Experimental Study of Time-Frequency Characteristics of Acoustic Emission Key Signals during Diorite Fracture

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Abstract. High in-situ stress and rock burst have been important issues for risk assessment of deep tunnelling. The issue of prediction and control of rock burst remains to be solved, though various researches have been done. Based on the Lhasa-Linzhi tunnel project of the Sichuan-Tibet railway, the laboratory test of acoustic emission for diorite was carried out in this study. The uniaxial compression test was developed on the diorite specimens collected in the field, and the acoustic emission signals was recorded. Decision tree model was used to filter and classify key signals. Based on the feature parameters, time-frequency characteristics, rupture scale and rupture mechanism of each sort of key signal were analysed. The result shows that the decision tree model has good classification effect and key signals was divided into four groups. Signal A contains high energy, which indicates macro crack propagation and linked up. Signal B and C are continuous signal, which appear before the inflection point of load curve and are helpful for early warning. A simple early warning model was established based on signals distribution, which divides the risk into four levels and provides measures for each stage.

Keywords: Acoustic emission, Diorite, Time-frequency characteristics, Decision tree

1. Introduction

In the process of rock fracture, the generation and expansion of cracks are accompanied by the release of energy, which mainly spreads in the form of elastic waves, forming a unique acoustic emission signal. Acoustic emission (AE) monitoring technology could realize the identification of rock internal structure failure by obtaining acoustic emission signals generated by rocks and analysing signal features, which has high application value in risk early warning and disaster control of rock tunnel engineering¹², and the relationship between acoustic emission signal characteristics and rock fracture has high research significance.

This research focus on three issues: first, test method. At present, most of the research on this problem in engineering field is based on indoor model test. Scholars have used uniaxial compression, triaxial compression, shearing, splitting, TBM linear cutting test, etc to obtain acoustic emission signal data³¹⁰; second, rock materials, rock samples for model test could be obtained by field collection or manual preparation. The acoustic emission signals generated by samples of different lithology have different
characteristics. Previous studies have used granite, marble, coal rock and sandstone as test materials; thirdly, data analysis methods, including filtering and classification of key acoustic emission signals, have been established by Yao Xulong et al. [11] Based on the energy contribution rate of the key signal selection method. The applicability of this method is verified by uniaxial compression tests of granite. Lai Xingping et al. [12] adopted the key signal selection method based on energy contribution rate and counts to study the time-domain characteristics of disaster signal in the process of water bearing coal and rock failure. Zhang Yanbo et al. [13-14] studied the time-frequency characteristics of key signals in uniaxial compression of granite based on clustering analysis, BP neural network, decision tree (DT) and other methods, and established a real-time early warning method of rock burst based on acoustic emission data of roadway rock burst simulation test.

However, the acoustic emission characteristics analysis of diorite fracture are not comprehensive, especially those related to typical rock tunnel project. The feature extraction process of decision tree model belongs to display analysis, which is conducive to quantitative statistics of key signal features. Therefore, diorite samples from Bayu tunnel of Sichuan-Tibet railway are used to monitor the acoustic emission signals of uniaxial compression test, and the decision tree classification method based on energy contribution rate is used to extract and classify the key signals, and the time-frequency characteristics of various key signals are analysed, and a set of early warning scheme based on signal feature recognition is established.

2. Decision tree method
All AE signals generated in the test were taken as ‘the whole signal set’, and the signals selected based on energy contribution rate were taken as the ‘reference signals’. The DT model is used to extract the key characteristic from the whole AE signal set, and find the difference between the key and noncritical signals. The whole signal set is divided into several subsets by the AE characteristic parameters, and each subset contains typical AE characteristic parameter. Finally, the statistical model determines the subset of key signals, and further extracts the characteristic of key signals. The flowchart of the method is shown in Figure 1.

