RESEARCH ON METHODS FOR SUPPRESSING PERIODIC NOISE IN THE BACKGROUND OF MICROSEISMIC DATA

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ABSTRACT

Addressing the issue of periodic noise in surface monitoring of microseismic data during hydraulic fracturing, which is caused by significant mechanical equipment and environmental interference, traditional methods have been found to be insufficient in their research of periodic noise. This paper conducts an analysis of the characteristics of periodic noise within actual microseismic data and introduces an effective method for the suppression of periodic noise in the microseismic background. The approach is primarily two fold: initially, it targets the suppression of continuous periodic noise present in the microseismic data, followed by the elimination of any remaining non-continuous periodic noise. The method presented in this paper is validated using a set of real microseismic monitoring outcomes, and the results substantiate the genuine effectiveness of the proposed technique.

KEY WORDS: Hydraulic fracturing · Microseismic signal processing · Background noise suppression · Periodic noise suppression

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INTRODUCTION

In the process of microseismic data monitoring, noise is typically categorized based on its regularity into periodic and random noise. Traditional methods for microseismic noise suppression primarily focus on the treatment of random noise, with relatively fewer research methods available for dealing with periodic noise in microseismic data (Chen et al.,2021; Lv,2019). For random noise, common approaches such as filtering and stacking across multiple channels are used to reduce its impact. Signals generated by microseismic events usually exhibit a certain degree of consistency and correlation, which random noise lacks. Consequently, random noise tends to cancel out during the stacking process.In contrast to random noise, periodic noise, due to its waveform similarity, cannot be processed through stacking and requires the design and application of specific methods for suppression. Therefore, periodic noise has a more severe impact on microseismic signals and is more challenging to remove. Consequently, effectively and accurately suppressing periodic noise has become a primary focus in current research.

In recent years, with the widespread application of microseismic technology in underground exploration and hydraulic fracturing monitoring, researchers have begun to focus on the issue of periodic noise in microseismic data. There are numerous methods currently used to address the issue of periodic noise suppression in microseismic data processing, primarily through time-frequency transformation and signal decomposition. For instance, Lyubushin utilized wavelet time-frequency analysis to suppress seismic noise (Lyubushin, 2021), while Mousavi et al. combined synchronized squeezing continuous wavelet transform with detection functions to remove periodic noise from signals (Mousavi & Langston, 2016). Additionally, decomposition and reconstruction-based methods have been widely applied to suppress periodic noise. Empirical mode decomposition (EMD) and ensemble empirical mode decomposition (EEMD) are used to process the frequency domain real and imaginary parts of signals to reduce both random and periodic noise (Chen & Fomel, 2018; Li et al., 2020). Complete Ensemble Empirical Mode Decomposition (CEEMD) and other variational mode decomposition (VMD) methods further improve these techniques by reducing redundant intrinsic modes and addressing the mode aliasing issue, offering stronger noise resistance (Sun et al., 2020; Qiao et al., 2021; Liu et al., 2023). Recently, tensor decomposition methods such as tSVD and HOSVD have provided a new perspective for noise suppression. These methods effectively enhance the signal-to-noise ratio by extracting low-rank components in multidimensional data, especially when dealing with multichannel microseismic data in a high-noise environment. By using cross-correlation and rearrangement techniques, combined with the SVD step, these methods can effectively identify and suppress noise components (Popa et al., 2021; Deriche et al., 2020). Moreover, stochastic noise suppression methods based on wavelet thresholding and Lipschitz exponents, as well as statistical dictionary learning approaches, have offered new solutions for automatic periodic noise suppression (Li et al., 2022; Yao et al., 2023; Zhang et al., 2022). These methods effectively identify and suppress noise by adaptively selecting appropriate threshold functions and updating dictionaries, thereby improving the quality of microseismic data. In recent years, there has been a growing number of researches that use neural networks for microseismic data denoising. For example, deep convolutional neural networks are used to remove noise by learning the features of microseismic data (Zheng et al., 2021; Zhao et al., 2022; Sun & Hou, 2022). Other neural networks, such as the JointNet (Wu et al., 2023), the U-Net (Chirtu & Radoi, 2022), and the Generative Adversarial Network (GAN) (Li et al., 2023) can also suppress the noise and improve the quality of microseismic data.

