Coal Rock Condition Detection Model Using Acoustic Emission and Light Gradient Boosting Machine

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Abstract: Coal rock mass instability fracture may result in serious hazards to underground coal mining. Acoustic emissions (AE) stimulated by internal structure fracture should carry lots of favorable information about health condition of rock mass. AE as a sensitive non-destructive test method is gradually utilized to detect anomaly conditions of coal rock. This paper proposes an improved multi-resolution feature to extract AE waveform at different frequency resolutions using Coilflet Wavelet Transform method (CWT). It is further adopt an efficient Light Gradient Boosting Machine (LightGBM) by several cascaded sub weak classifier models to merge AE features at different views of frequency for coal rock anomaly damage recognition. The results denote that the proposed method achieves excellent recognition performance on anomaly damage levels of coal rock. It is an effective method to detect the critical stability further to predict the rock mass bursting in time.

Keywords: Acoustic emission, light gradient boosting machine, coal rock stability.

1 Introduction

During coal exploitation or the construction of roads and tunnels, if the geologic strain energy of the roof of the working face is suddenly released, the underground workers will be injured seriously [Zhao and Jiang (2010)]. Some current methods including micro seismic monitoring, electromagnetic emissions method and ultrasonic non-destructive method and so on, are wildly proposed to detect internal structure of rock mass for mine catastrophic hazards predication [Liu, Li and Xu (2014)]. Micro seismic monitoring served as a mature technology has been widely used in practice. Also Major production makers renew relative produce unceasingly. However, Micro seismic monitoring method is similar to Seismic monitoring technology, which is a passive detection method and necessary to collect data in multi-channel ways to construct geological profile and find

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abnormal spot. The synchronization problems between channels threaten the accuracy of geological analysis.

Acoustic emission (AE) source from inner rock, carries lots of information about rock conditions variation [Feng, Kai, Wang et al. (2018)]. AE is different from other monitoring signal used in detection of rock damage, which is a wide band ultrasonic wave with the detailed description in the time resolution [Becker, Cailleau, Kaiser et al. (2014)]. At present the crucial problem of AE signal processing is the useful information extraction to recognize the rock condition [He, Miao and Feng (2010)]. Wavelets analysis is a useful method to decompose non-stationary time-varying signals into several time-frequency responses [Afshan, Sharif and Loganathan (2018)]. Based on previous researches, some useful characteristic frequency to present inner rock structure variation may be filtered clearly by Coiflet Wavelet Transform method (CWT). After five decomposing, the processed signal at different levels, respectively present rock condition in special views [Li, Yue, Yang et al. (2017)]. Also, as decomposition keeps going, the decomposed responses in both time and frequency domain may present the rock condition in more detailed ways. There is an attendant problem that decomposing results growing in exponential way overburdens computation complexity of following the recognition model. Besides, considering decomposition results fusion problems, the robustness and effectiveness recognition model should be solved urgently.

Many methods have been proposed to boost recognition performance on conditions of coal rock at crisis and burst damage levels such as Support Vector Machines (SVM) [Feng and Seto (1998)], Scoring Functions (SF) [Rummel (1982)] and Neural Network (NN) [Li, Deng, Yang et al. (2017)]. However, these mythologies applied into micro seismic signal could be hardly utilized into AE signal processing due to complex characteristics of itself records structure [Xie, Liu, Ju et al. (2011)].

To tackle this challenge, the Gradient Boosting served as fusion mythology [Friedman (2002)], could be applied to fuse above AE features at different views by cascading several sub classifiers further to boost recognition performances. Also, challenges of vanishing gradient problem from deep network structure could be solved effectively by residual learning. However, Gradient Boosting is necessary to scan all the data instances to estimate the information gain of all the possible split points. Its computational complexities are adversed to process big data. Ke et al. [Ke, Meng, Finley et al. (2017)] proposed an improved gradient boosting method named Light Gradient Boosting Machine (LightGBM) base on Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB). lightGBM method makes computational efficiency increasing and the feature space in quite sparse ways [Fang, Cai, Sun et al. (2018)].

Considering above all, the paper proposed a new coal rock stability recognition method based on AE signal from inner coal rock. After CWT processing, AE waveform are decomposed into several features in views of different frequency. LightGBM method is utilized to fuse different features for the current condition's recognition of coal rock mass. Combined with boosting strategy of ensemble learning method, this proposed method designs a serial cascaded sub RefineNet for each view of AE features. The paper is organized as follows. In Section 2, it focuses on presenting coal rock stability recognition model. In Section 3, the experiment and results will be introduced. Finally, the results will be concluded in Section 4.

