EICF-coal gangue recognition model. Section VI shows the relevant conclusions of the study.

II. THE PRESENTATION OF THE HF METHOD

In this paper, the vibration signal is used as the basis for determining coal or gangue, and the noise contained in the vibration signal comes from the vibration generated by the surrounding machine operation. In the field of coal gangue recognition, the noise frequency band of vibration acceleration signal is still unclear. Therefore, a hierarchical filtering (HF) method is proposed in this study. The different components of the signal processed by different filtering algorithms are filtered to study the noise distribution law, thereby reducing the noise rate. EMD and EEMD can adaptively decompose signals into several components from high frequency to low frequency, and the signal is filtered through the reconstruction of effective frequency band. Wavelet analysis can perform threshold quantization processing at different decomposition levels, thus the signal is filtered to different degrees. These three methods meet the requirements of processing different signal components, so they can be used for hierarchical filtering.

A. PRINCIPLE OF FILTERING ALGORITHM

1) EMD

Empircal Mode Decomposition (EMD) [24] is an adaptive decomposition of an original signal into several Intrinsic Mode Functions (IMFs) ranging from high frequency to low

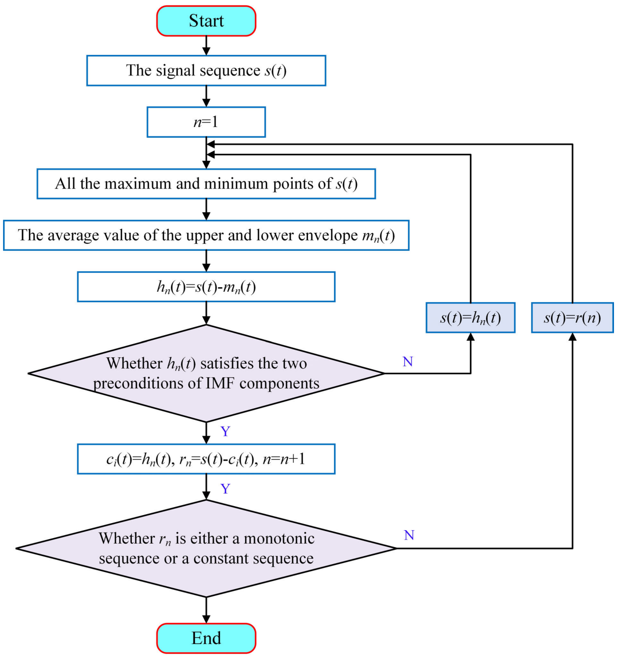


FIGURE 1. Flow chart of EMD.

frequency according to its own extreme characteristic scale. The feature scale contained in each IMF component corresponds to a certain frequency band, which can be used to filter the signal. The specific steps are as follows.

1. All the maximum and minimum points of the signal sequence $s(t)$ are taken, and these extreme points are connected respectively through cubic spline interpolation to obtain the upper and lower envelope of the signal sequence.

2. Take the average value of the upper and lower envelope, denoted as $m_1(t)$, subtract the average value from the original signal data sequence to obtain a new data se-quence $h_1(t)$:

$$h_1(t) = s(t) - m_1(t) \tag{1}$$

Judge whether $h_1(t)$ satisfies the two preconditions of IMF components: (1) In the data sequence, the extreme point and the zero crossing point are equal or one dif-ference, and (2) the average envelope defined by the local maximum and the local minimum of the signal at any time is 0. If so, $h_1(t)$ is the first IMF component of signal $s(t)$. If not, $h_1(t)$ is taken as the original data. The above steps are repeated until $h_k(t)$ obtained for the kth time meets the preset condition, and the first IMF component is denoted as $c_1(t) = h_k(t)$.

3. Separate $c_1(t)$ from $s(t)$ to obtain a new original signal sequence. Repeat the above steps from step1 until the remainder of r_n is either a monotonic sequence or a con-stant sequence.

Thus, the original signal $s(t)$ is decomposed by EMD into a series of IMFs and a linear superposition of the remaining parts.

$$s(t) = \sum_{i=0}^{N} c_i(t) + r_n(t) \tag{2}$$

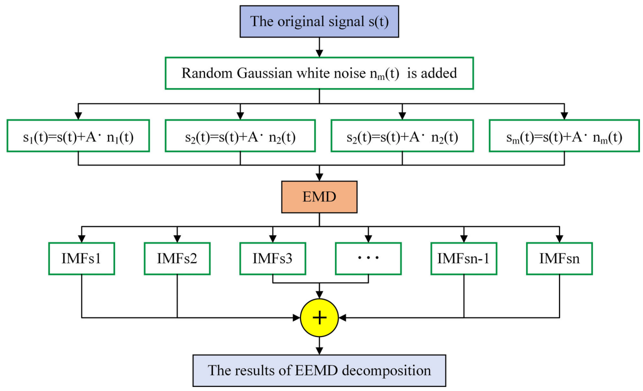


FIGURE 2. Flow chart of EEMD.

2) EEMD

Ensemble Empirical Mode Decomposition (EEMD) [25] is to solve the mode aliasing and other problems existing in EMD. It solves the problem of frequency mixing among IMF components by adding white noise to the signals. EEMD consists of the following steps.

1. Random Gaussian white noise $n_m(t)$ is added to the original signal $s(t)$.

$$s_m(t) = s(t) + A \cdot n_m(t) \tag{3}$$

where, A represents the amplitude coefficient of noise.

2. The denoised signal is decomposed by EMD to obtain each IMF component.

3. Repeat the above two steps, and add a different sequence of Gaussian white noise each time.

4. The results of EEMD decomposition are obtained by integrating the IMF components obtained each time.

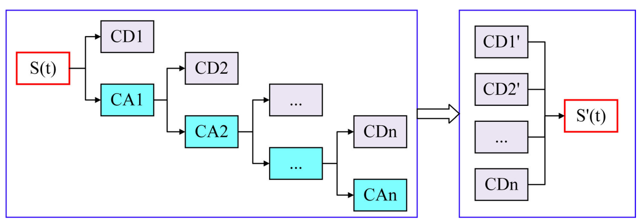


FIGURE 3. Flow chart of Wavelet.

