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Research on microseismic data noise suppression method based on adaptive spectral segmentation

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Abstract

Microseismic monitoring data are characterized by strong background noise and low signal-to-noise ratio (SNR), posing challenges for effective signal identification and real-time processing. Existing methods generally suffer from poor adaptability, low processing accuracy, and insufficient computational efficiency. To address these issues, this study proposes an adaptive spectral segmentation method for microseismic signal extraction. First, the Ramanujan subspace method is employed to suppress periodic noise and eliminate spectral peak interference. Subsequently, an adaptive band number determination criterion based on the sampling rate is established, and adaptive empirical Fourier decomposition is adopted to achieve optimized spectral segmentation. Finally, the Gini coefficient is introduced to establish an adaptive threshold screening mechanism for automatic reconstruction of effective signals. For real-time processing of multi-channel data, a unified filtering strategy based on statistical overlapping bands is proposed, enabling rapid processing of subsequent data using common bands. Experiments on synthetic and field data demonstrate that the proposed adaptive spectral segmentation method yields significant advantages: on synthetic data, SNR improvements of up to 4.65 dB over modal decomposition methods (e.g., empirical mode decomposition, ensemble empirical mode decomposition, and variational mode decomposition) and wavelet packet decomposition, along with a 72% reduction in multi-channel processing time using the unified filtering strategy. These results highlight its high adaptability and practicality for low-SNR microseismic signal processing.

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1. Introduction

Microseismic signals serve as critical information for revealing subsurface medium activities and are widely applied in geological exploration and engineering monitoring.^{1,2} However, these signals typically exhibit weak energy and are severely contaminated by strong background noise, resulting in extremely low signal-to-noise ratios (SNRs) and

posing significant challenges for effective information extraction.³ Therefore, the development of adaptive denoising techniques capable of adapting to complex noise environments has become an important research direction in this field.

Regarding microseismic noise suppression, existing methods have formed multiple technical routes. Traditional fixed-band filtering methods,^{4,5} though simple to implement, often lead to effective signal loss or noise residual when facing scenarios where signal and noise bands are intertwined, due to their fixed cutoff frequencies. Adaptive filtering techniques (e.g., least mean squares algorithms and their variants,^{6,7} Kalman filtering⁸) improve adaptability through dynamic parameter adjustment; however, their performance largely depends on accurate assumptions regarding noise statistical characteristics or system models.⁹ Deep learning methods, such as convolutional neural networks (CNN) and recurrent neural networks (RNN),^{10,11} demonstrate powerful performance when sufficient training data are available. However, their generalization capability is severely limited by the completeness of training sets; when geological conditions change or noise patterns are unknown, model transfer effects are often unsatisfactory. Additionally, they face inherent limitations, including high computational resource demands and weak process interpretability.

In contrast to the aforementioned methods, modal decomposition methods—including empirical mode decomposition (EMD),¹² its noise-assisted variants (e.g., ensemble EMD [EEMD]/complete EEMD)^{13–15} designed to alleviate mode mixing, and variational mode decomposition (VMD)^{16,17} grounded in a variational framework—share a common theoretical foundation: they decompose signals into basis functions or modes according to intrinsic time–frequency characteristics without prior model assumptions. However, these methods encounter a shared fundamental bottleneck: their decomposition processes are inherently susceptible to noise interference and lack effective component screening mechanisms. Specifically, the essence of modal decomposition lies in adaptively decomposing signals into intrinsic mode functions or sub-signals, with the decomposition logic relying on the signal's own time–frequency features. Yet under strong background noise, noise energy permeates multiple components, causing severe feature aliasing between noise-contaminated modes and signal-dominant modes across both frequency and time domains.

More critically, existing methods predominantly employ statistical criteria (e.g., correlation coefficient, kurtosis, sample entropy) for component selection; however, these criteria exhibit fundamental limitations. The correlation

coefficient method requires clean signals as references, which are unavailable under low-SNR conditions. Kurtosis is sensitive to non-Gaussian noise and is prone to misclassifying impulsive noise as effective signals; sample entropy tends to identify highly random noise as “complex signals.” These theoretical limitations of the screening mechanisms ultimately force effective signal reconstruction to rely on subjective manual judgment, severely restricting the degree of automation and engineering practicality of such methods.

The recently proposed empirical Fourier decomposition (EFD) method^{18,19} provides novel insights for signal decomposition by performing band segmentation based on empirical features such as local maxima of the signal's Fourier spectrum. Compared with EMD-like methods, EFD is built upon the solid theoretical foundation of the Fourier transform, offering a more deterministic and interpretable decomposition process. In contrast to VMD, EFD adaptively partitions frequency band boundaries, circumventing the need to preset the number of modes and thus exhibiting greater flexibility for microseismic signals with unknown frequency bands. However, this segmentation strategy, which relies on fixed empirical rules, still has notable limitations. On one hand, the strong periodic noise commonly present in actual microseismic data (manifested as discrete spectral spikes) severely interferes with its empirical criteria, leading to inaccurate band segmentation. On the other hand, the EFD method itself only performs signal decomposition without incorporating mechanisms for noise identification and component screening, making it difficult to apply directly to microseismic data processing in strongly noisy environments.

To address these issues, this study proposes an adaptive spectral segmentation (ASS) method. Specifically, for microseismic monitoring data, the Ramanujan subspace method (RSM) is employed to extract and suppress periodic noise, eliminating interference from discrete spectral peaks in subsequent segmentation processes.^{20,21} Based on microseismic signal spectral characteristics, an adaptive band number determination criterion is established, and an adaptive EFD (AEFD) is adopted to achieve optimized band segmentation. The Gini coefficient is introduced as a sparsity measure for components, and an adaptive threshold screening mechanism is established to automatically identify and reconstruct effective microseismic signals through superposition.

For processing multi-channel microseismic data, the overlapping band ranges from each channel are further statistically analyzed and used as the effective signal band for the entire fracturing monitoring segment. Based on this

unified band, rapid bandpass filtering can be implemented for subsequent microseismic data, significantly improving processing efficiency while also correcting single-channel data with poor reconstruction results, thereby ensuring the reliability and consistency of overall denoising effects. To validate the effectiveness of the ASS method, this study processes both synthetic and field data, conducting comparative analyses with traditional methods including EMD, EEMD, VMD, and wavelet packet decomposition (WPD). The results demonstrate that the ASS method exhibits excellent performance in improving SNR, maintaining signal waveform integrity, and adapting to complex noise environments, providing a highly adaptive and practical solution for microseismic monitoring data processing.

2. Methodology

The primary objective of this study is to suppress background noise in microseismic data to improve the SNR and enhance the identifiability of effective signals. To achieve this, we propose an ASS method. Its core idea is to automatically identify and reconstruct signal-dominated spectral components through a three-stage process: (i) periodic noise suppression using the RSM to eliminate discrete spectral interference; (ii) AEFD to partition the spectrum into meaningful bands based on the signal's sampling rate and spectral characteristics; and (iii) automatic component screening based on the Gini coefficient to select and reconstruct effective signals. The overall workflow of the ASS method is illustrated in [Figure 1](#).

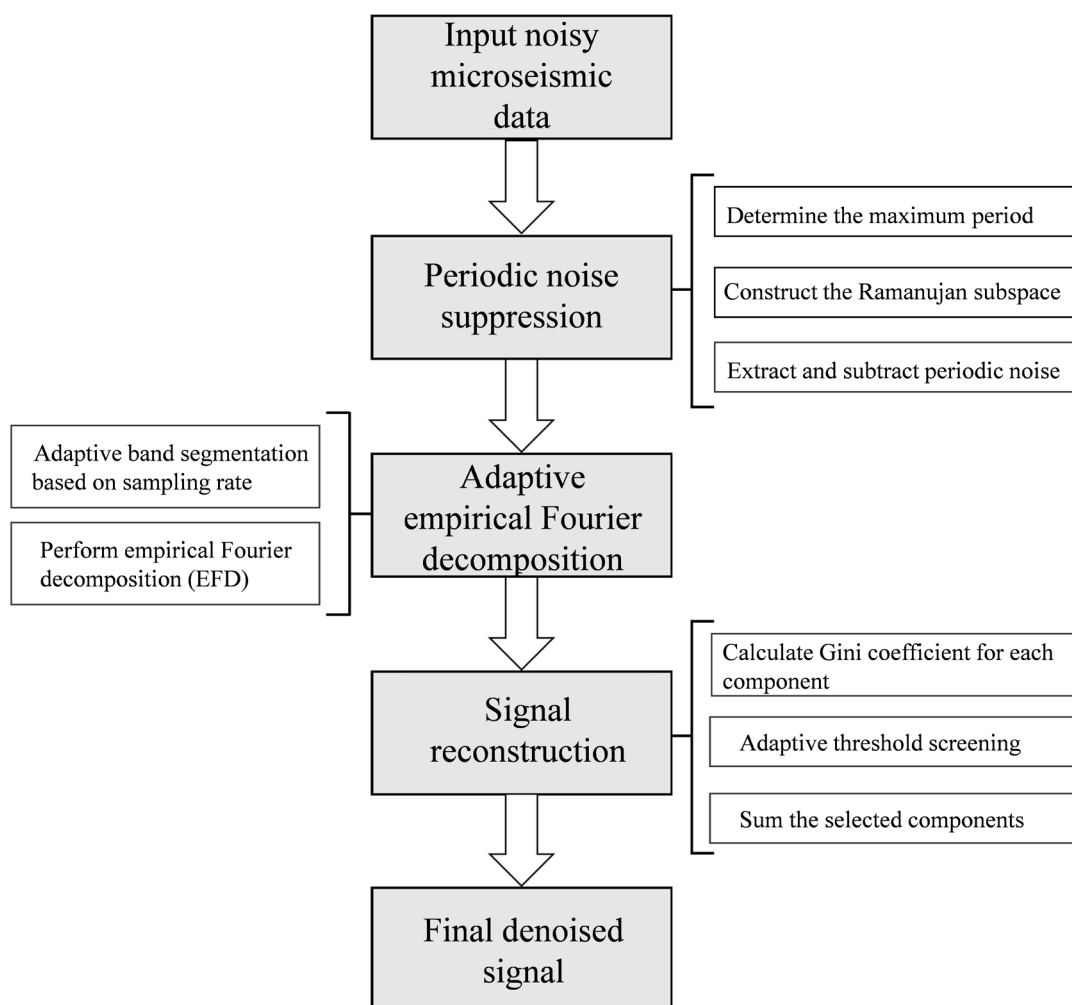


Figure 1. Flowchart of the proposed method

2.1. Periodic noise suppression

Periodic noise (e.g., power frequency interference and mechanical vibration) manifests as discrete spectral spikes in microseismic data, severely interfering with the accuracy of spectral segmentation. This study employs the RSM for periodic noise extraction and suppression.²² First, potential periodic components are identified based on the signal autocorrelation function. Let the microseismic signal be denoted as $x(n), n = 0, 1, \dots, N-1$. Its autocorrelation function is defined as:

$$R_{xx}(\tau) = \frac{1}{N} \sum_{n=1}^{N-k} x(n)x(n+k) \quad (1)$$

where τ represents the time lag. The peaks of $R_{xx}(\tau)$ correspond to periodic components in the signal. The threshold is set to 70% of the maximum autocorrelation function value (determined through sensitivity analysis), and the maximum lag exceeding this threshold is recorded as the maximum period P_{max} of the periodic noise.