2.1. Classification method
Characteristic parameters, such as absolute energy, duration, counts, rise time, average signal level, RMS voltage, main frequency and amplitude of main frequency are contained in the waveform of AE signal. In order to analysis the fracture scale, fracture mechanism and signal type after classification, six related parameters: AE counts, absolute energy, duration, RMS, dominant frequency and amplitude are selected as the characteristic parameters for extraction and analysis of rock fracture key signals. The information gain of each characteristic parameter is calculated, and the parameter with the largest gain is selected as the dividing node, so that the node has the highest "purity", which means the key signal and noncritical signal are divided more thoroughly. The larger the information gain, the more likely signals in each subset belong to the same category to the greatest extent. All the AE signals in the
test process are regarded as the whole sample set S, and the AE characteristic parameters are regarded as \( \{x_1, x_2, ..., x_n\} \). Information entropy is the most commonly used index to measure the purity of a set. Taking the first partition node as an example, the whole sample set S is being divided. The characteristic parameter \( k \) divides the sample signals into two groups: critical and noncritical signals. The proportion of the two types of signals is recorded as \( p_k \), and the information entropy of this classification is as follows:

\[
Ent(S) = - \sum_{k=1}^{2} p_k \log_2 p_k
\]  

Where \( Ent(S) \) is the information entropy of S.

Since the values of characteristic parameters of AE signal are consecutive, they are arranged in descending order, which is recorded as \( \{x_1^1, x_1^2, ..., x_1^n\} \). The median site \( \left( x_1^i, x_1^{i-1} \right) \) of interval \( [x_1^i, x_1^{i-1}] \) is taken as the undetermined demarcation point \( t \), by which the parameter values could be divided into subsets \( S_t^- \) and \( S_t^+ \). Since the quantity of samples in the subset is different, the weight \( S_t^-/S \) is given to them respectively. The formula of information gain is as follows:

\[
Gain(S, a) = Ent(S) - \sum_{\lambda \in \left[ -t, +t \right]} \frac{S_t^\lambda}{S} Ent(S_t^\lambda)
\]  

Where \( Ent(S_t^\lambda) \) is the information entropy of subset \( S_t^- \) and \( S_t^+ \).

Calculate the information gain of each undetermined partition point and the maximum value is selected as the information gain of characteristic parameter \( x_1 \). Similarly, the information gain of other parameters is calculated according to this method \( Gain(S, i) \) \( (i = x_1, x_2, ..., x_n) \), and the maximum value of parameter is selected as the root node. After that, the partition process recursively until all subsets contain the data of the same category. The division diagram is shown in Figure 2.

2.2. Over-fitting treatment

The AE signals of typical rock fracture events contain abundant information. If the key signals are analyzed directly, some noise contained in the signals may be regarded as their normal characteristic. Such problem is called over-fitting, which will reduce the generalization of the results. Therefore, in order to avoid over fitting and reduce the training and prediction time, pruning is necessary for DT model. Referring to the pruning processing method in reference [15-16], by comparing the accuracy of validation set before and after the division of root node and leaf node and eliminating off-group points of reference signals, the purity of the result is improved, thus reducing the risk of over fitting. Although there will be some differences between reference signals and the key signals selected by DT model after pruning, but the characteristics contained are not missing.

2.3. Feature extraction

In order to improve the generalization of the results of characteristics extracted from key AE signals, the key AE signals of all diorite samples in the test were taken as the key signal library. The decision tree model is used to select the appropriate AE parameters to extract the characteristic information of
key signals. Due to the visual classification process of DT model, the value of characteristic parameter of each key signal subset could be collected easily from partition nodes. Finally, the output which are determined as the key signal subset are found, and the characteristic node attributes in the decision path are selected from bottom to top, and the specific AE parameters of key signals could be obtained. According to the parameters, the rock fracture mechanism corresponding to the key signal is found.

3. Acoustic emission test

3.1. Samples preparation
The diorite samples were taken from the Bayu tunnel of Lalin Railway on Sichuan Tibet railway. The cutting direction was vertical to the side wall, and the original cylindrical sample with radius of 130 mm was obtained. The sample is processed into a standard cylinder with a diameter of 50 mm and a height of 100 mm. The machining accuracy meets the requirements of the nonparallel error of both ends < 0.05mm, and the error of the height and width direction of the test piece is < 0.3mm. The sample is shown in Figure 3. Six samples were used in the tests, which numbered BY1, BY2 … BY6.

![Figure 3. Samples for the test.](image)

(a). Original sample.  (b). Processed sample.

