Hearing what fractures say – A combination of seismic and speech recognition methods

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Summary

Just like linguists decode what human beings say, seismologists decipher what faults or fractures say. Fracturing of rock samples in laboratory generates acoustic emission (AE) – elastic energy related to very small "earthquakes". Acoustic emissions are of great importance in studying the fracturing mechanics because in laboratory experiments we are more informative about the stress conditions, the rock properties, and the fault plane geometry during the fracturing process. Different types of fractures, e.g. hydraulic fractures, stick-slip fractures, and micro cracks, may happen together (Figure 1) in a small rock sample in laboratory. Efficient methods to analyze AE signals are crucial to characterize fracture mechanisms processes and distinguish different fracturing processes. In this paper, we hear what fractures say be both the AE and audio recording data due to the rupture experiment of a pre-existing fracture in a PMMA cylindrical sample. Traditional seismic source location and moment tensor inversion and speech recognition methods are used to characterize the fracture properties.

Introduction

The history of acoustic emission goes back to the middle of the 20th century, before the terminology AE" was created. Obert and Duvall (1942) first detected small noise emitted from rock under compression and attributed these signals to microfractures in the rock. Kaiser (1950) recorded signals from the tensile specimens of metallic materials. Later, Schoeld (1961) used the terminology AE in his work.

Since the 1960's, much subsequent work has contributed to the development of AE techniques and applied the AE techniques to diverse engineering and scientific areas (Drouillard and Laner, 1978; Drouillard, 1987, 1996; Grosse and Ohtsu, 2008).

During the past 50 years, fracture characterization has become one of the most important application areas of AE techniques. Many early studies from 1960's to 1970's have used AE techniques to investigate fracturing and deformation processes of rocks (Savage and Mansinha, 1963; Scholz, 1967, 1968a,b; Lockner and Byerlee, 1977). Savage and Mansinha (1963) studied the radiation pattern of AE due to a tensile failure in a 2-D glass plate. Scholz (1968b) determined the microfracture frequencies by AE event detection, and AE was also located in space by Scholz (1968a) and found to locate fractures during the compression of granite. Lockner and Byerlee (1977) published the pioneering work of locate hydraulic fractures using AE. Since this early start of the laboratory study of seismic processes, much work has been done to learn the slip processes of tectonic earthquakes using the laboratory analog fracturing process, which was detected by AE (W Goebel et al., 2013; Kwiatek et al., 2014).

Recently, with the increasing interest in the hydraulic fracturing in unconventional oil/gas fields, AE-based laboratory hydraulic fracturing studies have drawn new attention in both academia and industry. Stanchits et al. (2011) studied the fracturing of porous rock induced by fluid injection. Ishida et al. (2012) injected supercritical liquid CO_2 into a borehole inside rock samples and monitored the AE due to hydraulic fracturing. Fu et al. (2015) conducted an experimental study on the interaction between hydraulic fractures and partially-cemented natural fractures. Hampton et al. (2015) investigated the fracture dimension when the laboratory hydraulic fracture interacted with a natural discontinuity. Goodfellow et al. (2015) studied the hydraulic fracture energy budget from the laboratory AE study.

Efficient and reliable detection, location, and source analysis methods for AE are crucial to produce fast and accurate results. The similarity of AE and earthquakes suggests it a possible method to study earthquake mechanism (Scholz, 1968a). Also, methods developed in modern seismology can be used to improve the AE analysis. For event detection, Swindell and Snell (1977) developed a processor automatic signal detection system. McEvilly and Majer (1982) introduced an automated seismic processor for microearthquake networks. Earle and Shearer (1994) used an automaticpicking algorithm to characterize global seismograms. Maeda (1985) suggested a method for reading and checking phase times in an auto-processing system of seismic wave data. Kao and Shan (2004) introduced the source-scanning algorithm to map the distribution of seismic sources in time and space. Kurz et al. (2005) summarized the strategies for reliable automatic onset time picking of AE. All the algorithms in that paper originated from seismic event detection.