3) WAVELET ANALYSIS

Wavelet analysis [26], [27], [28] gradually refines signals at multiple scales through the stretching and translation operation, and finally achieves time subdivision at high frequencies and frequency subdivision at low frequencies, which can automatically meet the requirements of time-frequency signal analysis. The specific steps of wavelet analysis are as follows.

1. By selecting the appropriate wavelet basis and the number of decomposition layers, the original signal is decomposed to obtain a set of wavelet coefficients.

2. Threshold quantization is performed on the high-frequency coefficients of each layer to obtain the estimated value of them.

3. Then the inverse wavelet transform is used to reconstruct the wavelet coefficients after threshold quantization, so as to get the denoised signal.

In this paper, the Symlet wavelet function with vanishing moment of 8 is selected, which has good regularity, continuity and symmetry, and can reduce phase distortion to a certain extent in signal analysis and reconstruction. In view of the shortcomings of the reconstructed signal with soft threshold deviating from the real signal and the signal reconstruction oscillation caused by hard threshold, the soft-hard compromise threshold can make the threshold function smoothly transition to the original wavelet coefficient at the threshold point. The threshold function is as follows.

$$\widetilde{\omega}_{j,k} = \begin{cases} \omega_{j,k} - a\lambda, & \omega_{j,k} \geq \lambda \\ 0, & \left|\omega_{j,k}\right| < \lambda \\ \omega_{j,k} + a\lambda, & \omega_{j,k} \leq -\lambda \end{cases} \tag{4}$$

where, $\lambda = \sigma\left(2\sqrt{\frac{\lg n}{n}}\right)$; $\omega_{j,k}$ is the wavelet transform coefficient; $\widetilde{\omega}_{j,k}$ is the wavelet coefficient obtained after soft threshold; n is the length of the signal to be denoised; σ is the standard variance of the noise; λ is the threshold value.

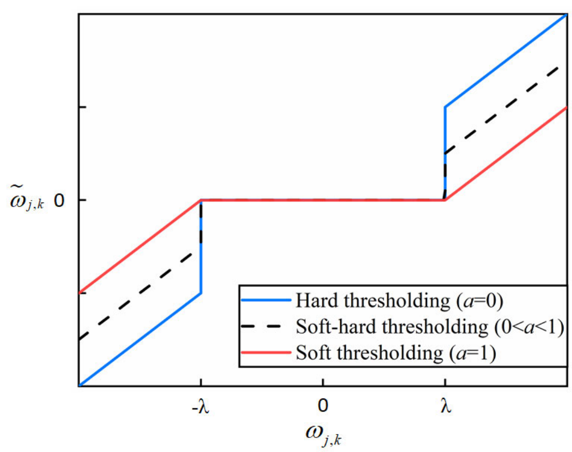


FIGURE 4. Schematic diagram of wavelet threshold.

The schematic diagram of the wavelet threshold is shown in Figure 4, where $a = 0$ is a hard threshold, and $a = 1$ is a soft threshold, and $0 < a < 1$ is a soft-hard compromise threshold. In this paper, $a = 0.5$ is selected as the soft-hard compromise threshold coefficient.

B. PRINCIPLE OF HF METHOD

The noise contained in the vibration signal of coal and gangue comes from the operation of top coal caving equipment, and the composition is relatively stable. Therefore, the method of accurate filtering of noise frequency band has strong adaptability and can effectively improve the recognition effect of coal gangue samples. However, due to the currently unclear frequency distribution of vibration signal noise, if the filtering scale is too small, the noise cannot be completely separated, and the filtering scale is too large, the effective information will be lost. In order to solve the problem of inappropriate filtering scale in signal denoising, the hierarchical filtering (HF) method is proposed in this study.

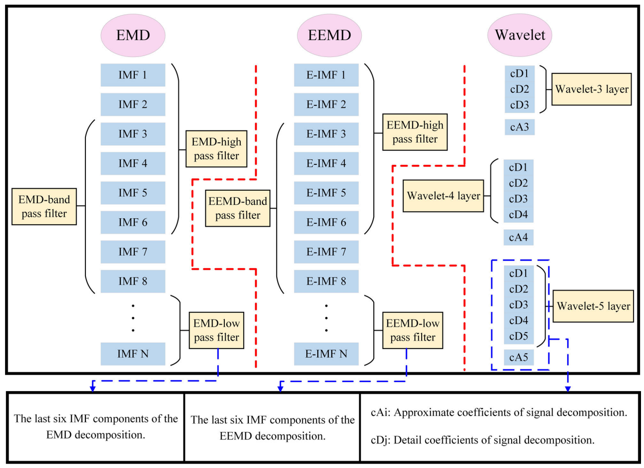


FIGURE 5. Schematic diagram of wavelet threshold.

The HF principle is shown in Figure 5. After sampling analysis, the signal will be decomposed into about 10 IMF components after EMD processing. The first six components, the middle six components and the last six components will be reconstructed respectively, and three kinds of filtered signals under the EMD method will be obtained. Vibration signals are processed by EEMD, and three kinds of filtered signals under EEMD method can be obtained similarly. Vibration acceleration signals are decomposed by 3 to 5 layers of wavelet, and the detail coefficients are reconstructed to obtain three kinds of filtering signals under wavelet analysis. The original signals can be decomposed into different frequency components by using EMD, EEMD and wavelet analysis, and the specific components can be reconstructed into new signals. That is, the waves of specific frequency bands are allowed to pass through, while the waves of other frequency bands are shielded, so as to retain the different information of the original coal gangues vibration signal. In this way, a signal processing method less affected by noise can be obtained by comparing the recognition accuracy of different reconstructed signals.

The HT method proposed in this paper uses EMD, EEMD and wavelet analysis to filter the signal in three different ways respectively, and a total of 9 HF methods with different scales are obtained. According to the recognition accuracy, the most appropriate filtering level under different algorithms is taken as the result of the HF method. After sampling and analysis, the signal is decomposed into about 10 IMF components by EMD and EEMD, and the actual number of components varies with coal gangue composition. And the filtering effect is tested on 3 to 5 layers of wavelet analysis. Therefore, they defined separately as shown in Table 1.

TABLE 1. Definition of HF methods.