After determining the maximum period P_{max} , the Ramanujan subspace is constructed based on $R_{xx}(\tau)$. The Ramanujan subspace is composed of Ramanujan sums $C_T(n)$, defined as:

$$C_T(n) = \sum_{\substack{k=1 \\ \gcd(k,T)=1}}^T e^{j2\pi kn/T} \quad (2)$$

where n is the index, T is equal to P_{max} , $\gcd(k, T)$ is the greatest common divisor of K and T , and $\gcd(k, T) = 1$ indicates that K and T are coprime.

The orthogonal projection of the signal x onto the Ramanujan subspace can be represented as:

$$x_T = B_T x / T \quad (3)$$

where B_T is the Ramanujan subspace matrix.

The periodicity measure $P(x_T, T)$ is calculated to identify and extract periodic noise, where this measure is determined by selecting basis vectors with relatively high energy in x_T . The periodic noise $x_{periodic}$ is reconstructed and subtracted from the original signal to obtain the preprocessed signal:

$$\tilde{x} = x - x_{periodic} \quad (4)$$

2.2. Adaptive empirical Fourier decomposition

Conventional EFD methods typically employ a fixed band

number for segmentation, making it difficult to adapt to variations in sampling rates and signal characteristics.^{18,19} For microseismic monitoring data, this study proposes an adaptive band number determination method based on the signal sampling rate. The preprocessed signal $\tilde{x}(t)$ is subjected to Fourier transform to obtain its spectrum $\tilde{X}(f)$: $\tilde{X}(f) = \mathcal{F}[\tilde{x}(t)]$. Here, $\mathcal{F}$ denotes the Fourier transform operation. For microseismic data with sampling rate f_s , the Nyquist frequency is $f_N = f_s/2$, and the spectral analysis range is $[0, f_N]$.

According to the energy distribution characteristics of microseismic signals, the effective frequency band range of microseismic signals typically does not exceed 60 Hz. To ensure that band segmentation covers the full frequency domain while maintaining the integrity of signal characteristics within individual bands, this study establishes the following adaptive band number determination criterion:

$$K = \left\lfloor \frac{f_s/2}{60} \right\rfloor = \left\lfloor \frac{f_s}{120} \right\rfloor \quad (5)$$

where $\lfloor \cdot \rfloor$ denotes the floor operation, and K is the band number. The physical significance of this criterion is: using 60 Hz as the characteristic bandwidth unit, the Nyquist frequency range is divided into several continuous bands. This adaptive mechanism ensures that under different sampling rate conditions, band segmentation can match the spectral characteristics of microseismic signals, avoiding over-decomposition (for high sampling rates) or under-decomposition (for low sampling rates) problems caused by fixed band numbers. It should be noted that the 60 Hz characteristic bandwidth originates from the spectral properties of hydraulic fracturing microseismic signals—effective event energy typically concentrates below 100 Hz, with dominant frequency bands often below 60 Hz. This observation is consistent with numerous studies in this field.^{22,23}

From a signal processing perspective, setting the characteristic bandwidth to 60 Hz ensures that the Nyquist frequency range ($f_s/2$) is divided into sufficiently fine bands to capture detailed spectral structures of effective signals, while avoiding excessive computational costs and spectral fragmentation from over-decomposition. The adaptive mechanism in **Equation 5** automatically adjusts the band number K according to the sampling rate, ensuring consistent physical interpretation of “one band per 60 Hz” across different acquisition systems.

It is important to emphasize that the 60-Hz value is not a fixed parameter, but a configurable prior that can be adapted to different applications. For example, natural

seismic signals with higher frequency content may require a larger unit, whereas mining-induced microseismicity with lower dominant frequencies may benefit from a smaller one. To validate this configurability and the appropriateness of the 60-Hz setting, we conducted a sensitivity analysis using bandwidths of 30 Hz, 80 Hz, and 120 Hz as the lower and upper limits. The results confirm that 60 Hz provides the optimal balance between resolution and robustness: 30 Hz leads to excessive spectral fragmentation ($K = 8$), while 80 Hz ($K = 3$) and 120 Hz ($K = 2$) suffer from insufficient resolution, causing signal-noise mixing. Therefore, 60 Hz was chosen as the default parameter used throughout the study.

The spectral maximum points $\{f_{peak}^{(m)}\}_{m=1}^M$ are selected and combined with initial uniform division boundaries $f_k^{(0)} = k \cdot f_s / (2K)$ uniform to optimize band boundaries:

$$f_k = \arg \min_{f_{peak}^{(m)}} |f_{peak}^{(m)} - f_k^{(0)}|, \quad \text{s.t. } |f_{peak}^{(m)} - f_k^{(0)}| < \frac{f_s}{4K} \quad (6)$$

A zero-phase filter bank $H_k(f)$ is constructed, and each band is filtered and inverse transformed to reconstruct time-domain components:

$$\hat{X}_k(f) = \hat{X}_{pre}(f) \cdot H_k(f), \quad x_k(t) = \mathcal{F}^{-1}[\hat{X}_k(f)] \quad (7)$$

yielding K band components $\{x_k(t)\}_{k=1}^K$.

2.3. Signal reconstruction and output

Automatically selecting effective microseismic signal components from the K components requires establishing a discrimination criterion. Microseismic signals exhibit significant sparsity (energy concentrated in a few sampling points), while noise energy is relatively uniformly distributed. The Gini coefficient can effectively measure this characteristic. The Gini coefficient is a statistical measure that quantifies the degree of inequality in a probability distribution. Its value ranges between 0 and 1, where a smaller value indicates a more uniform distribution, and a larger value indicates a more uneven distribution. In the fields of signal processing and machine learning, the Gini Coefficient is commonly used to assess the concentration of feature values.^{24,25} The calculation steps for the Gini coefficient are as follows:

For a given signal $f_k^{(0)} = k \cdot f_s / (2K)$, the steps to calculate its Gini coefficient $G(x)$ are:

- (i) Step 1: First, sort the absolute values of the signal in ascending order to obtain $x' = [x'_1, x'_2, \dots, x'_n]$, $x'_i \leq x'_{i+1}$.
- (ii) Step 2: Compute the cumulative sum of the sorted signal: $S_i = \sum_{j=1}^i x'_j$.

- (iii) Step 3: Compute the total sum of the absolute values of the signal: $S = \sum_{i=1}^n x_i$.
- (iv) Step 4: The Gini coefficient $G(x)$ is given by the following formula:

$$G(x) = \frac{1}{n-1} \left(n + 2 \sum_{i=1}^n \frac{i}{n} \frac{S_i}{S} - 2 \right) \quad (8)$$

This study proposes an adaptive threshold based on statistical distribution:

$$G_{th} = \mu_G + \alpha \cdot \sigma_G \quad (9)$$

where $\mu_G = \frac{1}{K} \sum_{k=1}^K G_k$, $\sigma_G = \sqrt{\frac{1}{K} \sum_{k=1}^K (G_k - \mu_G)^2}$. σ is a tuning coefficient (typically ranging from 0.5 to 1.0, with a default value of 0.8). Lower σ increases threshold stringency, reducing false positives but risking signal loss; higher σ relaxes threshold, improving signal completeness but increasing noise retention. The default $\sigma = 0.8$ is validated through sensitivity analysis as providing optimal balance for typical microseismic SNR ranges. This threshold dynamically adjusts according to data characteristics, enhancing the algorithm's robustness. Components that satisfy condition $G_k > G_{th}$ are selected for superposition reconstruction:

$$x_{signal}(t) = \sum_{k \in \mathcal{K}_{valid}} x_k(t), \quad \mathcal{K}_{valid} = \{k | G_k > G_{th}\} \quad (10)$$

The reconstructed signal constitutes the final denoising result. To validate the effectiveness of the method proposed in this section, we designed a set of experiments, including microseismic signals, periodic noise, and random noise. Specifically, the periodic noise was composed of sinusoidal signals with an amplitude of 0.5 and frequencies of 30 Hz and 130 Hz; the random noise was Gaussian white noise, and the microseismic signals were based on real, clean microseismic data.

We calculated the Gini coefficient and sample entropy values for these signals and conducted a comparative analysis. Sample entropy is a common parameter for measuring the complexity of time series, which reflects signal complexity by estimating the probability of new pattern generation within the time series. A larger sample entropy value indicates a more chaotic waveform, higher frequency, and greater complexity of the signal; conversely, a smaller sample entropy value suggests a more regular pattern and lower complexity of the signal. Specific details are illustrated in Figure 2.

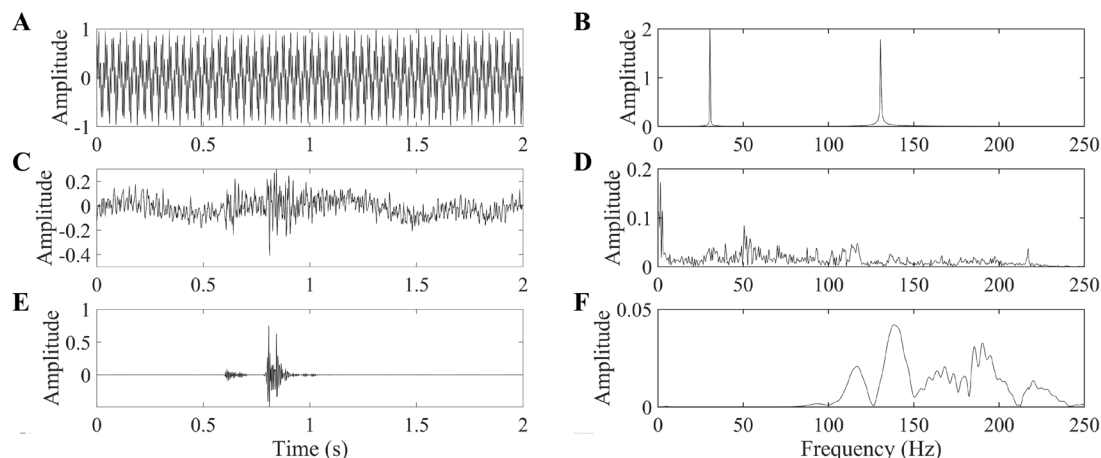


Figure 2. Composition of synthetic data. (A, C, E) The time-domain waveforms of (A) periodic noise, (C) random noise, and (E) the clean microseismic signal. (B, D, F) The corresponding frequency spectra of (B) periodic noise, (D) random noise, and (F) the clean microseismic signal.

We calculated the sample entropy and Gini coefficient for these three types of signals, and the results are shown in Figure 3. Sample entropy is a commonly used indicator for measuring the complexity of time series, reflecting the randomness and structural complexity of a signal by assessing the likelihood of new pattern generation within the sequence. A higher sample entropy value indicates a more irregular signal with more complex dynamic characteristics; conversely, it suggests that the signal pattern tends to be more regular.