3.2. Test equipment
The wdw-600c rock hydraulic servo testing machine of Geotechnical Engineering Laboratory of Tongji University was used to load the samples. The maximum test force was 600kN, the accuracy of test force indication was ± 0.5%, the resolution was ± 180000 yards, the accuracy of deformation indication was ± 0.5%, and the resolution was ± 180000 yards. Pxdaq1672g AE acquisition equipment is used for AE monitoring, with acquisition accuracy of 16bit and sampling rate of 10ms / s for each channel. Two sensors are fixed on the upper and lower positions of the sample side by using coupling agent, as shown in Figure 4.
3.3. Test process
In order to prevent the noise signal generated by the compression and sliding of the specimen in the early stage of loading, and improve the experimental efficiency. The test was carried out in a graded loading mode including preloading: the specimen was preloaded to 3kn, then loaded to 20KN at the rate of 0.1mm/s, then to 250kN at the rate of 0.05mm/s, and finally loaded to failure at the rate of 0.01mm/s, with an interval of 45S between each stage. The sampling threshold and gain of AE system are 55 dB and 40 dB respectively. In order to reduce the equipment noise, the testing machine and who can transmit receiver are grounded, and the equipment power is strictly controlled. The whole experiment process is recorded by camera, as shown in Figure 5.

4. Results and analysis
4.1. Selection of key signals
The method based on energy contribution rate is used to calibrate the reference key signal [11], and the cumulative contribution rate $\beta$ is 85%. The calibrated reference key signal and the overall AE signal are substituted into the decision tree model to screen and classify the key signals. The result of decision tree model screening is compared with the original reference signal, as shown in Table 1. It can be seen that the selection of key signals by decision tree model is consistent with the energy contribution rate method,
and the accuracy rate is more than 85%. Taking BY1 and BY2 as examples, the time-domain distribution map of the key AE signals screened by the two methods is drawn, as shown in Figure 6.

Table 1. Consistency of key signals.

| Sample | Reference/piece | Decision tree/piece | Common/piece | Consistent proportion/% |
|--------|----------------|---------------------|--------------|-------------------------|
| BY1    | 1959           | 1876                | 1823         | 93.1                    |
| BY2    | 1973           | 1822                | 1724         | 87.4                    |
| BY3    | 1842           | 1801                | 1746         | 94.8                    |
| BY4    | 1924           | 1878                | 1764         | 91.0                    |
| BY5    | 1936           | 1835                | 1772         | 91.2                    |
| BY6    | 1979           | 1805                | 1751         | 88.5                    |

Figure 6. Distribution of reference signals and key signals.

In high in-situ ground, the diorite structure is relatively dense, and the high energy AE signals are less in the early and middle stages of loading, and the low energy signals are mostly generated by the compaction and sliding of a few microcracks. In the vicinity of load inflection point, macro cracks appear and pass through, the cracks develop rapidly, and the rock is destroyed gradually, and more high-energy AE signals are generated. It can be seen from the time-domain distribution that the selected key signals are mainly concentrated near the load inflection point, corresponding to the rock failure process.

4.2. Classification of key signals

In the classification results of decision tree model, there are four classification subsets of key signals. The classification index range of each subset is extracted, and the characteristic parameters of class A, B, C and D key signals are synthesized, as shown in Table 2. The main classification basis of the four
types of signals is ring count and absolute energy, and the secondary classification basis is duration and RMS voltage.

### Table 2. Characteristic parameters of key signals.

| Subset | Counts/piece | Absolute energy/(mv \cdot ms) $10^3$ | Duration/ms | RMS/mV | Main frequency/kHz | Amplitude of main frequency /mV |
|--------|--------------|-------------------------------------|-------------|--------|---------------------|---------------------------------|
| A      | [4294, 11272] | [1.34, 4.12]                        | [83.2, 100] | [0.525, 4.709]     | [45.75, 93.8]                  | [1.323, 4.924]                 |
| B      | [1862, 4613]  | [0.38, 1.34]                         | [32.5, 100] | [0.342, 1.692]     | [15.75, 103.1]                 | [0.425, 1.762]                 |
| C      | [230, 1795]   | [0.09, 0.42]                         | [2.32, 36.1] | [0.142, 0.377]     | [26.26, 113.2]                 | [0.221, 0.560]                 |
| D      | [166, 2572]   | [0.13, 0.86]                         | [1.19, 17.3] | [0.102, 0.863]     | [26.40, 102.9]                 | [0.269, 1.166]                 |

### 4.3. Feature analysis — Signal type

According to the time-frequency characteristics of AE signals, the signals can be divided into two types: "burst type" and "continuous type". The time-domain distribution diagram of sudden signal shows single peak and high amplitude, which can be separated through the peak threshold. In the spectrum diagram, the signal component is relatively single and the main frequency is obvious; the time-domain distribution diagram of continuous signal shows that there are many peaks, small differences and inseparable, and in the frequency-domain distribution diagram, the signal components are rich, and the main frequency is not obvious\(^{[17]}\).

