

Automatic Arrival Identification System for Real-time Microseismic Event Location

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SUMMARY

We present an automatic arrival picking workflow as a preprocessing for the real-time microseismic event location, based on a data-adaptive spectral subtraction filtering and a kurtosis based arrival picking approach. We modified the characteristic functions using kurtosis to highlight the statistical property changes from the microseismic event onsets and adopt the eigenvalue decomposition on three component seismograph data to determine the polarization in order to distinguish P and S waves. The proposed arrival picking system is fully data driven and parameter free, which makes it a perfect option for an autonomous real-time microseismic event location solution. We have tested our arrival identification system on field data, and obtained encouraging results.

INTRODUCTION

Seismic subsurface imaging has always been an important topic in seismology, exploration geophysics and engineering. The development of unconventional resource exploitation in the last decade provides a new application of subsurface imaging to monitor hydraulic fracturing and water disposal. Nowadays, a typical seismic imaging process involves massive data collection from a large amount of sensors to a central place for processing. The whole process is expensive in terms of time and money. The real-time processing is highly needed as it would reduce the costs as well as risks of exploration and production activities (Song et al., 2015; Sun et al., 2015).

For unconventional exploration and development, the key task is to locate microseismic events. The traditional microseismic imaging is based on the arrival-time inversion with travel time picked. However, the travel time picking is challenging as the microseismic data often contain unidentifiable P or S-wave signals mingled with strong background noise (Wong et al., 2009; Du et al., 2000). Thus, the prerequisites of a fully autonomous real-time microseismic event location system are adaptive filtering and automatic arrival picking.

It is common to apply a bandpass (e.g. Butterworth) filter to attenuate low and high frequency noise to improve the signal-to-noise ratio of seismic data. However, this can be successful only for a few cases. In general, background noise has a frequency band that overlaps with that of the seismic signals. Douglas (1997) asked a famous question "Bandpass filtering to reduce noise on seismographs: Is there a better way?". In the most applications, the background noise can be viewed as a random and stochastic process. So, it is difficult to give an objective mathematical definition of the noise. We need a filter to reveal seismic signals embedded in random noise from the seismographs with little prior knowledge of the spectral content or temporal features (Du et al., 2000).

In the last decades, many automatic data processing algorithms for determining seismic wave arrival time have been developed. The commonly used algorithms include, but not limited to, characteristic function (CF) (Allen, 1978), the short- and long-time average ratio (STA/LTA) (Baer and Kradolfer, 1987), modified energy ratio (MER) (Wong et al., 2009), signal to noise ratio (SNR) selection (Li and Peng, 2016), Akaike information criterion (AIC) (Takanami and Kitagawa, 1991), cross-correlation (Molyneux and Schmitt, 1999), neural networks (McCormack et al., 1993), wavelet transform (WT) (Anant and Dowla, 1997), higher order statistics (HOS) such as skewness and kurtosis (Yung and Ikelle, 1997; Li et al., 2014), and hybrid HOS and WT (Saragiotis et al., 1999). These algorithms have been extensively used in earthquake and exploration seismology to pick first arrivals and other seismic phases. Recently, with some modifications, they can also be useful for picking body wave arrivals on microseismic data. However, despite their sophistication, these methods can be overly sensitive to noise, perform better in some locations than others, and often require human interventions.

This paper focuses on the pre-processings in the autonomous microseismic event location system. We firstly introduce an adaptive filtering approach based on the spectral subtraction method. Then, for the three component microseismic data, we propose a kurtosis based arrival picking method. The combination of these two steps results in a fully automatic arrival picking system, which is suitable for the real-time microseismic location. We demonstrate the effectiveness and promises of the proposed method with field data examples.

THEORY

Principle of Spectral Subtraction Method

The data-adaptive filter we use to spectacularly reduce the microseismic noise contamination in noisy seismographs is based on a spectral subtraction method (Upadhyay and Karmakar, 2015). In order to demonstrate its limitation, we display the filtered results using different parameters of a bandpass filter in Figure 1. The arrival location changes when different filter configuration parameters are adopted, which means the selection of bandpass filter will influence the following arrival picking results. Thus, it is not a good option for automatic arrival picking system (Douglas, 1997).

The noisy recorded data consist of the signal degraded by statistically independent additive noise, which can be expressed as

$$d[m] = s[m] + n[m], \quad (1)$$

where $d[m]$, $s[m]$ and $n[m]$ are the sampled recorded data, signal and additive noise, respectively. The background noise in the seismograph is assumed to be additive white noise with the zero mean.