The experimental results show that the Gini coefficient performs well in distinguishing the three types of signals: the maximum Gini coefficient appears in Group 3, corresponding to the real microseismic signal, while the Gini coefficients for periodic noise and random noise are relatively lower. In contrast, sample entropy failed to accurately identify the microseismic signal, with its maximum value appearing in Group 2 (random noise), indicating that sample entropy tends to misclassify highly random noise as “complex signals.” This demonstrates that, in the task of microseismic signal identification, the Gini coefficient possesses higher discriminative accuracy and robustness.

3. Application

3.1. Processing of simulated data

The synthetically generated microseismic data were used to mimic actual monitoring environments, with a sampling

frequency of 500 Hz. The noise composition was designed based on the dominant interference characteristics observed in hydraulic fracturing monitoring: (i) periodic noise from pumping equipment, power lines, and mechanical vibrations, which manifests as discrete spectral spikes; and (ii) random background noise from environmental sources and sensor electronics, which exhibits broadband Gaussian characteristics.

Based on field data analysis from the southwestern China monitoring site (Section 3.2), these two noise types collectively account for approximately 80–90% of the total noise energy in typical surface and near-surface microseismic arrays. Pulse noise (e.g., from electrical discharges, traffic, or drilling operations) and non-stationary harmonic interference, while present in some field conditions, represent secondary contamination sources whose suppression will be addressed in subsequent work.

Random noise was modeled as Gaussian white noise, and periodic noise was synthesized from sinusoidal signals with frequencies of 30 Hz and 130 Hz, respectively. The experiment sets the SNR to -19 dB. This value was selected to approximate the typical low-SNR conditions encountered in field microseismic monitoring, with the noise energy adjusted accordingly based on this SNR. The final synthesized simulated signal has a duration of 2 s. The structural composition of the simulated data and its spectral information are shown in Figure 4. The definitions of SNR and mean squared error (MSE) are as follows:

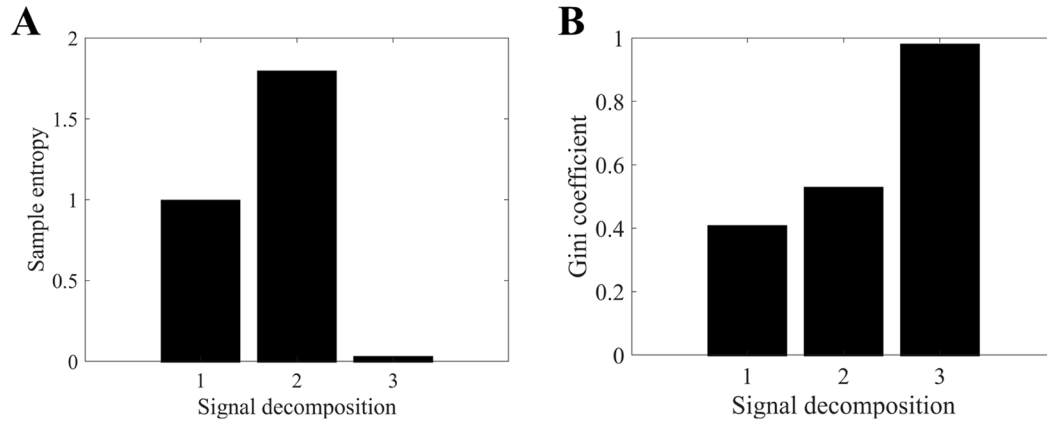


Figure 3. Comparison of (A) sample entropy and (B) Gini coefficient across the three types of signals

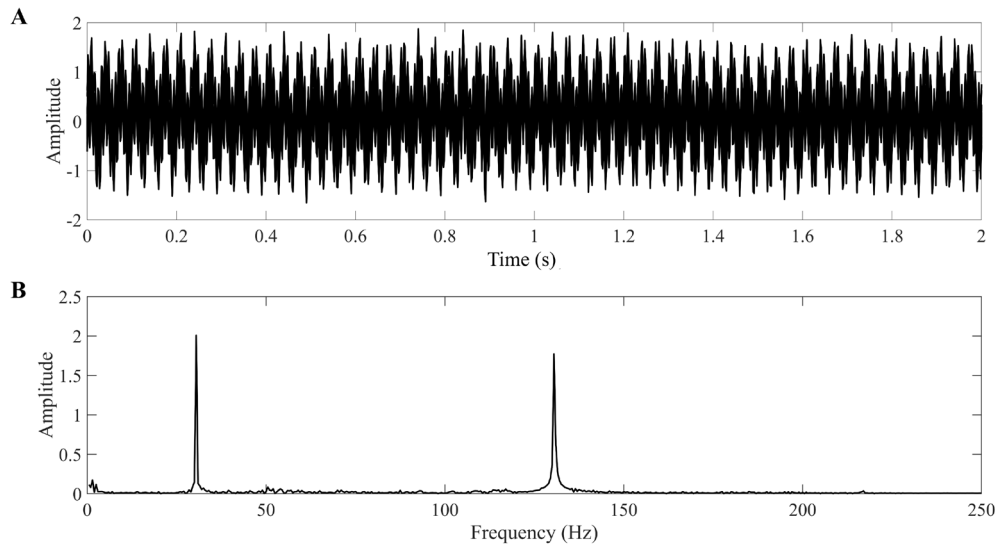


Figure 4. Synthetic simulated data showing the (A) time-domain waveform and (B) the frequency-domain spectrum.

$$SNR = 10 \lg \left(\sum_{t=1}^N \frac{F(t)^2}{(\hat{F}(t) - F(t))^2} \right) \quad (11)$$

$$MSE = \frac{1}{N} \sum_{t=1}^N (F(t) - \hat{F}(t))^2 \quad (12)$$

where $F(t)$ is the clean signal, $\hat{F}(t)$ is the noisy data, and N is the length of the signal $F(t)$, that is, the number of sampling points.

Periodic noise components were clearly observed in the synthetic data, which were processed using the proposed Ramanujan subspace method. First, periodic components were identified through autocorrelation function

analysis, with the threshold set to 70% of the maximum autocorrelation value, determining the maximum period as 50 sampling points (Figure 5). Based on this period, the Ramanujan subspace was constructed, and periodic noise components were extracted for spectral analysis. Results showed that the extracted noise spectrum was consistent with the preset 30 Hz and 130 Hz sinusoidal noise (Figure 6). After subtracting the extracted periodic noise from the original data, the denoised signal was obtained (Figure 7), demonstrating that periodic noise was effectively suppressed while the waveform and spectral structure of the effective signal remained intact.

To verify the rationality of the 70% threshold selection, processing effects under different thresholds (50%, 60%,

70%, 80%, and 90%) were tested. Results indicated that thresholds below 70% led to incomplete periodic noise removal, while thresholds above 70% increased the loss of effective signal; 70% was the optimal balance point (see Table 1). The 70% threshold used for periodic component detection in the autocorrelation function is determined based on sensitivity analysis of the synthetic data in this study. While this value proves effective for the hydraulic fracturing microseismic data, its optimal setting may vary across different application scenarios depending on the relative strength and characteristics of periodic noise.

In practice, this threshold can be adjusted according to two guiding principles: (i) if periodic noise components are exceptionally strong and well-separated from the signal in the frequency domain, a lower threshold (e.g., 60%) may suffice for reliable detection; (ii) if periodic noise is weak or spectrally overlapping with the signal, a higher threshold (e.g., 80%) is recommended to avoid false detection and signal distortion.

After completing periodic noise suppression, the AEFD method was applied to the processed data for frequency-domain segmentation. Based on the adaptive band-number determination criterion proposed in this study (Equation 5), the 0–250 Hz frequency range was partitioned into four bands. The segmentation results are shown in Figure 8. Zero-phase filters were constructed for each band, and the corresponding time-domain signals were reconstructed, yielding four time-domain signal components associated with distinct frequency bands, as shown in Figure 9.

To validate the appropriateness of the 60 Hz characteristic bandwidth, a sensitivity analysis was

performed using bandwidth settings of 30 Hz, 80 Hz, and 120 Hz as the lower and upper limits. These settings resulted in band numbers of 8, 3, and 2, respectively, according to Equation 5. The corresponding spectral segmentation results are presented in Figure 10. A qualitative assessment of segmentation performance indicates that the 60–80 Hz range provides an appropriate balance between resolution and completeness. The 30 Hz setting leads to excessive fragmentation ($K = 8$), dispersing effective signal energy across multiple adjacent bands, whereas the 120 Hz setting results in insufficient resolution ($K = 2$), causing merging of signal and noise components. In contrast, both the 60 Hz ($K = 4$) and 80 Hz ($K = 3$) configurations preserve the effective signal within one or two contiguous bands, thereby confirming the adaptability and robustness of the proposed criterion.

To select effective signals from each component, the Gini coefficient of each component was calculated (Figure 11). According to the adaptive threshold determination method (Equation 9), for this dataset $G_1 = 0.62$, $G_2 = 0.58$, and a $G_3 = 0.86$, with $\alpha = 0.8$, the resulting threshold was $G_{th} = 0.8$. Components satisfying $G_k > G_{th}$, specifically the third component, were identified as effective signals and reconstructed. These were superimposed and reconstructed as the final denoising signal.

As shown in Figure 12, after processing, the signal SNR improved from -19 dB to 3.11 dB, and the MSE decreased to 0.0073 . Compared with the original noisy signal, background noise was significantly suppressed, and the waveform characteristics of effective microseismic signals became clearly distinguishable.

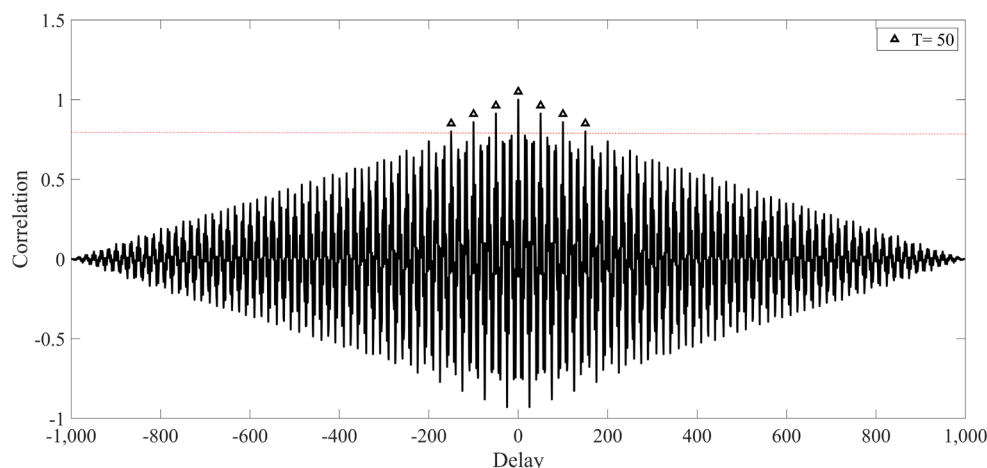


Figure 5. Autocorrelation function and period extraction results

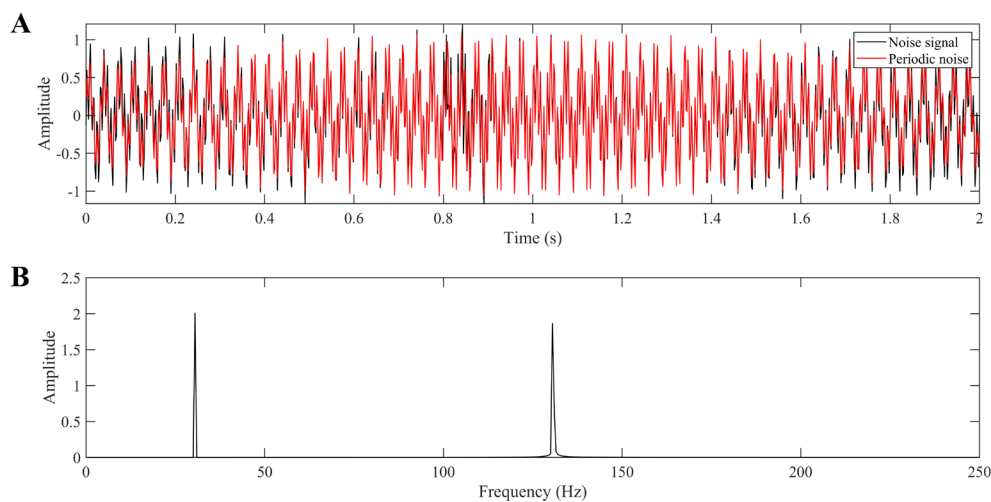


Figure 6. Extracted periodic noise and its spectrum. (A) The time-domain waveform. (B) The frequency-domain spectrum.

