



Iterative interferometry-based method for picking microseismic events



Naveed Iqbal^a, Abdullatif A. Al-Shuhail^{a,*}, SanLinn I. Kaka^a, Entao Liu^b,
Anupama Govinda Raj^b, James H. McClellan^b

^aCeGP at KFUPM, Saudi Arabia

^bCeGP at Georgia Institute of Technology, United States

ARTICLE INFO

Article history:

Received 24 July 2016

Received in revised form 9 March 2017

Accepted 13 March 2017

Available online 16 March 2017

Keywords:

Cross correlation

First-break

Time-frequency representation

P- and S-arrivals

ABSTRACT

Continuous microseismic monitoring of hydraulic fracturing is commonly used in many engineering, environmental, mining, and petroleum applications. Microseismic signals recorded at the surface, suffer from excessive noise that complicates first-break picking and subsequent data processing and analysis. This study presents a new first-break picking algorithm that employs concepts from seismic interferometry and time-frequency (TF) analysis. The algorithm first uses a TF plot to manually pick a reference first-break and then iterates the steps of cross-correlation, alignment, and stacking to enhance the signal-to-noise ratio of the relative first breaks. The reference first-break is subsequently used to calculate final first breaks from the relative ones. Testing on synthetic and real data sets at high levels of additive noise shows that the algorithm enhances the first-break picking considerably. Furthermore, results show that only two iterations are needed to converge to the true first breaks. Indeed, iterating more can have detrimental effects on the algorithm due to increasing correlation of random noise.

© 2017 Elsevier B.V. All rights reserved.

1. Introduction

Renewed interest in microseismic monitoring of hydraulic fracturing for the development of unconventional reservoirs has led the petroleum industry to invest in microseismic technology. The technology involves installing downhole and surface sensors to detect and localize microseismic events in order to image fracturing associated with fluid injection or extraction. The microseismic fracture image is used to understand the extent of fracture network. However, microseismic events are known to have very low signal-to-noise ratio (SNR) making it difficult to detect and accurately locate microseismic events. Many researchers have proposed seismic interferometry to increase the SNR of seismic data (Schuster, 2009; Snieder, 2004; Wapenaar et al., 2010a,b, 2008). Recent application of seismic interferometry in first-break enhancement through cross-correlation, summation, and convolution showed promising results when applied on seismic signals generated by an active source (e.g., Al-Hagan et al., 2014; Alshuhail et al., 2012; Bharadwaj et al., 2013; Mallinson et al., 2011).

Xiao et al. (2009) used seismic interferometry to locate microseismic events by cross-correlating the direct P and S arrivals from repeated sources. They tested their approach using an elastic model and found that the repeated sources enhance arrivals after stacking. Song et al. (2010) proposed an array-based waveform correlation method to enhance the detectability of microseismic events. They used a transformed spectrogram to identify the arrivals and found an improvement over an array-stacked short-time average/long-time average (STA/LTA) approach. There are various versions of STA/LTA method, which are based on energy, amplitude or entropy functions (Wong et al., 2009; Xiantai et al., 2011). There are other similar methods including multi-window method (Chen and Stewart, 2005) and modified energy ratio (MER) (Wong et al., 2009). Mousa et al. (2011) discussed a method based on digital image segmentation. Al-Shuhail et al. (2013) proposed a workflow to enhance microseismic events and reported that the last step in their workflow (i.e., convolving the enhanced and raw records) seemed responsible for leaking noise from the raw records into the enhanced data. This problem is eliminated by Iqbal et al. (2016) using singular-value decomposition in place of convolution.

Among the existing methods, STA/LTA method is the most widely used in earthquake seismology. The STA/LTA method processes the signals in two moving windows (long and short). The ratio of the average energies in the windows is calculated. In case of noise-free seismograms, the maximum value of numerical derivative of the

* Corresponding author.