HF methods	Definition
EMD - high pass filtering	The signal is decomposed by EMD and the first 6 IMF components are retained.
EMD - band pass filtering	The signal is decomposed by EMD and the 3 to 8 IMF components are retained.
EMD - low pass filtering	The signal is decomposed by EMD and the last 6 IMF components are retained.
EEMD - high pass filtering	The signal is decomposed by EEMD and the first 6 IMF components are retained.
EEMD - band pass filtering	The signal is decomposed by EEMD and the 3 to 8 IMF components are retained.
EEMD - low pass filtering	The signal is decomposed by EEMD and the last 6 IMF components are retained.
Wavelet - 3 layer	The signal is decomposed by 3 - layer wavelet and the approximate coefficient is filtered out.
Wavelet - 4 layer	The signal is decomposed by 4 - layer wavelet and the approximate coefficient is filtered out.
Wavelet - 5 layer	The signal is decomposed by 5 - layer wavelet and the approximate coefficient is filtered out.

The coal gangue vibration signal is processed through the above levels of filtering methods, and then the coal gangue recognition model is used to compare the accuracy of each sample set. The sample set with the highest recognition accuracy corresponds to the most suitable filtering scale for the coal gangue vibration signal.

III. ESTABLISHMENT OF COAL GANGUE RECOGNITION MODEL COUPLED WITH WRAPPER FEATURE SELECTION

Inputting all signal data into the model for recognition has the disadvantages of large amount of calculation and long training time, and it is difficult to meet the requirements of lightweight models and real-time. Therefore, for the standardized signal after preprocessing, appropriate features should be extracted to train the model and recognize coal and gangue. There are still two problems in the vibration signal feature extraction link: (1) the difference of selected features for coal gangue vibration signal is not obvious, and (2) the overall relevance of the model input data for object classification is insufficient. To solve these two problems, this study introduces wrapper feature selection method in the establishment process of coal gangue recognition model to find the feature combination with maximum correlation for target classification.

A. INTRODUCTION OF WRAPPER FEATURE SELECTION METHOD

In order to select appropriate vibration signal features for coal gangue recognition, wrapper feature selection method is introduced in this study [34], [35], [36], [37]. The principle of this method is the combination of feature selection and recognition algorithm, and the advantages and disadvantages of the feature subset are evaluated according to the recognition accuracy of the algorithm. And then the optimal feature subset is used to greatly improve the recognition accuracy. The principle of wrapper feature selection method applied to feature selection of coal gangue vibration signal is shown in Figure 6.

By extracting the same feature from different signals, the comprehensiveness of the recognition information can be increased based on the difference of the sensor position. Therefore, each feature row vector extracted from coal gangue vibration signals is regarded as a whole in this paper.

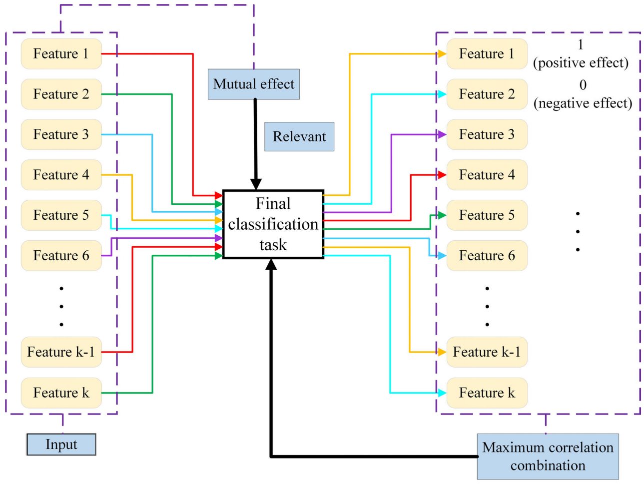


FIGURE 6. Feature selection of coal gangue vibration signal based on wrapper.

Firstly, feature vectors ($\mathbf{F}_1, \mathbf{F}_2, \mathbf{F}_3, \ldots, \mathbf{F}_k$) are input in the form of a matrix as an item, and the recognition algorithm is used to screen the features according to the difference of coal gangue vibration signals caused by each feature. According to the recognition accuracy, the features ranked in the top 50% are positive impact features, and the rest are negative impact features. The weight "0" is assigned to the vectors (negative impact features) that pull down the overall correlation level, and the weight "1" is assigned to the vectors (positive impact features) that improve the overall correlation level. Taking the dot product of the input feature vectors and their corresponding weight, the feature row vectors assigned with weight "0" are filtered out, so that 50% of the features with weak correlation are ignored. The model only considers the features with high recognition accuracy. Negative impact features will no longer be considered in the model. Thus, the initial feature selection is completed. In the mechanism of information fusion, the comprehensive influence effect is difficult to determine, so the boundary between effective information and invalid information is difficult to divide. Therefore, the overall correlation between the interaction of retained feature row vectors and the final classification task is studied. It has the advantage that it is not necessary to calculate the correlation coefficient of each vector separately, but to find the maximum correlation combination according to the final classification task. The remaining vectors $\left(\mathbf{F}_1, \mathbf{F}_2, \ldots, \mathbf{F}_{k/2}\right)$ are input as a whole, and $\sum_{j=1}^{k/2} C_{k/2}^{j}$ combined forms of row vectors with positive influence are fed into the recognition algorithm. Finally, the row vector arrangement assemblage with the maximum correlation, that is, the highest recognition accuracy, is selected as the final input data for model training. So as to complete the final feature selection. The pseudocode of the method coupling wrapper feature selection with recognition algorithm is shown in Figure 7.

```
Algorithm: Wrapper feature selection method
input: Training data
input: Test data
input: k: feature vectors
M ← [ ]
for i ← 1 to k do
    model1.fit (Training data)
    AC ← model1. score (Test data)
    M. append(AC)
end
N ← The feature indices with the top half highest accuracy
Q ← Generate all feature subsets of N
E ← [ ]
for j in Q do
    model2.fit (Training data)
    ACC ← model2. score (Test data)
    E. append(ACC)
end
n ← E.argmax()
output: Q[n] ← Maximum correlation combination
output: E[n] ← Highest recognition accuracy
```

FIGURE 7. Pseudocode of wrapper feature selection method.

