SIMULTANEOUS ENHANCEMENT AND DETECTION OF MICROSEISMIC EVENTS BASED ON AUTOCORRELATION

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ABSTRACT

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Microseismic monitoring is the main method of hydraulic fracturing evaluation, which is realized by locating the source. Before locating the source, it is necessary to determine the position of the valid signal in the receiving channel. But the data received is very complicated, including the dead trace, strong noise, invalid data, etc. In order to solve some cases, Methods of data enhancement and data detection are mentioned. However, there are some problems in the application of the enhancement method and detection method in microseismic monitoring. Therefore, This research improves the enhancement method to reduce the suppression of the P-wave by the original method and proposes a more efficient detection method based on autocorrelation. The test of synthetic data and filed microseismic data shows that the enhancement method improved and the detection method is effective.

KEY WORDS: microseismic monitoring, denoising, detection, autocorrelation, sensor array.

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INTRODUCTION

Microseismic monitoring is a technique for evaluating the effect of hydraulic fracturing that the main work is locating the source to know the subsurface fracturing of rock (Maxwell et al., 2005; Eisner et al., 2010). In standard processing workflow, microseismic event detection is an important process which it is removing a large amount of noise data and reduces the quantity of computation in subsequent processing (Iqbal et al., 2018). On the other hand, data with a higher signal-to-noise ratio (SNR) are obtained through enhancement, which greatly improves the subsequent processing effect. Commonly, the microseismic processing method is divided into the single-channel method and multi-channel method (Wang et al., 2020; Song et al., 2010). Due to the abundant information in multi-channel data, the multi-channel method is getting a better effect than the single-channel method generally.

Typically, downhole microseismic monitoring evaluates the hydraulic fracturing effect through source location. Before the source location, it usually needs to be pretreated, such as denoising and event detection. At present, there are many methods used in microseismic denoising, such as time-frequency analysis (Han et al., 2015; Akram et al., 2018) and machine learning (Pilikos et al., 2017)

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Among the time-frequency analysis method, usually achieves the denoising effect by using the frequency domain information, and it can also be used together in the time domain and frequency domain. At present, the method of intrinsic mode function (IMF) decomposition is used more and more widely, such as Complementary Ensemble Empirical Mode Decomposition (CEEMD) and Variational Mode Decomposition (VMD). Zuo et al. (2019) used the wavelet packet threshold to process the CEEMD IMFs which were selected by the autocorrelation coefficient. Finally, reconstruct the IMFs after noise suppression and IMFs without noise suppression. Li et al. (2019) using the time-frequency peak filtering to the VMD IMFs which selected by the desired signal coefficient and reconstruct all IMFs. Zhang, Dong and Xu (2020) reconstruct the VMD IMFs selected by the cross-correlation. Finally, using the Akaike information criterion (AIC) determine the location of valid data and reduce the residual fluctuations in other positions.

Among the frequency filtering method, it usually achieves the denoising effect by using the frequency domain information, and it can also be used together in the time domain and frequency domain, such as the bandpass filtering method. Shao et al. (2019) propose the joint sparse 3-C representation with a dictionary learning method which be solved by extended orthogonal matching pursuit. Experiments show that this method is better than the simultaneous denoising of 3-component data with the fixed dictionary method in retaining weak signals and removing noise. Zhang et al.

(2019) apply the Bayesian algorithm to the dictionary learning to judge whether it is noise or signal through dictionary and coefficient, then reconstruct the dictionary and sparse coefficient judged as the signal to the denoised data.

In downhole microseismic monitoring, due to the high sampling rate, usually 4000Hz, a large amount of random noise has a great impact on the calculation efficiency when processing data. Therefore, detection is usually needed to distinguish random data from effective signals, so as to improve computational efficiency. According to the data type, the detection methods are divided into a single-channel method (Vaezi et al., 2015) and a multi-channel method (Trow et al., 2018). In theory, detection robust based on multi-channel is better. According to the method, the common approaches include characteristic-function (CF), cross-correlation (CC), and migration-based methods (Mousavi, S. M., C. A. Langston, and S. P. Horton, 2016;). But in recent years, machine learning methods are used more and more in microseismic event detection.

Jiang et al. (2019) used the cross-correlation between the template microseismic event with the morphology multi-scale components of microseismic data to select the valid components. Finally, reconstruct these components to represent the CF of detection. Experiments show that this method performs well in low SNR microseismic data. To solve the problem of low SNR of ground microseisms, Long et al. (2019) propose a Fast Akaike information criterion (Fast-AIC) to detect the microseismic event. They pick up the first breakthrough AIC, correct the microseismic event time difference and stack it. Finally, using the short-time average ratio/long-time average ratio (STA/LTA) method to detect the microseismic event. Zhang, Lin and Chen (2020) combine the continuous wavelet transform (CWT) and the convolutional neural network (CNN) to be a novel antinoise classier for waveform and arrival picking. Comparative experiments show that this method has better antinoise ability than deep feedforward neural networks (DNN). Liu et al. (2021) construct a more efficient learning CNN referring to the Le-Net5. The CNN is trained by synthetic data, and the performance is good when processing the field data.