2 Materials and methods

2.1 Equipment

The experiments were performed by uniaxial compression equipment, where a servo-controlled testing machine (MTS815) increases stress cyclic loading on the test sample. According to the acting load stress-strain, AE records were recorded simultaneously.

AE records were collected from the Disp-24 acquisition system produced by PAC Corporation. R3 low frequency AE sensors have excellent performance on recording 20-180 kHz frequency signals, which is sensitive to capture slight AE signal made by the rock fracture. The selected data acquisition card, PCI-DSP-4, has four mutually independent channel with 10 MHz A/D converters respectively, the AE signal sample rate is set at 1MSPS.

2.2 Experimental materials and spectral data acquisition

The paper collected samples from Sanhejian Mine, Xuzhou, Jiangsu Province, China. According to the International Society for Rock Mechanics (ISRM), all samples were processed into cylindrical samples with 50 mm diameter and the 100 mm length. All processed samples were sealed in an airtight glass container with Vaseline to keep their original states [Jia, Wei, Wen et al. (2018)]. Also labeled by lithology including sandstone and coal.

As the stress load on samples increasing, samples condition change from the health to the macroscopic failure. Combined the relationship of stress-strain with the evolution procedure of samples facture, the AE records could be labeled by three tags including: safe, critical and burst. Safe is the steady condition including the initial loading stage and after the burst stage. Critical is the crucial condition with numerous cracks development standing for forthcoming burst. The burst stage is the terrible condition, where the rock mass is undergoing completely damage.

2.3 Multi-resolution AE feature extraction

Wavelets analysis is a useful method to decompose non-stationary time-varying AE signals into several time-frequency responses for further feature extraction. The previous researches show that the optimal wavelet decomposition level for feature appearing of 4 levels. AE records be decomposed into five resolutions using CWT as shown in Fig. 1.

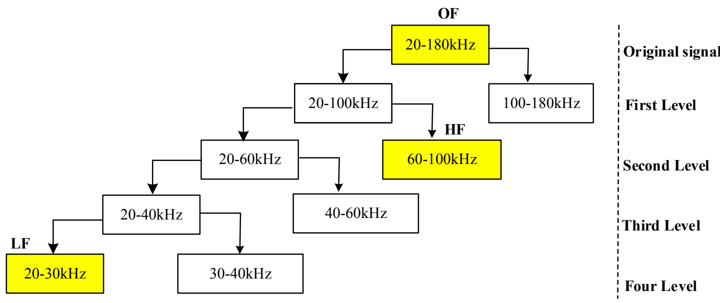


Figure 1: CWT decomposition structure

It is important to select crucial feature from these decomposed results to construct feature sets. The highest frequency part at the 1st level usually is viewed as random noise and filtered away. According to previous researches, these three yellow parts in Fig. 1 are selected as the multi resolutions of AE records. Original AE records are labeled by OF. Decomposed results at the high frequency scale of the 2nd level is labeled by HF. The other decomposed results at the low frequency scale of the 4th level are labeled by LF.

2.4 Coal rock condition detection model using AE and LightGBM

Ensemble learning represented by GBDT algorithm is widely used in big data processing, which can be used to enhance learning and generalization ability of model. LightGBM is a gradient lifting framework that serial weak classifiers including decision tree can be merged further to develop a strong classifier. It is more efficient, uses less memory, performs higher accurate, supports parallel learning and can handle large amounts data.

Supposed a sample set $\{y_i, \mathbf{x}_i\}_1^N$, where $\mathbf{x}=\{x_1,\ldots,x_n\}$ is input variables, y_i is input label. It is considering $f(\mathbf{x}_i)$ evaluated model at each sample point $\mathbf{x}_i$, the corresponding composite model will be taken as following:

$$F(x)=\sum_{m=0}^{M} f_m(x) \tag{1}$$

$F(x)$ is the composite model. $f_0(x)$ is an initial guess, and $\{f_m(x)\}_1^M$ are increment function named steps or boosts, which is defined by the optimization method. It is further to define $\Psi(y,F(x))$ as the loss function, which includes squared error, absolute error for regression and negative binomial log-likelihood for classification. The optimal parameter can be calculated by numerical optimization methods.