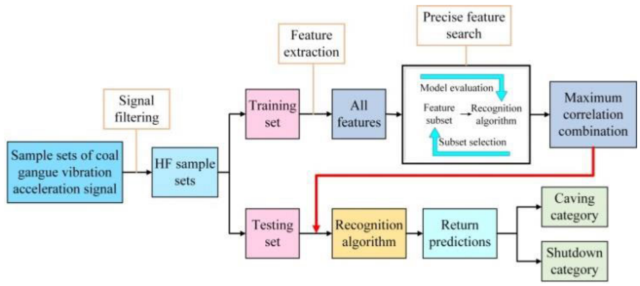


FIGURE 8. EICF-coal gangue recognition model.

B. ESTABLISHMENT OF EICF-COAL GANGUE RECOGNITION MODEL BY COUPLING WRAPPER FEATURES SELECTION METHOD AND RECOGNITION ALGORITHM

Wrapper optimization search strategies are mainly divided into three categories: Exact search algorithms, Sequential search algorithms and Random search algorithms. Among them, the exact search algorithm is guaranteed to find the globally optimal combination of features. Moreover, the process of feature selection in practical application only exists in the model training, and the corresponding maximum correlation combination is found and applied to a specific mining area. This process will not consume time, so the time complexity of the algorithm will not affect the real-time performance of top coal caving recognition. The schematic diagram of the EICF-coal gangue recognition model by coupling wrapper feature selection method is shown as Figure 8.

As shown in Figure 8, firstly, all of the original vibration acceleration signals of coal and gangue are processed by the HF method to obtain 9 sample sets. Part of the samples is randomly selected for model training from each sample set, and 12 time domain features of this part of the sample were extracted. Then the wrapper feature selection method based on the precise feature search is coupled with the recognition algorithms, and the recognition accuracy is used to evaluate the relevance of each subset. Finally, the model retains the feature subset with the highest recognition accuracy. The maximum correlation feature combination of the sample set under a specific algorithm is found. The effectiveness of different filtering methods can also be compared. From the total sample set, some samples other than the training set are selected as the test set. And the maximum correlation feature combination is directly applied to the model test as the target feature, so as to obtain the classification of unknown signal samples. The recognition results of each sample are compared with the actual category of the sample, and the recognition results of all samples are counted to obtain the recognition accuracy of the sample set. The highest recognition accuracy and the optimal feature subset were obtained by statistics and comparison of the test set recognition results.

IV. DATA ACQUISITION TEST AND THE ESTABLISHMENT OF COAL GANGUE RECOGNITION SAMPLE SETS

A. EXPERIMENTAL DATA ACQUISITION

The acquisition of coal gangue vibration signals is carried out in a laboratory environment. In order to make the test conditions as consistent as possible with the actual working conditions of top coal caving, this paper designs the top coal caving test bed based on the theory of ZF5600 hydraulic support, so the collected data is more real and reliable for coal gangue recognition research. The test bed is mainly composed of tail beam, tail beam jack, shield beam, top beam, column, insert plate, insert plate jack, fixed leg support, baffle board, bottom platform and hydraulic pump station. Then, on the premise that the main structure remains consistent, the main mechanism is equal-scaled by a ratio of 0.7. In order to meet the requirements of carrying out tests in the laboratory, the structure of columns and links is also reasonably reformed in the design and con-struction of the test bed.

The signal acquisition system mainly includes four parts: the constant voltage source, 1A102E general piezoelectric acceleration sensor, dynamic signal test and analysis system, DongHua Dynamic Analysis System (DHDAS). At the same time, noise reduction and anti-mixing filtering modules are added to the acquisition system. Acceleration sensors are arranged on the bottom surface of the tail beam to prevent the direct impact caused by the falling coal gangue and the abnormal contact of the adjacent frame. The arrangement of vibration acceleration sensors is shown in Figure 9.

Before starting the test, we prepared for coal gangue mixtures with a gangue content of 0 to 50%. According to

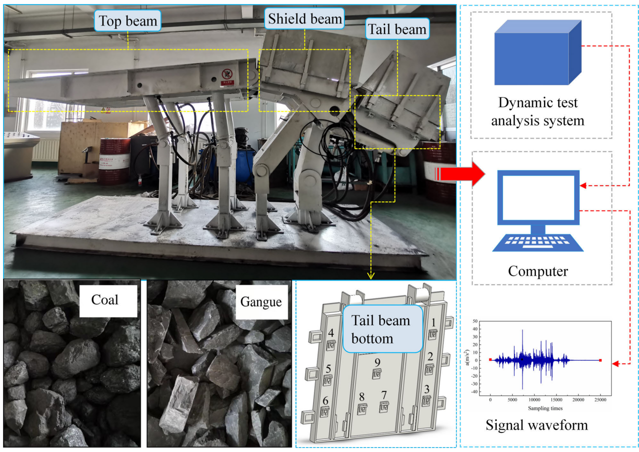


FIGURE 9. Flow chart of the test.

the relevant requirements of top coal caving, coal caving is stopped when the gangue mixing ratio reaches 20%-30%, and 25% are set as the shutdown standard in this paper. Since the composition and physical properties of coal gangue mixtures with gangue content of about 25% are the most similar, the vibration signals generated by their falling are the most difficult to define. Therefore, the maximum number of test groups is set up for the two samples of 20%-25% and 25%-30%. The number of test groups corresponding to different gangue mixing rates is shown in Table 2. With 25% as the boundary, the coal gangue mixed samples are divided into two categories: the coal gangue mixed samples with gangue content less than 25% are defined as the ''caving category'', with a total of 1098 groups, and the coal ganging mixed samples with gangue content greater than 25% are defined as the ''shutdown category'', with a total of 1125 groups. In this test, the quality of the coal gangue mixtures is controlled, and the error of the mixing ratio is controlled within 0.7%.

TABLE 2. Definition of HF methods.

Gangue rate	0-10%	10%-20%	20%-25%	25%-30%	30%-40%	40%-50%
Number of test groups	69	146	853	995	40	11

During the test, coal gangue mixtures are dumped on the top of the shielding beam, and they slide down to the upper surface of the tail beam to produce a certain vibration impact. The sampling frequency is set to 10000Hz. Inspired by the 2D information in image recognition [38], this study constructs signal feature matrix through multiple sensors to increase the comprehensiveness of recognition information. Vibration acceleration signals are collected simultaneously by 9 sensors arranged at the bottom of the tail beam, and transmitted to the DHDAS dynamic signal analysis system by the DH8302 and DH5925 dynamic signal test analysis system for storage. Data of 9 signals generated by each dropping test are stored into a file as a set of sample data under the mixed gangue rate. After the test, all signals collected during the test are preprocessed: the first data point with 0.25m/s^2 greater acceleration than the initial time is taken as the data point at time 0, and the effective time domain length of each signal is 2.5s. After preprocessing, each signal is a standardized time-acceleration signal with a length of 25001.