At present, template matching is an effective method (McClellan et al., 2018), but a part of events still not be recognized, due to the difference in source mechanisms. Therefore, Liu et al. (2017) have proposed the autocorrelation-based enhancement and detection method. In this approach, autocorrelation is used to eliminate the problem of microseismic event time difference in multi-channel data. Then, it builds a filter by stacking the autocorrelation function (ACF) to enhance the microseismic data across highlight the frequency. However, the enhancement result (Fig. 1) shows that this method attenuates the P-waves arrival, so there will be certain problems in microseismic applications. ACF can also highlight the frequency, but P-wave and S-wave have different frequency and P-wave energy attenuate quickly, so it highlights the S-wave frequency and suppresses the P-wave frequency generally twice. In the frequency domain, the ACF is the result of frequency domain multiplication due to Convolution Theorem. Therefore, the energy attenuation P-wave is suppressed and the S-wave is enhanced in the frequency domain. To avoid this weakness of the method, take the square root of the frequency domain of ACF.

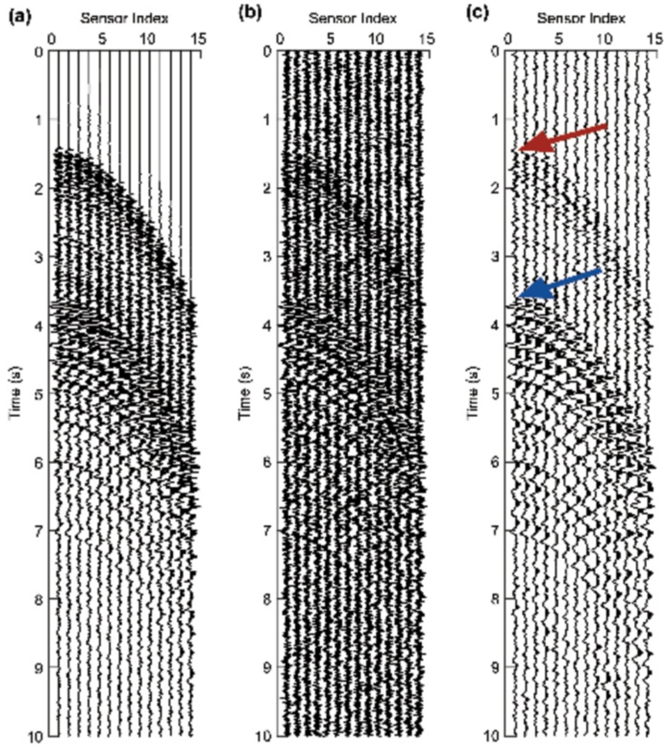

Fig. 1. (a) Original traces. (b) Noisy traces. (c) Denoising result.

According to the detection method, getting CF describes the frequency energy change across the stacking ACF. However, this method calculates the result slowly, which is contrary to the original intention of saving computing resources. Thus, in this paper, we propose a method of microseismic data detection based on the changes in ACF median and neighboring values in microseismic data and random noise. Since only the median and neighboring values of ACF need to be calculated, the calculation speed changes faster than the method of ACF energy stacking.

METHOD

Enhancement

Due to the frequency of the P-wave being different from the S-wave and the energy of the P-wave attenuating quickly, the ACF filter will highlight the S-wave and suppress the P-wave. Then, the next processing of the convolution filter will suppress the P-wave again. To alleviate this situation about the P-wave suppression, this paper proposes a method to modify the ACF filter. Due to the ACF can be regarded as the Inverse Fourier transform of the square of the data frequency domain, the resolvent is square in frequency in the domain which can obtain the characteristic of original data and eliminate the influence of P-wave.

According to the new method for constructing filters in detail, firstly carry out the modified ACF whose median value is replaced by the average of its neighboring value, then, stack the ACF of the array of data and get a simple filter. To eliminate the suppression of P-wave frequency, we are taking the square root of the frequency domain of ACF and using the inverse Fourier transform. The formula is shown below:

$$f = F^{-1}\left(\sqrt{F\left(\frac{1}{N}\sum_{i=1}^{N} acf_i\right)}\right) \tag{1}$$

where acf_i is the ACF, N is the number of the trace, F is the Fourier transform, F^{-1} is the inverse Fourier transform;

The next step is using the mirror average to maintain the symmetry of ACF. The formula is shown below:

$$f_m[i] = \frac{f[i] + f[-i]}{2} \tag{2}$$

where f is the result of the square root ACF in the frequency domain, f_m is the result of mirror average processing. Then, the filter is processed according to the truncation window of Liu et al. (2017) to remove the effect of the boundary. The formula is shown below:

$$w[t]=\begin{cases}1-\dfrac{|t|}{d} & \text{if } |t|\le d\\ 0 & \text{if } |t|>d\end{cases}$$
$$f_{new}=f_m\cdot w \tag{3}$$

where w is the weight coefficient, d is the set weight range, f_m is the result of the mirror average processing, and f_{new} is the final filter. Finally, enhance the data by using convolution filtering. The formula is shown as below:

$$\hat{x}_i=f_{new}*x_i \quad i=1,\ldots,N \tag{4}$$

where x_i is the original data, f_{new} is the final filter, $\hat{x}_i$ is the result of enhancement. Simplify the above steps into a flowchart shown as below (Fig. 2).