In the process of denoising microseismic data, although existing methods have achieved varying degrees of success, they still face a series of challenges and limitations. These challenges primarily include computational difficulties, complex parameter settings, and low computational efficiency. For example, decomposition and reconstruction-based methods such as EMD, EEMD, and CEEMD can theoretically separate noise and signals effectively. However, in practical applications, these methods may encounter the issue of mode aliasing, which not only increases computational complexity but also affects the denoising performance. Mode aliasing occurs when signals of different frequencies are incorrectly grouped into the same mode during decomposition, making it difficult to distinguish noise from the signal.Wavelet thresholding denoising methods require the selection of appropriate threshold functions and mother wavelets. The choice of these parameters often relies on experience and experimentation, lacking universal guidelines. Improper parameter settings may lead to suboptimal denoising effects, or even the introduction of artifacts or signal distortion. Moreover, matrix decomposition-based methods such as Singular Value Decomposition (SVD) excel in denoising but come at a high computational cost, especially when dealing with large matrices. This not only increases the demand for computational resources but also extends processing times, affecting the capability for real-time or near-real-time data processing. Traditional microseismic data processing methods, such as wavelet transform-based denoising techniques and signal processing methods based on Empirical Mode Decomposition, have achieved certain successes in suppressing non-periodic noise. However, they still fall short in the suppression of periodic noise. These methods often struggle to effectively differentiate between periodic and non-periodic components in the signal, particularly when the amplitude and energy levels of the noise vary significantly.Deep learning technology has shown great potential in the field of microseismic data processing, especially in denoising and feature extraction. However, it still faces several challenges and limitations. Firstly, deep learning models typically require a large amount of high-quality annotated data for training, and obtaining sufficient training data in microseismic monitoring can be both costly and time-consuming. Secondly, the issue of model overfitting is a key challenge. In the real-world scenario where data diversity and noise variability are high, a model may perform well on the training set but lack generalization capabilities when applied to new data.

In response to the current shortcomings and deficiencies in the suppression methods for periodic noise in microseismic data, it is particularly necessary to explore more effective and reliable methods to suppress periodic noise in microseismic signals. Addressing this issue, this paper proposes a suppression method for periodic noise in microseismic data. Periodic noise is categorized into continuous periodic noise and non-continuous periodic noise based on the duration of waveform regularity. For continuous periodic noise in microseismic data, this paper suggests a suppression method based on the autocorrelation function. This method can extract periodic components from the signal and suppress continuous periodic noise by eliminating these components in the frequency domain. For non-continuous periodic noise, these noise interferences typically do not exhibit fixed periodicity in their waveforms, and the amplitude and energy levels may also vary significantly, having only a certain degree of similarity in form. The autocorrelation function performs well in extracting continuous periodic signal components but is less effective in detecting and extracting non-continuous periodic noise. To address this issue, the paper proposes a method for suppressing non-continuous periodic noise. After suppressing continuous periodic noise in microseismic data, the signal is divided into multiple segments of varying lengths based on waveform characteristics, according to the waveform matching method presented in this paper. Through correlation analysis and Dynamic Time Warping (DTW) algorithm (Cai et al., 2021; Gomaa et al., 2017), these segmented signals are classified and mutually linearly eliminated, thereby achieving suppression of non-continuous periodic noise. By integrating these two steps, a better suppression effect on periodic noise in microseismic data can be achieved. To verify the effectiveness of the proposed method for removing periodic noise in microseismic data, a set of simulated data and a set of actual measured data were processed. Through result analysis, periodic noise in microseismic data was effectively suppressed, and the signal quality of microseismic data was significantly enhanced.

2 BACKGROUND PERIODIC NOISE SUPPRESSION METHOD RESEARCH

Research on Continuous Periodic Noise Suppression Methods

A stable mechanical equipment, when not affected by the external environment, should exhibit a regular periodic waveform characteristic. However, under noise interference, the periodic features can be obscured, making it difficult to separate the signal in the time domain. Conversely, in the frequency domain, the frequency value of periodic noise presents a discrete form, that is, discrete amplitude spectra or phase spectra in the frequency domain, while random noise and microseismic signals exhibit continuous amplitude spectra and phase spectra in the frequency domain. Therefore, if the discrete form phase spectra in the microseismic data frequency domain can be eliminated, the implicit periodic characteristics can be removed. The problem now becomes how to determine which frequency domain components in microseismic data spectra belong to periodic noise. This paper adopts the method of calculating the autocorrelation function of microseismic data time-domain waveform information and obtaining the frequency spectrum value of periodic noise as the frequency spectrum value of the implicit periodic noise in microseismic data. By using the autocorrelation function, which is a measure of the similarity of a signal with a time-shifted version of itself, one can identify the periodic components within the microseismic data. The discrete peaks in the autocorrelation function correspond to the periodicities in the signal, and by analyzing these peaks, one can extract the spectral components associated with the periodic noise.The auto-correlation function (ACF) of a continuous-time signal x(t) is defined as(Barot et al., 2020; Dvornik et al., 2021):

$$R_{xx}(\tau) = \lim_{T\to\infty}\frac{1}{2T}\int_{-T}^{T} x(t)x(t+\tau)dt \tag{1}$$

where τ is the time lag for continuous signals, k is the lag for discrete signals, T is the observation time for continuous signals, N is the number of samples for discrete signals, and x(t) represent the microseismic signal.The peaks in the ACF correspond to the periodicity of the signal. The lag τ or k at which the peaks occur can be related to the frequency f of the periodic noise by:

$$f = \frac{1}{P} \tag{2}$$

where P is the period of the noise, which is the inverse of the frequency. For discrete signals, the period P can be found by converting the lag k to a time interval and then finding the corresponding frequency.

