Rock Precursor Signal Recognition Based on Machine Learning

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Abstract. Due to the brittleness of hard rock, it is difficult to obtain the failure precursor signal, which endangers the safety of engineering. Therefore, this paper carried out uniaxial compression tests, monitored the compression process with the help of acoustic emission (AE) technology, and analyzed the characteristics of signal changes. In view of the fluctuation complexity of AE signals, it is difficult to effectively identify key information. Machine learning is introduced to identify AE precursor signals. The results show that the mutation point of AE is mainly concentrated in the yield failure stage, close to the peak point. Compared with ELM, RBF, and LSTM models, the Accuracy and AUC of CNN model are 0.90, which shows the excellent performance of the model. This method can provide insights into instability failure in rock engineering.

Keywords: Sandstone; Acoustic emission; precursor signals; Machine learning

1 Introduction

Due to the brittleness of rock materials, their deformation precursors are often not obvious before instability failure, showing strong abruptness, so the monitoring and early warning of rock instability failure has always been a difficult problem [1].

AE [2,3] is a non-destructive monitoring technology, which refers to the phenomenon of energy radiated outward in the form of sound waves in the process of closure, initiation, expansion, penetration and fracture of internal primary small cracks under the action of external force in the process of material deformation. Its characteristics contain rich information of the whole process of rock damage and destruction, which has important reference value for the early warning of sudden damage disasters. Since AE technology was applied to geotechnical engineering, many scholars have studied the characteristics of rock failure precursors from the aspects of AE b-value, characteristic parameters, main frequency [4-6], and have obtained many valuable research results. However, the precursor information of AE signals often relies on manual analysis, and its accuracy lacks verification. The rapid development of machine learning provides a good tool to solve the above problems. Thus, based on the uniaxial compression test of sandstone, this paper uses AE technology to monitor the whole process of uniaxial compression. The instability failure precursor signal is

G. Zhao et al. (eds.), *Proceedings of the 2024 6th International Conference on Civil Architecture and Urban Engineering (ICCAUE 2024)*, Advances in Engineering Research 262,
https://doi.org/10.2991/978-94-6463-688-8_34

analyzed based on the test results and AE signals. The instability precursor information data set of AE signal multi-parameters is constructed, and the machine learning model is used to identify the sandstone instability damage precursor signal. The model can provide reference for rock instability warning.

2 Experimental Process

The experimental sandstone was taken from a railway tunnel in northwest China. A core was drilled from a single intact rock mass and shaped into a standard cylindrical sample with dimensions of 50 mm in diameter and 100 mm in length. The two ends of the rock sample were polished to ensure that the parallelism of the two end faces was less than 0.05mm. The prepared rock samples were put into the drying box, dried at 105 ° C for 24h to constant weight, and removed after cooling to room temperature. Then, the rock samples were put into distilled water, and the vacuum pumping method was used to force saturation. The vacuum negative pressure was 0.1MPa, the pumping time was 6 h, and the vacuum water was filled for 24 h. Uniaxial compression test was carried out on the prepared rock, and the YAW-2000 rock rheological testing machine was used to perform uniaxial compression on the sandstone sample at a displacement of 0.05mm/min. The AE acquisition threshold value is set to 40 dB, the preamplifier is set to 45 dB, and the AE signal sampling rate is 5 MHz. To ensure adequate contact coupling between the sensor and the rock, the contact position between the rock sample and the sensor was wiped clean, and petroleum jelly was applied for coupling.

3 Results and Analysis

3.1 Analysis of Acoustic Emission Precursor Signals

AE signals usually contain a variety of noise, including high-frequency noise and low-frequency noise. These noises can obscure useful information in the signal, making subsequent signal processing difficult. This paper uses wavelet transform to process AE signals, and the results are shown in Fig. 1