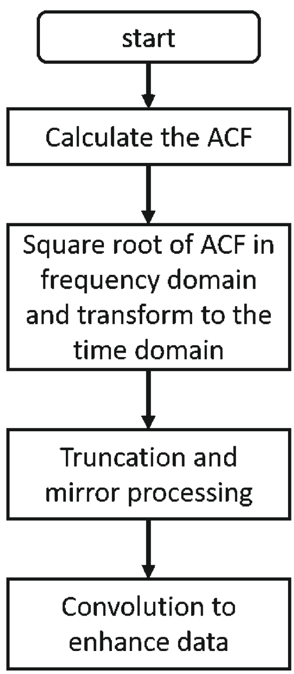

Fig. 2. The processing flow of enhancement.

Detection

In order to deal with a large amount of data, the data are usually preliminaries detected before processing the data. The preliminary detection focuses not on the identification of data, but on removing numerous invalid data fast. Liu et al. (2017) propose a method that stacks autocorrelation energy to detect the data. However, the calculation speed of this method is slow and fails to meet the requirements of fast processing for preliminary detection. Therefore, we propose a new method to preliminarily detect based on autocorrelation.

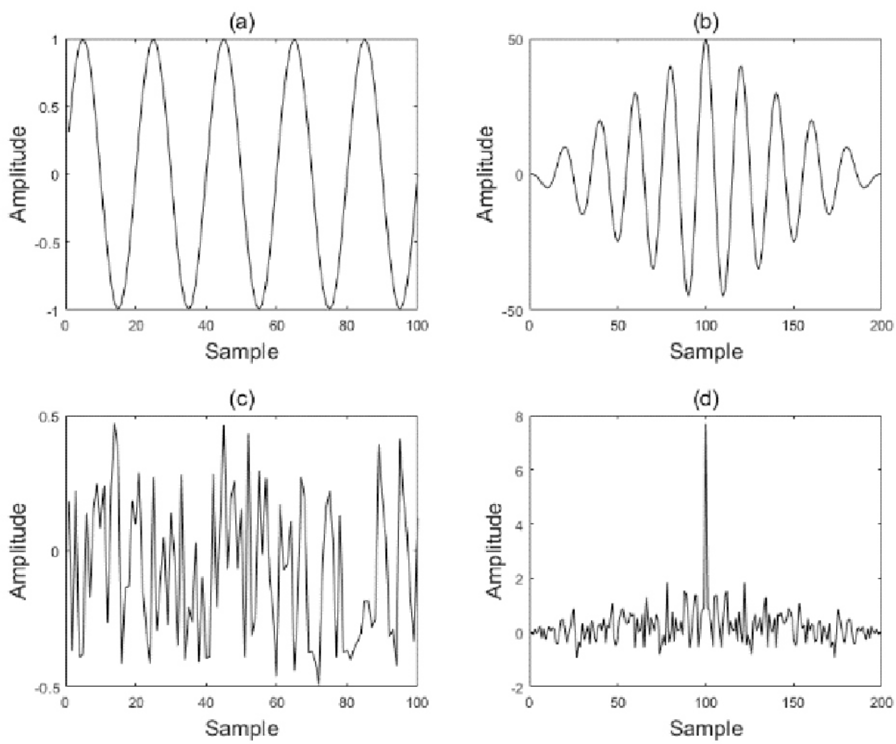

Fig. 3. (a) Synthetic periodic signal. (b) ACF of the synthetic periodic signal. (c) Random noise. (d) ACF of random noise.

According to the difference of ACF between random noise and periodic signal (Fig. 3), we propose a method to detect based on the median and neighboring of ACF. In Fig. 3, the median value in ACF of random noise is the abrupt value relative to the neighboring values, but the change of the median value is mild in ACF of periodic signal (Fig. 3). In addition, the ACF can ignore the time difference between array channels. Therefore, the proposed method of detecting microseismic is based on the average stacking of the ratios of neighboring and median. Due to the proposed method only needing the median and neighboring values in ACF, the calculation speed is faster than the stacking of the ACF energy.

Due to the symmetry of the ACF, the proposed method only calculates the left neighboring value of the median. The formula of the proposed method is defined as shown below:

$$\begin{aligned} &\mathrm{CF(i)} = \sum_{i=1}^{N} \frac{\mathrm{acf}_i[-1]/\mathrm{m}}{\mathrm{acf}_i[0]/\mathrm{n}} \\ &\mathrm{n} = \mathrm{m} + 1 \end{aligned} \tag{5}$$

where the $\mathrm{acf}_i[0]$ is the median value of the ACF, $\mathrm{acf}_i[-1]$ is the neighboring value of the median value, CF is the indicator of the valid data, n is the Sampling points in the time window.

SYNTHETIC DATA

Enhancement

In order to verify the effectiveness of the proposed method, we simulate the synthetic array data which have the time difference of data for a test. The synthetic array data includes high-frequency low-energy P-wave and low-frequency high-energy S-wave. This paper compares the proposed method with the original method (Liu et al., 2017) by using it to enhance the synthetic array data with random noise, respectively.