The Fourier transform is used to move from the time domain to the frequency domain. For a continuous-time signal, the Fourier transform $x(f)$ is:

$$x(f) = \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft}dt \tag{3}$$

where f is the frequency. Once the frequencies associated with the periodic noise are identified, these components can be eliminated from the frequency spectrum X(f) by setting them to zero or attenuating them.After eliminating the periodic noise components, the Inverse Fourier Transform (IFT) or Inverse Discrete Fourier Transform (IDFT) is applied to obtain the noise-suppressed time-domain signal:

$$x(t) = \int_{-\infty}^{\infty} X(f)e^{j2\pi ft}df \tag{4}$$

By following these mathematical steps, the periodic noise can be effectively identified and suppressed in the microseismic data, allowing for a clearer analysis of the subsurface activity.

Research on Suppression Methods for Non-Continuous Periodic Noise

After suppressing the periodic noise in microseismic data, non-continuous periodic noise with less regular patterns may still persist. These types of noise exhibit approximate similarities in waveform shape but differ in aspects such as waveform size. Therefore, identification and elimination of non-continuous periodic noise can only be based on these approximate waveform similarities. The method employed in this paper involves segmenting the microseismic signal and using the Dynamic Time Warping (DTW) algorithm to determine if there is similar waveform information between segments and to perform linear elimination.

The DTW algorithm algorithm is a powerful technique used to measure the similarity between two temporal sequences, which may vary in speed or have time axis distortions. It is particularly useful for comparing time series data that may not be perfectly aligned in time. The DTW algorithm operates by finding an optimal match between two sequences, warping the time axis of one sequence to align with the other as closely as possible(Mantilla et al., 2017; Makarova et al., 2017; Cai et al., 2022).

Given two time series $X = \{x_1, x_2, \dots, x_N\}$ and $Y = \{y_1, y_2, \dots, y_M\}$, the first step is to create an $N \times M$ distance matrix D, where each element d_{ij} represents the distance between the points x_i and y_j. This distance is often calculated using the Euclidean distance:

$$c_{i,j} = d_{i,j} + \min(c_{i-1,j}, c_{i,j-1}, c_{i-1,j-1}) \tag{5}$$

The optimal warping path through the cumulative distance matrix C is the one that minimizes the total cumulative distance $C_{N,M}$, which is the bottom-right corner of the matrix. This path is found by backtracking from $C_{N,M}$ to the origin (0,0), following the path of minimum cumulative distance at each step.To ensure that the warping path is valid, certain constraints are often applied. One common set of constraints is to limit the path to stay within a certain diagonal band around the main diagonal, which prevents excessive warping and aligns similar points in the sequences. The total cumulative distance $C_{N,M}$ after finding the optimal path is used as a measure of similarity between the two sequences. A smaller value indicates a closer match between the sequences.

Microseismic Signal Segmentation Method

The systematic segmentation method described in this text is designed to effectively identify and separate distinct segments within a microseismic signal based on changes in its waveform characteristics. Select an appropriate window size W based on the expected frequency and periodicity of the signal. The window should be large enough to capture local features but not so large that it obscures important details. Implement a sliding window that moves along the temporal axis of the signal, starting from the beginning. The window advances in steps equal to its size W. At each position t, the window encompasses a segment S(t) of the signal.or each window position, compute a set of descriptive features F that summarize the waveform information within the window. These features may include the mean μ, variance σ^2, and energy E:

$$\begin{aligned} \mu &= \frac{1}{W}\sum_{i=1}^{W} x_i \\ \sigma^2 &= \frac{1}{W}\sum_{i=1}^{W} (x_i - \mu)^2 \\ E &= \frac{1}{W}\sum_{i=1}^{W} x_i^2 \end{aligned} \tag{6}$$

Define a change threshold θ based on the statistical properties of the signal and empirical judgment. This threshold will be used to determine when a significant change in the signal occurs. Compare the feature differences between consecutive windows to assess the degree of change in the signal. If the difference in features exceeds the threshold θ, it indicates a significant change in the signal within that window. Mark the end point of the current window as a segmentation point whenever a significant change is detected. These points are recorded and used for subsequent signal segmentation, ensuring that each segment corresponds closely to a change in the waveform of the signal. Continue this process throughout the entire signal, marking segmentation points at each significant change. Based on these points, the original signal is divided into multiple sub-segments, each containing a continuous waveform information.