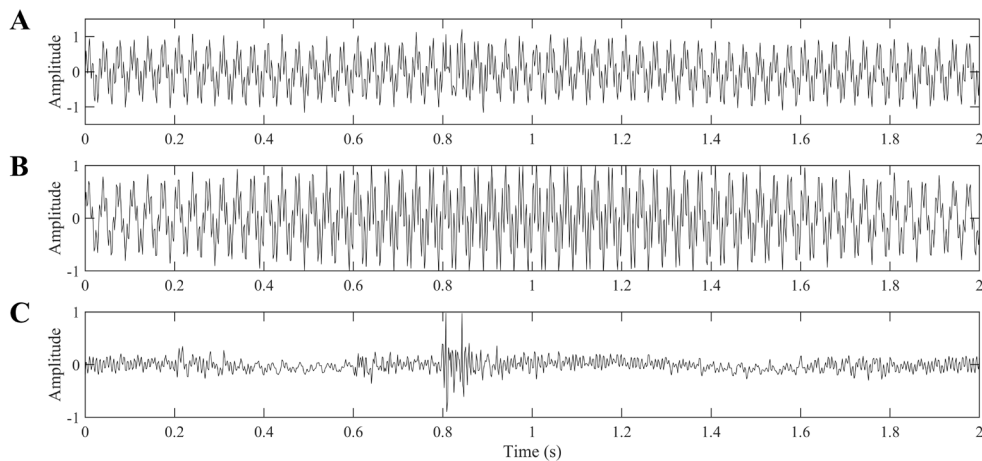


Figure 7. Periodic noise suppression of (A) simulated data, (B) the removed periodic noise, and (C) the denoised results.

Table 1. Sensitivity analysis of period detection threshold

Threshold coefficient	Periodic noise removal rate (%)	Effective signal fidelity (%)
0.5	62.3	98.7
0.6	78.5	97.2
0.7 ^a	94.2 ^a	95.8 ^a
0.8	96.8	89.1
0.9	98.5	82.3

Note: ^a indicates the optimal parameter result.

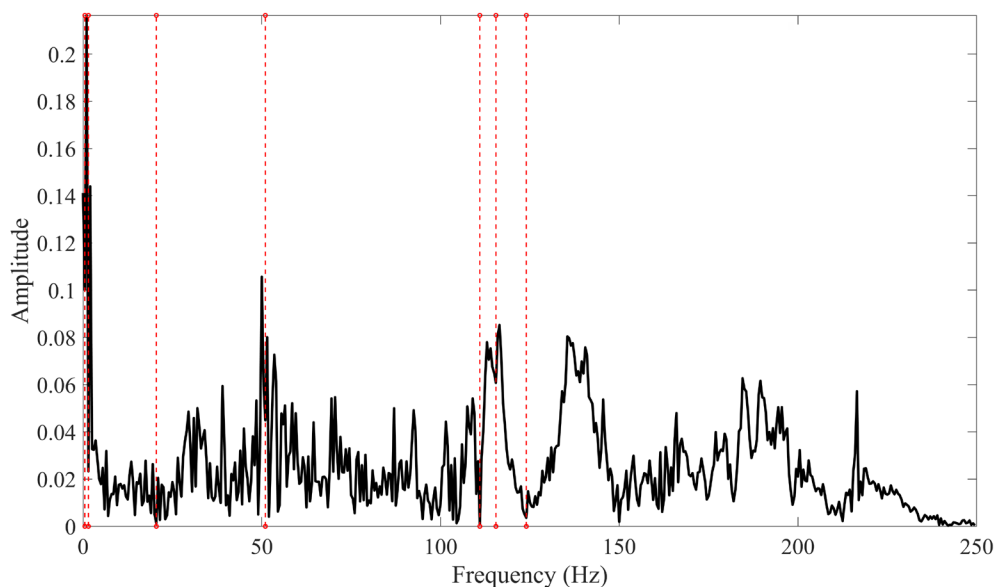


Figure 8. Frequency-domain segmentation

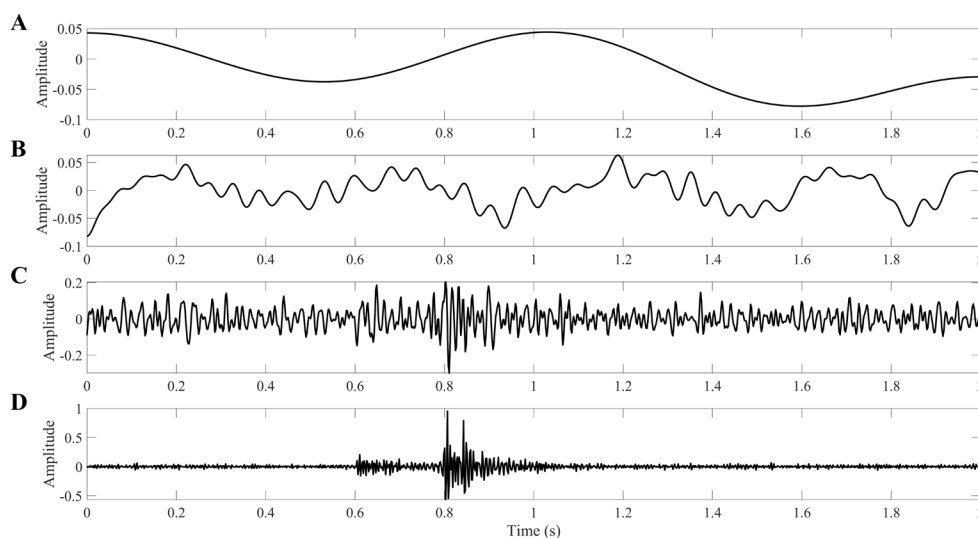


Figure 9. Waveforms corresponding to different segmented frequency bands. (A) 0–2 Hz, (B) 2–20 Hz, (C) 20–110 Hz, and (D) 110–250 Hz.

The adaptive threshold in **Equation 9** employs a tuning coefficient σ (default = 0.8) to balance signal preservation and noise rejection. To evaluate the stability of the algorithm with respect to this parameter, σ was systematically varied within the range [0.5, 1.0], and denoising performance was evaluated on the synthetic dataset. The results are presented in [Table 2](#).

Based on [Table 2](#), performance varies moderately with λ in the range [0.6, 1.0], with $\sigma = 0.8$ achieving the optimal

balance, including the lowest MSE (0.0035), the highest signal preservation (95.6%), and an acceptable SNR (2.11 dB). While $\sigma = 0.9$ yields a slightly higher SNR (3.01 dB), it results in increased MSE and reduced signal retention, indicating over-thresholding and the rejection of valid components. Conversely, $\sigma \leq 0.7$ leads to insufficient noise rejection. These results demonstrate that the algorithm maintains robust performance within $\sigma \in [0.7, 0.9]$, with 0.8 selected as the default for the studied microseismic

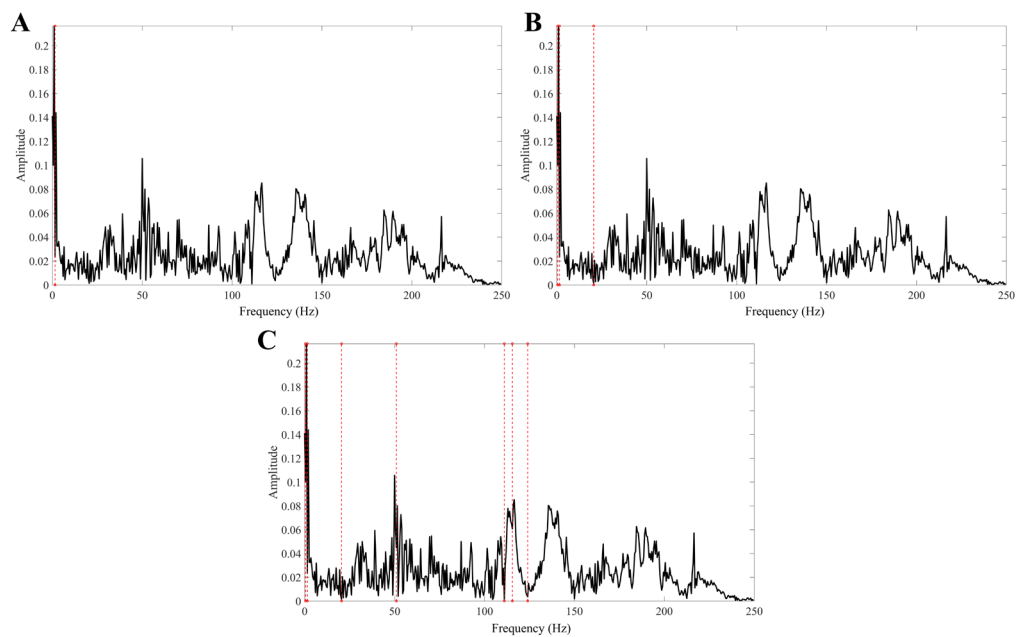


Figure 10. Results of spectral segmentation using different bandwidth units. (A) 120 Hz ($K = 2$), (B) 80 Hz ($K = 3$), and (C) 30 Hz ($K = 8$).

