Adaptive microseismic event detection and automatic time picking

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Summary

Event detection and time picking is a crucial processing step in passive seismic monitoring which is required to be accurate and time efficient considering the large size of data. The short time average and long time average ratio (STA/LTA) is considered the most popular event detection algorithm. The selection of window size and threshold criterion requires careful considerations and is a time-consuming process. The window size selection is studied in detail. A workflow is proposed in which the selection of threshold is made dynamic for each trace in the microseismic record using the Weibull distribution fit of the STA/LTA product of the three microseismic data components. Several time picking algorithms (Akaike information criterion, modified energy ratio and short and long time average ratio) are investigated. Akaike information criterion is used for the time picking because it is stable in focused time picking and is time efficient (it requires less user input). All the events (both weak and strong) present in the microseismic record are detected successfully using the proposed adaptive workflow.

Introduction

Microseismic monitoring is a valuable tool in understanding hydraulic fracture treatments at the reservoir scale. Microseismic data, typically broadband (10-1000 Hz) and characterized by a significant dynamic range (up to 80 dB), are continuously recorded at high sample rates over a period of hours, days or longer. The processing of such data is different from what is seen in traditional exploration seismic processing and provides a map as its basic output indicating the spatial positions of microseismic events highlighting the fracture geometry. One of the important processing steps involves the detection and picking of microseismic events which is done automatically considering the growing size of the seismological data and the subjective and time-consuming nature of its manual analysis.

There is a great variety of published event detection and time picking algorithms in both time and frequency domains for single as well as multi-component recordings. The short and long time average ratio (STA/LTA) technique is considered the most commonly used. It has several modified versions (Allen, 1978; Baer and Kradolfer, 1987; Earl and Shearer, 1994; Trnkoczy, 2002; and Wong et al, 2009) that use the absolute amplitudes, energies or the envelope function of the seismic trace to compute STA/LTA. The modified energy ratio (MER) and multi-window techniques (Chen and Stewart, 2005; Wong et al., 2009) are also very similar (involves energy and absolute amplitude ratios). The Akaike information criterion (AIC), based on the idea that a nonstationary character of seismic signals can be approximated by dividing a time series into locally stationary segments each modeled as an autoregressive process, is another well-known technique (Sleeman and Van Eck, 1999; Leonard, 2000; and St. Onge, 2010). Other algorithms, based on fractal dimensions, neural networks, higher order statistics, polarization filtering, time-frequency models and wavelet transform, are also well known.

The selection of the best algorithm out of so many is a difficult task and requires detailed knowledge about the algorithm parameters for a fair comparison. As suggested by Sharma et al. (2010), none of these algorithms are optimum under all situations. STA/LTA, being the most popular, is used here for event detection in the three component microseismic data. A workflow is proposed in which the selection of threshold is made dynamic for each trace in the microseismic record using the Weibull distribution fit of the STA/LTA product of the three microseismic data components. In search of a fairly accurate and efficient time picking method, several algorithms (e.g. STA/LTA, AIC, MER and Energy ratio) are investigated.

Theory and/or Method

Microseismic data used in this study is from a 6-stage multifrac teatment in a 1km long horizontal well in Central Alberta. Eight three component geophones were used to record the microseisms in a vertical well located approximately 300m away from the treatment well. The input microseismic data, 0.5 msec sampling rate, with signal to noise ratio (SNR) of 4.3 are displayed in Figure 1. The following definition of SNR (Küperkoch et al., 2010) is used:

$$SNR = 20log\frac{A}{A_0}, \tag{1}$$

where A_0 is the rms value of the noise amplitudes and A is the rms value of the signal amplitudes. The amplitudes before the first arrival represent the noise amplitude window.

The STA/LTA algorithm, being the most popular, is used here for event detection in the three component microseismic data. This algorithm can be described in a generalized fashion as follows:

$$(STA)_i = \frac{1}{ns}\sum_{j=i}^{i+ns}(CF)_j, \quad (LTA)_i = \frac{1}{nl}\sum_{j=i}^{i+nl}(CF)_j, \tag{2}$$

where ns and nl represent the number of samples in the short and long time windows respectively. CF is the characteristic function, normally energy but can be absolute amplitude, envelope function or the weighted time derivative of microseismic trace (Allen, 1978; Baer and Kradolfer, 1987; Earl and Shearer, 1994; Trnkoczy, 2002; and Wong et al, 2009). The window size and threshold are two important parameters in this algorithm.