Periodic Noise Suppression Within Segmented Data

For each pair of signal segments, apply DTW to each pair of segments to find the best match despite any time misalignments. Calculate the similarity S based on the total cost of the optimal DTW path, where a lower cost indicates higher similarity. Set a similarity threshold τ to determine if segments are similar enough to require processing. If the similarity S exceeds the threshold τ, the segments are considered similar. For similar segments, perform linear subtraction to eliminate the common waveform information, reducing noise.

DATA PROCESSING AND ANALYSIS

Simulation Data Analysis

To validate the effectiveness of the periodic noise suppression method proposed in this paper, we prepared a set of microseismic signal samples containing periodic noise. These samples were collected during an actual pressure construction process, with a signal sampling duration of 1 second and a sampling frequency of 500 Hz. Due to the complexity of the field environment, the data inevitably includes non-continuous periodic noise caused by various ground interference sources. The results can be seen in the figure below:

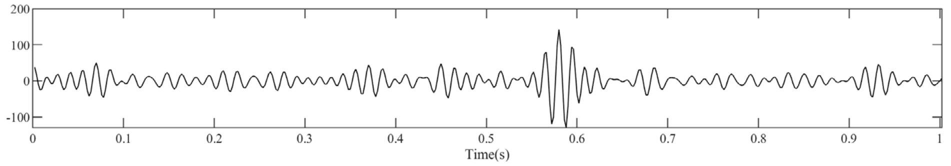

Fig. 1 Synthetic microseismic data containing discontinuous periodic noise

Subsequently, we obtained another segment of data with significant continuous periodic noise. This noise exhibits a stable periodic characteristic, allowing the periodic noise in the signal to be clearly observed, as shown in the figure below:

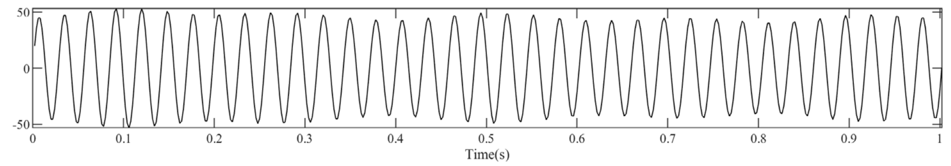

Fig. 2 Synthetic continuous periodic noise

By superimposing these two types of noise signals, we can obtain a simulated signal. The result can be seen in the figure below:

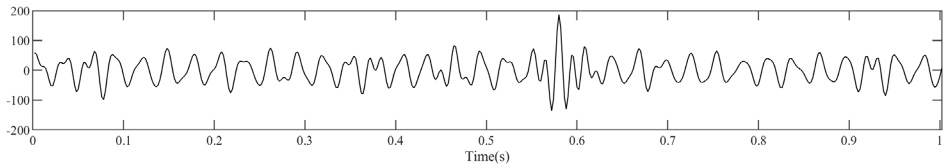

Fig. 3 Synthetic Simulation Signal

We applied the periodic noise suppression method based on the auto-correlation function to the simulated signal. We obtained its auto-correlation function, and based on this function, we were able to identify and extract the periodic components from the signal. The results can be seen in the figure below:

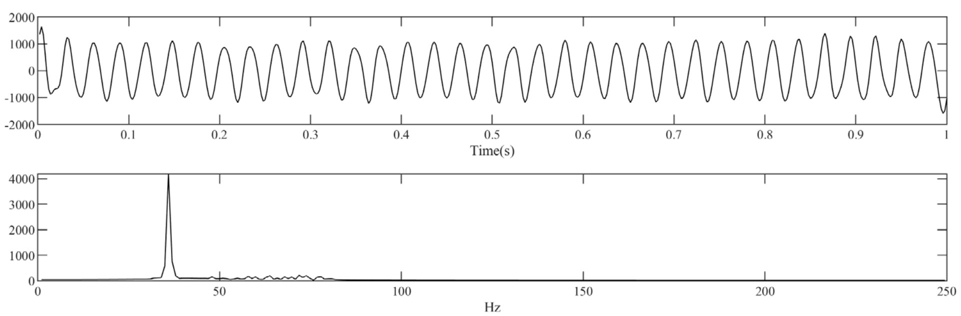

Fig. 4 Autocorrelation Function Extraction

By eliminating the discrete spectral values obtained from the auto-correlation function in the frequency spectrum of the simulated signal, we can effectively remove the periodic noise from the simulated data while preserving the useful signal information. The processing results can be seen in Figures 5 and 6:

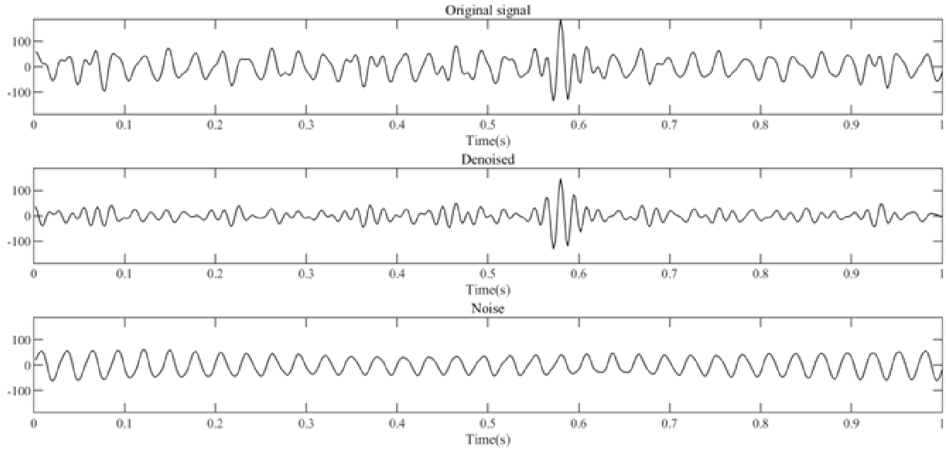

Fig. 5 Time Domain Analysis of Continuous Periodic Noise Suppression Results

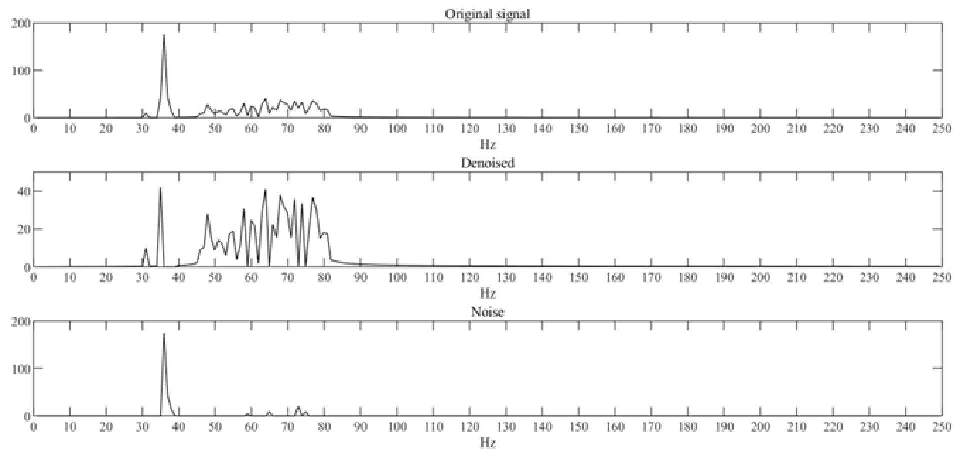

Fig. 6 Frequency Domain Analysis of Continuous Periodic Noise Results

Upon analyzing the results of the removal of periodic noise, it is observed that the continuous periodic noise is effectively suppressed. This indicates the effectiveness of the method proposed in this paper in suppressing continuous periodic noise.

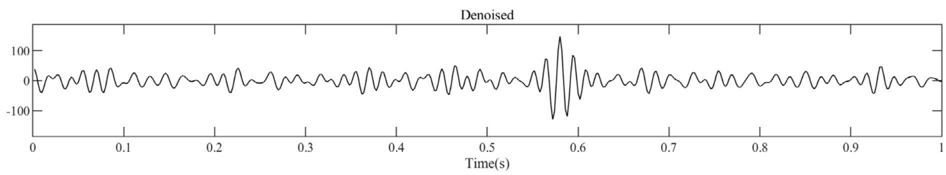

Fig. 7 Results of Continuous Periodic Noise Removal

There is a certain amount of non-continuous periodic noise present in the data, to address the non-continuous periodic noise present in the simulated data model, we employed a suppression method specifically designed for non-continuous periodic noise. A window length of 100 sample points was set, with a given change threshold of 0.8. The signal was segmented into multiple sections, and the results can be seen in the figure below:

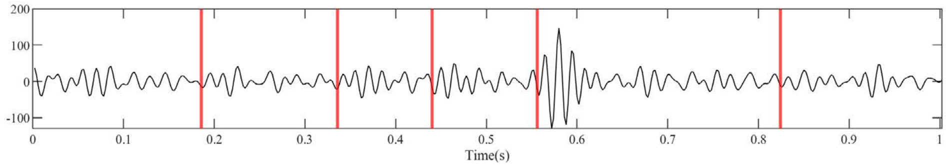

Fig. 8 Signal Segmentation Results

Using the DTW method, we obtained the similarity distances between each segment. The smaller the distance, the higher the waveform similarity between the two segments. The similarity distances between the signal segments can be seen in the figure below:

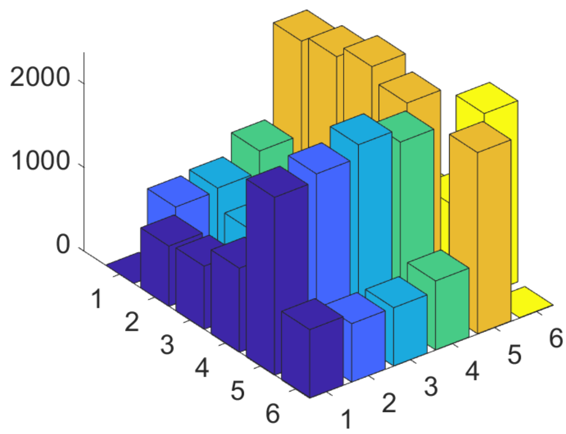

Fig. 9 Waveform Similarity Distance Between Signal Segments

By reducing the noise within the segments that are grouped as similar, we can further decrease the interference of non-continuous periodic noise, enhancing the accuracy and reliability of the signal. The final results after removing non-continuous periodic noise can be seen in the figure below:

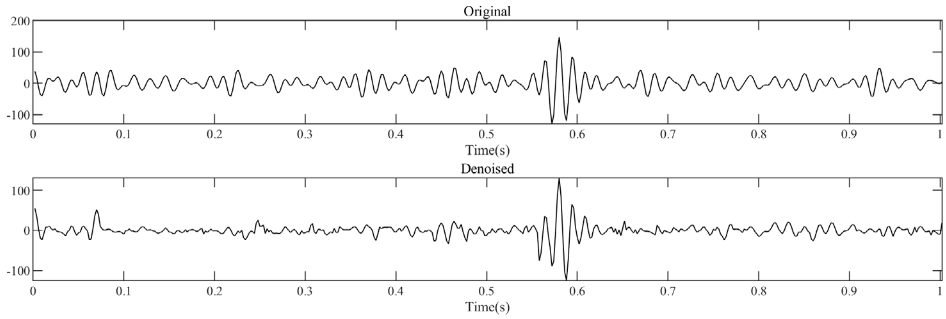

Fig. 10 Discontinuous Periodic Noise Suppression Results

Analysis of Field Data Processing

The microseismic data used comes from a tight oil and gas field in China, located in a hilly area, and hydraulic fracturing is employed for extraction. To monitor the dynamic changes in the underground reservoir, ground-based monitoring methods are used for microseismic data collection. The sampling interval is set at 0.02 seconds to ensure high-frequency resolution and accuracy of the data. A segment of microseismic data was randomly extracted from the monitoring results of a certain fracturing operation for processing. Upon observation, the actual microseismic data waveform was found to be severely interfered with by periodic noise. To address this interference, we will employ a periodic noise suppression method based on the auto-correlation function and a method for suppressing non-continuous periodic noise.

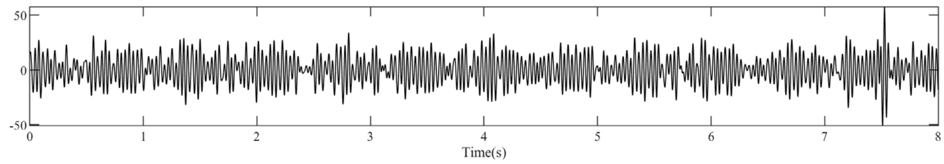

Fig. 11 Actual Noisy Microseismic Data

Firstly, we will apply the periodic noise suppression method based on the auto-correlation function to process the monitored data segment. The auto-correlation function is used to extract the regular periodic information within the data and to obtain its spectral result, as shown in the figure below:

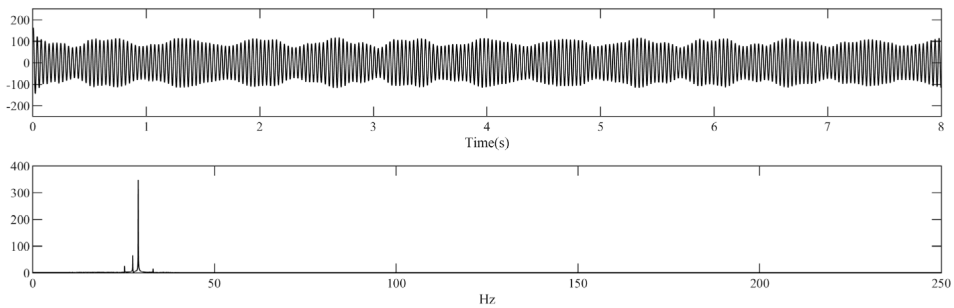

Fig. 12 Autocorrelation Function Extraction Result Analysis

Based on the spectral information of the periodic noise obtained from the auto-correlation function, we perform noise suppression in the frequency domain by setting the discrete spectral peaks in the actual microseismic data spectrum to zero. The result of the noise suppression can then be obtained. The time-domain waveform corresponding to the extracted discrete frequency spectrum represents the long-lasting periodic noise that has been removed. The time-domain and frequency-domain results of the long-lasting periodic noise removal are shown in the figures below:

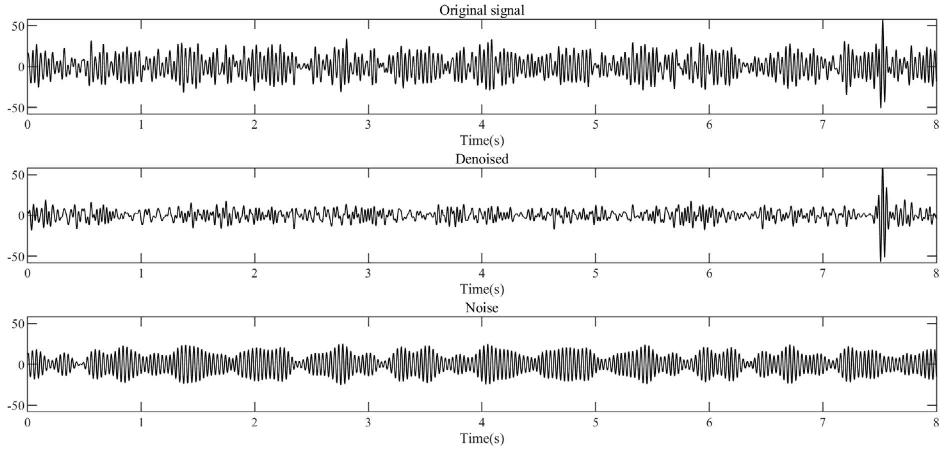

Fig. 13 Time Domain Analysis of Continuous Periodic Noise Suppression Results

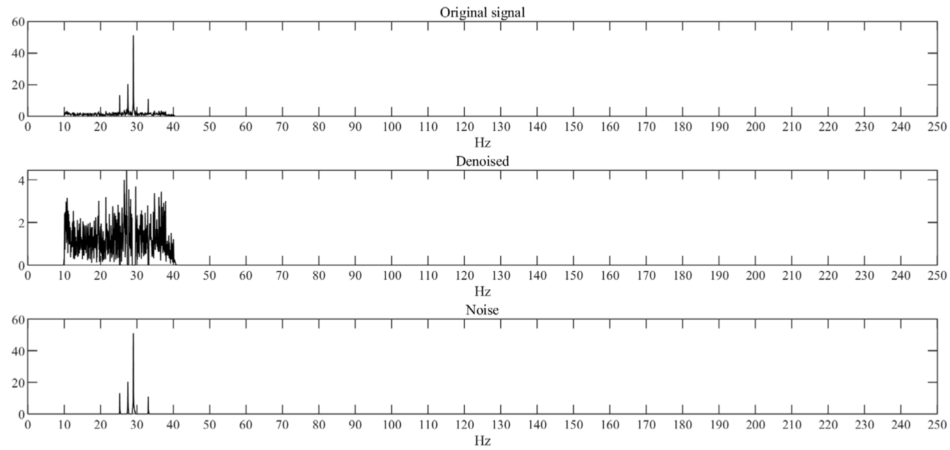

Fig. 14 Frequency Domain Analysis of Continuous Periodic Noise Suppression Results

The results of removing the long-lasting periodic noise in the microseismic data using the method proposed in this paper are shown in the figure below:

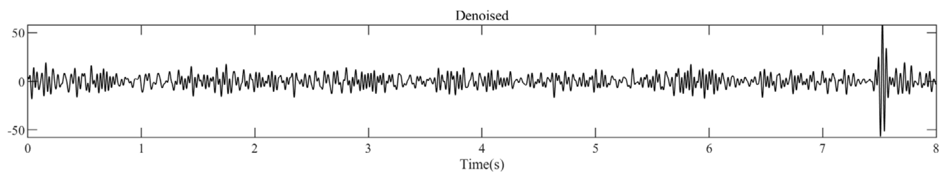

Fig. 15 Results of Continuous Periodic Noise Removal

After the aforementioned processing, we conduct a correlation analysis to determine if there is any remaining continuous periodic noise. If no continuous periodic noise is detected, the processed results are then outputted. Following the suppression of long-lasting periodic noise in the microseismic data using the method proposed in this paper, no continuous periodic noise is present in the data. However, some non-continuous periodic noise remains. To address this, we apply the non-continuous periodic noise suppression method described in this paper.The signal is first segmented into multiple sections based on the characteristics of waveform changes, and then divided by red vertical lines for segmentation, as shown in the figure below:□

