



# Similarity assessment of acoustic emission signals and its application in source localization



Shiwan Chen<sup>a</sup>, Chunhe Yang<sup>b</sup>, Guibin Wang<sup>b</sup>, Wei Liu<sup>a,\*</sup>

<sup>a</sup>State Key Laboratory of Coal Mine Disaster Dynamics and Control, Chongqing University, Chongqing 400044, China

<sup>b</sup>Institute of Rock and Soil Mechanics, Chinese Academy of Sciences, Wuhan, Hubei 430071, China

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## ABSTRACT

In conventional AE source localization acoustic emission (AE) signals are applied directly to localize the source without any waveform identification or quality evaluation, which always leads to large errors in source localization. To improve the reliability and accuracy of acoustic emission source localization, an identification procedure is developed to assess the similarity of AE signals to select signals with high quality to localize the AE source. Magnitude square coherence (MSC), wavelet coherence and dynamic timing warping (DTW) are successively applied for similarity assessment. Results show that cluster analysis based on DTW distance is effective to select AE signals with high similarity. Similarity assessment results of the proposed method are almost completely consistent with manual identification. A novel AE source localization procedure is developed combining the selected AE signals with high quality and a direct source localization algorithm. AE data from thermal-cracking tests in Beishan granite are analyzed to demonstrate the effectiveness of the proposed AE localization procedure. AE events are re-localized by the proposed AE localization procedure. And the accuracy of events localization has been improved significantly. The reliability and credibility of AE source localization will be improved by the proposed method.

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## 1. Introduction

Acoustic emission technologies (AET) have been extensively applied in many geotechnical engineering applications such as mines, radioactive waste repositories and geothermal reservoirs and, owing to its high sensitivity to the initiation and growth of cracks, in materials and structures. Acoustic signals spontaneously generated from micro-cracking provide information about the size, location and deformation mechanisms of these events as well as properties of the medium through which the acoustic waves travel [1,2].

In-depth analysis of AE, such as, fracture process and damage evaluation [3–7], damage quantification of rock masses [2,8] and the mechanism of failure processes [9–14], require localization techniques to extract the coordinates of the acoustic emission events as accurately as possible. Extensive researches on the improvement of the determination of AE locations have been carried out [15–20]. Ge [21,22] provided an overview of direct and iterative algorithms as well as an in-depth analysis of several major AE and micro-seismic (MS) source localization methods.

Kundu [23] also analyzed various AE localization techniques under different conditions.

AE source localization methods can be categorized into two groups [22]: non-iterative methods (USBM and Inglada algorithm) and iterative methods (Geiger, Thurber and Simplex algorithm). It is generally accepted that the iterative methods are of particular importance for their flexibility in dealing with localization functions. It is suggested that one should use as many sensors as possible for source localization. More sensors can provide better array geometry, and the optimization can be applied for over-determinate functions [24], but the location results from iterative and optimization are statistical solutions, not the accurate solutions, which may reduce the credibility and reliability of location results, especially when signals with obvious error are included in the analysis. Kurz et al. [20] proposed an approach combining direct solution with the permutation approach, which has certain advantages concerning stability, accuracy and performance to the iterative method in certain applications. But it is still a statistical solution by permutation approach.

For certain AE/MS events, unrealistic location results may be derived without physical status (P- or S- wave of AE/MS signals) identification and same source identification. Ge et al. [21,25,26] emphasized the importance of identifying arrival types as many

\* Corresponding author.

E-mail address: [whrsmliuwei@126.com](mailto:whrsmliuwei@126.com) (W. Liu).

arrivals (more than 50% of total arrivals) are due to S-waves or even not related signals called outliers, which are regarded as P-wave triggering. The mixing of P-wave, S-wave and outlier arrivals will introduce large and systematic errors to the location system, which is regarded as the primary reason responsible for poor MS source location accuracy. Arrival time difference analysis and residual analysis were developed by Ge and Kaiser [25] to address this problem in MS localization.

For AE source localization, there is not any quality assessment or waveform analysis of AE signals so far, which limits the accuracy and credibility of AE source localization in two ways: *i.* Whether signals selected to localize the source are generated from the same source. Since the acoustic emissions are extremely abundant, especially when approaching the failure of rock, signals detected by sensors in the event definition value time may be generated from distinct sources, which will introduce large errors for AE location as well as any other AE analysis; *ii.* Signals of poor quality in a defined AE event are used for localization. It is well-known that AE signals can be easily influenced by attenuation, reflection, refraction and mode conversion, which will result in difficulty for the accurate onset time determination of AE signals. Hence, more attention concerning on waveform should be paid to improve the quality of signals used for localization, to improve the reliability of AE technology.