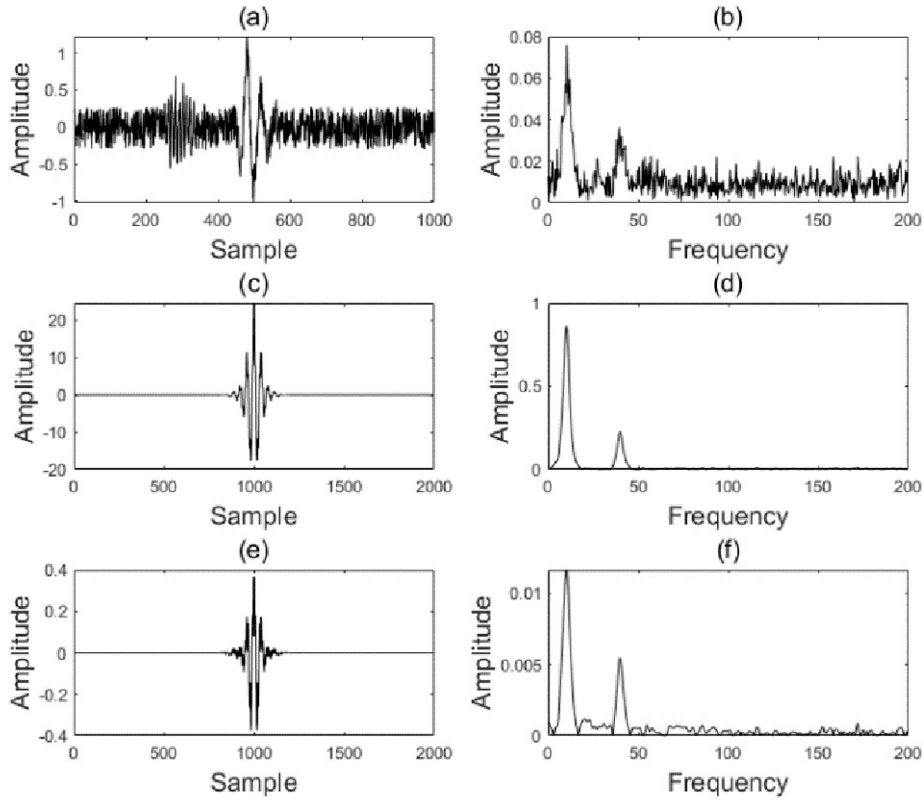

Fig. 4. (a) A trace data in the synthetic array data. (b) The frequency spectrum of (a). (c) The original stacking filter. (d) The frequency spectrum of (c). (e) The improved stacking filter. (f) The frequency spectrum of (e).

In Fig. 4, the filters are from the synthetic data which is the S-wave setting low frequency and P-wave is setting high frequency. In addition, the energy of the P-wave is lower than that of the S-wave. Through spectrum comparison, it can be seen that although the noise suppression of the improved method is worse than the original method, the improved method can better preserve the frequency of low-energy valid data.

The synthetic pure data, adding noise data ,and the result of enhancement by the original method and proposed method are shown as below in Fig. 5.

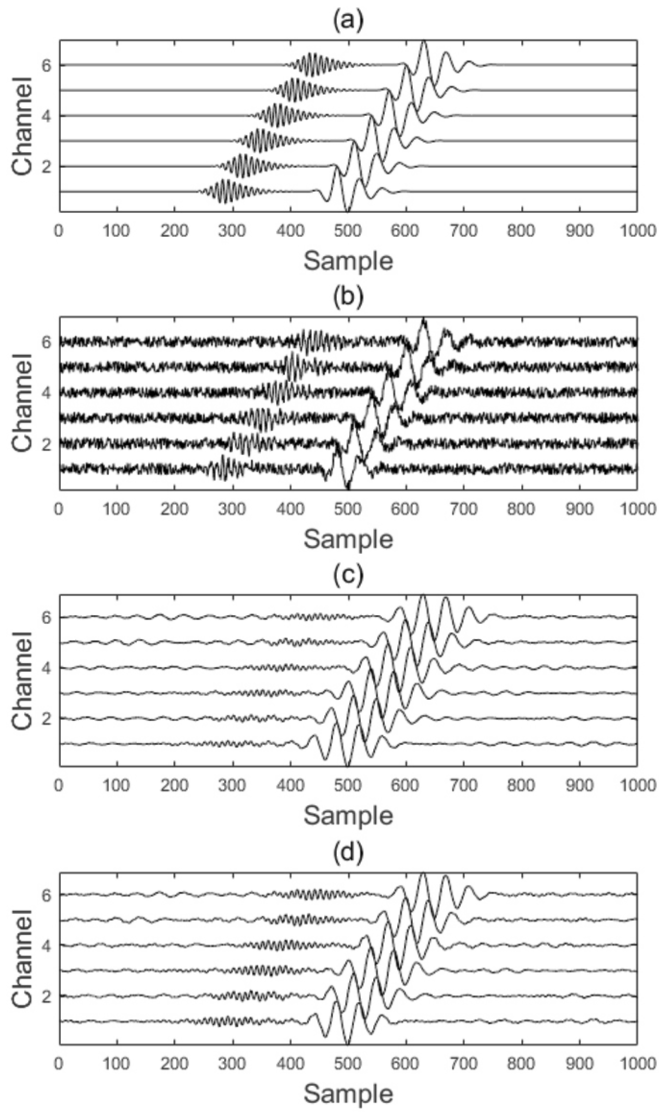

Fig. 5. (a) The synthetic array data without noise. (b) The synthetic array data with noise. (c) The result of denoising by the original method. (d) The result of denoising by the improvement method.