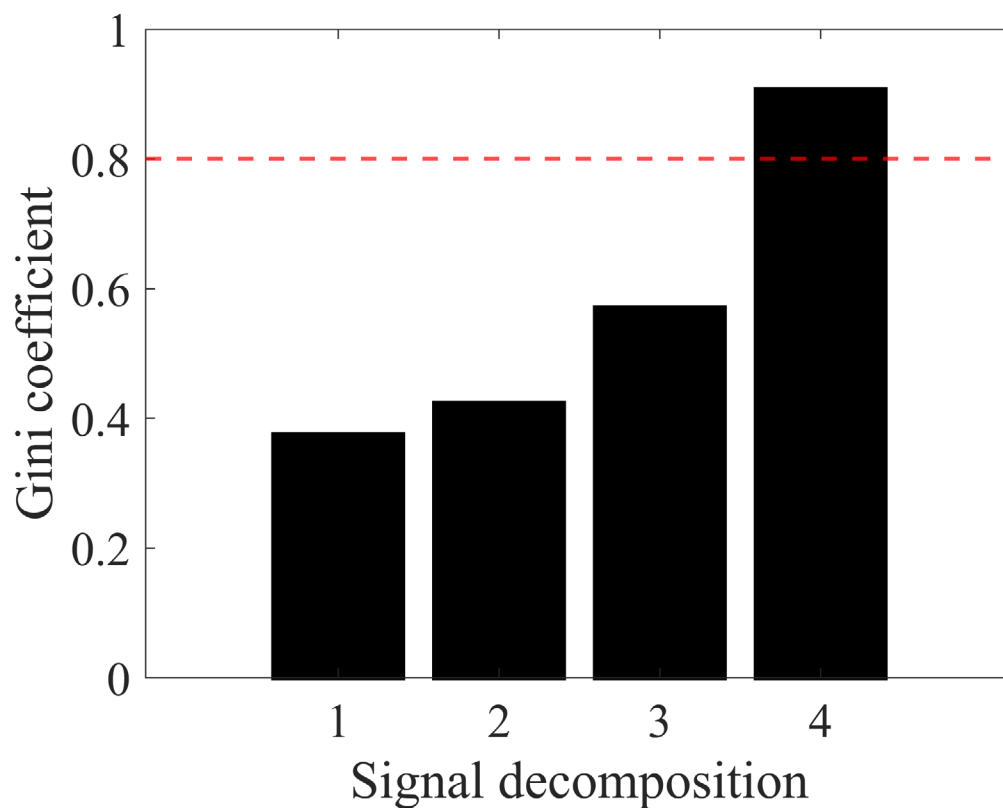


Figure 11. Gini coefficients calculated across different frequency ranges

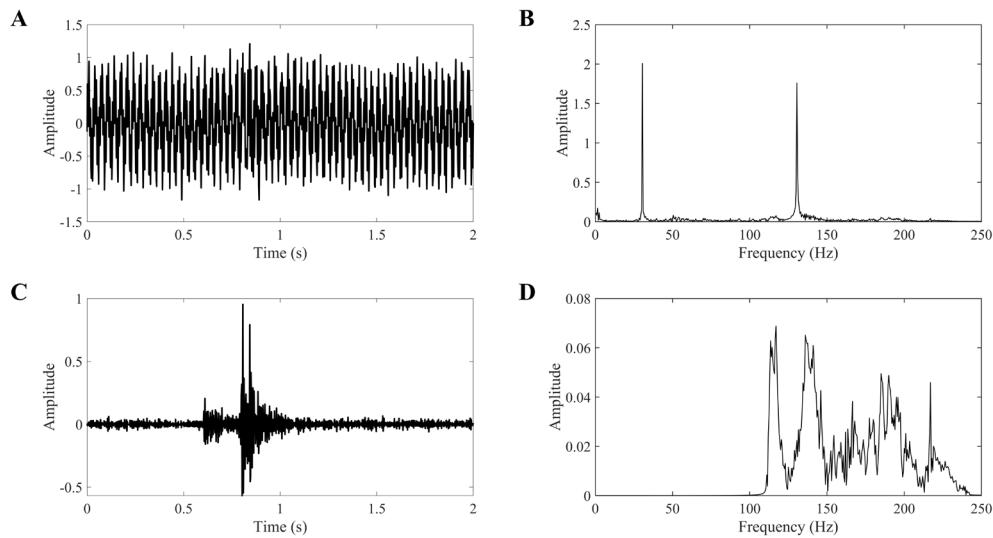


Figure 12. Results obtained using the adaptive spectral segmentation method. (A) original signal and (B) its frequency spectrum, and (C) denoised signal and (D) its frequency spectrum.

Table 2. Sensitivity analysis of Gini coefficient threshold parameter σ

Threshold	Output signal-to-noise ratio (dB)	Mean squared error	Signal preservation rate (%)
0.6	1.85	0.0081	77.1
0.7	2.16	0.0076	80
0.8 ^a	2.11 ^a	0.0035 ^a	95.6 ^a
0.9	3.01	0.0075	79.6
1.0	2.34	0.0097	75

Note: ^a indicates the optimal parameter result.

data.

To illustrate the necessity of periodic noise suppression, a comparison was conducted using only AEFD processing (without periodic noise suppression). As shown in Figures 13 and 14, interference from periodic spectral peaks degrades the frequency-domain segmentation performance of AEFD, resulting in residual noise in the reconstructed waveforms and reduced denoising effectiveness (SNR = -5.23 dB, MSE = 0.0415). This comparison demonstrates the importance of incorporating periodic noise preprocessing prior to AEFD.

Empirical mode decomposition, EEMD, and VMD were used as comparative methods to process the same simulated data. The parameters for each method were set

as follows: EEMD noise standard deviation = 0.2, iteration count = 100; VMD bandwidth constraint = 2,000, noise tolerance = 0, mode number = 4, convergence tolerance = 1×10^{-7} . WPD was additionally employed, using the Daubechies 8 (db8) wavelet with decomposition level 4, soft thresholding with “sqrtwolog” universal threshold, and Shannon entropy-based optimal basis selection. The decomposition results and reconstructed signals after Gini coefficient screening are shown in Figure 15. From the time-domain waveforms and frequency spectrum comparisons, while traditional methods partially suppress noise, they suffer from mode mixing, residual periodic noise, and wavelet-induced artifacts, leading to signal distortion.

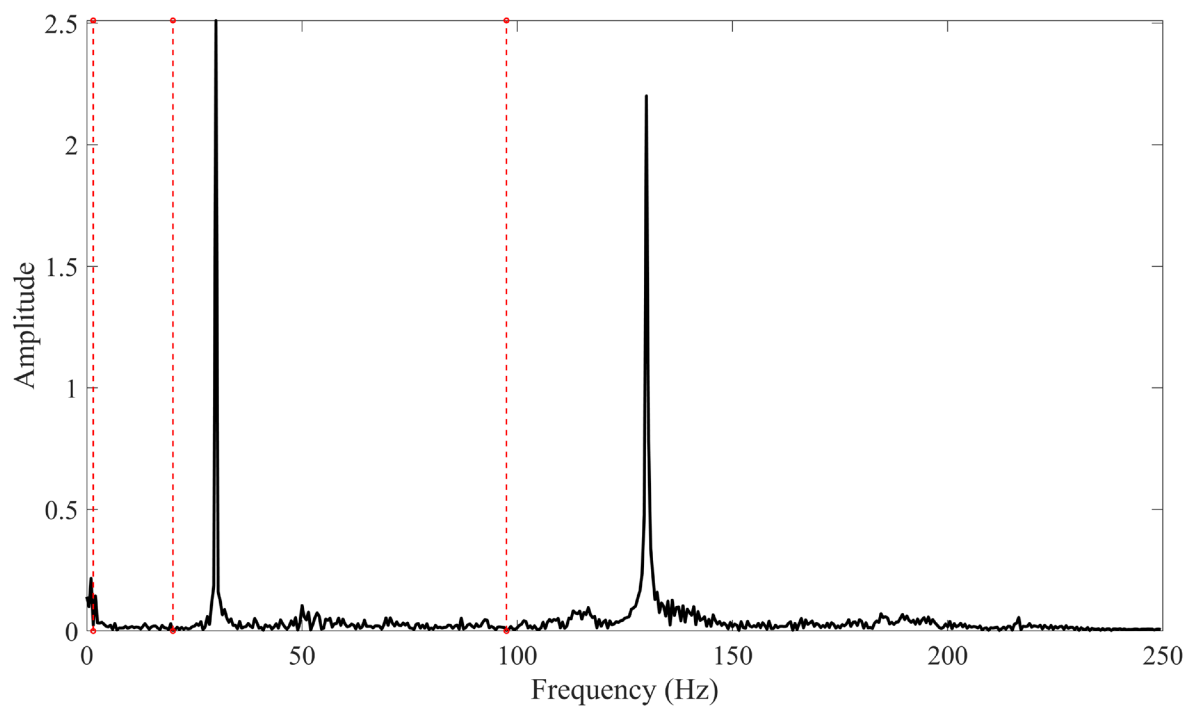


Figure 13. Frequency-domain segmentation results obtained by applying adaptive empirical Fourier decomposition directly to the original data without periodic noise suppression

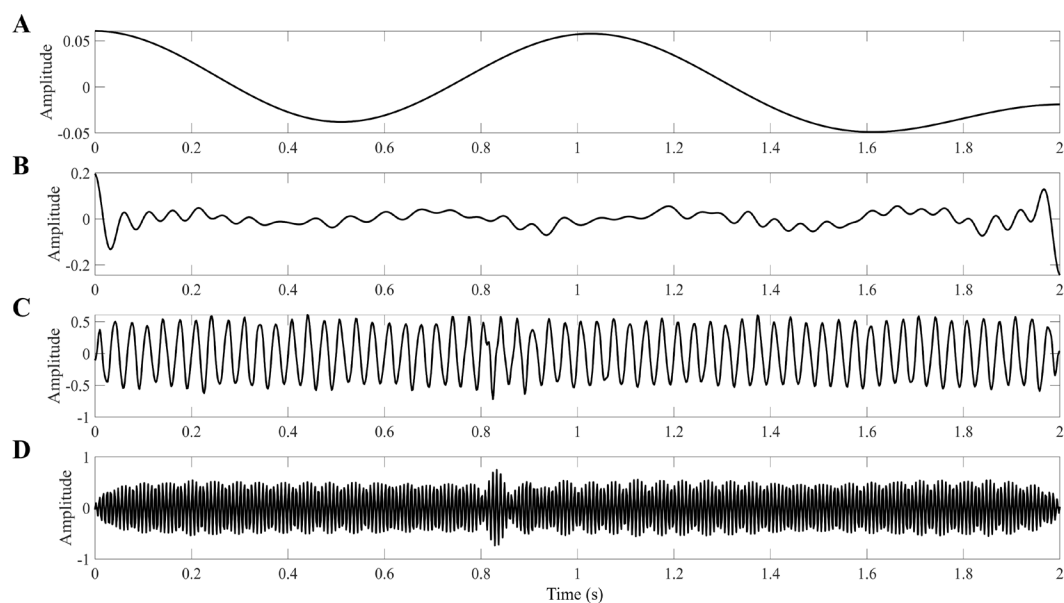


Figure 14. Waveform components obtained from frequency-domain segmentation without periodic noise suppression. (A) 0–2 Hz, (B) 2–20 Hz, (C) 20–96 Hz, and (D) 96–250 Hz.