Grosse et al. [2] developed the magnitude square coherence (MSC) method to classify the mechanism by the coherence sum calculated by integration of the magnitude squared coherence functions, to quantify the similarity of different AE signals. The MSC method is effective in crack mechanism classification, because AE signals caused by different mechanisms are characterized by completely different frequencies. Wavelet coherence (WTC) is a powerful tool to analyze the relationship of time series in time-frequency space. Grinsted et al. [27] discussed the cross wavelet transform and wavelet coherence for examining relationships in time frequency space between two time series. Squared wavelet coherence was used to analyze the relationship of two series. Nazarahari et al. [28] developed a multi-wavelet optimization approach using similarity measures for electrocardiogram signal classification.

Dynamic time warping distance (DTW) is widely used in evaluating similarity of time series in pattern classification [29,30], automatic speech recognition [31,32], time series classification [33] and partial shape matching applications [34]. Alzate et al.

[29] demonstrated the suitability of DTW for the classification of seismic patterns. Izakian et al. [34] selected the fuzzy clustering technique based on the DTW distance to capture the shape similarity between time series. The proposed method generated more acceptable results in the precision of the clustering. Bankó and Abonyi [35] presented a new algorithm called correlation based dynamic time warping, combining DTW and the principal component analysis to measure the similarity of highly correlated multivariate time series.

The purpose of this paper is, first, to clarify the MSE in AE localization process. AE data from thermal-cracking of Beishan granite, the pre-selected host rock for a Chinese high-level radioactive waste repository, will be analyzed as an example. Then, similarity assessment techniques, magnitude squared coherence, wavelet coherence and dynamic timing warping are applied successively to select signals with high quality for localization. Finally, events defined by systems with obvious errors are re-localized with the selected signals based on arrival time determined by AIC-picker.

## 2. Experiment and MSE illumination

### 2.1. Thermal-cracking test

The existing laboratory experiment data of thermal-cracking experiments were used to clarify MSE phenomenon and to assess similarity of AE signals. Granite samples collected from Jiji Cao quarry, Beishan, Gansu, China were heated to high temperature at 5 °C/min by the heater emplaced in the center of the sample, as shown in Fig. 1 [36]. The size of the granite block is  $200 \times 200 \times 200 \text{ mm}^3$ . The grain size of the sample ranges from about 0.5 to 5 mm and their mineralogical composition, determined by X-ray Diffraction (XRD), was: 65.59% feldspar, 34.09% quartz and 5.32% mica. The results of ultrasonic wave velocity tomography test conducted before thermal-cracking test shows that the velocity of the ultrasonic wave ranges from 3200 to 3400 m/s. Without complex loading system applied in this experiment, the AE data are of high quality, characterized by high signal-to noise ratio.

### 2.2. AE signal detection

AE signals were recorded by a PCI-2 24-channel system (Physical Acoustic Corp) [37]. The peak definition time (PDT), hit definition time (HDT), and hit locking time (HLT) were set as 50, 100, and 200  $\mu\text{s}$  respectively. The threshold for AE detection was set to 35 dB. A total 12 sensors were used to monitor the thermal-cracking evolution process.

A proper setting of the PDT ensures correct identification of signal peak for rise time and peak amplitude measurements. In the AE signal acquisition process, the AE sensor detects the signal and then exact time of arrival when an arrival signal passes the threshold. When the signal amplitude reaches a maximum and starts to decline, the data acquisition (DAQ) card notes the maximum amplitude, and waits an additional peak definition time (PDT) to see if the previous signal amplitude is exceeded (Fig. 2). If it is, the measurement continues. If there is no higher amplitude signal within the PDT, the previous amplitude is defined as the peak amplitude [38], as shown in Fig. 2.

As the signal continues after the peak, the card always records the time of the last threshold crossing. If there is no further crossing within the hit definition time (HDT), the last recorded time defines the end of the signal. With this hit definition method, spurious AE events are inevitable in some conditions, as shown in Fig. 2  $t_1 \mu\text{s}$  ( $t_1 < \text{HDT}$ ) after the end of the first signal, another

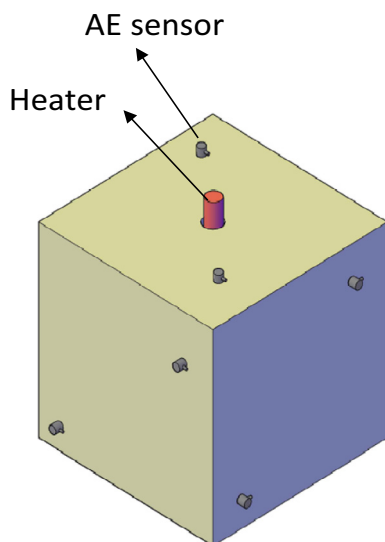


Fig. 1. Thermal-cracking test set-up: location of AE sensors and the heater.

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