Microseismic events enhancement and detection in sensor arrays using autocorrelation-based filtering

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ABSTRACT
Passive microseismic data are commonly buried in noise, which presents a significant challenge for signal detection and recovery. For recordings from a surface sensor array where each trace contains a time-delayed arrival from the event, we propose an autocorrelation-based stacking method that designs a denoising filter from all the traces, as well as a multi-channel detection scheme. This approach circumvents the issue of time aligning the traces prior to stacking because every trace’s autocorrelation is centred at zero in the lag domain. The effect of white noise is concentrated near zero lag; thus, the filter design requires a predictable adjustment of the zero-lag value. Truncation of the autocorrelation is employed to smooth the impulse response of the denoising filter. In order to extend the applicability of the algorithm, we also propose a noise prewhitening scheme that addresses cases with coloured noise. The simplicity and robustness of this method are validated with synthetic and real seismic traces.

Key words: Passive seismic, Denoising, Detection, Sensor array, Autocorrelation, Filter design.

1 INTRODUCTION
Microseismic monitoring is of great interest for its capability of providing valuable information for many oil and gas related applications such as hydraulic fracturing monitoring, unconventional reservoir characterisation, and CO₂ sequestration (Phillips et al. 2002; Maxwell, White and Fabriol 2004; Warpinski 2009; Duncan and Eisner 2010). In practice, microseismic monitoring is performed using downhole, surface, or near-surface arrays (Duncan and Eisner 2010). Recently, there has been a preference for surface arrays that can be deployed more economically and efficiently. However, recorded surface microseismic signals are much noisier than downhole data because surface or near-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 recorded microseismic data is rather low, especially for the data collected using surface arrays. The noise adversely affects the accuracy of many microseismic analyses such as P-wave and S-wave arrival picking, event detection and localisation, and focal mechanism inversion (Sabbione and Velis 2010; Zhang, Tian and Wen 2014; Zhu, Liu and McClellan 2015). In fact, the majority of microseismic events induced by hydraulic fracturing have a typical moment magnitude \( M_W < -1 \) (Song et al. 2014).

We 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 to improve SNR as it is well known for seismic applications (Yilmaz 2001). However, for microseismic data time alignment of the traces, which is the prerequisite of stacking, is generally unknown.
Thus, researchers have developed algorithms based on cross-correlation to find the relative time delays between traces (Grechka and Zhao 2012; Al-Shuhail, Kaka and Jervis 2013). In contrast to the case of an active seismic where the source generates a controllable active wavelet, the wavelet of a microseismic event is unknown, although some empirical knowledge of the frequency-domain characteristics may be available. The cross-correlations are usually computed from noisy traces rather than from a clean signal template. Therefore, the maximal value of the cross-correlation may occur at an incorrect lag because of the noise. To bypass this bottleneck, we propose denoising and detection schemes using stacked autocorrelograms, which are automatically aligned at the zero lag. The simplicity and robustness of the proposed schemes are demonstrated by using both synthetic and real data. In the literature, stacked cross-correlation and autocorrelation have already shown promising results in different scenarios (Wapenaar et al. 2010a, b; Zhang et al. 2014; Liu et al. 2016).

2 DENOISING

Problem formulation

Assume that the sensor array for microseismic monitoring has N channels. Each recorded trace contains a microseismic waveform 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 \( \sigma^2 \). For simplicity, we first consider only white noise whose power spectrum is flat; the coloured noise scenario, whose power density has different amplitudes for different frequencies, will be discussed in a later section.

Theoretically, seismic traces received on different sensors are convolutions of the same source wavelet with Green’s functions that are determined by the real Earth and source locations (Stein and Wysession 2002; Aki and Richards 2009). Nonetheless, a high resemblance between different traces originated by the same source and collected by spatially close sensors is usually observed (Arrowsmith and Eisner 2006). Therefore, it is reasonable to assume that \( s_i(t) \) are all the same waveform but with different time delays, i.e., \( s_i(t) = s(t - \tau) \). In addition, we assume that \( n_i(t) \) are uncorrelated with the waveform \( s(t) \) and independent from each other; uncorrelated noise on different channels is a common assumption for the validity of any stacking technique.

