

An improved method for hydrofracture induced microseismic event detection and phase picking

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ABSTRACT

The ability to detect small microearthquakes and identify their P and S phase arrivals is a key issue in hydrofracture downhole monitoring because of the low signal-to-noise ratios. We apply an array-based waveform correlation approach (matched filter) to improve the detectability of small magnitude events with mechanisms and locations similar to a nearby master event. After detecting the weak events, we use a transformed spectrogram method to identify the phase arrivals. We have tested the technique on a downhole monitoring dataset of the microseismic events induced by hydraulic fracturing. We show that, for this case, one event with a signal-to-noise ratio around 6dB, which is barely detectable using an array-stacked short-time average/long-time average (STA/LTA) detector under a reasonable false alarm rate, is readily detected on the array-stacked correlation traces. The transformed spectrogram analysis of the detected events improves P and S phase picking.

INTRODUCTION

Low-permeability oil reservoirs and gas shales are problematic to produce, often requiring multiple stages of hydraulic fracturing in order to create connected pathways through which hydrocarbons may flow. During hydrofracturing, many induced microearthquakes occur. These induced microearthquakes are extremely important for mapping the fractures and evaluating the effectiveness of hydraulic fracturing. Their locations are used to determine fracture orientation and dimensions, which is further used to optimize the late-stage treatment (Walker, 1997; Maxwell and Urbancic, 2002; Philips et al., 2002). Microearthquake locations also provide helpful information on reservoir transport properties and zones of mechanical instability, which can be used for reservoir monitoring and new well planning (Kristiansen et al., 2000; Willis et al., 2008; Willis et al., 2009). In this paper, we propose a systematic approach to improve the low-magnitude hydrofracture event detection and phase identification.

Most microearthquakes are small and often are hard to detect. A noisy borehole environment further complicates the detection process. For downhole monitoring, as is the case for our study, additional difficulties for event location come from the limited receiver geometry, where usually only one monitoring well is available. In this case, additional information on wavefront propagation direction must be obtained to constrain the event azimuth (De Meersman et al., 2009; Eisner et al., 2009a). Although S-wave polarization has been proposed to compute the event azimuth (Eisner et al., 2009b), most methods still rely on P-wave polarization. However, most hydrofracture events typically radiate smaller P-waves than S-waves. Therefore, identification of the weak P-wave arrivals is crucial for downhole microearthquake location. The quality of P-wave arrival

picking determines the precision of earthquake locations (Pavlis, 1992), and the accuracy of event azimuth relies heavily on the P-wave vector (Eisner et al., 2009a).

In earthquake seismology, waveform correlation of strong events, known as master events, is used to detect weaker events (Gibbons and Ringdal, 2006; Michelet and Toksöz, 2007). These correlation-based detectors are especially useful to lower the detection threshold and increase the detection sensitivity. Previous studies have also shown that the correlation detector can be effective as long as the separation between the master event and the target event is less than the dominant wavelength (Gibbons and Ringdal, 2006; Arrowsmith and Eisner, 2006; Michelet and Toksöz, 2007). In this study, we adapt the method to hydrofracture monitoring by choosing a master event and using it as our cross-correlation template to detect small events, which share a similar location, fault mechanism and propagation path as the master event (Eisner et al., 2006). We compare the single component, single geophone correlation detector with an array stacked three-component (3-C) correlation detector. A significant improvement results from array stacking and matching the polarization structure. Moreover, the array stacking of correlation traces suffers no coherence loss and requires no knowledge of the velocity model as is the case with a conventional beam of array waveforms dependent on a plane-wave model (Kao and Shan, 2004).

To locate the detected events, we need to identify their P- and S-wave arrivals. Typically the STA/LTA type algorithm is used to pick P- and S-wave arrivals (Earle and Shearer, 1994). The problem with this algorithm is that it is very sensitive to background noise level, which can change significantly during hydraulic fracturing. We propose a transformed spectrogram based approach to identify P- and S-wave arrivals where the

influence of high background noise is reduced. This method can act as an initial picking of P- and S-wave arrivals. The transformed spectrogram picking results can be further refined using an iterative cross-correlation procedure proposed by Ronen and Claerbout (1985), Rowe et al. (2002).