Select a representative signal from the four types of signals, draw its time-domain distribution map, and obtain its spectrum through FFT fast Fourier transform, as shown in Fig. 7. It can be seen that the amplitude of class a signal is high, but the waveform attenuation is fast, which is characterized by sudden signal, single main frequency, concentrated spectrum distribution and obvious centroid. The frequency of class D signal is dense, the waveform is continuous, and it is not separable in time domain. In frequency domain, the medium and high frequency components increase, and the rupture information is complex and the signal activity is strong.

(a) Waveform: Signal A.  
(b) Spectrum: Signal A.
The time-domain distribution of signal B and C shows weak continuous. After FFT transform, the spectrum distribution curve is relatively flat, the centroid is relatively not obvious, and it contains rich frequency components. The ring count and energy level of signal B is higher than that of signal C. Therefore, from the AE signal ring count and waveform characteristics, it can be seen that signal A belongs to sudden signal, signal B and C have certain continuity and activity, while signal D is obvious continuous signal.

4.4. Feature analysis — Fracture scale

Existing studies have shown that the absolute energy and dominant frequency amplitude of the signal are positively correlated with the rock fracture scale, and the characteristic signal generated by large-scale macro fracture has the characteristics of low dominant frequency, high amplitude and high energy [18].

It can be seen from Table 2 that the main frequency difference of the four types of key signals is small, and they all have the characteristics of low main frequency. However, the energy and amplitude
of various signals are quite different. By drawing the normalized amplitude energy distribution diagram of various signals, as shown in Figure 8, it can be seen that the amplitude and energy of class a signals are generally greater than those of the other three types of signals, and the normalized energy and amplitude are mostly distributed in the range of 0.1 ~ 0.4. The energy of signal B and D are the second, and that of signal C is the least. In the amplitude distribution, the amplitude distribution of signal B is relatively concentrated, mostly distributed in the range of 0 ~ 0.1, with a small number of high amplitude signals; the amplitude distribution of signal D is relatively scattered, and there are many high amplitude signals with high amplitude; while the overall amplitude of signal C is the smallest and the distribution is relatively scattered.

![Figure 8. Distribution of amplitude and energy of key signals.](image)

Therefore, there are a large number of high-energy characteristic signals in a signal, and the corresponding rupture scale is the largest; the energy of B and D signals is the second, and the fracture scale is smaller; and the meso damage scale of signal C is the smallest.

4.5. Feature analysis — Fracture mechanism

The research shows that the mechanism of crack formation can be characterized by the RA and AF values of AE signal [19]. Among them, Ra value is the ratio of rise time to amplitude, AF value is the ratio of ringing count to duration. In general, the AE signals generated by shear cracks have higher Ra value and lower AF value, while those generated by tensile cracks have lower Ra value and higher AF value. By drawing the distribution of RA and AF values of various signals, the corresponding fracture mechanism can be explored.
4.6. Early warning model — Structure failure mechanism

Taking BY1 as an example, the time-domain distribution diagram and load curve of four kinds of signals are drawn, as shown in Figure 10. It can be seen from the figure that the time distribution of various...
signals in the loading process is quite different, the signal distribution before the load inflection point is less, and the signal distribution after the inflection point is more. According to the mechanical characteristics of rock micro crack cracking, combined with the previous analysis and existing research results [20-22], the corresponding relationship between the key AE signals and the rock structure failure mechanism can be obtained.

Figure 10. Time domain distribution of each signal.

(1) Signal A are concentrated in the inflection point area of rock load, and the signal characteristics are continuous signals with high strength and high activity. When the rock is in the macro fracture stage, a large number of cracks crack at the same time, accompanied by a large number of continuous AE signals. The signal is a continuous signal with high intensity and high activity [20], which is consistent with the characteristics of signal A. Therefore, signal A should be used to deal with the macro crack propagation and transfixion which has great damage to the structural stability.