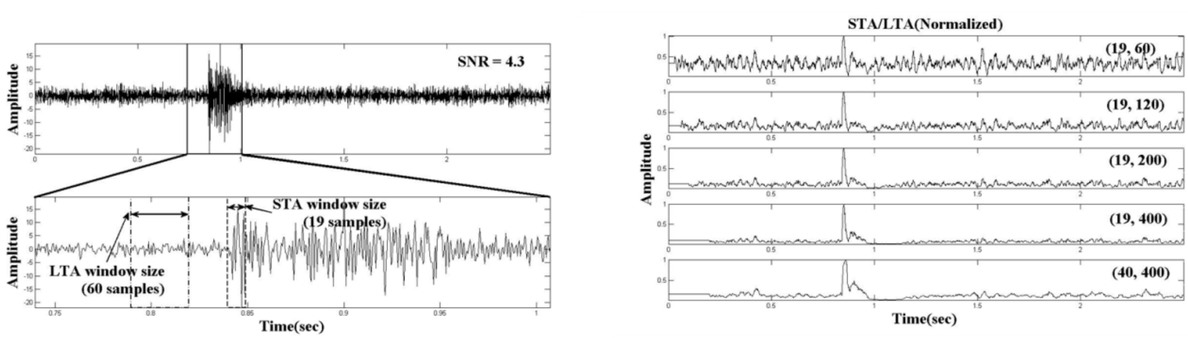

Figure 1: Left: Input microseismic data and its zoomed view. STA and LTA size are based on 2-3 periods of signal and a few periods of noise respectively. Right: Normalized STA/LTA with different window sizes.

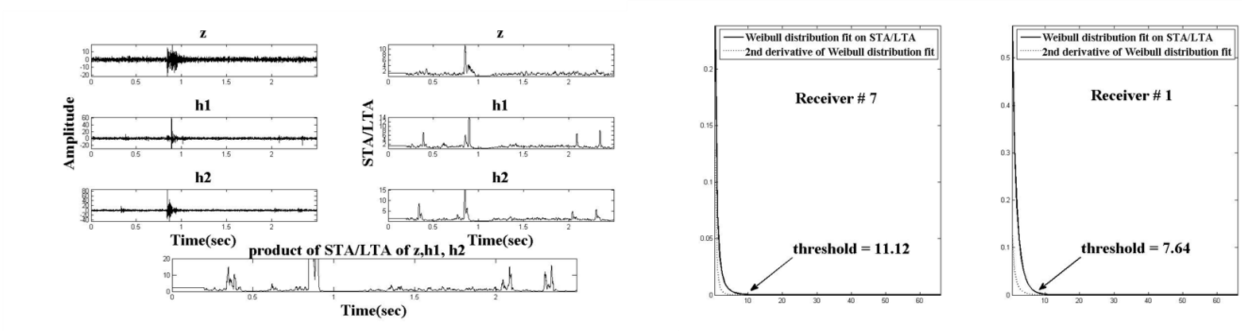

Figure 2: Left: Input microseismic data (Receiver 7) and their STA/LTA response. Right: Threshold determination for Receiver 7 and 1 using the Weibull fit on STA/LTA and its second derivative.

STA and LTA window size should be more than few periods of the recorded microseismic signal and noise respectively. However, a too short STA window produces meaningless fluctuations in STA/LTA, a long STA window is not very sensitive to the rapid increases in the amplitude of the signal and a very long LTA window results in the obscuring of weak arrivals following the strong microseismic arrivals (Saari, 1991; Earle and Shearer, 1994; Trnkoczy, 1999; Munro, 2004; and Sharma et al., 2010). Wong et al., 2010 recommends the STA window size to be 2 - 3 times the dominant period of the seismic signal and LTA window size to be 5 - 10 times longer than STA window size. Figure 1 shows the STA window size on the input microseismic data which is initially taken as 2-3 times the dominant period of the microseismic signal and LTA window size (initially taken as more than few periods of the microseismic noise). The STA/LTA from initial selection is very responsive to background noise fluctuations and may result in several fake detections. For event detections, it is desired to have a strong signal peak on STA/LTA and low smooth noise values. Since the data shown in the figure has a very high SNR (4.3), any combination in [(19, 120), (19, 200), (19, 400), (40, 400)] seems to work well for event detection but to avoid fake detection in the low SNR data, the values between [(19, 400), (40, 400)] are used. In general, however, a STA window size equal to 2-3 or a little more times the dominant period of the microseismic signal and LTA window size equal to or greater than 10 times the STA window size should produce good STA/LTA results. The detection threshold is another key parameter in seismic event detection. The detection threshold can be dynamic as well as a constant value for the whole dataset. The disadvantage of using a constant threshold value for event detection in the whole data is that the SNR varies considerably from record to record and even between traces in a record and a constant threshold value may not be very effective in the event detection. In the proposed workflow, an attempt is made to keep the user input minimum in the event detection process. Therefore, STA/LTA is computed for all three components and their product is taken. This reduces the incoherent noise, enhances the coherent signal. Figure 2 shows the STA/LTA response of three microseismic data components and their product. To avoid the numerical instability in the computation of STA/LTA in case one of the geophone component is dead, a small factor $\varepsilon = 10^{-6}$ is added in the data after the mean value subtraction. For the threshold, a Weibull fit is applied on the STA/LTA product data distribution for each subset of the data under investigation (Figure 2).The probability density function of a Weibull random variable x is:

$$f(x;\,\gamma,k) = \begin{cases} \frac{k}{\gamma}\left(\frac{x}{\gamma}\right)^{k-1} e^{-\left(\frac{x}{\gamma}\right)^{k}}, & x \geq 0 \\ 0, & x < 0 \end{cases} \tag{3}$$

where $k > 0$ is the shape parameter and $\gamma > 0$ is the scale parameter of the distribution. At $k = 1$, the Weibull distribution is identical to the exponential distribution. The second derivative of the Weibull fit is computed. The threshold value is determined once the difference between Weibull fit and its second derivative reaches a value α (0.05 - 0.001). All the events above the threshold value are detected for each microseismic trace. These events in the geophone array are then grouped on minimum number of traces (0.5*(total number of traces in the array) + 1) criterion. A reference event sample number is stored to use in the automatic time picking analysis using the AIC algorithm in a window centered on the reference sample number. AIC is chosen because it is more stable in different SNR data and requires less user input (Figure 4).

