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Microseismic Events Enhancement in Sensor Arrays Using Autocorrelation Based Filtering

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SUMMARY

Passive microseismic data are commonly buried in noise, which presents a significant challenge in microseismic data analysis and event detection. In this work, we consider the situation where a sensor array provides multiple traces that each contain an arrival from the event, and propose an autocorrelation-based method that designs a denoising

Introduction

Microseismic monitoring is of great interest for its capability to provide valuable information for many oil and gas related applications, such as hydraulic fracturing monitoring, unconventional reservoir characterization, and CO2 sequestration (Phillips et al., 2002; Maxwell et al., 2004; Warpinski, 2009; Duncan and Eisner, 2010). In practice, microseismic monitoring can be performed using downhole, surface, or near surface arrays (Duncan and Eisner, 2010). Recently, there is a preference for surface arrays which can be deployed more economically and efficiently. However, recorded surface microseismic signals are much noisier than downhole data, because surface arrays are susceptible to both coherent and incoherent noise.

Consequently, it is challenging to extract useful information from the recorded microseismic data. Typically, the signal-to-noise ratio (SNR) of the recorded microseismic data is rather low, especially for data collected using surface arrays. The noise adversely affects the accuracy of many microseismic analyses, such as P-wave and S-wave arrivals picking, event detection and localization, and focal mechanism inversion (Zhang et al., 2014; Sabbione and Velis, 2010).

We only consider the case of a sensor array that records multiple traces, and assume that the microseismic signal of interest is present in all the traces. Therefore, stacking is one of the primary techniques to consider for improving SNR, as is well known for seismic applications. However, for passive recording of microseismic data the prerequisite of stacking, namely time alignment of the traces, is generally unknown. To address this shortcoming, researchers have developed algorithms based on cross-correlation to find the relative time delays between traces (Al-Shuhail et al., 2013). In contrast to the case of active seismic where a source generates a controllable active wavelet, the wavelet of a microseismic event wavelet is unknown, although some empirical knowledge of the frequency characteristics may be available. Therefore, the cross-correlations can only be computed from noisy traces rather than a clean signal template. The maximal value of the cross-correlation may occur at a lag different from the true relative time delay because of the noise. To bypass this bottleneck, in this paper, we propose novel denoising and detection schemes using stacked autocorrelograms.

Mathematical Model of Microseismic Data

Assume the sensor array for microseismic monitoring has N channels. Each recorded trace contains a microseismic waveform $s_i(t)$ contaminated by noise, i.e.

$$x_i(t) = a_i s_i(t) + n_i(t), \quad i = 1, \ldots, N, \tag{1}$$

where a_i are amplitude scaling factors, and $n_i(t)$ is zero mean additive white Gaussian noise (AWGN) with variance σ^2. For simplicity, we first consider only white noise; an extension to the colored noise scenario involves prewhitening will be discussed in the future work.

Theoretically, seismic traces recorded on different sensors are convolutions of one source wavelet with Green's functions determined by the real earth, and the source and sensor locations (Aki and Richards, 2009). Nevertheless, high resemblance among different traces originated by the same event and collected by spatially close sensors is usually observed (Arrowsmith and Eisner, 2006). Therefore, it is reasonable to assume that $s_i(t) = s(t - \tau_i)$, i.e., the same waveform with different time delays. In addition, we assume the $n_i(t)$ are uncorrelated with the waveform $s(t)$ and independent of each other; uncorrelated noise on different channels is a common assumption for the validity of any stacking technique.

The processing is performed on digital signals, so the time variable t is sampled at a rate $f_s = 1/\Delta t$, i.e., $t_l = t_0 + (l-1)\Delta t$ for $l = 1, \ldots, L$. On each trace, we consider a finite time window of data which contains L time samples, so the signals can be written as

$$x_i[l] = a_i s_i[l] + n_i[l], \tag{2}$$

where $x_i[l] = x_i(t_l)$ and $l = 1, \ldots, L$. In this paper, we adopt the conventional definition of signal-to-noise ratio (SNR) in the i-th channel to measure the level of AWGN, which is defined as

$$\mathrm{SNR}_i = 10\log_{10}\left(\frac{a_i^2\|s_i\|_2^2}{\|n_i\|_2^2}\right). \tag{3}$$

Denoising Filter Design

Stacking coherent signals that contain uncorrelated noise over multi-channels is an efficient way of improving the SNR. This simple method is widely used in active seismic data and seismological data processing. However, there is an obstacle to applying this coherent summation scheme to passive microseismic data — the relative time delays among traces must be known, but these delays would have to be found by picking events such as peaks from the noisy data itself.