(2) Signal B are concentrated in the stage before and after the inflection point of rock load and after the whole rock fracture. Before and after the load inflection point, energy is accumulated in the rock, and the crack is expanding continuously; however, after the macro failure of the rock, the internal stress does not reach the equilibrium immediately, and the AE activity is still active [21]. Therefore, the signal B is the cracking and spreading fracture accompanied by the macro fracture of rock, and because most of the energy in the rock is released in the macro fracture stage, the signal B is far less than the signal A in the fracture scale.

(3) The AE characteristics of signal C are continuous tension signals with high activity and low energy. Because the crack before the macro fracture, in addition to crack at the crack tip, but also along the crack surface sliding, so this kind of signal AE waveform amplitude will not be large, the duration is long, the signal intensity is small [22], so the signal C corresponds to the local tension slip cracking before macro fracture.

(4) Signal D are distributed in the early stage of loading and post peak stage of rock fracture, with weak signal intensity and activity. In the post peak stage, the whole rock has been fractured, and a large number of micro cracks are formed in the internal rapid cracking of the rock, so a lot of sudden AE signals are generated. The amplitude of AE waveform varies greatly with the crack size. Therefore, signal D corresponds to the continuous tension shear composite crack caused by sliding friction between cracks at the initial loading stage and after fracture stage.

4.7. Early warning model — Risk classification

According to the time-domain distribution characteristics of various kinds of signals and their corresponding failure mechanism, it can be seen that the B and C signals are more distributed before the load inflection point, which is of great significance for the early warning of rock failure; the type a signal corresponding to the beginning of macro-scale damage is a sign of disaster occurrence; signal D is
mainly distributed in the initial stage of loading and the stage after failure, which is of great significance
to the early warning of rock failure Early warning helps less.

![Figure 11. Risk classification.](image)

According to the signal distribution characteristics and the failure process of the specimen, the early
warning model is qualitatively divided into four stages, which is shown in Figure 11. The warning signs
and prevention and control measures of each stage are shown in Table 4.

### Table 4. Risk classification and control measures.

| Risk level | Warning signs | Control measures |
|------------|---------------|------------------|
| Level 1    | Signal B starts to generate No visible crack | Local reinforcement, Strengthen monitoring Prepare emergency plan |
| Level 2    | Signal B generates continuously Signal C starts to generate Small cracks appear on the surface | Take protective measures and strengthen monitoring Evacuate people nearby |
| Level 3    | Signal B and C generate continuously Signal A starts to generate Obvious cracks appear on the surface | Evacuate all nearby personnel and machinery Strengthen protective measures |
| Level 4    | Signal A generates continuously Cracks begin to connect A few rock debris fall off | Evacuate all personnel on site and wait for the destruction to end |

### 5. Conclusion

The main conclusions of this research are as follows:

- A decision tree model for extraction and classification of AE key signals for diorite uniaxial
compression was built. Compared with the classification method based on energy contribution rate, it has higher consistency.

- The key signals were divided into four categories, and the time-frequency characteristics, fracture scale and fracture mechanism of all kinds of signals were studied. The results show that most of the four types of signals are continuous and shear failure. The fracture scale of signal A is the largest, corresponding to the propagation and transfixon of macro crack. Signal B mainly ejected from the generation and propagation of small-scale cracks near before macro damage or post damage peak. Signal C correspond to micro shear and slip fractures before macro fracture. Signals D correspond to local small-scale tension-shear composite fractures. The destructive process of diorite sample could be indicated accurately by such four signals.
According to the distribution characteristics and fracture mechanism of the four kinds of signals in the loading process, Signal B and C were selected as the key signal types of early warning of damage, and signal A marked the beginning of macro damage. A risk early-warning model was established qualitatively, which provides reference for on-site risk monitoring.

In this paper, the AE characteristics of diorite under uniaxial compression test were studied. The research results have several limitations, and different lithology and loading methods may lead to different results. In order to simulate the stress characteristics of rock tunnel surrounding rock better, triaxial compression, TBM cutter wire cutting and other loading methods can be selected in the later research, and other rock and structure samples can be tried.

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