METHODOLOGY

Correlation detector

The seismic waveforms observed at any receiver can be modeled as a convolution of the source, medium and receiver response (e.g. Stein and Wysession, 2002):

$$D(t) = S(t) * G(t) * R(t), \quad (1)$$

where $D(t)$ is the recorded seismic data, $S(t)$, $G(t)$, and $R(t)$ represent the source wavelet, medium Green's function and receiver response, respectively. Thus, nearby events sharing a similar source mechanism will have similar waveforms observed at the same receiver (Arrowsmith and Eisner, 2006). This is the basis for the cross-correlation detector. Once a master event with a good signal-to-noise ratio is identified by the standard STA/LTA detector, it can be used as the master event to cross-correlate with the nearby noisy record. If the 3-C waveforms of the master event are denoted as $\mathbf{w}_{N,\Delta\tau}^{j,k}(t_M)$:

$$\mathbf{w}_{N,\Delta\tau}^{j,k}(t_M) = [w^{j,k}(t_M), w^{j,k}(t_M + \Delta t), \dots, w^{j,k}(t_M + (N-1)\Delta t)]^T, \quad (2)$$

where component index is $k = 1, 2, 3$; geophone index is $j = 1, 2, \dots, J$; t_M is the starting time of the master event. The inner product between $\mathbf{w}_{N,\Delta\tau}^{j,k}(t)$ and $\mathbf{w}_{N,\Delta\tau}^{j,k}(t_M)$ is defined

as

$$\langle \mathbf{w}_{N,\Delta t}^{j,k}(t), \mathbf{w}_{N,\Delta t}^{j,k}(t_M) \rangle = \sum_{i=0}^{N-1} w^{j,k}(t_M + i\Delta t) w^{j,k}(t + i\Delta t), \quad (3)$$

and the single-component, single-geophone correlation detector is given by [Gibbons and Ringdal \(2006\)](#),

$$C_{\mathbf{w}}^{j,k}(t)_{N,\Delta t} = C[\mathbf{w}_{N,\Delta t}^{j,k}(t), \mathbf{w}_{N,\Delta t}^{j,k}(t_M)] = \frac{(\mathbf{w}_{N,\Delta t}^{j,k}(t_M) \cdot \mathbf{w}_{N,\Delta t}^{j,k}(t))}{\sqrt{(\mathbf{w}_{N,\Delta t}^{j,k}(t) \cdot \mathbf{w}_{N,\Delta t}^{j,k}(t)) (\mathbf{w}_{N,\Delta t}^{j,k}(t_M) \cdot \mathbf{w}_{N,\Delta t}^{j,k}(t_M))}}. \quad (4)$$

Data redundancy contained in the array and three components can be utilized by introducing another two forms of correlation detector, that is,

$$C_{\mathbf{w}}^k(t)_{N,\Delta t} = \sum_{j=1}^J C_{\mathbf{w}}^{j,k}(t)_{N,\Delta t}, \quad (5)$$

$$C_{\mathbf{w}}(t)_{N,\Delta t} = \sum_{k=1}^3 \sum_{j=1}^J C_{\mathbf{w}}^{j,k}(t)_{N,\Delta t}. \quad (6)$$

Equation 5 represents the single-component, array-stacked correlation detector ([Gibbons and Ringdal, 2006](#)). Equation 6 gives the three-component, array-stacked correlation detector. We will see later in this paper that stacking across the array and three components brings additional processing gain which will facilitate the detection of events with low signal-to-noise ratios. It is worth pointing out that for detection purposes, the stacking of correlation traces is performed without move-out correction. An implicit assumption is that we are dealing with events close to the master event. On the other hand, the move-out in the $C_{\mathbf{w}}^{j,k}(t)_{N,\Delta t}$ across the array can be used to locate events relative to the master event if sufficient receiver aperture is available, such as the surface monitoring case with a two-dimensional receiver coverage (see [Eisner et al., 2008](#)).

A high cross-correlation coefficient on $C_{\mathbf{w}}^{j,k}(t)_{N,\Delta t}$, $C_{\mathbf{w}}^k(t)_{N,\Delta t}$ or $C_{\mathbf{w}}(t)_{N,\Delta t}$ indicates the arrival of a microseismic event. A simple threshold for the cross-correlation coefficient serves as an efficient event detector. A further advantage of this detection

method is that the master event can be updated with time to capture the fracture propagation.