B. ESTABLISHMENT OF SAMPLE SETS FOR COAL GANGUE RECOGNITION

As shown in Figure 10 (a) and (b), by comparing the standardized coal gangue vibration acceleration signals, there are great differences between their time domain waveforms, so the time domain features are selected for analysis.

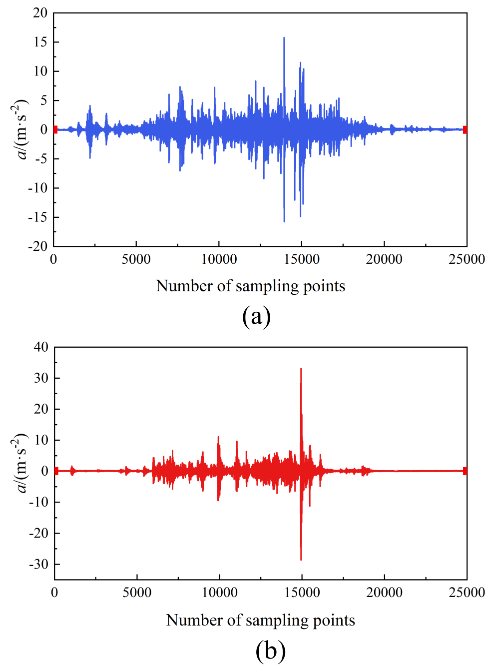


FIGURE 10. Time domain waveform of coal gangue vibration signal. (a) Time domain waveform of coal vibration signal; (b) Time domain waveform of gangue vibration signal.

The time domain features are divided into dimensional and dimensionless time domain features. The dimensional time domain features are sensitive to the signal characteristics, but they are easily affected by environmental interference and are not stable enough. The dimensionless time domain features are relatively stable, and can eliminate the interference caused by the change of conditions or external environment, but the discrimination is not strong. In this paper, 12 representative time domain features are selected, including 6 dimensional time domain features and 6 dimensionless time domain features, as shown in Table 3 and Table 4.

In Section II, we propose a hierarchical filtering method. Now we take the EMD-high pass filtering method as an example to introduce the establishment process of its corresponding EMD-high pass filtering the sample set.

As shown in Figure 11, a set of data obtained from each top coal caving test consists of 9 vibration acceleration signals. Each signal in this group of data is processed by EMD-high

TABLE 3. Dimensional time domain features.

Time domain features	Formula	Implication
Mean value(T_1)	$T_1=\frac{1}{n}\sum_{i=1}^{n}x(i)$	The first moment of signal
Variance(T_2)	$T_2=\frac{1}{n}\sum_{i=1}^{n}\left[x(i)-T_1\right]^2$	Degree of data dispersion
Standard deviation(T_3)	$T_3=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[x(i)-T_1\right]^2}$	Degree of data dispersion, and the original signal unified dimension
Root amplitude(T_4)	$T_4=\left(\frac{1}{n}\sum_{i=1}^{n}\sqrt{\lvert x(i)\rvert}\right)^2$	Effective value of the signal
Root mean square(T_5)	$T_5=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[x(i)\right]^2}$	Effective value of the signal
Peak to peak value(T_6)	$T_6=\max\left[x(i)\right]-\min\left[x(i)\right]$	Signal variation range size

TABLE 4. Dimensionless time domain features.

Time domain features	Formula	Implication
Skewness factor(T_7)	$T_7=\dfrac{\frac{1}{n}\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^3}{\left[\frac{1}{n}\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2\right]^{\frac{3}{2}}}$	Distribution of variables
Crest factor(T_8)	$T_8=\dfrac{\lvert\max\left[x(i)\right]\rvert}{\frac{1}{n}\sum_{i=1}^{n}\lvert x(i)\rvert}$	Detect the presence of shocks in the signal
Kurtosis factor(T_9)	$T_9=\dfrac{\frac{1}{n}\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^4}{\left[\frac{1}{n}\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2\right]^2}$	Represent the smoothness of the waveform and describe the distribution of the variables
Abundance index(T_{10})	$T_{10}=\dfrac{\max\lvert x(i)\rvert}{\left(\frac{1}{n}\sum_{i=1}^{n}\sqrt{\lvert x(i)\rvert}\right)^2}$	Sensitive to signal mutation
Form factor(T_{11})	$T_{11}=\dfrac{\lvert\max\left[x(i)\right]\rvert}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[x(i)\right]^2}}$	Detect the presence of shocks in the signal
Pulse indicator(T_{12})	$T_{12}=\dfrac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[x(i)^2\right]}}{\frac{1}{n}\sum_{i=1}^{n}\lvert x(n)\rvert}$	Detect the presence of shocks in the signal

pass filtering, and 12 time domain features are extracted to obtain its 12 × 9 time domain feature matrix. According to the gangue content of the coal gangue mixture, it is divided into ''caving category'' and ''shutdown category'', so as to convert the coal gangue recognition problem into a binary classification problem. 9 hierarchical filtering methods of EMD-high pass, EMD-band pass, EMD-low pass, EEMD-high pass, EEMD-band pass, EEMD-low pass, wavelet-3

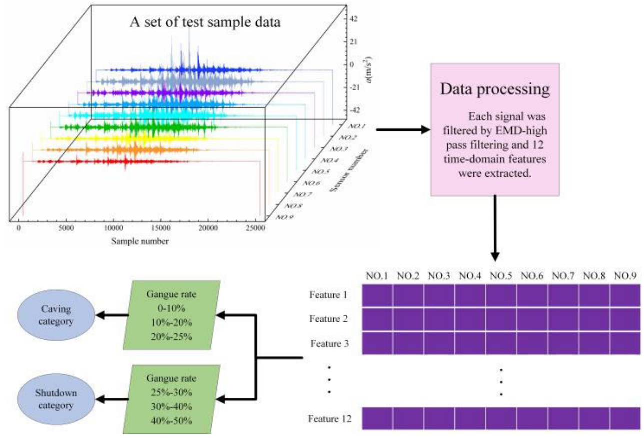


FIGURE 11. Establishment of EMD-high pass filtering sample set.

layer, wavelet-4 layer, wavelet-5 layer correspond to 9 hierarchical filtering sample sets respectively. According to the gangue content of the coal gangue mixed sample, it is divided into ''Caving category'' and ''Shutdown category'' with 25% as the bound, so as to convert the coal gangue recognition problem into a binary classification problem.