An existing scheme by Al-Shuhail et al. (2013) advocated the use of stacked cross-correlation functions (CCF) as a denoising filter. This method requires a step that aligns the cross-correlations, which in turn depends on picking the maximal values of the cross-correlations. In low SNR scenarios, the alignment result may not be satisfactory, because the largest value of the cross-correlation is likely to be produced by the noise at a wrong location.

In order to avoid this crucial but sensitive step of alignment, we propose a *denoising filter based on stacking autocorrelations* of the traces, which are automatically aligned at zero lag. The new denoising approach is implemented with the following three steps:

1. Compute the autocorrelation function (ACF) of each trace (denoted by $\star$) and then stack them

   $$r_s[\tau] = \frac{1}{N}\sum_{i=1}^{N}(x_i \star x_i)[\tau], \tag{4}$$

   where $\tau = -L+1,\ldots,0,\ldots,L-1$ is the lag index of the ACF.

2. Define the denoising filter's impulse response as $f[\tau] = \hat{r}_s[\tau]w_d[\tau]$, where

   $$\hat{r}_s[\tau] = \begin{cases} \frac{1}{2}\big(r_s[-1]+r_s[1]\big) & \text{if } \tau = 0 \\ r_s[\tau] & \text{otherwise} \end{cases} \tag{5}$$

   The zero-lag value of the ACF is replaced with the average of its neighboring values, $r_s[1]$ and $r_s[-1]$. The justification for this change is that the ACF of additive white noise is $L\sigma^2\delta[\tau]$ which is nonzero only for $\tau = 0$. Thus $r_s[\tau]$ has a large peak at $\tau = 0$ which must be reduced by $L\sigma^2$; the neighboring values provide an estimate of the correct zero-lag value of the signal only.

3. A truncation window $w_d[\tau]$ is then applied to take ACF values only for $|\tau| < d$, so that the negligible values in the filter (away from $\tau = 0$) will be eliminated. A proper truncation window that shortens the filter length will improve the computational efficiency as well. Various truncation windows are available, but we adopt a simple triangle window

   $$w_d[\tau] = \begin{cases} 1-|\tau|/d & \text{if } |\tau| \le 0 \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

   where $2d+1$ is the length of the truncation window.

4. Convolve $f[\tau]$ with each noisy trace in the collection. The result of these convolutions provides the N denoised traces $\hat{x}_i[l] = (f * x_i)[l]$ for $i = 1,2,\ldots,N$.

Compared with a cross-correlation based design, this new autocorrelation-based approach has about the same computational complexity, since computing one ACF is comparable to computing one CCF, i.e., $L\log(L)$. In fact, some overhead is removed by avoiding maximal value searching and aligning.

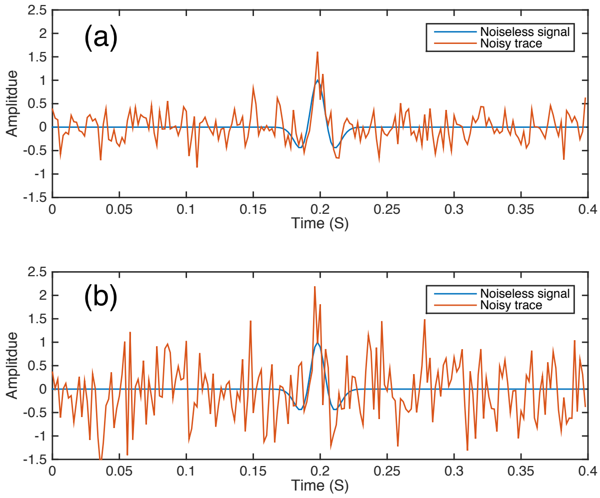

Figure 1 *Noiseless and noisy traces, (a) $\sigma = 0.3$, SNR=−6.03 dB; (b) $\sigma = 0.6$, SNR=−12.01 dB.*

Denoising example: Ricker Wavelet

In this work, we assume that there are 200 traces and all $a_i = 1$. The waveform $s(t)$ is a Ricker wavelet with center frequency of 30 Hz with normalized peak value. The sampling frequency is 500 Hz and each trace has 200 time samples. The noise added is AWGN of $\sigma = 0.3$ and 0.6, which give SNRs −6.03 dB and −12.01 dB, respectively.