In Fig. 5, the both original method and the proposed method have suppressed the noise, but the original method removes more background noise than the proposed method, which can also be known from the filter spectrum (Fig. 4). Even though the former can remove more noise, the latter can reduce the suppression of P-wave and get clearly a first break.

Detection

In order to improve the computational efficiency of detection, the proposed method only uses the median and neighboring to detect the data. Therefore, this paper compares the computational efficiency and robustness of the two methods with synthetic data. The computational efficiency can be evaluated by computation time. Regarding robustness, we construct the data which includes the dead trace (excluding valid data) in array data.

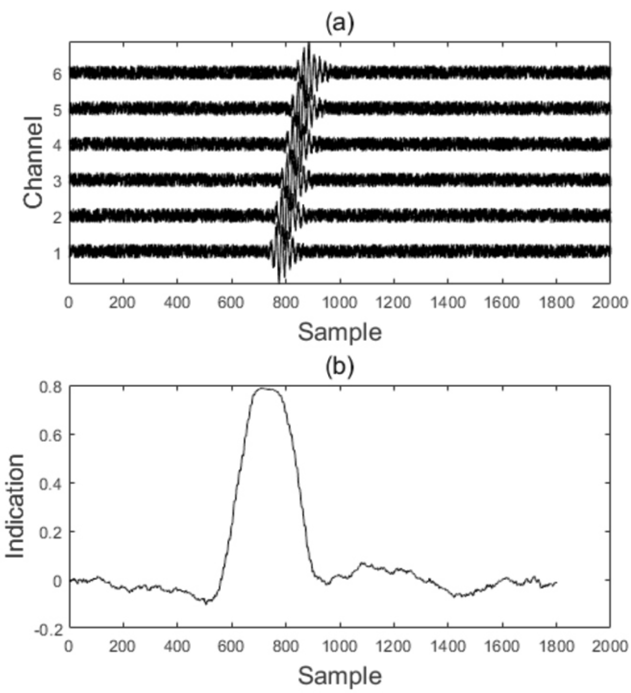

Fig. 6. (a) The synthetic array data without a dead trace. (b) The result of the detection.

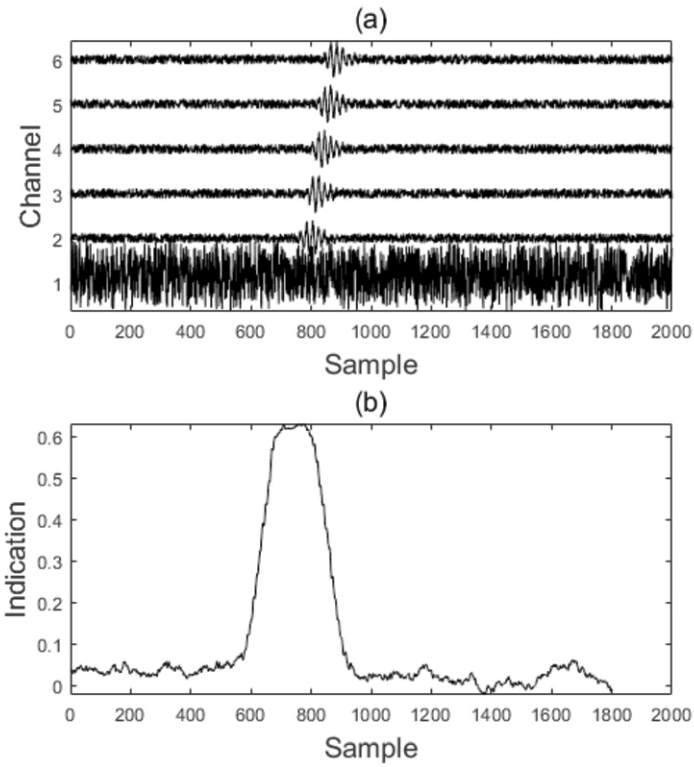

Fig. 7. (a) The synthetic array data with dead trace. (b) The result of the detection.

In order to verify the effectiveness of the proposed method, we synthesize 6 trace array data with noise. Fig. 6 is the synthetic array data without a dead trace and its detection result, and Fig. 7 is the synthetic array data with dead trace and its detection results. It shows that the proposed method is effective and has certain adaptability to death trace.

FIELD MICROSEISMIC DATA

Enhancement

In order to further verify the effectiveness of the proposed method, we use field microseismic data to test.

The filters and their spectrum are shown in Fig. 8, compared with the field data, the original method suppresses the P-wave frequency, and the improved method retains the P-wave frequency.