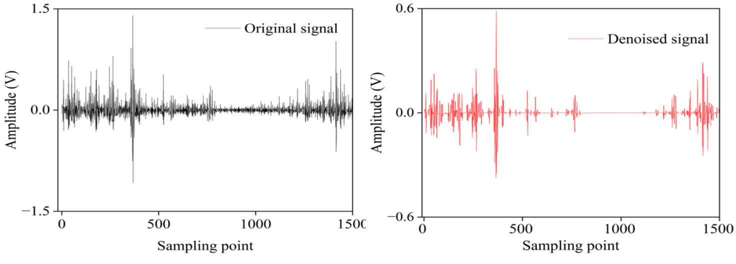

Fig. 1. The denoised signal

The relationship curves of AE ringing count, stress and time are depicted in Fig. 2a. The stage I and II ringing counts and cumulative ringing counts increase slowly, and there is no obvious AE activity condition. Stage III: the sandstone ringing counts and cumulative ringing counts began to increase, and there was a sudden increase point. With the increase of stress, micro-cracks begin to occur inside the rock, and AE are more likely to occur. In stage IV, the AE signal is significantly enhanced, and the cumulative ringing counts increases in stages. Meanwhile, the stress reaches its peak, the microcracks inside the sample are connected, and the macroscopic cracks appear outside the sandstone, which shows that there are more AE signals and the interval time is short before the instability failure.

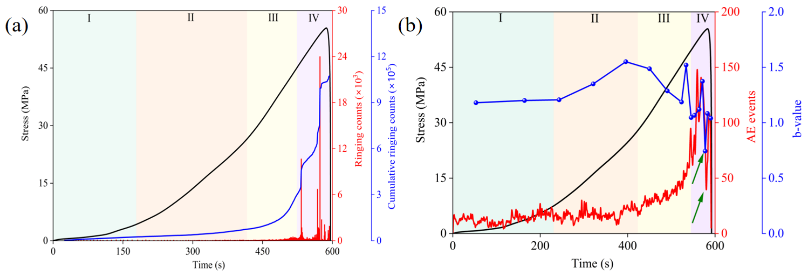

Fig. 2. AE signals and stress curve: (a) Ringing counts (b) AE events and b-value

It can be seen from Fig. 2b that in stage IV, AE signals first increase due to the sudden increase in crack propagation speed, but the b-value and AE events suddenly decrease near the stress peak. This corresponds to the formation of large-scale fractures in the sandstone.

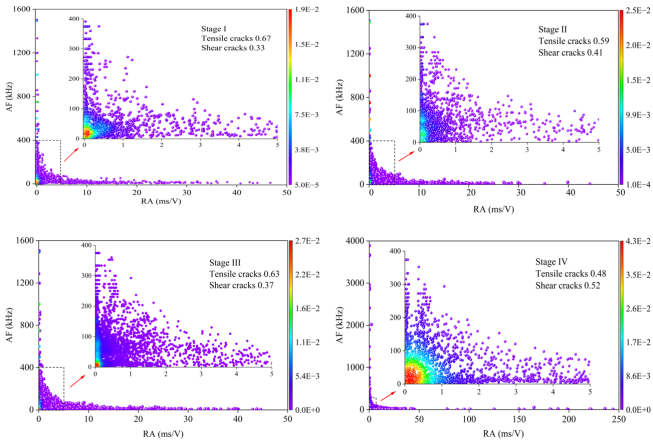

Fig. 3. RA-AF distribution diagram of sandstone

Fig. 3 shows the crack evolution in the uniaxial compression process, and it can be found that the number of shear cracks exceeds the number of tensile cracks in stage IV. It is worth noting that in stage IV, high RA and high AF appear respectively, which indicates that the specimen has a large crack, which can be used as a precursor signal of instability.

3.2 Analysis of Machine Learning Results

Construction of Data Sets.

AE data of stage III and Stage IV were selected for analysis, and the AE ringing count, event rate, b-value, RA and AF were calculated at an equal time interval (0.5s), and the state of stage III was set to 0, and the state of stage IV was set to 1. Thus, the data set had 5 input features and 1 output label, and the state feature data of each specimen were randomly separated according to 7:3 to form a training set and a testing set. Among them, 1123 sets of stable labels and 369 sets of unstable labels, totaling 1492 sets of data.

Model Evaluation.

The performance of the model was evaluated by confusion matrix (see Table 1) and evaluation indexes of classification model, Accuracy, Precision, Recall, F1-score and AUC.

Table 1. Confusion Matrix

Confusion Matrix		Actual value	
		Positive	Negative
Predicted Value	Positive	TP	FP
	Negative	FN	TN

K-fold cross-validation is an evaluation method to verify the performance of classification models. The principle is to randomly divide the total data into K groups, select 1 group as the verification set, and the remaining K-1 group of data as the training set for K rounds of extraction, and finally obtain the performance evaluation results of K rounds, and take its mean value and standard deviation to obtain the comprehensive performance evaluation of the model [7].