$$\begin{aligned} F^*(\mathbf{x}) &= \arg\min_{F(\mathbf{x})} E_{y,\mathbf{x}} \Psi(\mathrm{y}, F(\mathbf{x})) \\ &= \arg\min_{F(\mathbf{x})} E_{\mathbf{x}}[E_y(\Psi(\mathrm{y}, F(\mathbf{x}))\big| \mathrm{x}] \end{aligned} \tag{2}$$

Steepest-decent is taken to be

$$f_m(x) = -\rho_m g_m(x) \tag{3}$$

with

$$g_m(x) = \left[\frac{\partial E_y(\Psi(y, F(x)) \mid x]}{\partial F(x)} \right]_{F(x)=F_{m-1}(x)} \tag{4}$$

and

$$F_{m-1}(x) = \sum_{i=0}^{m-1} f_i(x) \tag{5}$$

The multiplier ρ_m by the line search is calculated as following:

$$\rho_m = \arg\min_{\rho} E_{y,x} \Psi(y, F_{m-1}(x) - \rho g_m(x)) \tag{6}$$

It is calculated the updated $F_m(x)$ that the current approximation at the m-th iteration is given as $F_{m-1}(x)$. The best greedy step towards the minimizing solution $F^*(x)$ is calculated to be $h(x;a)$. $h(x;a)$ is utilized to take place the above unconstrained function $g_m(x)$ in the steepest decent strategy. The solution can be obtained to be:

$$a_m = \arg\min_{a,\rho} \sum_{i=1}^{N} \left[-g_m(x_i) - \rho h(x_i; a) \right]^2 \tag{7}$$

The updated $F_m(x)$ is approximation to be:

$$F_m(x) = F_{m-1}(x) + \rho_m h(x_i; a_m) \tag{8}$$

LightGBM adopts an efficient leaf growth strategy with depth limitations named Gradient-based One-Side Sampling (GOSS). The advantages of strategy include traveling all the leaves before splitting to the definition of information gain, attention on those instances with larger gradients, keeping splitting and repeats in the cycle. It proves that larger gradients will contribute more to the information gain. GOSS can achieve a more accurate gain estimation than uniformly random sampling. Besides, the maximum depth of GOSS is utilized to prevent overfitting in Leaf-wise [Guolin, Meng, Finley et al. (2017)].

The other advantage of LightGBM is feature sparsity using Exclusive Feature Bundling (EFB). It bundles exclusive features into a single feature using Histogram-based Algorithm, which can build the same feature histograms as those from individual features. In this way, the complexity of GBDT model reduces from O (#data×#feature) to O (#data×#bundle), while #bundle << #feature. Then the training of GBDT model can be significantly speed.