Automatic Arrival Detection

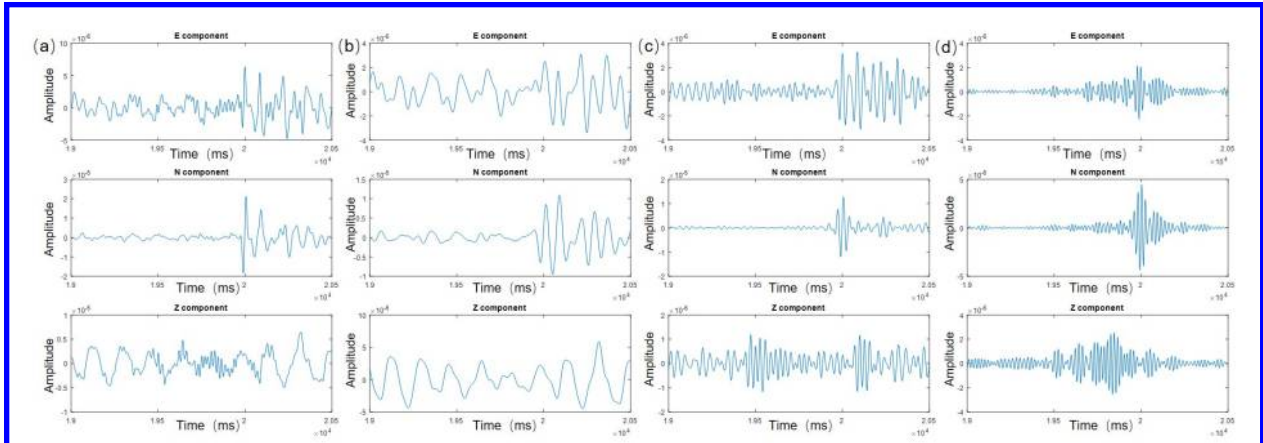


Figure 1: Bandpass filter examples of three channel seismograph data: (a) Original data, (b) 0-10 Hz bandpass filtered results, (c) 10-20 Hz bandpass filtered results, and (d) 20-30 Hz bandpass filtered results. Note that the filtered results from different spectral bands show different arrival times, which means an inappropriate bandpass filter might change the arrival picking results.

Because the signal is non-stationary and time variant, the noisy recorded data are often processed on a window-by-window. The representation in the short-time Fourier transform (STFT) domain is given by

$$D(\omega, k) = S(\omega, k) + N(\omega, k), \quad (2)$$

where k is the window number. In the following, because the operations are in sliding windows, for simplicity, we drop k .

Since the signal is assumed to be uncorrelated with the background noise, the short-term power spectrum of $d[n]$, which is denoted as $\|D(\omega)\|^2$, as no cross-terms. Then,

$$\|D(\omega)\|^2 = \|S(\omega)\|^2 + \|N(\omega)\|^2 \quad (3)$$

The clean signal can be estimated by subtracting a noise estimated from the received signal.

$$\|\hat{S}(\omega)\|^2 = \|D(\omega)\|^2 - \|\hat{N}(\omega)\|^2 \quad (4)$$

As the additive noise is assumed as uncorrelated with the signal, its spectrum can be determined from the seismograph segments without signal. The estimated of the noise spectrum $\|\hat{N}(\omega)\|^2$ is obtained by averaging the received noisy segment.

$$\|\hat{N}(\omega)\|^2 = \frac{1}{L} \sum_{j=0}^{L-1} \|D_{ns}(\omega)\|^2, \quad (5)$$

where L is the number of consecutive windows of noisy segment (NS). If the background noise is stationary, equation (5) converges to be the optimal when a longer average is taken.

The spectral subtraction can also be viewed as a filter, equation (4) can be manipulated to be the product of the noisy recorded spectrum and the spectral filter as:

$$\begin{aligned} \|\hat{S}(\omega)\|^2 &= \left(1 - \frac{\|\hat{N}(\omega)\|^2}{\|D(\omega)\|^2}\right) \|D(\omega)\|^2 \\ &= H(\omega) \|D(\omega)\|^2, \end{aligned} \quad (6)$$

where $H(\omega)$ is the gain function and known as spectral subtraction filter (SSF). The $H(\omega)$ is a zero phase filter, with its magnitude response in the range of $0 \leq H(\omega) \leq 1$.