Transformed spectrogram phase picking

The correlation detector determines the occurrence of microseismic events. To locate the events, P and S arrivals must be picked at each 3-C geophone. Weak P arrivals pose a special challenge for time picking. To alleviate this problem, we use a transformed spectrogram approach to enhance weak P arrivals and to facilitate the P and S phase picking. We apply the multi-taper method, proposed by Thomson (1982), to calculate the spectrogram. The basic idea of the multi-taper spectrogram is that the conventional spectral analysis method suppresses the spectral leakage by tapering the data before Fourier transforming, which is equivalent to discarding data far from the center of the time series (setting it to small values or zero). Any statistical estimation procedure which throws away data has severe disadvantages, because real information is being discarded. The multi-taper method begins by constructing a series of N orthogonal tapers, and then applies the tapers to the original data to obtain N sets of tapered data. Because of the orthogonality of the tapers, there is a tendency for the N sets of tapered data to be nearly uncorrelated. If the underlying process is near-Gaussian, those N sets of tapered data are therefore nearly independent. Thus, the sum of Fourier transforms of these N sets of tapered data will give us an unbiased, stable and high-resolution spectral estimate. The multi-taper spectrogram is then differentiated with respect to time to enhance the phase arrival. Next, a transformed spectrogram is formed by multiplying the differentiated spectrogram with the original spectrogram to highlight two features of a phase arrival:

high energy increase and high energy (Gibbons et al., 2008). Mathematically, let the spectrogram estimate within time window $[t, t + L]$ be $A(f, t, L)$, the transformed spectrogram can be expressed as:

$$S(f, t) = (\log[B(f, t, L)] - \log[B(f, t - L, L)]) \log[B(f, t, L)], \quad (7)$$

$$B(f, t, L) = A(f, t, L) / \min_{\{f, t\}} A(f, t, L). \quad (8)$$

The characteristic function of this transformed spectrogram is defined over the signal frequency range $[f_1, f_2]$ as:

$$\bar{S}([f_1, f_2], t) = \max \left\{ \frac{1}{N_f} \sum_{f=f_1}^{f_2} S(f, t), 0 \right\}, \quad (9)$$

where N_f is the number of frequency points over the microseismic signal frequency range $[f_1, f_2]$. The expression for $S(f, t)$ is a multiplication of two terms: the first differential term represents the energy change from the previous time window $[t - L, t]$ to the current time window $[t, t + L]$, while the second term gives the energy within the current time window. The normalized spectrogram $B(f, t, L)$ ensures a positive value of the second term in equation 7 so that $S(f, t)$ is a monotonically increasing function with respect to the first energy change term. Therefore, the two positive peaks on $\bar{S}([f_1, f_2], t)$, which highlight the two features of a phase arrival: high energy and high energy increase, will give the P- and S-wave arrivals. Furthermore, considering P- and S-waves may have different signal-to-noise ratios (SNR) on different components, this transformed spectrogram phase picking approach is applied to all 3 components. The P- and S-wave arrivals are identified on the transformed spectrogram of the component that has the maximum SNR.

FIELD DATA EXAMPLE

A microseismic survey was performed during the hydraulic fracturing stimulation of a carbonate reservoir in Oklahoma. An 8-level three-component geophone array was deployed in the monitoring well at a depth from 1385 m (4545 ft) to 1492 m (4895 ft), where we refer to the shallowest as level 1 and the deepest as level 8. The treatment well is approximately 440 m (1450 ft) away from the monitoring well. The perforation was conducted at a depth of 1530 m (5030 ft). Figure 1a shows a segment of the continuous microseismic record. Unfortunately, level 8 failed to work, so only waveforms from 7 levels are available. Figure 1b shows that the most energetic part of low-frequency noise is concentrated mainly below 75 Hz. Additional signal spectral analysis demonstrates that most signal energy is below 300 Hz. Therefore, a band-pass filter of [75 300] Hz was applied to the raw data to get an enhanced signal as shown in Figure 1c. Figure 2 shows the three components (Z, X, Y) of the band-pass filtered data. The band-pass filtered data in Figure 2 show several microseismic events. The three largest events, noted as event 1, 2, and 3 with S-wave arrivals on level 1 at approximately 19.3 s, 8.3 s, and 28.0 s, are detected by the standard STA/LTA event detection algorithm. Another two smaller events (event 4, 5) around 13.5 s and 2.3 s are noticeable, but are hard to detect by the single-geophone STA/LTA detector. To calculate the signal-to-noise ratio (SNR) of these 5 events, we define:

$$SNR(dB) = 10 \log_{10} \frac{\left\{ \sum_{k=1}^3 \sum_{j=1}^7 \sum_{t=1}^{N_1} [s_{\Delta\tau}^{j,k}(t)]^2 \right\} / N_1}{\left\{ \sum_{k=1}^3 \sum_{j=1}^7 \sum_{t=1}^{N_2} [n_{\Delta\tau}^{j,k}(t)]^2 \right\} / N_2}, \quad (10)$$

where $s_{\Delta\tau}^{j,k}(t)$ and $n_{\Delta\tau}^{j,k}(t)$ denote the k -th component data of the event and noise segment recorded at the j -th receiver, with N_1 and N_2 being microseismic signal and noise

window length. The calculated SNRs for event 1-5 on the band-pass filtered data are 15.3 dB, 12.4 dB, 11.7 dB, 6.5 dB and 6.1 dB, respectively.

The largest event around 19.3s is selected as the master event. Figure 3 shows the vertical component (the Z component) cross-correlation template, where both P- and S-wave arrivals are included. We apply three forms of correlation detector to the three-component data in Figure 2. Figure 4b gives the one-geophone one-component correlation result (Level 1, the vertical component), while Figure 4c and 4d gives the array-stacked correlation traces using the vertical component only and all three components respectively. Compared to the band-pass filtered data on Figure 4a, the one-geophone one-component correlation detector does not increase the SNR, which indicates the existence of some correlated noise. Figure 4c, however, gives better SNRs for two weak events 4 and 5 by stacking the vertical component correlation traces across all 7 geophones. The noise correlation level has decreased from 0.2 in Figure 4b to 0.05 in Figure 4c after cross-geophone stacking. The correlation level for the weakest event 5 in Figure 4c is 0.45. This means that, by stacking the one-component correlation traces, the SNR for the weakest event 5 has increased from 6.1 dB in Figure 4a to 19.0 dB in Figure 4c. Figure 4d represents the array-stacked correlation traces across all three components. The noise correlation level further decreases to 0.03. The SNR for the weakest event 5 increases to 22.5 dB in Figure 4d. This additional 3.5 dB SNR gain over Figure 4c comes from matching in polarization structure by using all three components. Even for the master event (i.e. the strongest event), the SNR on the 3-C array-stacked correlation detector has been boosted from the original 15.3 dB in Figure 4a to 30.4 dB in Figure 4d. Two weak events 4 and 5 are easy to identify in Figure 4d.

For comparison, we also apply the STA/LTA detector to the array-stacked three-component data. Before stacking, a moveout correction is used to align the waveforms from different geophones. Here the moveout is estimated by cross-correlating the master event waveform segments between geophone pairs. Figure 4e gives the sum of three single-component STA/LTA ratios of the stacked band-pass filtered data after the moveout correction. The STA and LTA window lengths are selected to be 3 and 15 times the dominant period (16 ms and 80 ms). While events 1, 2, 3 and 4 clearly stand out in Figures 4e, event 5 is hard to detect under a reasonable false alarm rate. The SNR of the weakest event 5 increases from 6.1 dB to 14.6 dB. This 8.5 dB SNR gain, resulted from moveout corrected array-stacking, is smaller than the 16.4 dB gain in the 3-C array-stacked correlation detector. Moreover, a spurious event around 14.8 s (labeled as ‘*’ in Figure 4e) is actually caused by the large noise recorded mainly by geophones 4 and 3 (Figure 2), which is not seen in the correlation detector (Figure 4d). This demonstrates the utility of the array-stacked correlation detector over the array-stacked STA/LTA detector. The three-component array-based correlation detector can effectively enhance the SNR of small microseismic events, and therefore is suitable to detect small-magnitude events with waveforms similar to a master event. In practice, we can use the STA/LTA detector to identify several large events, which can then be used as master events to detect their nearby weak events.