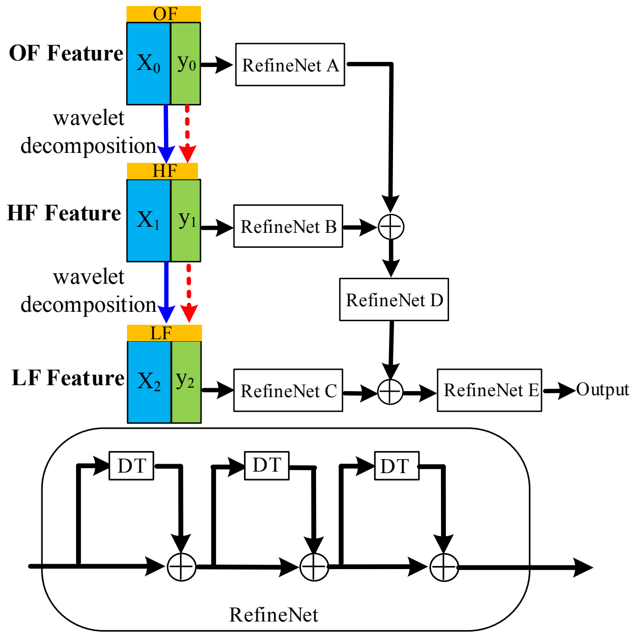


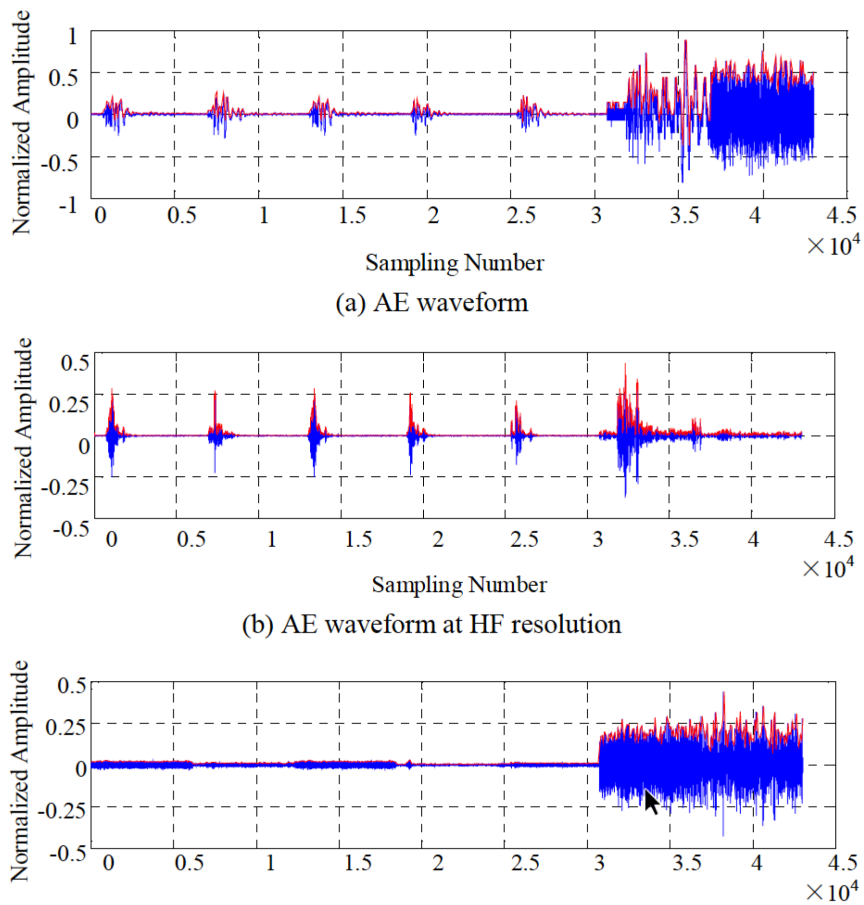
Figure 2: Coal rock condition detection model frame

To further merge three different views of features together, the fusion strategy is considered and described in Fig. 2. First of all, three weak classifiers named RefineNet A, B and C are trained by OF HF and LF feature respectively. Then, results of RefineNet A and RefineNet B are mapped into the cascade RefineNet D. Finally, results of RefineNet D and RefineNet C are mapped into the cascade RefineNet E. The synthesized output of RefineNet E can be expressed the coal rock condition detection results.