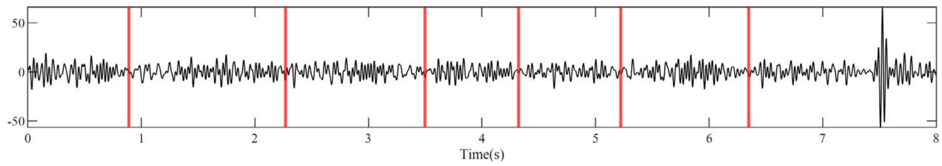

Fig. 16 Signal Segmentation Processing Results

For the segmented signals, we use the DTW algorithm to calculate the similarity distance between waveforms. The closer the similarity, the lower the height of the peak in the result, as shown in the figure below:

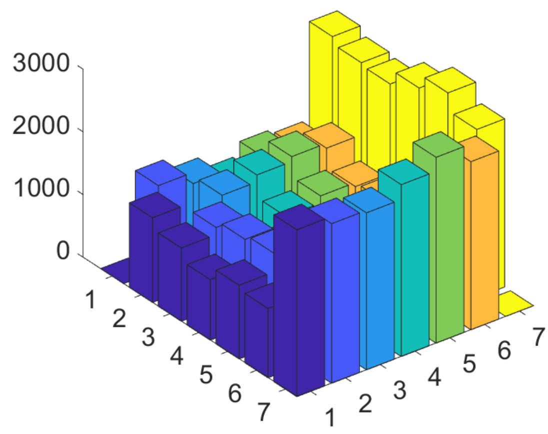

Fig. 17 Display of Waveform Similarity Distance

By reducing the signals that are classified into the same group, we can further reduce the interference of non-continuous periodic noise, enhancing the accuracy and reliability of the signal. The results after suppressing non-continuous periodic noise are shown in the figure below:

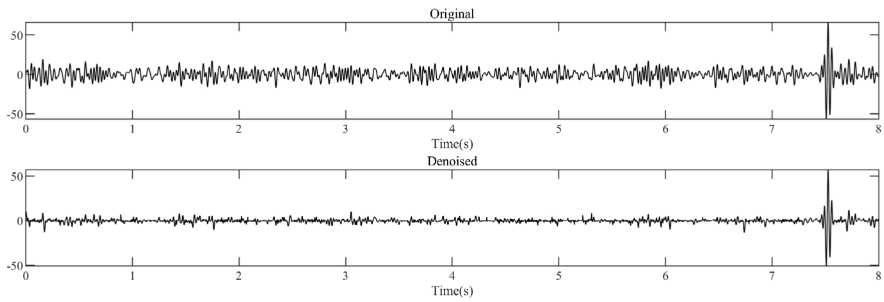

Fig. 18 Results After Suppression of Continuous Periodic Noise

Based on the analysis of actual measured data, we can conclude that the method proposed in this paper for removing periodic noise from microseismic data is effective in practical applications. By processing the data with this method, the quality of microseismic data can be significantly improved, enhancing the reliability of the signal and the extraction of valid information.

CONCLUSION

In ground monitoring of hydraulic fracturing, microseismic data is often affected by mechanical equipment and environmental noise, particularly periodic noise, which poses challenges for accurate data analysis. In response to the severe impact of periodic noise in microseismic background noise and the limitations of traditional noise suppression methods in handling precision, this paper proposes an effective method to suppress periodic noise in microseismic data, including both continuous and non-continuous periodic noise. The specific conclusions are as follows:

1. Traditional microseismic data noise suppression methods mainly target random noise and do not have specialized algorithms for dealing with periodic noise in microseismic data.

2. Correlation functions can be used to extract regular periodic functions from microseismic data, which are then transformed into the frequency domain. The frequency domain values are precisely eliminated from the original signal spectrum to suppress continuous periodic noise.

3. Microseismic data is segmented into signal segments containing multiple non-periodic waveforms based on waveform transformation characteristics. The DTW algorithm is used to calculate the similarity distances between these signal segments, and signal segments that meet the threshold criteria are matched and reduced to eliminate approximately regular noise.

4. The method proposed in this paper is highly applicable, easy to operate, and can effectively suppress periodic noise in microseismic data, improving the signal-to-noise ratio of microseismic signals.

Declarations

Consent for publication All the authors give consent for the publication.

Conflicts of interest The authors declare no conflicts of interest.

Data availability

Data will be made available on request.

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