For each detected event, we use the multi-taper based transformed spectrogram approach as described in equations 7-9 to identify the P- and S-wave arrivals and compare them to standard STA/LTA picks (Earle and Shearer, 1994). We calculate the characteristic function $\bar{S}([f_1, f_2], t)$ to pick the P- and S-wave arrivals on each 3-C

geophone for each detected event. Here $[f_1, f_2]$ is set as the microseismic signal frequency range, $[75, 300]$ Hz. The method is applied to all three components to get the optimal P- and S-wave arrival picks. The P- and S-wave arrivals can be picked either separately from the component which has the best P- and S-wave SNRs or together from the sum of $\bar{S}([f_1, f_2], t)$ over all three components. In our study, both methods give similar P- and S-wave picks. For level 1 geophone, Figure 5 compares the manual picks (solid line), transformed spectrogram picks (dash line) and STA/LTA picks (dash-dot line) for the master event. P- and S-waves have the highest SNR on the horizontal and vertical component separately. Thus, the P-wave arrival is determined from the horizontal component, while the S-wave arrival is obtained from the vertical component. For this large event, the arrivals given by both methods are close to the manual picks, signifying that we can use STA/LTA detector to identify master events and determine t_M . The arrivals identified by the peaks on $\bar{S}([75, 300], t)$ are close to the onset of phase arrivals, while the STA/LTA picks tend to give the peak arrival times. For the weakest event, as shown in Figure 6, the STA/LTA picks have little agreement with manual picks due to the high noise level, while the transformed spectrogram picks are consistent with manual picks. This illustrates that the transformed spectrogram facilitates picking of weak phase arrivals. The noise level has less influence on the characteristic function due to the differentiation term in equation 7. The shape of the characteristic function depends on the signal energy distribution over the time and frequency, and the window length L . The choice of L depends on the balance between the sharpness of the P and S peaks (i.e. the resolution of arrival picks) and the occurrence of spurious peaks. From our experience, three to four times the dominant period is a good value.

CONCLUSIONS

In this paper, we have proposed a systematic approach for hydrofracture event detection and phase picking. By field test, we have demonstrated that once a large event is detected by the standard STA/LTA detector, it can be used as the master event. A three-component array-stacked correlation detector using this master event template can effectively increase the detectability of nearby small-magnitude events. Unlike conventional array stacking of the waveform data from one single event, the array stacking of correlation traces between two close events suffers no coherence loss and requires no knowledge of the velocity model. Under the same false alarm rate, the array-stacked correlation detector gives better results than array-stacked STA/LTA detector, because the correlation detector uses full waveform information. The three-component, array-stacked processing is superior to a single-component, single-geophone correlation detector. The processing gain increases with the increased number of geophones. The limitation of the correlation detector is that it is only capable of detecting the events that are within one dominant wavelength from the master event. However, this limitation could be alleviated by updating the master event. For phase picking, we applied the transformed spectrogram approach to identify the weak arrivals. The P- and S-wave arrivals are picked from the component that has the highest signal-to-noise ratio for P- and S-wave vector separately. The transformed spectrogram captures two features of a phase arrival in the time-frequency domain: high energy and high rate of energy increase; therefore it improves phase picking. Detection and phase identification of small-magnitude microseismic events have potential for not only hydrofracture monitoring but also reservoir surveillance.

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FIGURE CAPTIONS

Figure 1: (a) A 32s raw vertical velocity data record from a three-component downhole geophone array. (b) Amplitude spectrum of the panel in (a) after summing over all traces. (c) The panel in (a) after [75, 300] Hz band-pass filtering.