V. COAL GANGUE RECOGNITION EXPERIMENT AND RESULT ANALYSIS

A. SELECTION OF RECOGNITION ALGORITHM

Through the top coal caving test and data processing, 9 hierarchical filtering sample sets of coal gangue recognition are obtained. For the classification task that has been determined, the coal gangue vibration signal can be collected in advance, and the known labels and data can be used for supervised learning, so as to improve the learning efficiency and recognition accuracy. This paper verifies the model by several supervised learning methods. In this section, Multilayer Perceptron (MLP) [39], [40], Gaussian Naive Bayes (GaussNB) [41], Linear Discriminant Analysis (LDA) [42], Quadratic Discriminant Analysis (QDA) [43] and Stacking [44] are selected as recognition algorithms which have good recognition effect in various fields. LDA is used as the secondary learner, and the other three algorithms are used as the primary learners to form the Stacking ensemble learner. The coal gangue recognition sample sets are used to verify the EICF-coal gangue recognition model coupled with the wrapper and recognition algorithm. The hyperparameters of recognition algorithms are defined in Table 5.

The following part carries out recognition experiments on hierarchical filtering sample set (HF-sampling set), recognition model coupling wrapper feature selection method (RM-coupling wrapper) and the coal gangue recognition model coupling wrapper based on HF method (EICF-coal gangue recognition model). The recognition results of these three methods are compared with that of the original signal sample set under single algorithms (Original sampling set), so as to verify the performance of the EICF-coal gangue recognition model.

TABLE 5. Definition of hyperparameters for the recognition algorithm.

Recognition algorithm	Hyperparameters	Definition
MLP	activation	relu
	alpha	0.0001
	max_iter	200
	learning_rate	constant
GaussNB	alpha	1.0
	fit_prior	True
	class_prior	None
	binarize	0.0
LDA	slover	svd
	n_components	None
	tol	1.0e-4
	convariance_estimator	None
QDA	prior	None
	reg_param	0
	store_covariance	False
	tol	1e-4
Stacking	classifiers	MLP, GaussNB, QDA
	meta_classifier	LDA
	meta_classifier	True
	verbose	3

TABLE 6. Recognition accuracy of HF-sampling set under different recognition algorithms.

Hierarchical filtering		MLP	GaussNB	LDA	QDA	Stacking
EMD	high pass	0.910	0.753	0.935	0.885	0.918
	band pass	0.773	0.575	0.905	0.695	0.788
	low pass	0.933	0.678	0.910	0.785	0.940
EEMD	high pass	0.898	0.333	0.950	0.878	0.903
	band pass	0.655	0.775	0.748	0.533	0.630
	low pass	0.888	0.775	0.908	0.730	0.898
Wavelet	3 layer	0.955	0.558	0.980	0.865	0.950
	4 layer	0.975	0.595	0.945	0.903	0.970
	5 layer	0.933	0.630	0.945	0.930	0.943
HF-sampling set		0.975	0.775	0.980	0.930	0.970
Original sampling set		0.955	0.833	0.970	0.933	0.960

TABLE 7. Recognition accuracy of different recognition algorithms and their coupling models.

	MLP	GaussNB	LDA	QDA	Stacking
Original signal sample set	0.955	0.833	0.970	0.933	0.960
RM-coupling wrapper	0.983	0.868	0.983	0.958	0.983

B. COAL GANGUE RECOGNITION EXPERIMENT BASED ON HF METHOD

In this section, the validity of HF method is verified by comparing HF-sampling set with the original sampling set. According to the establishment principle of hierarchical filtering sample set, the original coal gangue vibration signals are input to obtain 9 coal gangue recognition sample sets: EMD-high pass, EMD-band pass, EMD-low pass, EEMD-high pass, EEMD-band pass, EEMD-low pass, wavelet-3 layer, wavelet-4 layer, wavelet-5 layer. For each sampling, 400 sets of data from the "caving category" and "shut-down category" are taken as the training set, and another 200 sets are taken as the test set, respectively. Comparison of recognition accuracy (keep 3 significant digits) between HF-sampling set and original signal sampling set under different recognition algorithms is shown in Table 6.

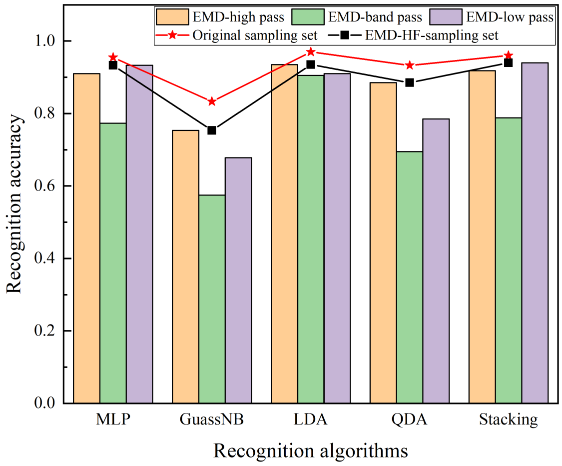
The recognition accuracy of HF-sampling set at different layers under different recognition algorithms is shown in Table 6. Compared with the Original sampling set, it is found that the coal gangue recognition accuracy is improved under the three recognition algorithms of MLP, LDA and Stacking. Under the LDA recognition algorithm, the recognition accuracy of the two sample sets reaches the highest, and the use of the HF method improves the recognition accuracy of coal gangue from 97% to 98%.