Processing is performed on digital signals, sampled at a rate \( f_s = 1/\Delta t \), so that the time variable \( t \) becomes \( t_i = t + (l - 1)\Delta t \) for \( l = 1, \ldots, L \). On each trace, we consider a finite time window of data that contains \( L \) time samples; hence, the signals can be written as

\[ x_i[l] = a_i s_i[l] + n_i[l], \quad l = 1, \ldots, L, \tag{2} \]

where \( x_i[l] \) is the \( i \)th trace. In this work, we define the signal-to-noise ratio (SNR) of the \( i \)th channel as the ratio of the signal energy to the AWGN energy, i.e.,

\[ \text{SNR}_i = 10 \log_{10} \left( \frac{a_i^2 \| s_i \|^2}{\| n_i \|^2} \right). \tag{3} \]

As a reference, we use the peak-signal-to-noise ratio (PSNR) as well

\[ \text{PSNR}_i = 10 \log_{10} \left( \frac{a_i^2 P_i^2}{\sigma^2} \right). \tag{4} \]

where \( P_i \) is the peak value of \( s_i(t) \). When the wavelet duration is short, the PSNR is more intuitive than SNR because its value is not affected by the signal length.

2.1 Denoising filter design

The proposed approach is implemented with the following three steps.

1. Compute the autocorrelation function (ACF) of each trace (denoted by \( * \)) and then stack the ACFs,

\[ r_s(\tau) = \frac{1}{N} \sum_{i=1}^{N} (x_i * x_i)[\tau]. \tag{5} \]

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 a windowed version of the modified ACF, \( f(\tau) = \hat{r}_s(\tau) w(\tau) \), where

\[ \hat{r}_s(\tau) = \begin{cases} \frac{1}{2} [r_s(-1) + r_s(1)], & \text{if } \tau = 0 \\ r_s(\tau), & \text{otherwise}. \end{cases} \tag{6} \]

The zero-lag value of the ACF is replaced with the average of its neighbouring values, i.e., \( r_s[1] \) and \( r_s[-1] \). The justification for this change is that additive white noise has an ACF that is \( \omega^2 \delta[\tau] \), where \( \delta[\tau] \) is the discrete Dirac delta impulse function and only gives non-zero value at \( \tau = 0 \). Thus, the ACF \( r_s[\tau] \) has a large peak at \( \tau = 0 \), which needs to be reduced by \( \omega^2 \); the average of the neighbouring values provides an estimate of the correct zero-lag value of the signal-only ACF.

3. A truncation window \( w(\tau) \) is then applied to the zero-lag region, if necessary, 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; however, we adopt a simple triangle window

\[
 w_d[\tau] = \begin{cases} 
 1 - |\tau|/d, & \text{if } |\tau| \leq d \\
 0, & \text{otherwise,} 
\end{cases} 
\]  

(7)

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 \( \tilde{x}_i[l] = (f \ast x_i)[l] \) for \( i = 1, 2, \ldots, N \).

In Fig. 1, we show the stacked autocorrelation \( r_s[\tau] \) and the filter \( f[\tau] \) based on it for the case of a 30 Hz Ricker wavelet sampled at \( f_s = 500 \) Hz, which is also treated in the denoising example for synthetic data in Section 3.1. The spiky peak in \( r_s[\tau] \) at zero lag is removed by the average operation (6) to obtain \( f[\tau] \).

Compared with a cross-correlation-based method, this new autocorrelation-based approach has approximately the same computational burden since computing one ACF or one cross-correlation function (CCF) is \( O(L \log_2(L)) \). In fact, some overhead is removed by avoiding the search for the maximal value needed for alignment.

2.2 Frequency response analysis

In order to evaluate the performance of the designed filter, we examine the frequency response of the filter \( f[\tau] \) since the analysis of the filter performance is easier to conduct in the frequency domain. The Fourier transform (\( \mathcal{F} \)) of the ACF \( r_s[\tau] \) is

\[
 R_s(e^{j\omega}) = \mathcal{F}[r_s(\tau)] 
\]

\[
 = \frac{1}{N} \sum_{i=1}^{N} X_i(e^{j\omega})X_i(e^{j\omega}) 
\]

\[
 = \frac{1}{N} \sum_{i=1}^{N} \left[ a_i^2 |S_i(e^{j\omega})|^2 + |N_i(e^{j\omega})|^2 \right] + a_iS_i(e^{j\omega})\overline{N_i(e^{j\omega})} 
\]

\[
 + a_i N_i(e^{j\omega})\overline{S_i(e^{j\omega})} \approx |S(e^{j\omega})|^2 \frac{1}{N} \sum_{i=1}^{N} a_i^2 
\]

\[
 + \frac{1}{N} \sum_{i=1}^{N} |N_i(e^{j\omega})|^2, 
\]

(8)

where the last line is derived from the assumption that the signal \( s(t) \) and noise \( n_i(t) \) are uncorrelated. The two terms in equation (8) are scaled versions of the power spectrum of the signal (i.e., magnitude squared) and the power spectrum of the noise that is a random variable at each frequency \( \omega \). If we assume that \( a_i = 1 \) for all \( i \), then there is no scaling of the first term. The second term is the expected value of the noise power spectrum, which, for white noise, is equal to \( L\sigma^2 \) for all frequencies.