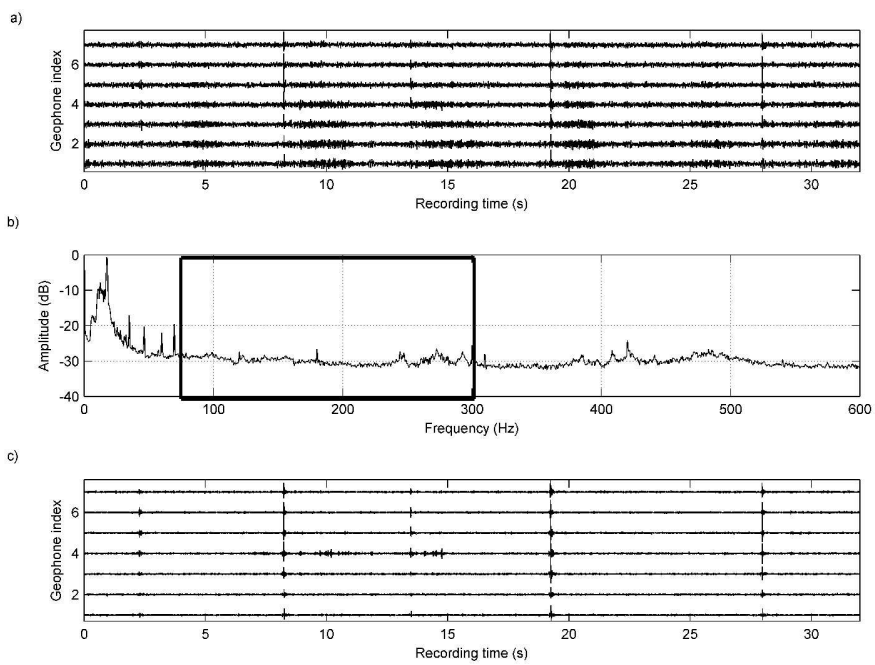
Figure 2: [75, 300] Hz band-pass filtered velocity data: (a) Z component (same as Figure 1(c)), (b) X component, (c) Y component (Events 1, 2, 3 are detected by the STA/LTA detector, with event 1 selected as the master event for the correlation detector. Events 4 and 5, although visible, are hard to detect by the single-geophone STA/LTA detector.).

Figure 3: Master event waveform as the cross-correlation template (vertical component of event 1 as shown in Figure 2(a)).

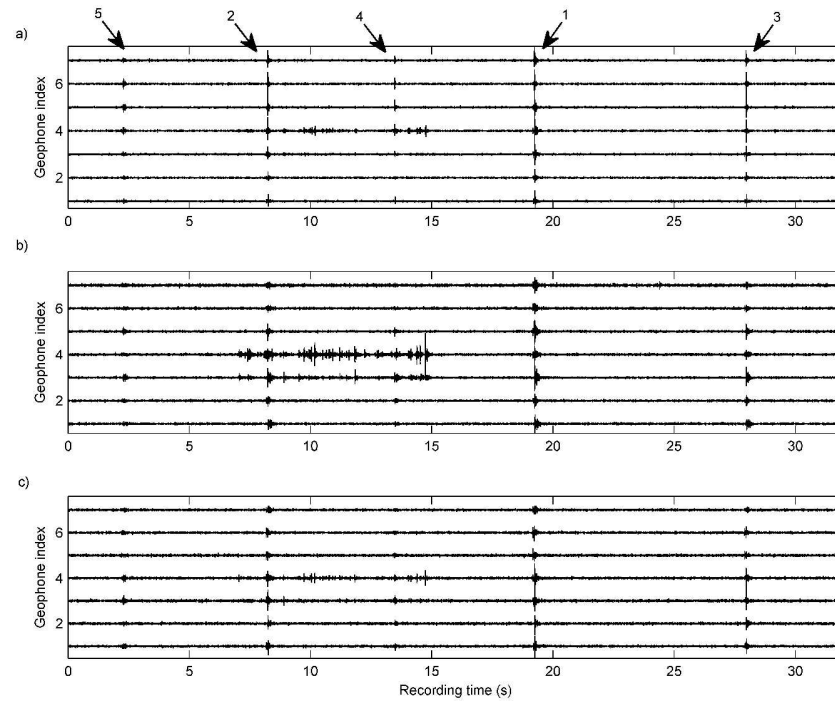
Figure 4: (a) [75, 300] Hz band-pass filtered vertical velocity data from geophone 1. (b) One-component, one-geophone correlation detector output. (c) One-component, array-stacked correlation detector output. (d) Three-component, array-stacked correlation detector output. (e) Three-component, array-stacked STA/LTA detector output.

Figure 5: Comparison of manual picks (solid line), transformed spectrogram picks (dash line), and STA/LTA picks (dash-dot line). (a) P-wave arrival picks on band-pass filtered X component data from geophone 1 for event 1 (the master event). (b) S-wave arrival picks on band-pass filtered Z component data from geophone 1 for event 1. (c) Characteristic function, as specified in equation 9, $\bar{S}([75, 300], t)$ for the X component data, where P-wave arrival is identified as the first major peak. (d) $\bar{S}([75, 300], t)$ for the Z component data, where S-wave arrival is identified as the second major peak. (e) STA/LTA function for X component data. (f) STA/LTA function for Z component data.