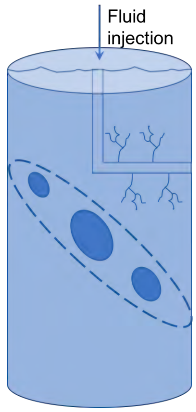

Figure 1: Top: The schematic of different fracture types in a laboratory core sample.

For earthquake location, Lomax et al. (2000) developed a Bayesian location algorithm to determine the location, as well as the uncertainties. A double difference location algorithm was introduced to mitigate the effects of an inaccurate velocity model on location and improve the accuracy of the relative location (Waldhauser and Ellsworth, 2000). Recent studies for microseismicity and tremor earthquakes have produced more ecient location algorithms dealing with a large data set with low signal-to-noise ratio. Zhang et al. (2014) introduced a new method for earthquake depth determination by stacking multiple-station autocorrelograms. Zhang and Wen (2015) suggested an effective method for small event detection and location. Grigoli et al. (2013) developed an automated seismic event location by travel-time stacking. Frank and Shapiro (2014) introduced an automatic detection of low-frequency earthquakes (LFEs) based on a beamformed network response location.

For the AE source analysis, the most common method used the first-P polarity and the moment tensor inversion method using the first-P amplitude (Pettitt, 1998; Graham et al., 2010). Although the first-P amplitude moment tensor inversion methods are also used in seismology, many studies of microseismicity used the waveform-based moment tensor inversion method to determine the source mechanism (Li et al., 2011 a,b; Song and Toksöz, 2011; Gu, 2016). The goal of this chapter is to characterize fractures in laboratory-scale rock samples (cm) using the analysis methods from seismology. In this study, I implemented several event detection, location, and moment tensor inversion algorithms to the AE data from the fracturing experiment of Berea sandstone.

In addition to these seismic, nowadays many developed speech recognition algorithms (e.g., *siri* in your iphone) also provide us more efficient ways to characterize AE signals and infer the mechanisms of fractures. In this paper, we show the application of segmental dynamic time warping (S-DTW) algorithm to AE data. The S-DTW algorithm has been used frequently in unsupervised speech pattern recognition (Park and Glass 2005, 2008; Jansen 2010).

Laboratory fracturing

The AE data are collected from the newly-built AutoLab 1500 laboratory system and the National Instrument (NI) data acquisition system at the rock mechanics lab at MIT (Figure 2).

The pressure vessel is divided into two chambers separated by a moveable piston (Figure 2c). The specimen resides in the lower pressure chamber, which replicates the overburden pressure. The higher pressure in the upper chamber moves the piston into contact with the sample assembly. When the pressure in the upper chamber is greater than that in the lower chamber, a directional force is applied to the specimen.

The piezoelectric (PZT) sensors are attached to the rock sample, and connected to the NI data acquisition systems to collect AE data. The dominant response frequency range of the PZT crystal is between 300 kHz to 1 MHz.

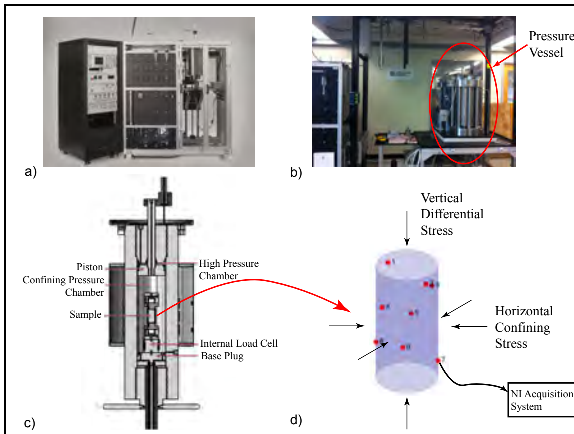

Figure 2: The schematic of the experimental system. a) The AutoLab 1500 laboratory system (New England Research:AutoLab 1500 Instruction Manual); b) The photo of the pressure vessel taken in the rock mechanics lab at MIT; c) The schematic of the pressure vessel (New England Research: AutoLab 1500 Instruction Manual). d) The schematic of the cylindrical rock sample. The red circles show the position of the sensors on the surface of the cylinder. The sensor is connected to the NI acquisition system to collect the AE signals.