We can now justify the definition of \( \hat{r}_s[\tau] \) in equation (6). Compared with \( r_s[\tau] \), the designed filter is slightly modified from the autocorrelation by removing the peak at zero lag. However, the frequency response is beneficially manipulated for denoising purposes. For ease of exposition, we assume that \( a_i = 1 \) for all \( i \). When the sampling frequency is high

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enough and noise is white, \( f[0] = \frac{1}{2}(r_s[-1] + r_s[1]) = r_s[-1] \) turns out to be an accurate approximation of the energy of \( s(t) \). We can then decompose \( r_s[0] \) into two parts

\[ r_s[0] = \hat{r}_s[0] + p. \] (9)

Again, because signal \( s(t) \) and noise \( n(t) \) are uncorrelated,

\[ r_s[0] = \frac{1}{N} \sum_{i=1}^{N} ||x_i^2|| = ||s||^2 + \frac{1}{N} \sum_{i=1}^{N} ||n_i||^2. \] (10)

and

\[ \hat{r}_s[0] \approx ||s||^2. \] (11)

Subtracting equation (11) from equation (10), we obtain

\[ p \approx \frac{1}{N} \sum_{i=1}^{N} ||n_i||^2 = \frac{1}{NL} \sum_{i=1}^{N} ||N(e^{j\omega})||^2. \] (12)

by Parseval’s theorem. Therefore, \( p \) is approximately the average energy of the noise over all traces.

We reformulate \( r_s[\tau] \) as

\[ r_s[\tau] = \hat{r}_s[\tau] + p\delta[\tau]. \] (13)

For a certain frequency \( \omega \), the frequency response of the filter \( \hat{r}_s[\tau] \) is expected to be the power of the signal at \( \omega \) when the noise is white,

\[ \mathbb{E}[F(\hat{r}_s[\tau])]] = \mathbb{E}[F(r_s[\tau] - p\delta[\tau])] = \mathbb{E}[F(r_s[\tau])] - p \]

\[ \approx \mathbb{E}\left[\frac{1}{N} \sum_{i=1}^{N} |X_i(e^{j\omega})|^2 \right] - \frac{1}{NL} \sum_{i=1}^{N} ||N(e^{j\omega})||^2 \]

\[ \approx \mathbb{E}\left[\frac{1}{N} \sum_{i=1}^{N} |S_i(e^{j\omega})|^2 \right] + \mathbb{E}\left[\frac{1}{N} \sum_{i=1}^{N} |N(e^{j\omega})|^2 \right] - \frac{1}{NL} \sum_{i=1}^{N} ||N(e^{j\omega})||^2 \approx \mathbb{E}\left[\frac{1}{N} \sum_{i=1}^{N} |S_i(e^{j\omega})|^2 \right]. \] (14)

Here, we can see that the proposed filter \( \hat{r}_s[\tau] \) (without truncation) shifts the frequency response amplitude of \( r_s[\tau] \) down by \( p \). The frequency response of the filter is literally an estimation of the power spectrum of the signal.

Due to the focal mechanism of the seismic source, the waveforms received on the sensor array can have different amplitudes and phases (i.e., the signs of \( a_i \)). Corrections to the signs are helpful when we stack the traces or perform the cross correlations. Otherwise, stacking waveforms of different signs would cancel each other rather than enhance them. One advantage of ACF-designed filter \( f[\tau] \) over cross-correlation-based method is that \( f[\tau] \) is not affected by the signs of \( a_i \).

Essentially, stacking autocorrelation is equivalent to stacking squared frequency response amplitude in the frequency domain where all \( a_i \) are squared as in equation (8). The dispersion of wave is another phenomenon harmful to the stacking techniques in the time domain. However, the stacked autocorrelation is not affected by dispersion, for the same reason. Although the idea of enhancing the signal in the frequency domain is widely used, one obvious advantage of the proposed scheme is that it produces a band-pass filter that adapts to the received signals instead of using a filter whose pass band is specified a priori.