The Wiener filter is an optimal filter that minimizes the mean square error criterion. Here, it is assumed that the signal and noise obey normal distribution and do not correlate. The Wiener filter $H_{wiener}(\omega)$ can be expressed in terms of the power spectral density of clean signal $P_s(\omega)$ and the power spectral density of noise $P_n(\omega)$ as

$$H_{wiener}(\omega) = \frac{P_s(\omega)}{P_s(\omega) + P_n(\omega)} = \frac{\|\hat{S}(\omega)\|^2}{\|D(\omega)\|^2} \quad (7)$$

If $\|\hat{N}(\omega)\|^2 = 0$, then $H_{wiener}(\omega) = 1$ and no attenuation takes place, whereas if $\|\hat{N}(\omega)\|^2 = \|D(\omega)\|^2$, then $H_{wiener}(\omega) = 0$. Therefore, the frequency component is completely nulled.

Under these assumptions, we construct a data-adaptive filter from the data decontaminated of noise. Figures 2 and 3 show the SSF applications in seismograph segments with strong background noise and signal, respectively. In these two figures, noise has been removed and the wanted signal is kept. Since the noise corrupting the seismographs is stochastic, the resulting residual due to the real, non-stationary nature of microseismic signal can be kept after filtering. The applications show excellent signal-to-noise recovery is possible, rendering such data usable for both arrival time and waveform analysis.

Kurtosis based Arrival Picking Method

Allen (1978) introduced the concept of characteristic function (CF), by which the characteristic of the seismic trace is specified. However, it should be noted that Allen does not use CF to determine the arrival times, but instead STA/LTA ratios of the CF. Li et al. (2014) proposed a short-term kurtosis and long-term kurtosis ratio (S/L-Kurt) based approach, which was inspired by the STA/LTA method. According to the review and comparison work by Akram and Eaton (2016), S/L-Kurt method shows excellent performance over several traditional arrival picking methods. Thus, we propose to use the S/L-Kurt ratio of the CF to detect arrival onsets.

Automatic Arrival Detection

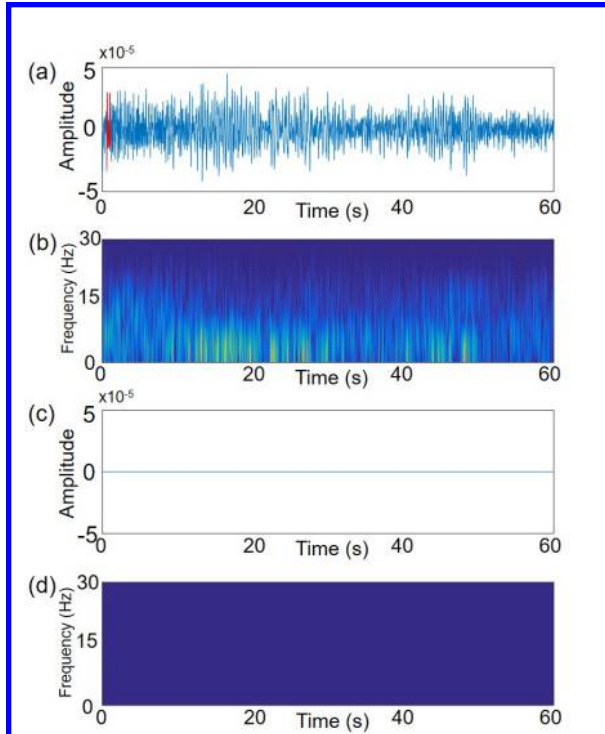


Figure 2: Spectral subtraction example of a noisy microseismic data segment. (a) Noisy seismic data; (b) Spectrum; (c) Filtered result; (d) Filtered spectrum.

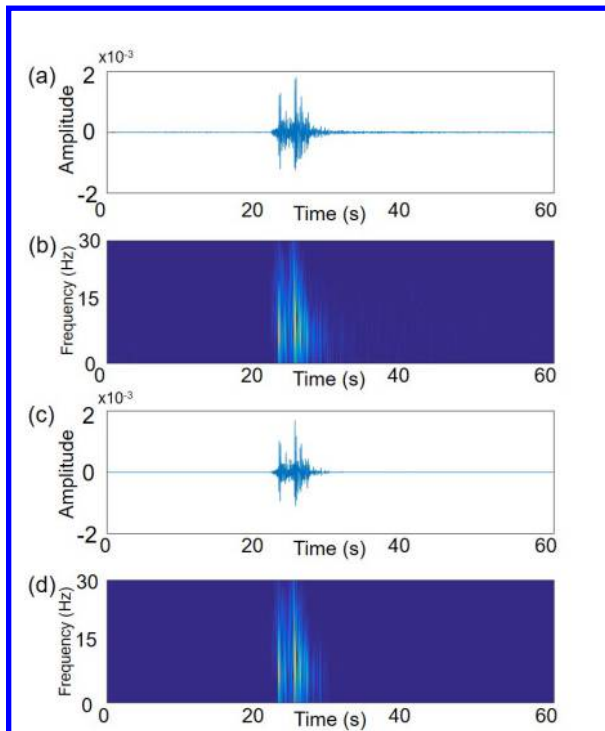


Figure 3: Spectral subtraction example of a microseismic data segment with an event. (a) Seismic data; (b) Spectrum; (c) Filtered result; (d) Filtered spectrum.