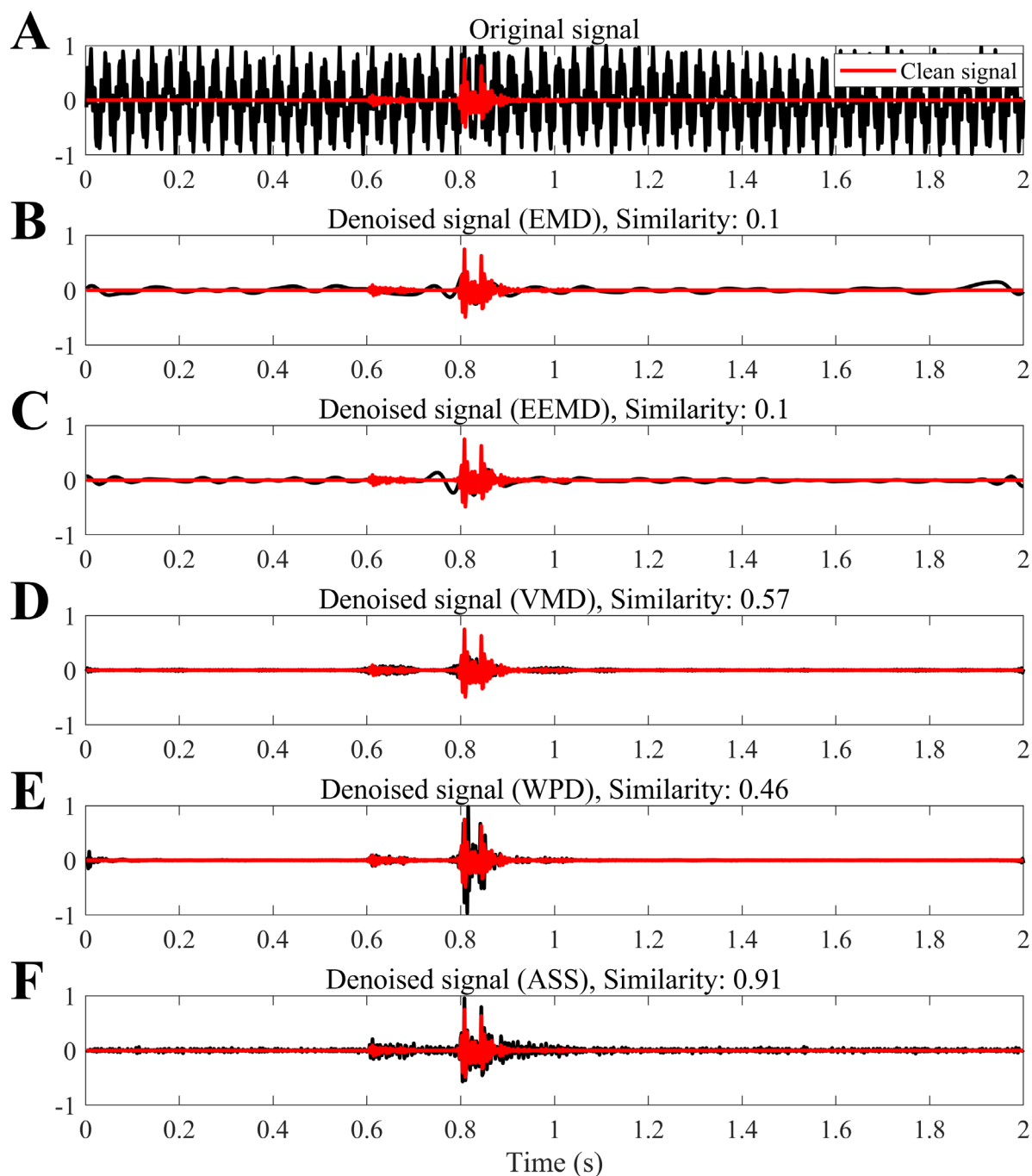


Figure 15. Comparison of denoising results obtained using different methods. Clean signal versus (A) original signal, (B) EMD results, (C) EEMD results, (D) VMD results, (E) WPD results, and (F) ASS results.

Abbreviations: ASS: Adaptive spectral segmentation; EEMD: Ensemble empirical mode decomposition; EMD: Empirical mode decomposition; VMD: Variational mode decomposition; WPD: Wavelet packet decomposition.

The quantitative results are shown in Table 3. The proposed ASS method significantly outperforms the three traditional methods in both SNR and MSE metrics, achieving the best denoising effect. Furthermore, the waveform correlation coefficient of the ASS method (0.91) is significantly higher than that of EMD (0.1), EEMD (0.1), WPD (0.46), and VMD (0.18), demonstrating its advantage in preserving signal waveform integrity.

Table 3. Comparison of signal-to-noise ratio and mean square error results of different denoising methods

Method	SNR (dB)	MSE
ASS	3.11 ^a	0.0073 ^a
EMD	-0.67	0.0258
EEMD	-0.39	0.0241
VMD	-1.14	0.0315
WPD	-1.46	0.0402

Note: ^a indicates the optimal parameter result.

Abbreviations: ASS: Adaptive spectral segmentation; EEMD: Ensemble empirical mode decomposition; EMD: Empirical mode decomposition; MSE: Mean squared error; SNR: Signal-to-noise ratio; VMD: Variational mode decomposition; WPD: Wavelet packet decomposition.

To validate the suppression performance against random noise (non-periodic noise), frequency components identified as invalid by AEFD decomposition (primarily high-frequency bands) were reconstructed as residual noise and compared with the original random noise added in the synthetic experiment.

Figure 16 illustrates the comparison between the removed random noise and the original random noise. Both waveform structures and spectral distributions exhibit high similarity in terms of frequency range and energy distribution, indicating effective identification and separation of random noise components. It should be noted that due to the band-segmentation characteristic of AEFD, a proportion of high-frequency effective signal energy may be filtered together with noise, resulting in slight energy deficiency in the low-frequency band of the removed noise spectrum compared to the original noise. Overall, the method demonstrates satisfactory performance in suppressing random noise.

To validate method performance across different sampling rates, synthetic microseismic data were generated using a three-layer velocity model (2,500, 3,000, and 3,200

m/s; thickness: 500, 700, and 600 m) with impulsive source excitation. Noise was added to achieve SNR = -19 dB. Two sampling rates were tested—250 Hz and 1,000 Hz—with results shown in Figure 17 (250 Hz) and Figure 18 (1,000 Hz). Table 4 presents quantitative comparisons.

Table 4. Comparison of signal-to-noise ratio and mean squared error results across different sampling rates

Signal type	250 Hz		1,000 Hz	
	SNR	MSE	SNR	MSE
Original signal	-19	0.2375	-19	0.9486
Periodic denoised	-1.2	0.0039	1.69	0.0081
Final denoised	13.9	0.0001	6.47	0.0026

Abbreviations: MSE: Mean squared error; SNR: Signal-to-noise ratio.

The results demonstrate that the ASS method maintains effective noise suppression across varying sampling rates. To systematically verify the robustness of the proposed method under varying noise conditions, six channels of synthetic microseismic data were constructed, as shown in Figure 19A. While the effective microseismic waveform remains identical across all channels, independent noise realizations with different energies were added to each channel, generating a sequence of synthetic records with progressively varying SNRs. Specifically, the SNRs for the six channels were set from -26 dB to -21 dB, with an increment of 1 dB per channel. This design aims to: (i) evaluate the method's sensitivity and robustness to different noise energy levels, and (ii) simulate the trace-to-trace SNR variations commonly encountered in field monitoring due to changes in noise sources or signal attenuation.

For this dataset, the proposed ASS algorithm, along with traditional EMD, EEMD, and VMD algorithms, were used for denoising. The processing flow and corresponding results of the ASS algorithm are shown in Figure 19. Firstly, periodic noise suppression was independently applied to each trace of data (Figure 19B), followed by AEFD for ASS and Gini coefficient screening (Figure 19C). After processing each trace independently, the effective signal frequency bands identified by the Gini coefficient in each trace were statistically analyzed. The analysis revealed that the effective signal spectra primarily overlapped in the

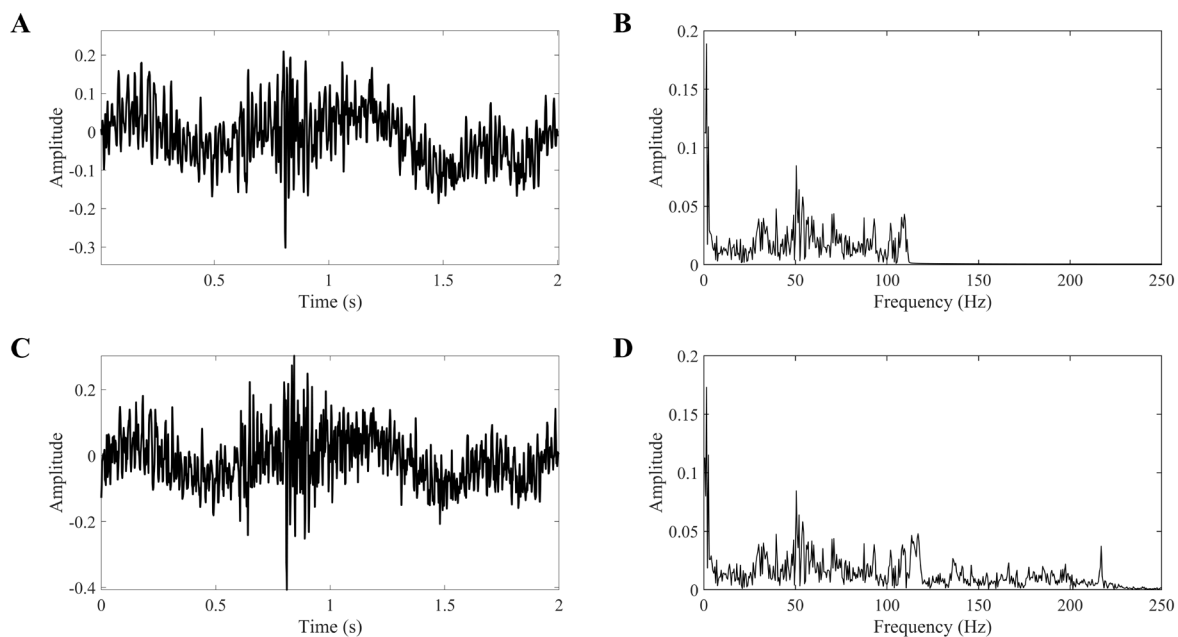


Figure 16. Random noise suppression results. (A) Random noise removed by the proposed method and (B) its corresponding amplitude spectrum, and (C) actual random noise added to the synthetic data and (D) its corresponding amplitude spectra.