In Figure 12, the recognition results of the HF-sample set obtained by the three filtering methods of EMD, EEMD and wavelet analysis are respectively compared with the Original sampling set. According to Figure 12 (a) and (b), the recognition accuracy of the results obtained by HF-sampling set based on EMD and EEMD under five algorithms is lower than that of the Original sampling set. Therefore, EMD and EEMD filtering have negative effects on the filtering of coal gangue vibration acceleration signals. It can be seen from Figure 12 (c) that the recognition accuracy of the HF-sampling set based on wavelet is improved under the MLP, LDA and Stacking recognition algorithms. This shows that under specific algorithms, wavelet analysis has a positive effect on signal filtering, with recognition accuracy improving by 1%. Combined with Table 6, the HF method has a certain effect on the improvement of recognition accuracy under specific algorithms, but its effectiveness is not obvious when used alone.

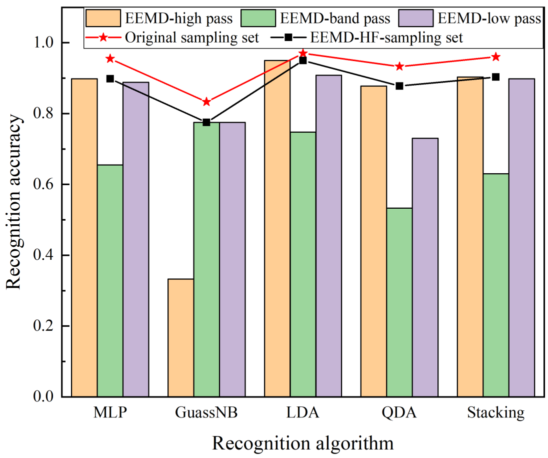
C. VALIDATION OF WRAPPER FEATURE SELECTION METHOD

In order to verify the validity of wrapper feature selection method in this study, the recognition results of the Original signal sample set under different recognition algorithms are compared with the recognition results when the recognition algorithm coupling wrapper feature selection method is used (RM-coupling wrapper), as shown in Table 7.

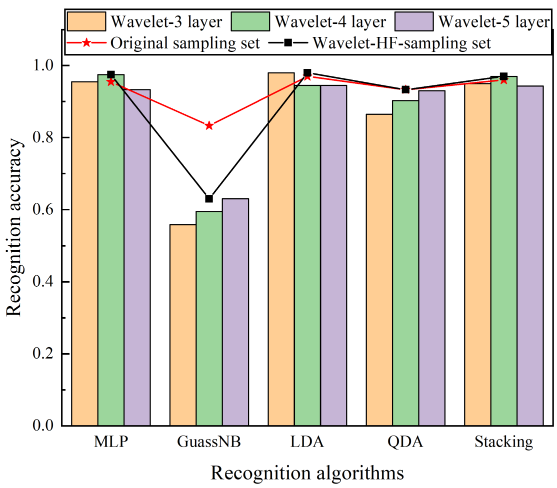
According to Table 7, the recognition accuracy of RM-coupling wrapper is higher than that of Original signal sample set under five recognition algorithm, which is in-creased by 1.3%-3.5%. Under the wrapper feature



(a) EMD



(b) EEMD



(c) Wavelet analysis

FIGURE 12. **Recognition accuracy of HF-sampling set based on different filtering methods.**

selection method, the highest recognition accuracy is improved from 97% to 98.3%.

As shown in Figure 13, it is more obvious that the recognition results of the RM-coupling wrapper are always higher

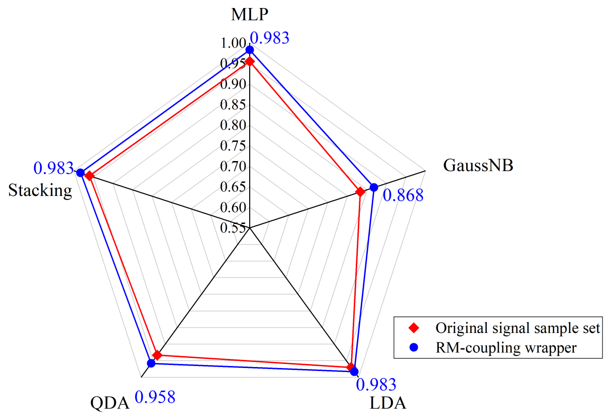


FIGURE 13. **Comparison of recognition results between Original signal sample set and RM-coupling wrapper.**

than those of the Original signal sample set under the five recognition algorithms. Coupling the recognition algorithm with the wrapper feature selection method effectively retains the most effective features for target classification under the algorithm, so as to improve the classification ability obviously. The accuracy of coal gangue recognition before and after using wrapper feature selection method in this study proved its absolute effectiveness, and the recognition accuracy reached 98.3%.

In addition, in order to further verify the validity of the wrapper feature selection method used in this paper, we recognized 9 HF sample sets by a commonly used wrapper feature selection method - Recursive Feature Elimination (RFE), as shown in Table 8.

TABLE 8. **Recognition results of 9 HF sample sets by RFE method.**

HF sample sets		Recognition accuracy
EMD	High pass	0.5
	Band pass	0.5
	Low pass	0.5
EEMD	High pass	0.5
	Band pass	0.5
	Low pass	0.485
Wavelet	3 layer	0.82
	4 layer	0.7275
	5 layer	0.495

As shown in Table 8, the highest recognition accuracy of HF sample set at each layer is only 0.82 by using REF method, which is far from the actual requirement of coal gangue recognition. Therefore, it can be proved that the wrapper feature selection method used in this research has obvious advantages for the coal gangue recognition model.

TABLE 9. Recognition accuracy of EICF-coal gangue recognition model.

Hierarchical filtering		MLP	GaussNB	LDA	QDA	Stacking
EMD	high pass	0.945	0.735	0.947	0.951	0.958
	band pass	0.838	0.664	0.897	0.860	0.871
	low pass	0.952	0.818	0.915	0.878	0.958
EEMD	high pass	0.905	0.644	0.929	0.890	0.908
	band pass	0.772	0.612	0.797	0.681	0.776
	low pass	0.960	0.878	0.913	0.900	0.962
Wavel-et	3 layer	0.981	0.883	0.969	0.968	0.983
	4 layer	0.988	0.883	0.973	0.974	0.990
	5 layer	0.976	0.886	0.958	0.975	0.980
EICF-coal gangue recognition model		0.988	0.886	0.973	0.975	0.990

TABLE 10. Coal gangue recognition accuracy under four models.