The kurtosis is a statistical value characterizing the Gaussianity of a given distribution. It is a positive scalar defined as the standardized fourth moment about the mean. Using a probabilistic notation, the kurtosis K is defined as:

$$K \equiv \frac{E[(X - \mu)^4]}{\{E[(X - \mu)^2]\}^2} = \frac{m_4}{\sigma^4}, \quad (8)$$

where X is a random variable, E is the expectation operator, μ is the mean, m_4 is the fourth central moment, and σ is the standard deviation.

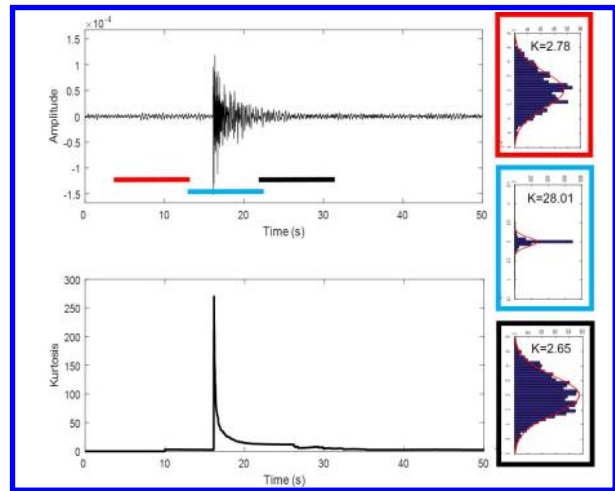


Figure 4: Example of a kurtosis characteristic function calculated on a seismic trace. In this example, a 10 s sliding window is used. The horizontal colorful bars indicate the three kurtosis windows examined below. Kurtosis and histograms of sample distributions for the three windows are shown on the right. The red line shows the normal distribution curve. The kurtosis value of the red, blue and black windows are 2.78, 28.01 and 2.65, respectively. Since the kurtosis of a normal distribution is 3, the sample distributions before and after the arrival are close to random noise, while the sample signal including the arrival clearly shows super Gaussian distribution.

Figure 4 shows an example of field seismograph with its kurtosis characteristic. The background noise shows normal distribution, while the arrival shows super Gaussian distribution, so we can distinguish them with the kurtosis value. The S/L-Kurt method is effective for arrivals because it reduces any bias in the short-term kurtosis (STK) and long-term kurtosis (LTK) windows.

The STK and LTK windows preceding the i th time index are computed as follows:

$$STK_i = \frac{1}{(ws - 1)\sigma_i^4} \sum_{j=i-ws}^i (X_j - \bar{X}_{ws})^4, \quad (9)$$

where $\sigma_i^2 = \frac{1}{(ws-1)} \sum_{j=i-ws}^i (X_j - \bar{X}_{ws})^2$, which is the standard deviation of the short-term window and \bar{X}_{ws} is the sample mean in the short-term window.

$$LTK_i = \frac{1}{(wl - 1)\sigma_i^4} \sum_{j=i-wl}^i (X_j - \bar{X}_{wl})^4, \quad (10)$$

Automatic Arrival Detection

where $\sigma_i^2 = \frac{1}{(wl-1)} \sum_{j=i-wl}^i (X_j - \bar{X}_{wl})^2$, which is the standard deviation of the long-term window and \bar{X}_{wl} is the sample mean in the long-term window.

The S/L-Kurt is then given as

$$S/L - Kurt_i = \frac{STK_i}{LTK_i + \varepsilon}, \quad (11)$$

where ε is a small number to avoid division by zero.

The S/L-Kurt method was originally a single channel operation. In order to further utilize the three component microseismic data, we use two polarization parameters to distinguish between P and S waves, and noise. The wave types and orientations affect the polarization of signal onsets. We assume the data have three orthogonal ground-motion records corresponding to the east, north, and vertical components (respectively noted E, N, and Z). Then, the onset polarization could indicate the types (surface or body), phase (P or S) of the wave.