3 Experiment and result analysis

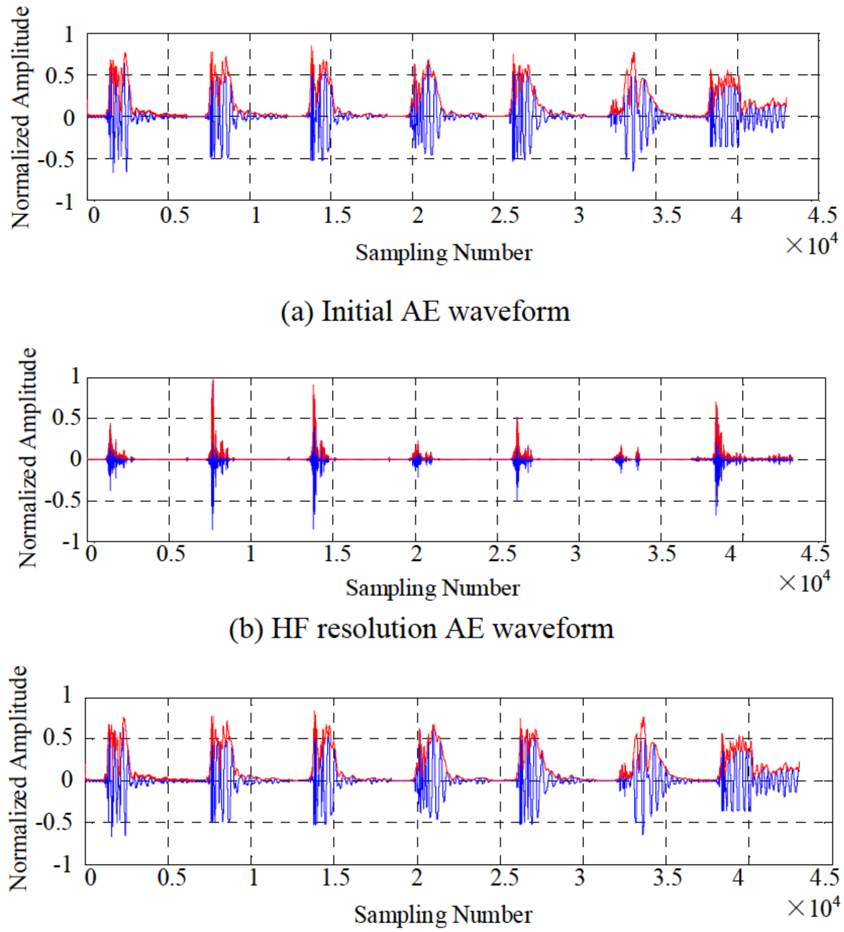
3.1 AE waveform pre-processing

AE waveform is firstly processed by normalization. Then. Based on multi-resolution AE feature extraction method, waveform at HF and LF resolutions can be calculated from original waveform at OF resolution using the CWT method. Fig. 3 presents AE waveform of coal at OF, LF, HF resolutions, Fig. 4 shows AE waveform of rock at OF, LF, HF resolutions respectively.



(c) AE waveform at LF resolution

Figure 3: AE from coal at three different resolutions



(a) Initial AE waveform

(b) HF resolution AE waveform

(c) LF resolution AE waveform

Figure 4: AE from sandstone at three different resolutions

The collected original AE waveform in Figs. 3(a) and 4(a) presents obvious discontinuous tendency in the time domain. Each interval of signal fluctuations are response to large energy releasing of coal rock, which has a great possibility of the internal crack growing [Li, Feng, Zhao et al. (2017)]. As crack growing, the stain-stress of internal samples keeps changing to hold the whole sample in steadies. If crack stops growing, the stain-stress of internal samples will achieve new balance and AE signal will disappear. Figs. 3(b) and 4(b) presents AE feature waveform at HF resolution that these are more detailed in high frequency components generated by tiny cracks. Figs. 3(c) and 4(c) show AE feature waveform at the LF resolution that these are low-frequency components generated by large cracks. Considering the relationship between various cracks effects and coal rock instability grade, AE feature at the LF resolution is an important criterion to evaluate and predict the coal rock failure.

3.2 Feature vector construction

Based on extracted AE waveform at different views, the feature vector is further to construct for coal rock condition detection. AE served as non-stationary signal, is divided into some equal frames to keep the characteristic approximately constant in a short time interval. By general agreement, the frame length and the frame shift are set at 512 and 256 respectively. Various feature vector at different views are constructed including: short-time releasing energy, zero-crossing, average amplitude and short-time kurtosis as shown in Tab. 1.

Table 1: Feature list

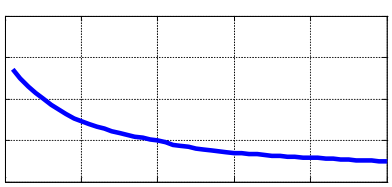
Index	Feature description
1	Stress-strain records
2	Short-time releasing energy and its statistics
3	Zero-crossing and its statistics
4	Average amplitude and its statistics
5	Short-time kurtosis and its statistics

3.3 Estimation stability of coal rock conditions

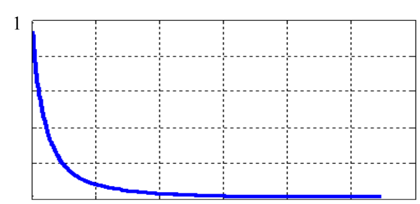
During the experimental process of the sample compression, combined with the status of the sample under loading, coal rock condition could be labeled as safe, crisis and burst conditions. As the name suggests, safe condition presents coal rock samples keeping in safety. The crisis condition shows lots of cracks development in coal rock surface and interior, where large stress-strain loading on the samples. The Burst condition brings completely the damage stage and the sample getting into shattering. Then, Safe, Crisis and Burst conditions at the coal sample the training data were 1521, 958 and 1235 items, and testing data were 507, 318 and 431 items. The items of sandstone sample the training data were 1533, 859 and 1127, items of the testing data were 310, 304 and 427.