Analysis of Model Results.

The evaluation metrics such as Accuracy, Precision, Recall and F_1-value are calculated according to the confusion matrix of different models, and the results are shown in Table 2 and Fig. 4. According to the figure and table, among the four models, all the indicators of the CNN model are stronger than the other three models. CNN models were correctly identified, and the Accuracy was 0.90, the Precision was 0.96, the Recall was 0.91, the F_1-value was 0.93 and the AUC was 0.90. The model parameters were excellent, and the classification results were more accurate. In general, CNN model has better classification results and lower error.

Table 2. Evaluation metrics for classification model

	Accuracy	Precision	Recall	F_1-score	AUC
ELM	0.88	0.94	0.89	0.91	0.88
RBF	0.82	0.91	0.76	0.83	0.81
CNN	0.90	0.96	0.91	0.93	0.90
LSTM	0.85	0.93	0.87	0.90	0.85

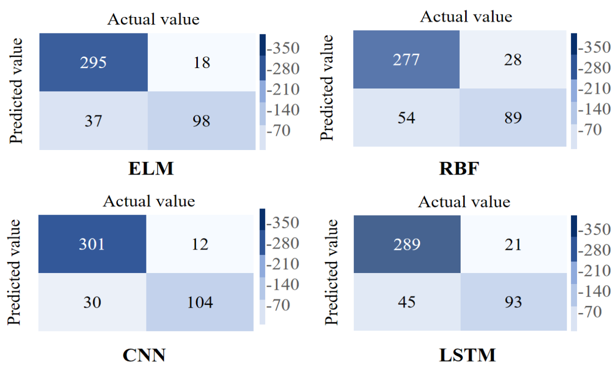

Fig. 4. Confusion Matrix

The error curve of K-fold cross-validation is shown in Fig. 5, and the CNN model shows good generalization ability. The error of the machine learning model gradually decreases with the increase of K, and the error of the CNN model reaches the minimum value of 0.079 when K is 7.

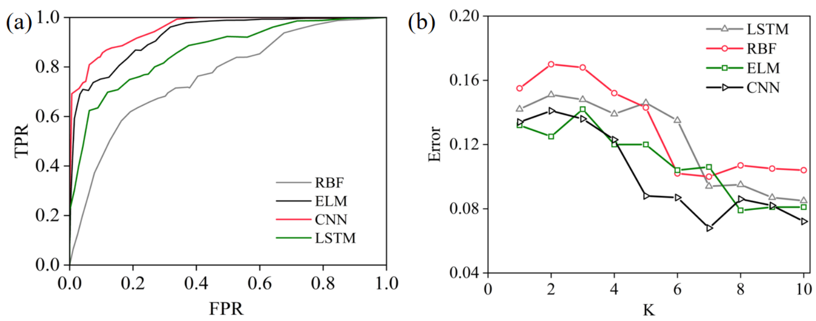

Fig. 5. Model evaluation metrics: (a) AUC curve; (b) K-fold cross-validation curve

Model Discussion.

Through the above analysis, CNN classification has better accuracy and low error, and shows better performance through K-fold cross-validation. CNN model can automatically extract task-relevant high-level features from raw data. This is particularly critical for complex and high-dimensional data such as AE signals, which often contain a lot of noise and redundant information. In contrast, RBF, LSTM and ELM may require more manual feature engineering or, in some cases, fail to capture the association between local features as effectively as CNN. Besides, the actual engineering is inevitably affected by noise, so the AE noise reduction process is carried out. However, the dataset is limited to specimens from sandstone, which neglects the diversity of rock types. To improve the applicability of machine learning in various working conditions, the authors construct a dataset containing multiple rock types in their next work.

4 Conclusions

In this paper, the whole process of uniaxial compression of sandstone is monitored by AE technology. Based on the machine learning model, the precursor signals of AE during the instability failure of sandstone are identified, and the following conclusions are mainly obtained:

1. AE signal can be used as a precursor signal of rock failure, and is mainly concentrated in stage IV.
2. Combining machine learning with the data set constructed based on AE parameters, the damage precursor signal of AE is more accurately identified.
3. Compared with ELM, RBF, LSTM models, CNN model has better performance, the Accuracy and AUC are 0.90. The error of K-fold calculation further shows the excellent performance of CNN model.

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