Models	MLP	GaussNB	LDA	QDA	Stacking
Original sampling set	0.955	0.833	0.970	0.933	0.960
HF-sampling set	0.975	0.775	0.980	0.930	0.943
RM-coupling wrapper	0.980	0.868	0.983	0.958	0.983
EICF-coal gangue recognition model	0.988	0.886	0.973	0.975	0.990

D. PERFORMANCE VERIFICATION OF EICF-COAL GANGUE RECOGNITION MODEL BASED ON THE HF METHOD AND COUPLED WRAPPER FEATURE SELECTION

We have verified the relative validity of HF method in section V(B), and the absolute effect of wrapper feature selection method on accuracy improvement in section V(C).

In this section, we use the EICF-coal gangue recognition model based on the HF method and coupled wrapper feature selection to analyze the recognition accuracy under five recognition algorithms, as shown in Table 9.

As shown in Table 9, the recognition accuracy of the EICF-coal gangue recognition model under MLP, LDA, QDA, and Stacking all reaches more than 97%. The recognition accuracy is the highest under Stacking, reaching 99%.

In Table 10, we compare the four recognition results of the Original sampling set, the HF-sampling set, the RM-coupling wrapper and the EICF-coal gangue recognition model.

As shown in Table 10, the HF method plays a certain effect on improving the accuracy of coal gangue recognition, it is not applicable to all algorithms. The RM-coupling wrapper improves the recognition accuracy under any algorithm, which proves that the coupled wrapper feature selection method is relatively effective than the HF method for improving the recognition accuracy. Although the recognition effect of GuassNB is poor, it did not have a negative impact on the overall recognition accuracy as the primary learner of Stacking.

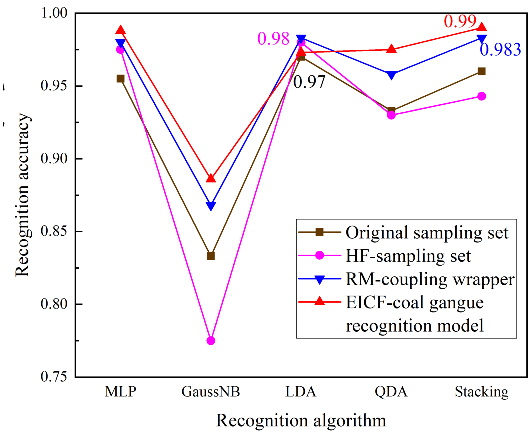


FIGURE 14. Coal gangue recognition accuracy under four models.

As shown in Figure 14, by comparing the coal gangue recognition accuracy under different algorithms, the highest recognition accuracy of the Original sampling set under the five algorithms is 97%, and the recognition accuracy can reach 98% by using HF method, and the recognition accuracy can be improved to 98.3% by RM-coupling wrapper. The EICF-coal gangue recognition model achieves the highest recognition accuracy under Stacking ensemble learning algorithm, which is 99%.

VI. CONCLUSION

Aiming at the problem of low recognition accuracy caused by unclear noise frequency band, insufficient correlation of effective features and difficulty in analysis in the current coal gangue recognition, this paper proposes a hierarchical filtering method and establishes the coal gangue recognition model coupled with wrapper feature selection method. Using the vibration acceleration signal collected by the simulation test bed to verify the performance of the model, the following conclusions can be obtained.

1. The vibration and impact simulation test bed was built, and the signal extraction test was carried out on the difficultly distinguished coal gangue mixtures with gangue content of 0 to 50%, and 2223 sets of vibration acceleration data were obtained.

2. The recognition accuracy of the coal gangue vibration signal sample set processed by the HF method is improved under the MLP and LDA algorithms.

3. The EICF-coal gangue recognition model coupled with wrapper feature selection method and most recognition algorithms achieved the highest recognition accuracy. And compared with the original samples, the recognition accuracy of the difficultly distinguished coal gangue sample set can be effectively improved under the five algorithms in this study, which proves that the model has strong generalization ability.

4. Under the combined effect of the HF method, wrapper feature selection method and Stacking, the recognition accuracy of coal gangue reaches 99%.

This paper proves the filtering effect of HF method for coal gangue vibration acceleration signals, and the effectiveness of the coal gangue recognition model coupled wrapper feature selection method with Stacking. It provides a direction for the research of coal gangue recognition method for top coal caving, and lays a foundation for the intelligent mining of coal mine. Although the HF method plays a certain effect on improving the accuracy of coal gangue recognition, it is not applicable to all algorithms. And this method does not take response speed as the index of performance analysis of this model. Therefore, more in-depth vibration signal filtering research and the estab-lishment of coal gangue recognition models with higher accuracy, good real-time performance and strong generalization ability will be the future research direction.

CONFLICTS OF INTEREST

The author(s) confirm that this article content has no conflicts of interest.

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HE LI was born in Shandong, China, in 1987. He received the B.S. degree in mechanical engineering from the Changchun University of Science and Technology, Changchun, China, in 2010, and the M.S. and Ph.D. degrees in mechanical engineering from the Harbin Institute of Technology, Harbin, China, in 2013 and 2018, respectively. He is currently an Associate Professor with the College of Mechanical and Electronic Engineering, Shandong University of Science and Technology. His research interest includes ultrasonic bearings.

YAO ZHANG received the bachelor's degree in safety engineering from the Shandong University of Science and Technology, in 2020, where she is currently pursuing the master's degree in mechanical and electronic engineering. Her research interests include mechatronics engineering and pattern recognition.

YANG YANG (Member, IEEE) received the Ph.D. degree in mechanical and electronic engineering from the Shandong University of Science and Technology, in 2020. He is currently an Academic Associate Professor with the Shandong University of Science and Technology. He has published more than 50 papers as a principle person. His research interests include pattern recognition, signal processing, artificial intelligence technology, classification and recognition algorithms, mechanical design electromechanical integration, and intelligent control.

QINGLIANG ZENG received the Ph.D. degree in machine design and theory from the China University of Mining and Technology, in 2000. He is currently a Professor with the Shandong University of Science and Technology and Shandong Normal University. He is an expert for climbing project of Taishan Scholars. He has participated more than 40 projects funded by the National Sci-Tech Support Plan, National 863 Program, and Natural Science Foundation of China. He has published more than 100 papers as a principle person. His research interests include electromechanical integration, condition monitoring and fault diagnosis, and virtual prototype.