In the experiment, the parameters settings are: the learning rate 0.1, the number of leaves 100, the max depth 12 and the number of trees is $n\_estimators = 3000$, the objective function is negative binomial log-likelihood for classification.

The recognition performance on accuracy has been demonstrated in Fig. 5. Algorithm stop trained at 547 iterations, due to its early stopping rules. The loss function shown in Fig. 5 presents an excellent computational convergence be utilized to detect rock sample conditions.



(a) Coal samples



(b) Sandstone samples

Figure 5: The loss of coal rock condition detection model

The recognition rate of coal rock conditions using the proposed method are respectively shown in Tab. 2. Among the averaged recognition rate of three coal conditions, the Burst condition performs 93.28%, which is 2.87% and 6.91% over the Safe and Crisis condition. Similarly, among the averaged recognition rate of three sandstone conditions, the Burst condition performs 98.36%, which is 3.84% and 5.82% over Crisis and safe condition. By contrast, the averaged recognition rate of sandstone Burst condition reaches 98.36% presenting better performance, which is 5.08% over the averaged recognition rate of coal Burst condition. The averaged recognition rate of sandstone Burst condition reaches 94.52%, which is 8.15% over the averaged recognition rate of coal Crisis condition. The averaged recognition rate of sandstone Burst condition reaches 92.54%, which is 4.11% over the averaged recognition rate of coal Safe condition. So there seems the proposed method is a useful method to detect coal rock whether steadily or not. From the view of lithological, the proposed method performs better adaptability of the sandstone.

Table 2: Recognition result of coal rock sample

Sample	**Coal Recognition Result (%)**			**Sandstone Recognition Result (%)**		
	Safe	**Crisis**	**Burst**	**Safe**	**Crisis**	**Burst**
Safe	**90.41**	6.58	3.01	**92.54**	4.35	3.11
Crisis	9.76	**86.37**	3.87	3.27	**94.52**	2.21
Burst	4.05	2.67	**93.28**	0.91	0.73	**98.36**

3.4 Analysis of coal rock recognition performance on different methods

We use the above network to carry out the experiments to analyze coal rock recognition performance on different methods. Tab. 3 presents the recognition performance with SVM and BP algorithm. Since multi-class results must be figured out in this paper, the libsvm toolbox invented by Lin from Taiwan University was chosen to improve the tradition two-classify. Parameters of BP algorithm are: the learning rate $\eta = 0.1$, the training derivation 0.0001 and the max training time $J = 1000$. The Bp is a single-hidden-layer including input, hidden and output layers which has a 14-nodes input layer a 3-nodes output layer and a hidden layer with number of nodes in 7 and 15 named BP1 and BP2 respectively.

Tab. 3 tabulated the average recognition results of three status of coal rock mass using BP and SVM methods. It can be seen that the BP1, BP2 and SVM methods present 21.71%, 17.71% and 9.76% under proposed method for coal condition detection. And the BP1, BP2 and SVM methods present 23.03%, 24.25% and 12.8% lower than proposed method at sandstone conditions detection. So the proposed method achieves obviously better performance on coal rock condition detection.

Table 3: Comparison of SVM and BP

Average Recognition Result (%)		
	Coal	Sandstone
BP1	68.31	72.11
BP2	72.31	70.89
SVM	80.26	82.34

4 Conclusions

In this paper, a novel multi-resolution feature fusion method based on residual learning frame was proposed for rock mass degradation condition evaluation. AE datasets were collected from uniaxial compression. AE waveform features at three different resolutions extracted by Coiflet wavelet reconstruction. After CWT processing, AE signals are decomposed into several features in views of different frequency. AE feature vectors made by tress-strain records, short-time releasing energy, zero-crossing, average amplitude and short-time kurtosis. LightGBM method is utilized to fuse different features for the current condition of coal rock mass recognition. Combined with boosting strategy of ensemble learning method, this proposed method designs a serial cascaded sub RefineNet for each view of AE features. The proposed algorithm was tested to evaluate the degradation conditions of coal rock. The results show that it has excellent performance in evaluating the three critical conditions including safe, crisis, and burst.

In the further work, more useful feature vectors will be selected and the optimal feature fusion strategy will be searched for the analysis of the practical application of coal rock damage evaluation and prediction.

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