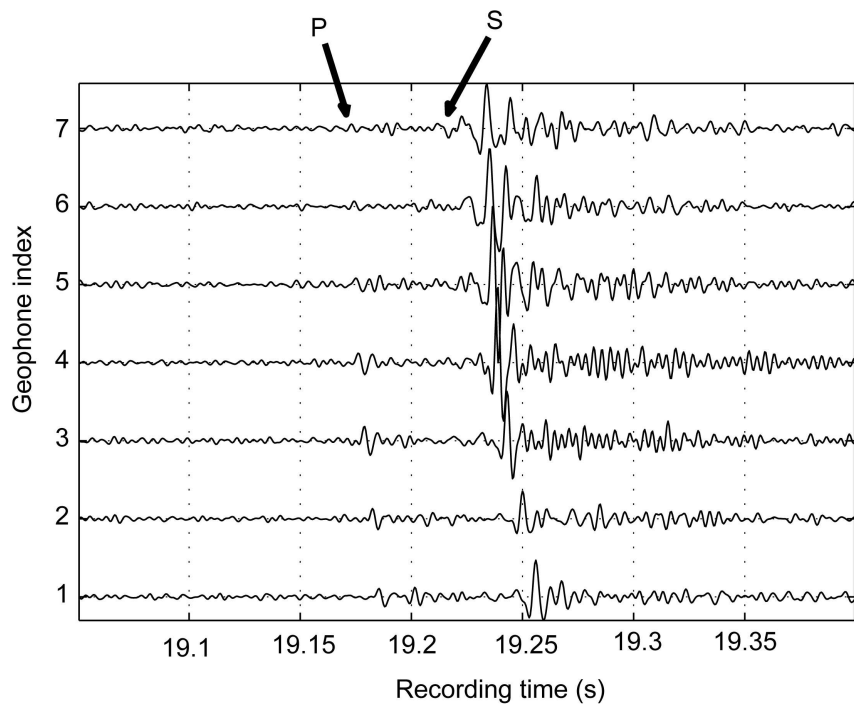
Figure 6: Comparison of manual picks (solid line), transformed spectrogram picks (dash line), and STA/LTA picks (dash-dot line). (a) P-wave arrival picks on band-pass filtered X component data from geophone 1 for event 5 (the weakest event). (b) S-wave arrival picks on band-pass filtered Z component data from geophone 1 for event 5. (c) Characteristic function, as specified in equation 9, $\bar{S}([75, 300], t)$ for the X component data, where P-wave arrival is identified as the first major peak. (d) $\bar{S}([75, 300], t)$ for the Z component data, where S-wave arrival is identified as the second major peak. (e) STA/LTA function for X component data. (f) STA/LTA function for Z component data.



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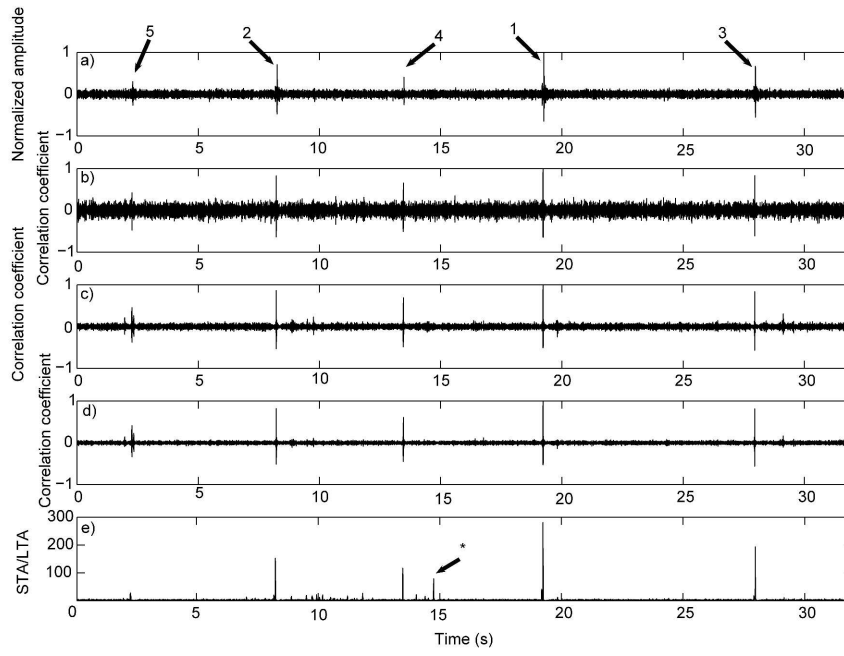