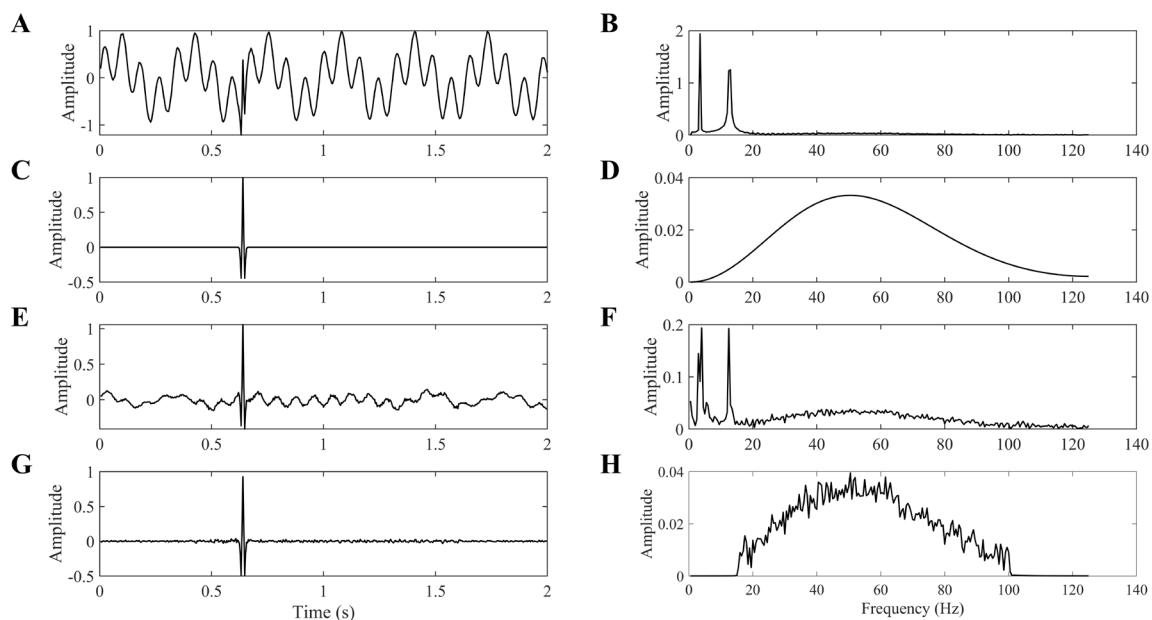


Figure 17. Denoising results for the 250 Hz sampling rate. (A) Noisy data and (B) its corresponding amplitude spectrum, (C) clean signal and (D) its corresponding amplitude spectrum, (E) periodic noise suppression result and (F) its corresponding amplitude spectrum, and (G) final denoised result and (H) its corresponding amplitude spectrum.

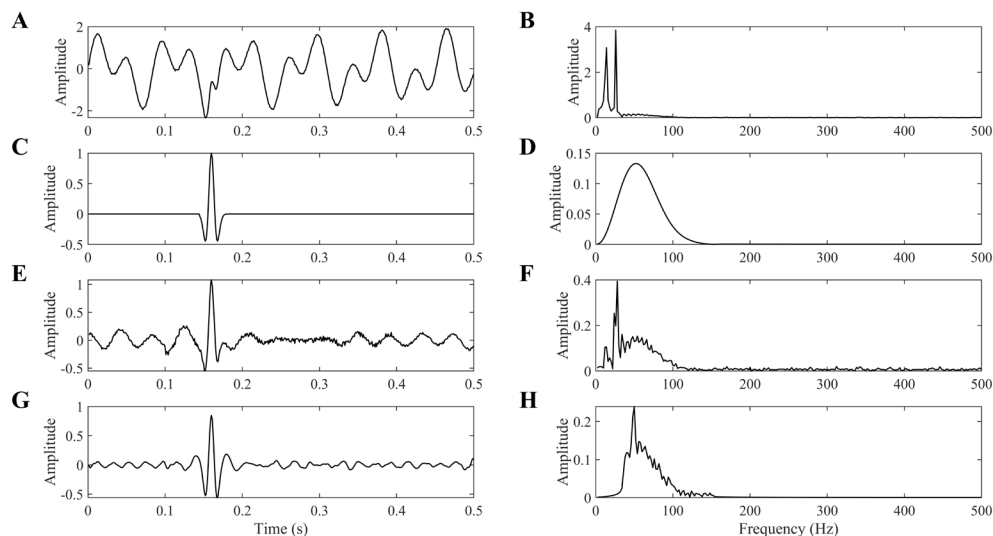


Figure 18. Denoising results for the 1,000 Hz sampling rate. (A) Noisy data and (B) its corresponding amplitude spectrum, (C) clean signal and (D) its corresponding amplitude spectrum, (E) periodic noise suppression result and (F) its corresponding amplitude spectrum, and (G) final denoised result and (H) its corresponding amplitude spectrum.

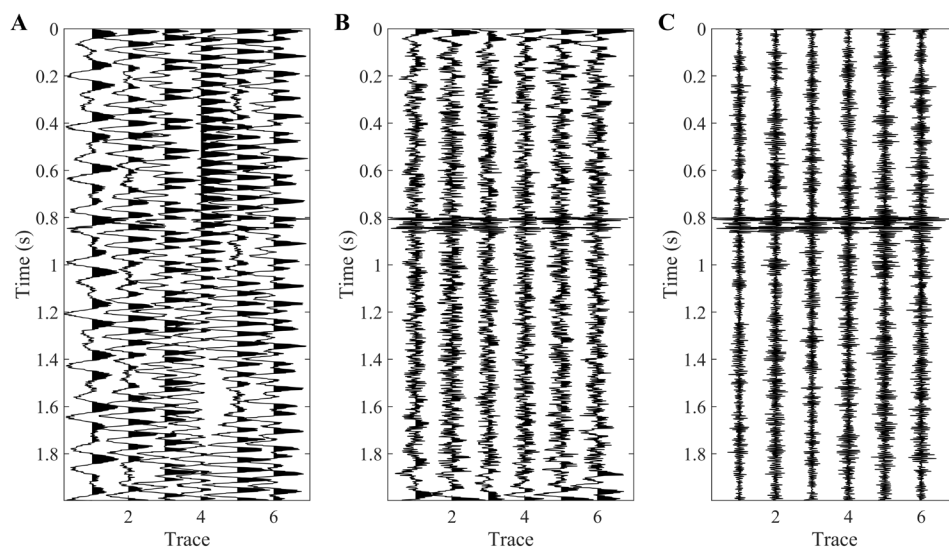


Figure 19. Processing of multi-channel simulated data using the adaptive spectral segmentation method. (A) Original microseismic data, (B) results after periodic noise suppression, and (C) denoising results obtained using the adaptive empirical Fourier decomposition method.

100–200 Hz range (occurrence frequency: 83%). Based on this statistical pattern, a uniform 100–200 Hz band-pass filter was applied to the preliminary ASS results of all traces, yielding the final multi-trace denoising result, as shown in Figure 19C.

The denoising results from different methods are compared in Figure 20. Although EMD, EEMD, VMD, and WPD methods can suppress background noise to

some extent, their denoising results still retain significant periodic and random noise components, leading to insufficient clarity and continuity of the effective signals. The quantitative comparison results are shown in Figure 21. The ASS method maintains the highest output SNR and lowest MSE across all SNR levels, attributable to its adaptive signal decomposition, which more accurately distinguishes effective signal characteristics from noise.

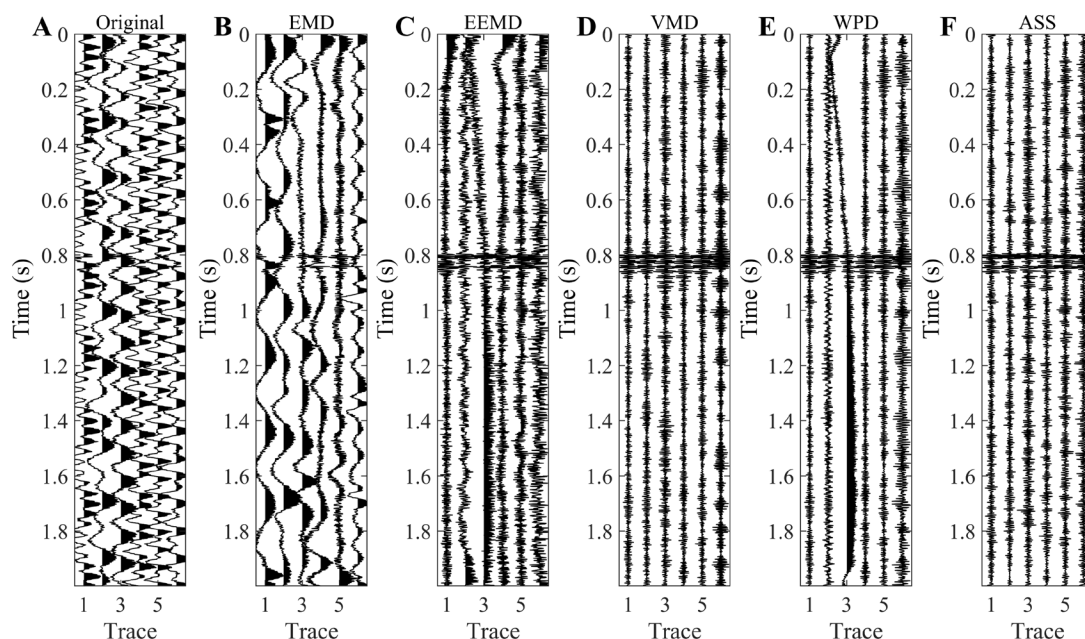


Figure 20. Comparison of denoising results obtained using different methods. (A) Original data, (B) EMD results, (C) EEMD results, (D) VMD results, (E) WPD results, and (F) ASS results.

Abbreviations: ASS: Adaptive spectral segmentation; EEMD: Ensemble empirical mode decomposition; EMD: Empirical mode decomposition; VMD: Variational mode decomposition; WPD: Wavelet packet decomposition.

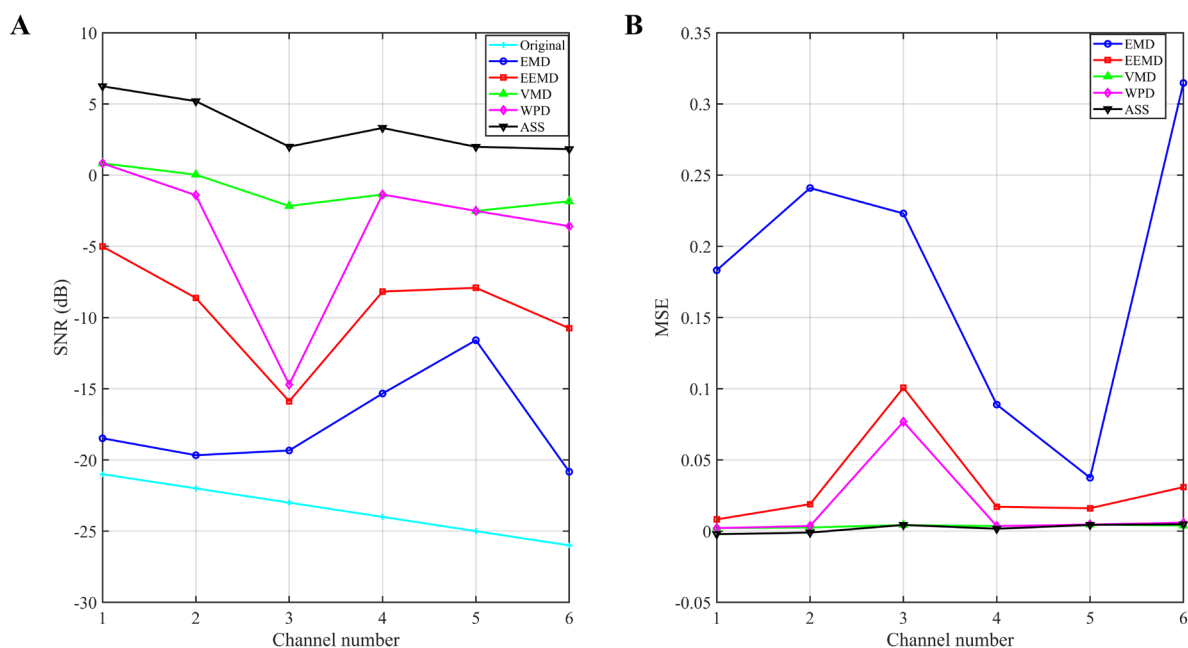


Figure 21. Comparison of (A) signal-to-noise ratio and (B) mean squared error results obtained using different denoising methods.