Examples

The adaptive technique is able to detect efficiently the microseismic events and requires less user input. The only input required for the proposed workflow is the window size for STA/LTA. This is tested on a full record (8 geophones and 5000 samples) from which receiver 7 and 1 are presented in the previous figures. Figure 3 displays two out of four detected events from this record using the proposed workflow. There is great variation in the event strength in this record. The window sizes used here are 25 and 400 samples for STA and LTA windows respectively. The threshold value is determined automatically for each microseismic trace and events are detected. A reference event sample number is stored to use in the automatic time picking analysis using the AIC algorithm in a window centered on the reference sample number. Figure 4 shows the picked p-wave arrival times on the event shown in Figure 3. The first few traces have poor SNR as compared to the other traces in the microseismic event record. In the good SNR (trace number 4-8), the results of the picked times are very good while these are not of high quality in poor SNR traces. This is the similar kind of behavior as seen in the left hand side of Figure 3 which is a time picking result comparison of different techniques for different SNR data.

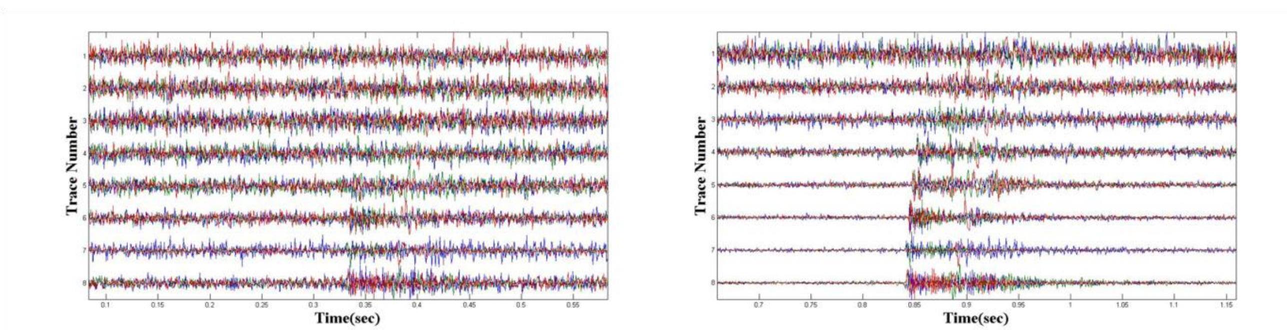

Figure 3: Examples of the detected microseismic events using the adaptive event detection technique.

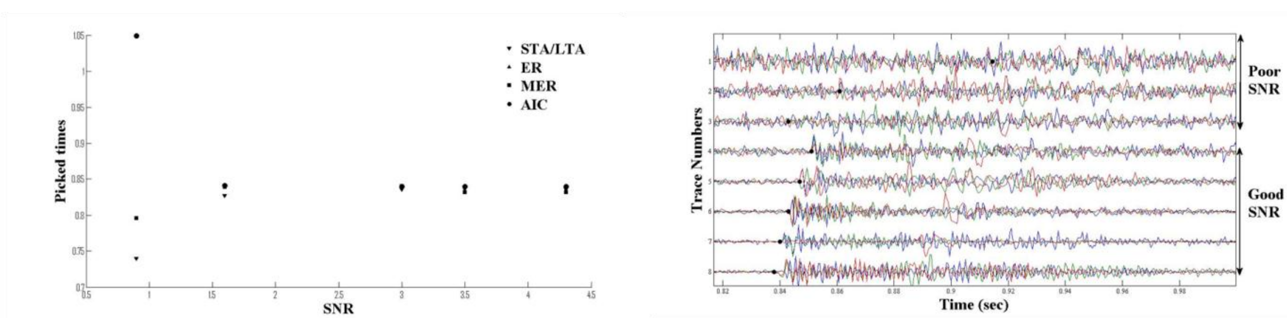

Figure 4: Left: Automatic time picking results for different SNR data. Right: AIC picking results on the detected microseismic event.

Conclusions

The selection of window size and amplitude threshold value is very critical in the STA/LTA algorithm for detecting microseismic events. Quantitatively, STA window size should be 3 or more times the dominant period of the signal and LTA to be 10 or more time bigger than the size of STA window. Because of the variability in the SNR of the data, the use of a dynamic threshold criterion is considered more efficient in the event detection. AIC algorithm is more stable in variable SNR. The proposed adaptive workflow for event detection and time picking is time efficient, fairly accurate and requires less user input.

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