Configuration of a 3×3 covariance matrix over the three components is the first step.

$$\mathbf{C} = \begin{pmatrix} Cov(E,E) & Cov(E,N) & Cov(E,Z) \\ Cov(N,E) & Cov(N,N) & Cov(N,Z) \\ Cov(Z,E) & Cov(Z,N) & Cov(Z,Z) \end{pmatrix}, \quad (12)$$

where $Cov(\bullet)$ denotes the covariance.

Because the covariance matrix in equation (12) is symmetric and real, the eigenvalues are real and the eigenvectors form an orthogonal base. We organize eigenvalues so that $\lambda_1 \geq \lambda_2 \geq \lambda_3$ with $U_i, i = 1, 2, 3$ as the eigenvector.

Two polarization parameters: the degree of rectilinearity and the dip of maximum polarization (Baillard et al., 2014) are used in this study. The first polarization parameter, the degree of rectilinearity, is defined as

$$Rec \equiv 1 - \frac{\lambda_2 + \lambda_3}{2\lambda_1} \quad (13)$$

For example, $Rec = 0$ for circular polarization $\lambda_1 = \lambda_2 = \lambda_3$, and $Rec = 1$ for rectilinear polarization $\lambda_1 = 1$, and $\lambda_2 = \lambda_3 = 0$. P and S waves are body waves, so their degree of rectilinearity is close to 1.

The second parameter is the dip of maximum polarization (the orientation of the principle eigenvector), defined as

$$Dip \equiv \arctan \left(\frac{U_1(3)}{\sqrt{U_1(2)^2 + U_1(1)^2}} \right) \quad (14)$$

Possible values range from -90° to 90° . A horizontal maximum polarization vector has $Dip = 0^\circ$. P waves have high dip values due to their polarization along the near-vertical incidence ray ($\sin(|Dip(k)|)$ is close to 1). In contrast, S waves are polarized horizontally, and $\sin(|Dip(k)|)$ is close to 0.

We then define a dip-rectilinearity function as

$$DR(k) \equiv Rec(k) \times \text{sign}[\sin(|Dip(k)|) - \alpha], \quad (15)$$

where α is a user-defined parameter to distinguish between P and S waves. The $DR(k)$ will be positive for P waves and negative for S waves. The onset is declared P if the DR value of the window centered on the pick is greater than zero, while the onset is declared S if the DR value of the window centered on the pick is smaller than zero.

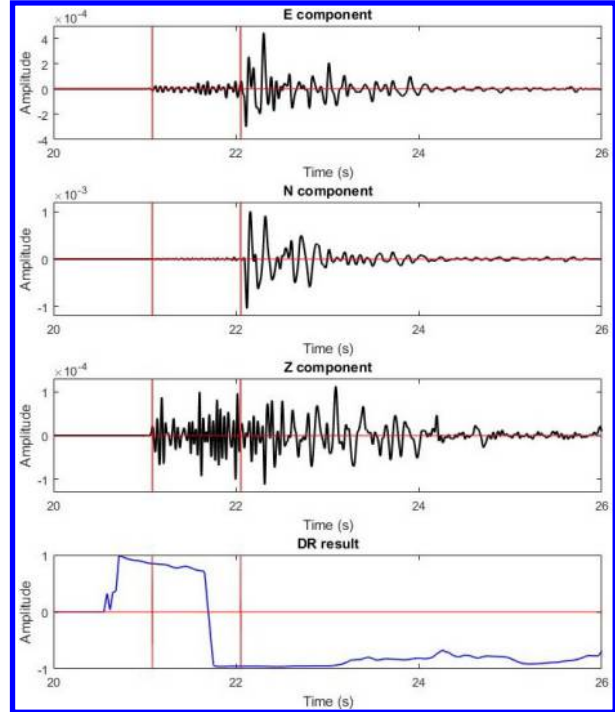


Figure 5: Example of the proposed kurtosis based arrival picking method. Three component seismic data are plotted in black, while the picking results are plotted in red. And the DR value is plotted in the bottom panel. As discussed in equation (15), the first arrival can be declared P wave and the second can be declared as S wave.

CONCLUSIONS

We introduce a fully autonomous preprocessing system for real-time microseismic event location with adaptive filtering and kurtosis based arrival picking. We briefly introduce the objectives and principals of the proposed approach. Due to the space limit, only field applications are included, which show the effectiveness of the proposed system.

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EDITED REFERENCES

Note: This reference list is a copyedited version of the reference list submitted by the author. Reference lists for the 2017 SEG Technical Program Expanded Abstracts have been copyedited so that references provided with the online metadata for each paper will achieve a high degree of linking to cited sources that appear on the Web.

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