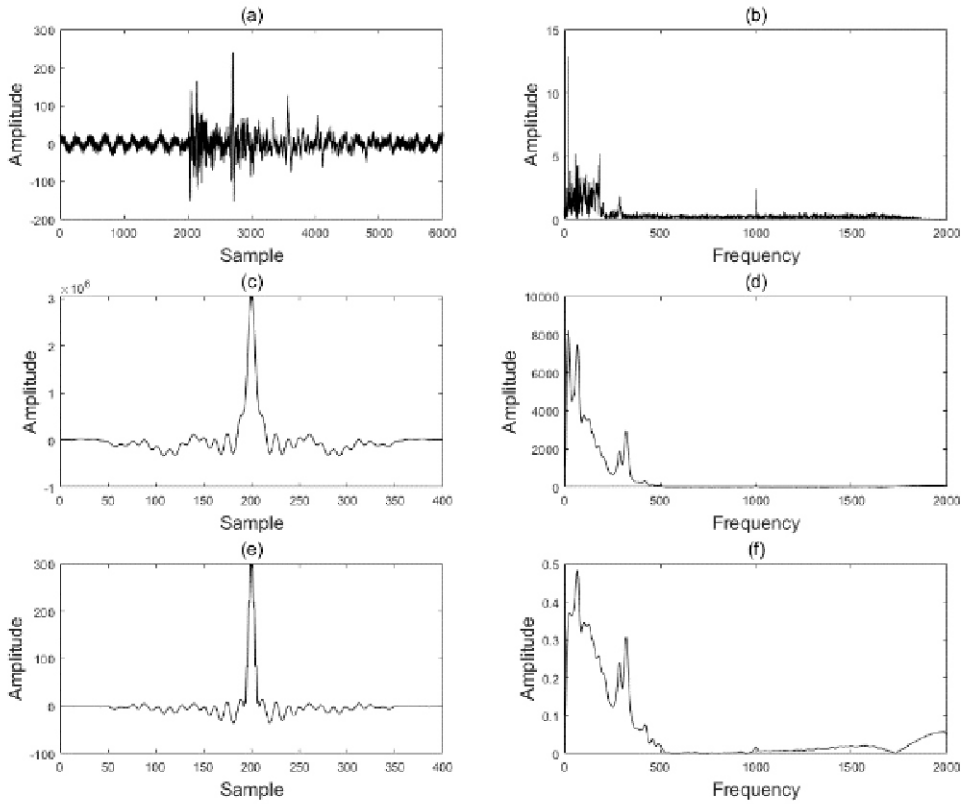

Fig. 8. (a) A trace data in the field array data. (b) The frequency spectrum of (a). (c) The original stacking filter. (d) The frequency spectrum of (c). (e) The improved stacking filter. (f) The frequency spectrum of (e).

According to Fig. 8, Although there are still some reservations about some high frequencies, the improved filter retains the frequency of P-wave better. Finally, the field microseismic array data are denoised by using a convolution filter, and the result of enhancement is shown as below in Fig. 9 where we compare the original method with proposed method and Fig. 10 is its corresponding time spectrum.

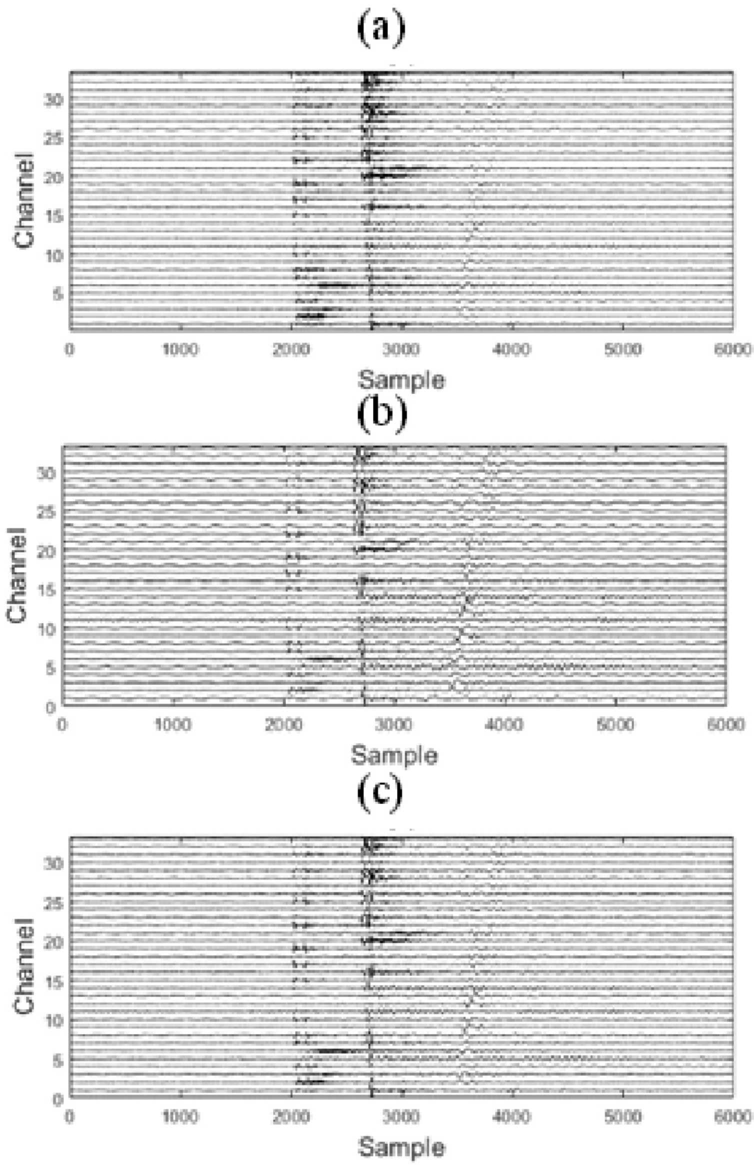

Fig. 9. (a) The original field data. (b) The enhancement results of original method. (c) The enhancement results of improved method.