Hearing what fractures say

The AE data used in this paper were from the rupture of pre-existing fracture in a PMMA cylinder sample. The sample was PMMA machined to a cylinder with the diameter of 38.10 mm and length of 77.47 mm. The P velocity is 2770 m/s and the S is 1395 m/s. Eight PZT sensors were placed over the surface of the cylinder. The distribution of the position of sensors is shown in Figure 3. PZT sensors are always suffered from the limited frequency bands. The confining pressure was 4 MPa, and the differential stress increased from 10 MPa until the fracture began to slip. We started the AE acquisition when the fracture began to slip. The sound from the slip can also be heard by human beings. In this paper, we also audio recorded the sound during the fracture rupture process by a sampling rate of 48kHz.

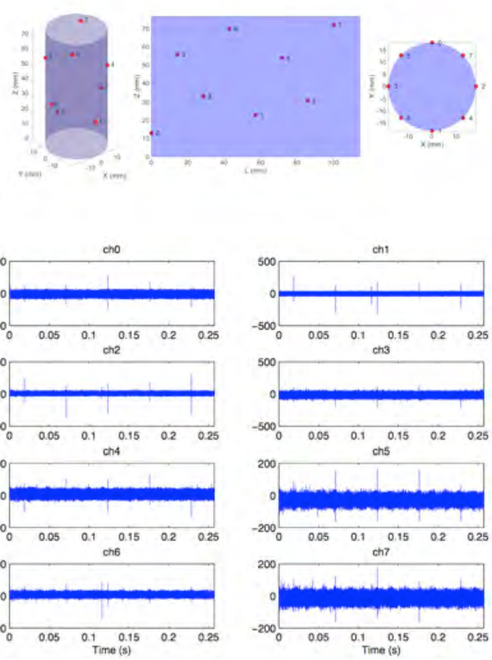

Figure 3: Top: Sensor distribution for the PMMA stick-slip experiment. Bottom: The waveforms example from 8 channels.

Method

The processing of the AE data implemented in this paper includes automatic event detection, location, and moment tensor inversion. We use the STA/LTA algorithm to detect events from continuous AE recording. The simplest grid search algorithm is used to locate AE events. The P-amplitude based moment tensor inversion (FMTI) uses simplified Green's function to generate the forward Green's functions of each moment elements. This simplification assumes a homogenous and isotropic media in the space where the elastic waves propagate. The data for the inversion are the amplitude of the P waves.

We also applied the spectrum analysis to the audio recording of laboratory fracturing sounds. A segmental dynamic time warping (S-DTW) algorithm is applied to the waveforms to recognize different sound source.

Results

The locations of AE events (Figure 4) almost delineate the pre-existing fracture with the strike of 45 degrees clockwise from the north and dip of 64 degrees. The source mechanism of one example event on the pre-existing fault plane also indicates a double-couple dominant normal fault.

Because of high noise lever of several sensors and the limited sensor numbers, the locations of AEs do not exactly locate at the fracture plane. The increase of sensor sensitivity and numbers will improve the both location and source mechanism results.

In addition to these regular seismic processing of AE data, we also apply the S-DTW algorithm to recognize the "speech" of a stick-slip normal fault in the sample. The acoustic dotplot for the audio recording show the similarity of signal segments during the whole recording. The brighter the dot color, the more similarity of the signal segmetns. The red line segmetns in the diagonal direction indicate the same signal perttern during the fracture ruptures. This result shows many sound segments of the fracture "speech" has the same patterns, which means repeated events with same mechnism occured during the ruptrue process.

Conclusions

Fracturing of rock samples in laboratory is useful to mimic different fracture processes, e.g., hydraulic fracturing and rupture of pre-existing faults.

By interpreting the sound of fractures, either AEs or audio recording, we can decipher the mechanism of different fractures. Our work show both seismic and speech recognition methods for processing and interpreting the sound of fractures.