Recall the truncation window in equation (7) applied to the filter, which expedites the convolution step. In addition, the truncation of the filter introduces a smoothing effect in its frequency response. Usually, the smoothing effect is beneficial to the denoising filter performance.

2.3 Noise whitening

One of the basic assumptions behind the proposed denoising scheme is that of additive white noise. In practice, seismic noise is often coloured when it is related to the environment, weather, or human activities. Hence, the autocorrelation of the noise could be far from an impulse function. Therefore, we would not be able to eliminate the noise’s frequency response by manipulating the stacked autocorrelation value only at the zero-lag position. To generalise for the coloured noise case, we advocate a noise whitening scheme based on the linear prediction theory.

Before discussing the whitening algorithm to flatten the noise spectrum, we state two assumptions: (i) the samples of...
the coloured noise are from a stationary random process; and (ii) we have a snapshot of the noise-only data of sufficient time duration. This second assumption would be practical for microseismic monitoring since the noise-only data can be recorded before the fluid injection activities are started.

Let $v(t)$ be the stationary, coloured noise signal. Any wide-sense stationary random process can be modelled using an autoregressive (AR) model if the order of the model is chosen large enough (Makhoul 1975; Kay 1988). Then we can apply a linear prediction filter with coefficients $\{c_k\}$ to predict the next sample using $P$ previous samples

$$\hat{v}[l] = \sum_{k=1}^{P} c_k v[l - k], \quad (15)$$

where $P$ is the order of the prediction filter. In general, the prediction is not perfect, so there will be a prediction error sequence

$$e[l] = v[l] - \hat{v}[l]. \quad (16)$$

The optimal linear predictive coding (LPC) coefficients minimise the prediction error power of the $P$th-order linear predictor (Kay 1988). This operation has been shown equivalent to maximising spectral flatness at the output of the prediction error filter (Gray Jr. and Markel 1974; Markel and Gray Jr. 1976). For an AR($P$) process, the optimal prediction coefficients are the AR($P$) parameters. The prediction error filter thus acts as a whitening filter that decorrelates the input AR process to produce white noise as its output. Determining $P$ is the model order selection problem that can be handled by using the fact for a linear predictor of order $q$, satisfying $q > P$ where $P$ is the true order of the AR process and the error power is constant (Kay 1988). Even if the order of the AR($P$) process and the order $q$ selected for the linear predictor are not the same, the output prediction error will be white if $q \geq P$.

The block diagram with the linear predictor used as a whitening filter is shown in Fig. 2. In the $z$-transform domain, the whitening filter $H(z)$ is given by

$$H(z) = 1 - A(z), \quad (17)$$

where $A(z)$ is the linear prediction filter

$$A(z) = \sum_{k=1}^{P} c_k z^{-k}. \quad (18)$$
The prediction coefficients $c_k$ can be computed using the autocorrelation method of AR modelling. This involves estimating the autocorrelation sequence from the time series and solving the Yule–Walker equations through Levinson–Durbin recursion (Ljung 1987; Kay 1988). The design of the whitening filter for each trace can be carried out during an initial noise-only segment of data. Then we whiten each noisy trace before designing the denoising filter $f[τ]$.

3 Denoising Examples

3.1 Synthetic data: Ricker wavelet

For synthetic data, we assume that there are 200 traces with identical amplitude scaling, i.e., $a_j = 1$. The waveform $s(t)$ is a Ricker wavelet with a centre frequency of 30 Hz and a normalised peak value. The sampling frequency is 500 Hz, and each trace has 200 time samples. Based on the signal-to-noise
The ratio (SNR) given in equation (3), two cases are considered: -6.03 and -12.01 dB, where the additive white Gaussian noise (AWGN) has $\sigma = 0.3$ and 0.6, respectively. In Fig. 3, we show noiseless signals superimposed on noisy versions for these two cases. Recall that plots of the stacked ACFs shown previously in Fig. 1 were generated for the case of $\sigma = 0.3$.

For conciseness, we present only the first 20 noisy traces of these two noise levels in Fig. 4(a) and (c), respectively. The final denoising results by the proposed scheme are shown in Fig. 4(b) and (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 (i.e., peak-signal-to-noise ratio (PSNR)=17.60 dB). Additionally, the high-noise case, the denoised data have SNR=0.51 dB (i.e., PSNR=10.84 dB).