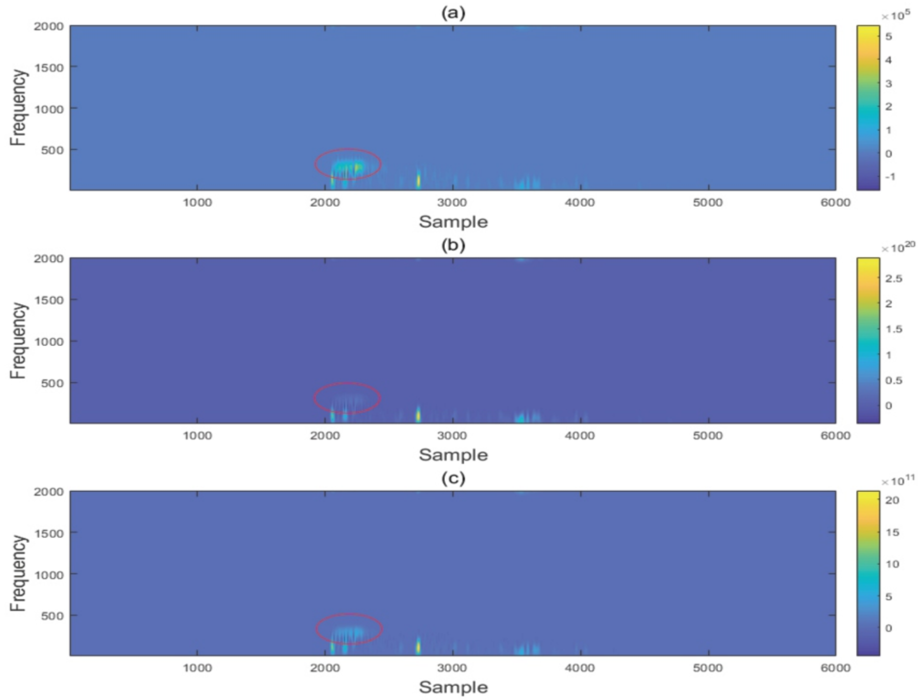

Fig.10. (a) The time spectrum of original trace data. (b) The time spectrum of the original method result. (c) The time spectrum of the improved method result.

Due to the energy of the S-wave being strong and the energy of the P-wave being too weak, it is obvious that the P-wave is suppressed in two methods. Although not obvious, the improved method can reduce the situation of P-wave being suppressed (as shown in the red circle in Fig. 10). There is a phenomenon that after the original method is processed, the background high-frequency noise is removed, but the obvious low-frequency fluctuation is retained, which is obviously not conducive to the processing of microseismic. And this phenomenon has not happened in the result processed by the improved method. The original method almost only retains the signal frequency band, but the signal and the noise frequency overlap. If the original method is used to denoise, the boundary between the signal and the noise will be blurred (Vera Rodriguez et al., 2012; Mousavi and Langston, 2016). The improved method not only retains the low frequency but also retains part of the high frequency so that the signal mutation part is retained.

Detection

In this part, the proposed detection method is applied to the field data to further verify the effectiveness of the method. In order to verify that the method should deal with the abnormal situation of the field data, the field data used in the experiment include several typical data with high SNR, low SNR, and dead trace. The result of detection is shown below in Figs. 11-13.

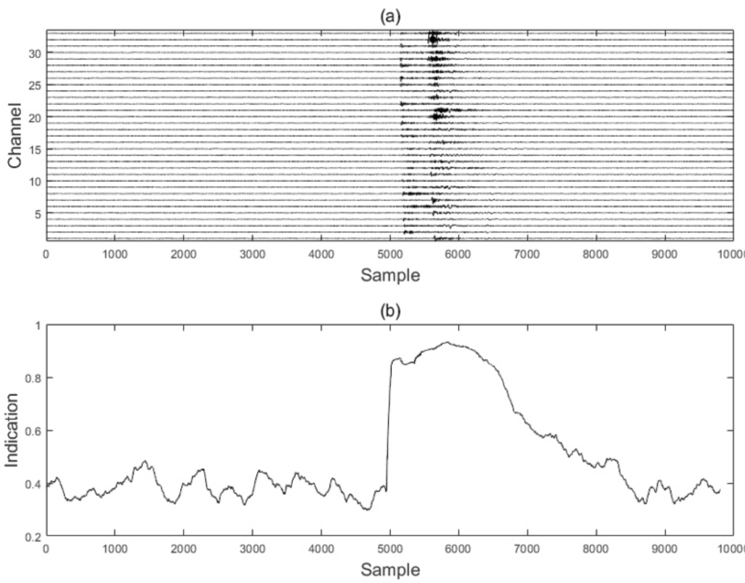

Fig. 11. (a) The field microseismic array data with high-SNR. (b) The CF detection of the proposed method.