E-mail addresses: naveediqbal@kfupm.edu.sa (N. Iqbal), ashuhail@kfupm.edu.sa (A.A. Al-Shuhail), skaka@kfupm.edu.sa (S.I. Kaka), eliu@gatech.edu (E. Liu), agr6@gatech.edu (A.G. Raj), jim.mcclellan@gatech.edu (J.H. McClellan).

ratio is close to the first-arrival time. In the MER method, the concept of STA/LTA is modified in such a way that the two windows are of equal length and move adjacent to each other. The peak of the cubic power of energies ratio in the two windows is close to a first-break. The other technique to detect the first breaks includes interferometry approach where cross-correlations of all the distinct pair of traces are carried out. Then, the cross-correlations are aligned to a specific instant and summed up. The resulting stacked cross-correlation is considered as a filter to denoise the noisy traces by convolving the stacked cross-correlation with the traces.

In this study, we propose a first-break picking approach based on seismic interferometry. The proposed approach applies the basic steps of seismic interferometry (cross-correlation and summation) iteratively in order to minimize the sum of squared errors (SSE) between successive iterations. We use both synthetic and real microseismic data to demonstrate that this new approach significantly enhances first breaks, thus making it easy to pick event arrival times. Consequently, the enhanced signals with accurate picking of first breaks will likely improve microseismic event localization over the reservoir.

2. Proposed method

The proposed method has two phases: reliable/accurate first-break estimation on a reference trace and estimation of the relative time delays from the reference trace to all other traces with an enhanced cross-correlation function (CCF). Assume there are M raw microseismic traces, $x_m[n]$ for $m = 1, \dots, M$ of length L_T and sampling interval Δt . With M traces, the number of unique CCFs is $Q = (M/2)(M - 1)$.

The success of the proposed method depends on the correct picking of a reference first-break on at least one trace; therefore, we have given special attention to this step. Consequently, we use the time-frequency contents of the traces simultaneously in the time-frequency domain, which will make the process of first-break manual picking more reliable. Time-frequency representation is not a new concept and many high resolution time-frequency decompositions have been developed. The short-time Fourier transform (STFT) and the continuous wavelet transform are well-known time-frequency transforms that can recover the signal contents if they do not overlap in the time-frequency domain (Diallo et al., 2005; Kulesh et al., 2007; Roueff et al., 2004). There are other transforms such as the empirical mode decomposition (Huang et al., 1998), synchrosqueezing transform (Daubechies et al., 2011), matching pursuit (Mallat and Zhang, 1993) and basis pursuit (Bonar and Sacchi, 2010; Vera Rodriguez et al., 2012; Zhang and Castagna, 2011), to name a few. The time-frequency representation has been used for travel-time picking in the past (Herrera et al., 2015; Saragiotis et al., 2013; Zhang and Zhang, 2015). In this work, we have tested various time-frequency transforms and found the spectrogram method to be most effective. Hence, we use the spectrogram method proposed by Auger and Flandrin (1995) to pick a reference trace $x_r[n]$ whose first-break n_r is the most clear in the time-frequency domain.

For spectrogram, Fast Fourier Transform (FFT) is applied on a subset of data points (N). This subset of data is selected using a window $\mathbf{w} = [w_0, w_1, \dots, w_{L_w}]$. First, FFT is computed for data points of length L_w , then the window is moved h data points and again FFT is calculated. Here, h is called the step size. This procedure is repeated until the window covers the last L_w data points. Mathematically,

$$Y(p, q) = \sum_{j=0}^{L_w-1} y_{j+qh} w_j \exp\left(\frac{-i2\pi j p}{L_w}\right), \quad p = 0, 1, \dots, L_w - 1,$$

$$q = 0, 1, 2, \dots, \frac{N - L_w}{h} \quad (1)$$

The spectrogram is calculated as $|Y(l, n)|^2$. We have used the Hamming window of length (L_w) quarter of the trace length and the overlap is $L_w - 1$ i.e., $h = 1$). These parameters are optimized using simulations.