In order to track the intermediate steps of the scheme, we compare the stacked autocorrelation and the designed filter side by side in Fig. 1 for the low-noise case. Then Fig. 5 illustrates the filter with and without truncation for the $\sigma = 0.3$ and $\sigma = 0.6$ cases. The effect of smoothing in the frequency domain is then shown in Fig. 6, which displays the frequency responses of the filters in Fig. 5.

### 3.2 Field data

In order to test the validity of the proposed scheme with microseismic data that would be received by a surface sensor array, we generate a set of 182 traces with different time
Figure 7  (a) Original traces. (b) Noisy traces, SNR = −2.53 dB. (c) Denoising result. P- and S-wave arrivals are indicated using red and blue arrows, respectively.

Figure 8  (Blue) The true waveform and (red) its noise contaminated version SNR = −2.53 dB.
Figure 9 Spectrogram of the (a) original trace; (b) noisy trace, SNR = −2.53 dB; and (c) de-noising result. The red and green circles indicate the P- and S-wave arrivals, respectively.

delays from a single seismic trace. The waveform used in this study comes from the High Resolution Seismic Network operated by Berkeley Seismological Laboratory, University of California, Berkeley, and the Northern California Seismic Network operated by the U.S. Geological Survey, Menlo Park, and is distributed by the Northern California Earthquake Data Center. The sampling frequency is 250 Hz, and each trace contains data for 10 seconds. We rescale every trace to have a normalised peak value of 1.0 and regard them as clean data. We then add AWGN of σ = 0.2 to the clean data, which gives

Figure 10 Impulse response of the ACF-designed filter (a) without truncation and (b) truncated and windowed to −190 ≤ τ ≤ 190. Frequency response (c) without truncation and (d) truncated and windowed to −190 ≤ τ ≤ 190.
The denoising result using the ACF-designed filter with a truncation window of $\tau = 190$ is shown in Fig. 7(c). We observe that the denoising scheme not only clearly recovers the P- and S-wave arrivals (indicated using red and blue arrows, respectively) but also well preserves the waveform from noisy traces where precise manual detection of the signal is almost impossible. The denoising result for a sample trace is shown in Fig. 9, where we note that the P- and S-wave arrivals are preserved in the regions indicated by red and green circles, respectively, on the spectrogram in Fig. 9(c). As a reference, we present the filter with and without truncation and the corresponding frequency response amplitude in Fig. 10, where the smoothing effect is easy to see.

The methodology described above was tested on a real dataset. However, due to the proprietary nature of the dataset, we are unable to include those results. This is the reason we used the simulation in Fig. 7 that is generated by manually shifting real traces. As we indicated earlier, the prerequisite for this method to work is that the recorded data across all sensors in the array must have similar frequency content (although the waveforms may be altered slightly). With the proprietary real dataset, we obtain results similar to what is shown in Fig. 7 above.

Finally, note that this method is effective in suppressing uncorrelated noise, not correlated (i.e., coloured) noise. Consequently, we do not expect our method to be applicable in all cases.
noise scenarios. In the next section, we show that some preconditioning can be performed to decorrelate additive noise when prior knowledge is available.

3.3 Examples for noise prewhitening

In order to verify the necessity and validity of prewhitening for microseismic data with additive coloured noise, we consider 200 microseismic noisy traces of SNR = −10 dB (the PSNR is not calculated since the noise is not AWGN). The first 20 noisy traces are shown in Fig. 11(a). The power spectrum of the noise is higher for low frequency and is identical for all sensors. A prewhitening filter of degree 20 is learned from the signal segments that contain only noise. The output of the prewhitening filter is shown in Fig. 11(b). Figure 11(d) shows the superiority of the prewhitened and denoised result to denoising without prewhitening in Fig. 11(c).

In order to demonstrate the validity of the prewhitening process, we compare the noise power spectrum of noise-only segment on the first sensor before and after whitening (see Fig. 12). We can see that the power spectrum of the noise is effectively flattened.

4 DETECTION

In order to alleviate the computational burden when processing large datasets acquired with passive monitoring, it is always desirable to have an accurate detection of seismic events as the first component of the microseismic data processing pipeline. The total workload can be significantly reduced if we apply further processing only to the part of data that contains detected seismic events. Conventional detection schemes are commonly based on changes in certain characteristics along single traces such as trace energy, absolute value of amplitude, short-term-average/long-term-average (STA/LTA)-type algorithms (Earle and Shearer 1994), and waveform correlation with strong events (Gibbons and Ringdal 2006; Michelet and Toksöz 2007; Song et al. 2010), to name a few. However, these methods require either good signal-to-noise ratio or isolated strong events that serve as a template. Otherwise, they typically produce many false alarms when an aggressive threshold is employed to detect small events.