Acknowledgement

This project was sponsored by MIT Earth Resource Laboratory (ERL), Total and Kuwait Foundation for the Advancement of Sciences.

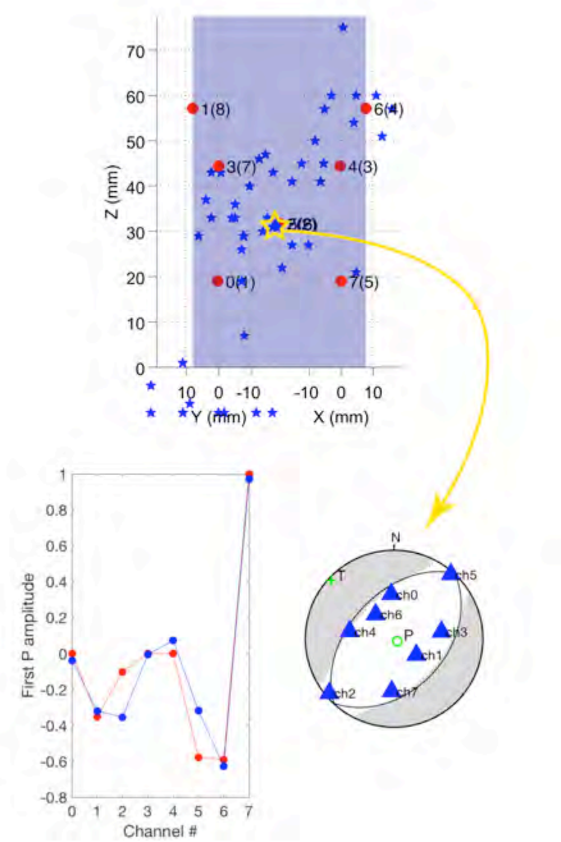

Figure 4: Top: The location of AE events (blue star) delineate the pre-existing practure inside the PMMA sample. Bottom: One source mechanism solution example for a selected event, which is marked as a big yellow star in the Top figure. The left panel shows comparison of the normalized observed (blue) and theoretical (red) first-P amplitude. The right panel shows the source mechanism solution presented by a top-view beach ball. The blue triangles show the projection of sensors on the focal planes.

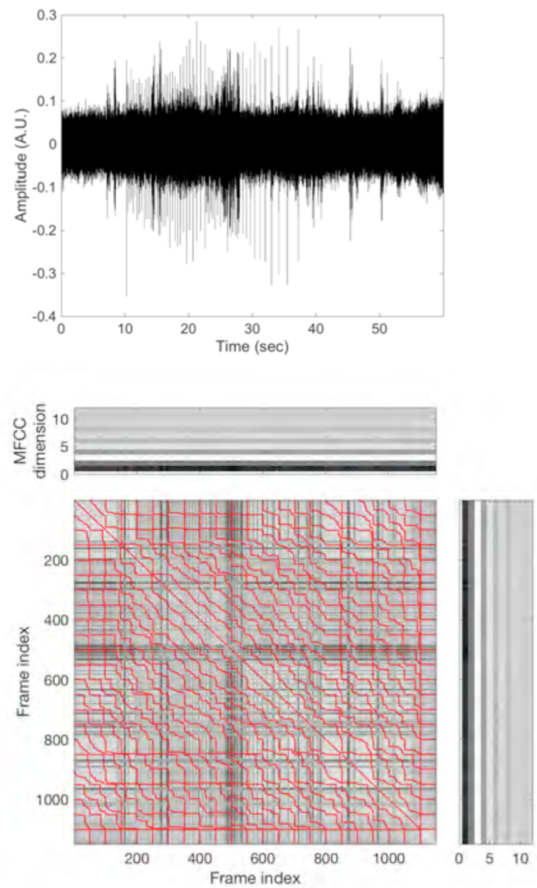

Figure 5: Top: Audio recording during the rupture of the PMMA sample. Bottom: Acoustic dotplot for the audio recording. The brigter color show the lower distortion. The red lines show the segmetal DTW alingnment path. The red line segments in the diagonal direction show the two corresponding signal segmetns are similar.