Fig. 11 shows the 33 trace field data with high SNR and its result of detection by the proposed method. The results show that the proposed method is feasible for the field data and the detection value of background noise is less than 0.5. Therefore, for this block data, we set a threshold of 0.5, and take the received data with a detection value greater than 0.5 as valid data and the received data less than 0.5 as invalid data.

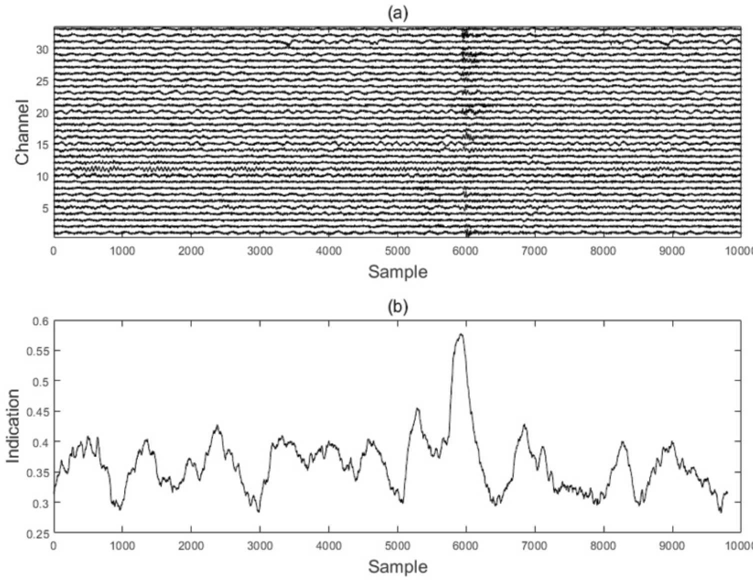

Fig.12. (a) The field microseismic array data with low-SNR. (b) The CF detection of the proposed method.

Fig. 12 shows the 33 trace field data with low SNR and its result of detection by proposed method. In array data of Fig. 12, most of trace is getting the low-SNR. Compared with Fig. 11, the detection value in Fig. 12 is less obvious than that in Fig. 11, but it can still be detected by the threshold method.

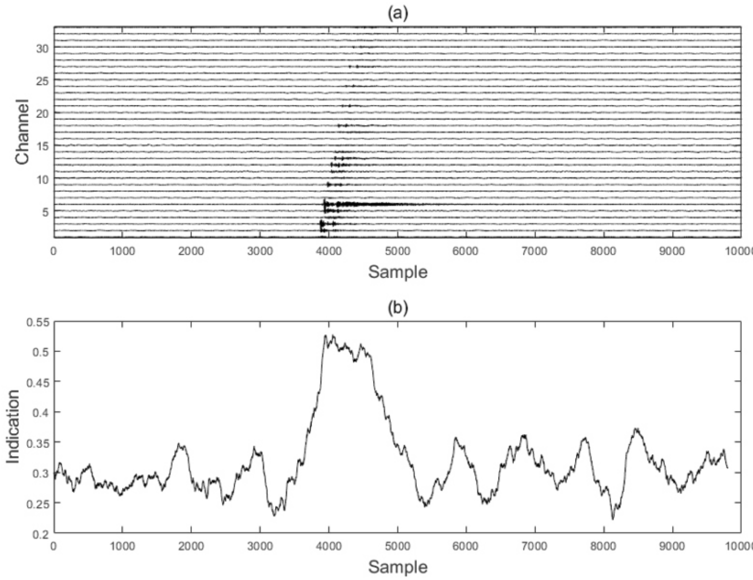

Fig. 13. (a) The field microseismic array data with dead traces. (b) The CF detection of proposed method.

Fig. 13 shows the 33 trace field data with dead trace and its result of detection by proposed method. In the array data of Fig. 13, some get high-SNR, some get low-SNR and the rest are dead traces. Through the detection results, show that the proposed method can still effectively detect the data.

Based on the basic principle of the detection method, we can know that it mainly detects limited bandwidth data and filter random data. Thus, a large number of invalid data are removed, to reduce the overall amount of calculation.

CONCLUSION

It is an effect that enhances and detects the microseismic array data by stacking ACF. However, the enhancement method is not conducive to the treatment of microseisms because it suppresses P-waves and the calculation of this detection method is slow, which is contrary to the original intention of saving computing resources. Therefore, in this paper, we propose methods to overcome the above shortcomings. According to the enhancement, we change the way of filter construction to reduce the P-wave suppression by the original method and propose a more efficient autocorrelation detection method the proposed method has achieved our purpose, but there is a problem about noise with the same frequency, such as the low-frequency noise in field microseismic which a situation of existing low-frequency in each trace. Thus, the autocorrelation stacking method is not suitable for noise with a similar frequency attribute. According to the detection, in order to meet the rapid requirements of preliminary detection, we use the mutation attribute of median value to detect the data quickly. It has a certain effect in exploring the data with the observable frequency of the array, but it also shows that the noise with the limited bandwidth in the array will be identified incorrectly. Therefore, this method is only suitable for rough fast detection.

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