The reference time index n_r will be utilized to calculate the absolute timings of the enhanced first breaks after the second step which involves multiple cross correlations. The units of n_r are number of samples, which can be converted to time using the sampling interval (i.e., $t_r = (n_r - 1)\Delta t$). Another step in the method is to accurately find the relative time delays of all other traces to the reference trace. Then, the first-break for an arbitrary trace is the sum of t_r and the relative delay to the reference trace. See Algorithm 1 for a detailed description of the proposed scheme.

Notation: For two distinct traces, the CCF is defined as

$$\Phi_{lm}[\tau] = x_l \otimes x_m = \sum_n x_l[n] x_m[n + \tau], \quad (2)$$

where \otimes denotes the cross-correlation operator and τ is the lag index, and $-L_T \leq \tau \leq L_T$, where L_T denotes the length of the traces (i.e., total number of samples).

The algorithm uses $\tau_{lm} = \underset{\tau}{\operatorname{argmax}}\{\Phi_{lm}[\tau]\}$ as the initial picks of the relative delays. These delays enable CCF stacking (step 3 of Algorithm 1) which is a key step in this proposed scheme, where we iteratively perform cross-correlation of the CCFs to mitigate the negative impact of the high noise on the first-break picking. However, in the sequel we will also see that over iterating this scheme will ultimately harm the results.

Algorithm 1. Iterative first breaks picking method based on CCF.

Input: Raw microseismic traces $x_m[n]$, $m = 1, \dots, M$.

Initialization : Manually pick the first-break n_r of the reference trace.

Step 0: Set iteration counter $i = 0$.

Compute cross-correlation between trace l and m , $\Phi_{lm}^i[\tau]$

$$\Phi_{lm}^i[\tau] = x_l \otimes x_m \text{ for } l < m, m = 2, \dots, M \text{ and } -L_T \leq \tau \leq L_T$$

Step 1: Pick relative time delays between the reference trace r and all other traces

$$\tau_{rm}^i = \begin{cases} \underset{\tau}{\operatorname{argmax}} \Phi_{rm}^i[\tau] & r < m \\ 0 & r = m \\ -\underset{\tau}{\operatorname{argmax}} \Phi_{rm}^i[\tau] & r > m \end{cases}$$

Output: first breaks for all traces: $n_m^i = n_r + \tau_{rm}^i$, $m = 1, \dots, M$.

Step 2: If $i \geq 1$, compute iterative sum of squared errors, ISSE(i) via

$$\text{ISSE}(i) = \sum_{m=1}^M (n_m^i - n_m^{i-1})^2 = \sum_{m=1}^M (\tau_{rm}^i - \tau_{rm}^{i-1})^2$$

Terminate the iteration if ISSE(i) increases.

Step 3: Align the maxima and stack the CCFs

$$\Phi_s^i[\tau] = \frac{1}{Q} \sum_{l < m} \Phi_{lm}^i[\tau - \tau_{lm}^i], \text{ where } \tau_{lm}^i = \underset{\tau}{\operatorname{argmax}} \Phi_{lm}^i[\tau]$$

Step 4: Update the CCFs via cross-correlation and truncation

$$\hat{\Phi}_{lm}^{i+1}[\tau] = \Phi_{lm}^i \otimes \Phi_s^i[\tau]$$

$$\Phi_{lm}^{i+1}[\tau] \leftarrow \hat{\Phi}_{lm}^{i+1}[\tau] T[\tau],$$

where $-L_T \leq \tau \leq L_T$ and $T[\tau]$ is a truncation window such that

$$T[\tau] = \begin{cases} 1 & \text{for } -N_T \leq \tau \leq N_T \\ 0 & \text{otherwise} \end{cases}$$

Step 5: $i \leftarrow i + 1$. Go to Step 1.

Download English Version:

<https://daneshyari.com/en/article/5787148>

Download Persian Version:

<https://daneshyari.com/article/5787148>

[Daneshyari.com](https://daneshyari.com)