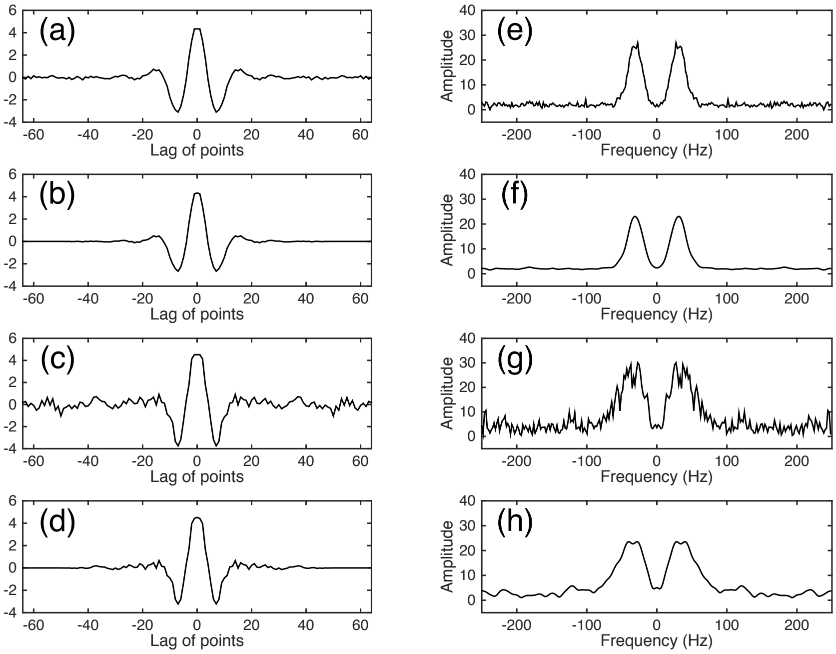

Figure 2 *Designed filter for (a) $\sigma = 0.3$, without truncation; (b) $\sigma = 0.3$, with truncation; (c) $\sigma = 0.6$, without truncation; (d) $\sigma = 0.6$, with truncation. The truncation windows length is 100 sample points. And frequency response of the filters (e) $\sigma = 0.3$, without truncation; (f) $\sigma = 0.3$, with truncation; (g) $\sigma = 0.6$, without truncation; (h) $\sigma = 0.6$, with truncation.*

For conciseness, we present only the first 20 noisy traces of these two noise levels in Figure 3(a) and 3(c), respectively. The final denoising results by the proposed scheme are shown in Figure 3 (b) and 3(d). In both cases, the microseismic events in these very low SNR datasets are significantly enhanced. For the low noise case, the denoised data have SNR=2.51 dB. Additionally, the high noise case, the denoised data have SNR=0.51 dB. In order to track the impact of the scheme in the intermediate steps,

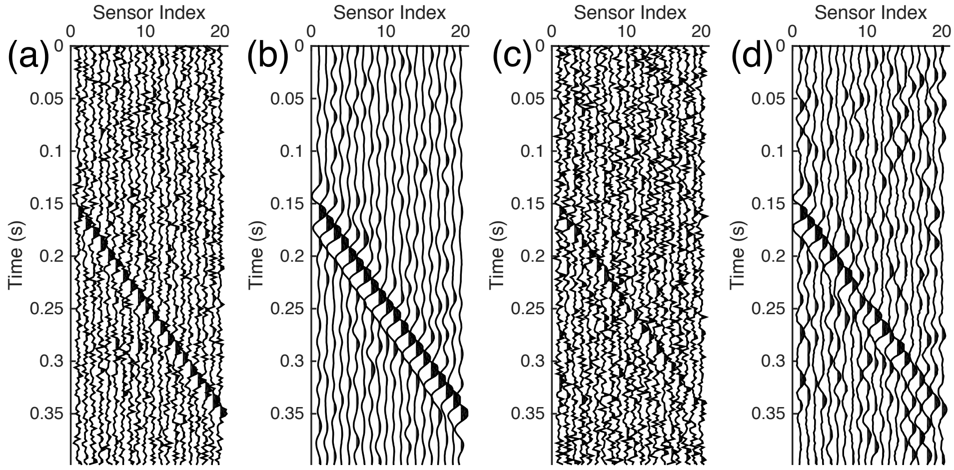

Figure 3 (a) noisy traces, only show 20 traces, $\sigma = 0.3$; (b) denoising result of the $\sigma = 0.3$ case; (c) noisy traces, only show 20 traces, $\sigma = 0.6$; (d) denoising result of the $\sigma = 0.6$ case.

we compare the designed filters and their frequency responses. Figure 2(a)–(d) illustrates the filter with and without truncation for the $\sigma = 0.3$ and $\sigma = 0.6$ cases. In addition, the effect of smoothing in the frequency domain is shown as well. The frequency response of the filters are displayed in the Figure 2(e)–(h), where we can clearly see that the out band uncorrelated noise is suppressed.

Conclusions

Microseismic data is typically rather noisy, which requires a denoising step before further processing and applications. In this study, we show that the denoising method based on autocorrelation can effectively suppress uncorrelated noise without knowing the time offsets.

Acknowledgements

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