In the foregoing sections, we have shown that the stacked autocorrelation can efficiently estimate the frequency characteristics of a common waveform in the presence of AWGN for multi-channel microseismic data. If waveforms originating from the same seismic event are received across the array of sensors, high coherence is commonly observed. Based on this fact, we devise a multi-channel detector that is capable of exploiting the information on all channels at once.

In order to achieve a reasonable detection resolution in the time domain, we adopt a sliding window technique from the conventional schemes. The detection indicator \( \eta(t) \), which corresponds to the sliding window starting at \( t \), is defined as follows:

\[
\eta(t) = \frac{1}{N} \sum_{i=1}^{N} \max_{\omega} \left| \mathcal{F}[x_i \star x_i] \right|.
\]  

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where $x_i(t)$ is the $i$th trace truncated (and weighted) by the sliding window starting at $t$. Since the denominator $\|F\{x_i \star x_i\}\|_1$ is proportional to the energy of $x_i$, each trace is normalised prior to summation in equation (19). Therefore, the detector defined in equation (19) measures only the resemblance of the traces, which is independent of their amplitudes. In data from natural micro-earthquakes or microseismic data from hydraulic fracturing, the amplitudes of signals could vary significantly across a sensor array. Thus, the normalisation in equation (19) for all traces is necessary.

5 DETECTION EXAMPLE

In this section, a synthetic example using a seismic data section obtained by manually time-shifting a real seismic trace plus random noise is shown in Fig. 13 to demonstrate the effectiveness of the pre-detection indicator $\eta(t)$ based on the stacked autocorrelation as proposed in equation (19). The synthetic data shown in Fig. 13(a) and (c) include 30 traces that were delayed with a linear moveout between 15 and 20 seconds from a single real seismic trace that consists of both P- and S-wave phases. The seismic trace is from the same dataset.

Figure 13 Synthetic multichannel data using 30 real seismic traces with linear moveout totalling 5 seconds contaminated by AWGN of (a) $\sigma = 0.1$ and (c) $\sigma = 0.4$. Pre-detection results using the indicator (19) are shown in (b) and (d), respectively.
as Fig. (7)(a), whose sampling frequency is 250 Hz. Additive white Gaussian noise of $\sigma = 0.1$ (for high signal-to-noise ratio (SNR)) at peak-signal-to-noise ratio (PSNR) = 20 dB and $\sigma = 0.4$ (for low SNR at 8 dB) is used in Fig. 13(a) and (c), respectively. We use a sliding window of length 0.5 seconds with an overlap of 0.4 seconds and then compute $\eta(t)$ with a 128-point fast Fourier transform.

In the high-SNR case, the detection indicator $\eta(t)$ returns obvious high values during the time frames of the coherent signal arrival, whereas the rest of the time seems to exhibit a noise floor at about $-33$ dB. Setting a threshold at $-29$ dB would give nearly perfect detection of the simulated microseismic events in the time domain. In the low-SNR case, the noise floor stays at about the same value, but the detection region has much smaller values and it would be more difficult to set a threshold to separate the true arrivals from the noise floor. Since $\eta(t)$ measures the coherence among traces, the noise floor does not change with the additive noise amplitudes. Thus, as the noise amplitudes increase, the $\eta(t)$ values within the coherent signal region decrease and will eventually fall below the noise floor. As demonstrated in Fig. 13(d), our proposed detection indicator $\eta(t)$ can deal with a PSNR as low as 8 dB using hard thresholding. Furthermore, improving the peak detector with methods such as smoothing or polynomial fitting can further reduce the lower-bound of detection PSNR.

6 CONCLUSION

Surface microseismic data, which is typically noisy, requires robust detection and an explicit denoising step before further processing. We have presented a multi-channel denoising and detection method based on autocorrelations that can effectively suppress uncorrelated noise without knowing relative time offsets. A prewhitening scheme extends the applicability of this denoising filter to more general and practical scenarios of microseismic monitoring. The effectiveness of the detection, denoising scheme, and prewhitening for coloured noise is tested using synthetic and real seismic waveforms.

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