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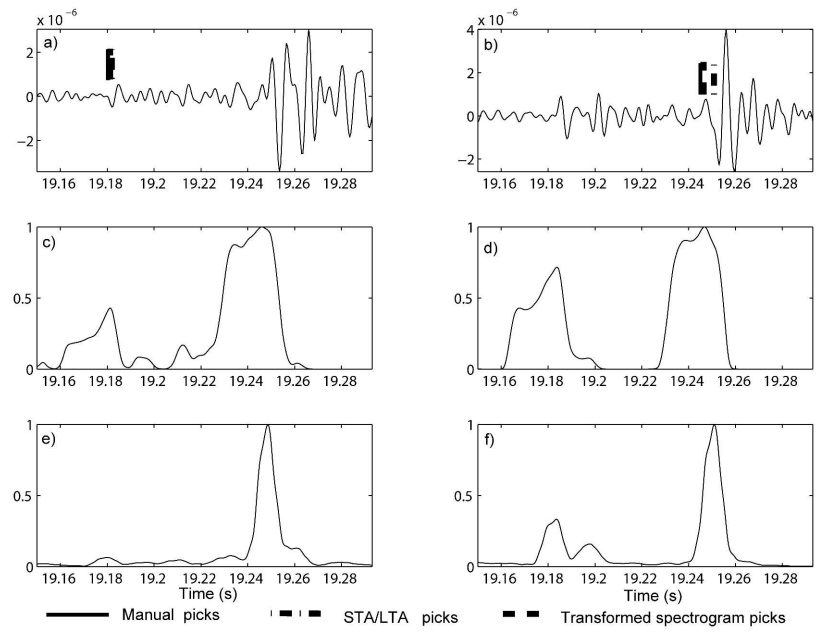
Song et al. Fig. 3

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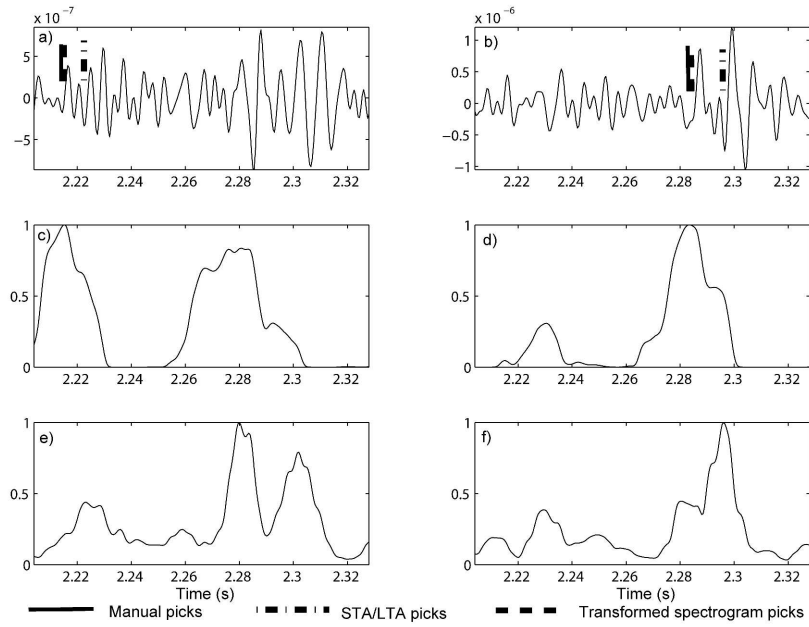
Song et al. Fig 4

176x164mm (600 x 600 DPI)



Song et al. Fig. 5

176x160mm (600 x 600 DPI)



Song et al. Fig. 6

176x158mm (600 x 600 DPI)