Abbreviations: ASS: Adaptive spectral segmentation; EEMD: Ensemble empirical mode decomposition; EMD: Empirical mode decomposition; VMD: Variational mode decomposition; WPD: Wavelet packet decomposition.

To comprehensively evaluate computational efficiency, we recorded the average processing time for single-trace data (2 s, 500 Hz sampling rate, 1,000 sampling points) across 100 independent runs. Although the ASS method requires slightly more single-trace processing time than VMD due to the RSM preprocessing step, it possesses a decisive efficiency advantage in multi-channel applications: when processing batches of microseismic data from the same region, representative effective signal frequency bands can be statistically derived from preliminary multi-trace analysis. This frequency range can then be applied for rapid band-pass filtering of subsequent data.

In this experiment, complete ASS processing for the first trace took 0.15 s, statistical analysis of the common frequency band took 0.05 s, and rapid filtering for each subsequent trace took 0.01 s, yielding a total time of 0.25 s for six traces. This represents a 72% reduction in total processing time compared to independent ASS processing (0.90 s), 67% versus EMD (0.76 s), 65% versus EEMD (0.72 s), 63% versus WPD (0.61 s), and 58% versus VMD (0.60 s). Furthermore, the common frequency band determined by majority rule enables identification and correction of abnormal traces, enhancing reliability in practical monitoring.

3.2. Processing of field data

The measured data used in this study were collected from a hydraulic fracturing unconventional oil and gas extraction area in southwestern China, with a sampling rate of 500 Hz. To conduct an in-depth analysis of microseismic signal characteristics, a segment of fracturing microseismic data from one well was selected. Multi-channel waveform data containing the effective fracturing signal period (mainly concentrated between 0.9–1.1 s) were extracted for analysis (Figure 22A). Affected by various interferences such as environmental noise, fracturing equipment vibration, and human activities, the data exhibit an extremely low SNR, with effective signals being strongly masked and accompanied by noticeable periodic noise. The estimated SNR of the field microseismic data used in this analysis ranges from approximately –15 dB to –5 dB.

The proposed ASS method was employed to process this adjacent multi-channel microseismic data. The specific steps include: (i) using the RSM to suppress periodic noise; (ii) applying AEFD to partition the signal in the frequency domain (with the adaptive determination of $K = 4$ based on the 500 Hz sampling rate); and (iii) screening effective components for reconstruction based on the adaptive Gini threshold.

During the processing of the nine adjacent channels, some channels—due to complex noise composition—

resulted in suboptimal AEFD spectral partitioning, making it difficult to clearly identify the effective signal's phase axis (Figure 22C). To address this issue, by statistically analyzing the effective frequency bands determined by the Gini coefficient from each channel, it was found that the 1–35 Hz range was the most common overlapping band (seven times, 77.8%). Based on this statistical result, a uniform 1–35 Hz band-pass filter was applied to all channel data. The corrected results are shown in Figure 22D. This correction strategy effectively enhanced the overall noise suppression performance and waveform consistency.

To further validate the effectiveness of the ASS method, the processing results were compared with those from three traditional methods: EMD, EEMD, VMD, and WPD. The comparison results are shown in Figure 23. The comparative analysis based on Figure 23 indicates that the ASS method has a clear advantage in suppressing both periodic and random noise, enabling more distinct recovery of effective signals. In contrast, under the same conditions, the traditional methods still exhibit residual noise and poorer signal continuity. This demonstrates that while traditional methods possess some noise suppression capability, their adaptive decomposition ability is limited when dealing with low-SNR, complex noise backgrounds in real-world microseismic data, making it difficult to achieve reliable and effective signal extraction.

To quantitatively evaluate the denoising performance of different methods on the same field dataset, we conducted a comparative analysis using P-wave first arrival picking as an objective metric. The short-term average/long-term average algorithm²⁶ was applied to the denoised results from each method to automatically detect P-wave arrivals, with a short-term window length of 40 samples and a long-term window length of 80 samples. The picking errors were then calculated by comparing these automated picks with the manually picked reference arrivals, with the statistical results summarized in Table 5.

Table 5. Quantitative comparison of P-wave arrival picking errors for different denoising methods

Method	Mean absolute error (ms)
EMD	272
EEMD	80
VMD	190
WPD	247
ASS	15

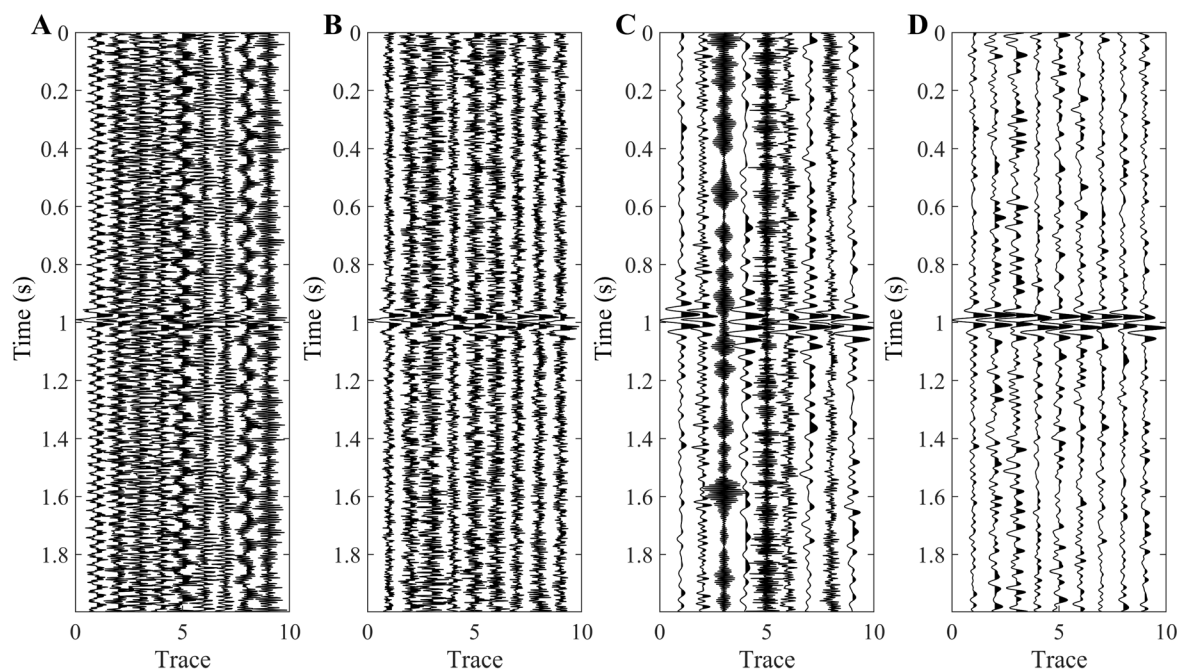


Figure 22. Processing of field data using the adaptive spectral segmentation method. (A) Original microseismic data, (B) results after periodic noise suppression, (C) denoising results obtained using the adaptive empirical Fourier decomposition method, and (D) results after applying appropriate filtering.

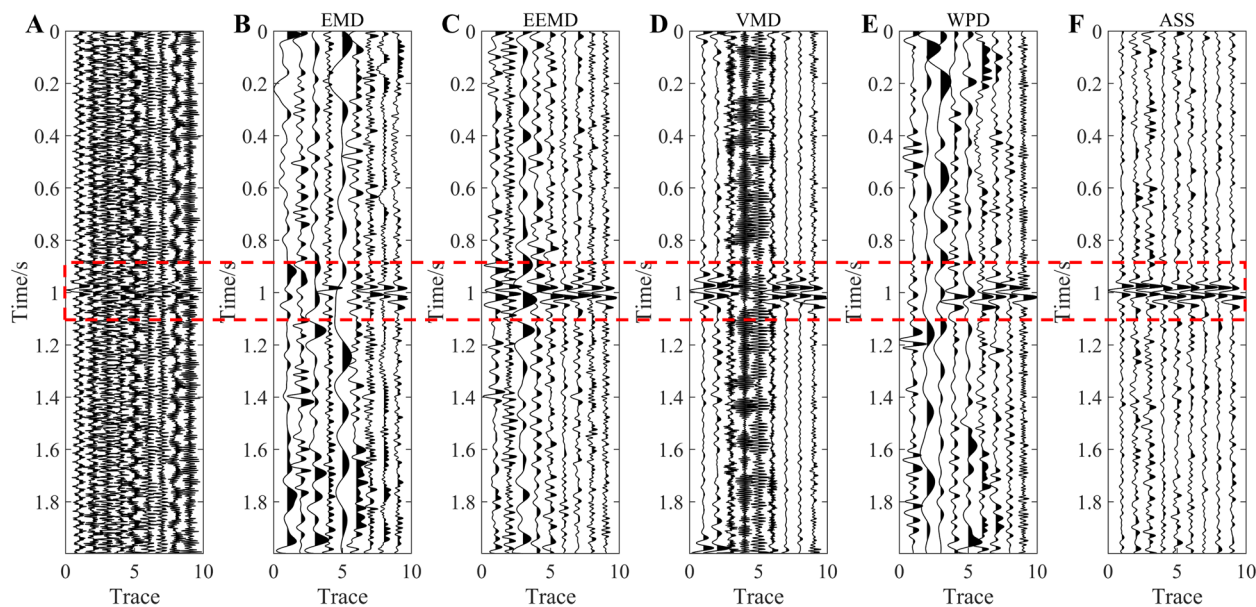


Figure 23. Comparison of denoising results for field data obtained using different methods. (A) Original microseismic data, (B) EMD results, (C) EEMD results, (D) VMD results, (E) WPD results, and (F) ASS results. The red dashed boxes indicate the main distribution regions of the effective signals. Abbreviations: ASS: Adaptive spectral segmentation; EEMD: Ensemble empirical mode decomposition; EMD: Empirical mode decomposition; VMD: Variational mode decomposition; WPD: Wavelet packet decomposition.

As shown in Table 5, the ASS method achieves the highest picking accuracy, with a mean absolute error of only 15 ms. In comparison, EMD, EEMD, VMD, and WPD all exhibit significantly larger deviations. These results indicate that traditional methods suffer from either incomplete suppression of in-band noise or excessive attenuation of signal components when processing complex field data. The quantitative evidence confirms that while conventional decomposition-based methods possess some noise suppression capability, their limited adaptive decomposition capacity makes it difficult to achieve reliable signal extraction when dealing with low-SNR microseismic data characterized by complex noise backgrounds. In contrast, the ASS method demonstrates superior performance in both noise reduction effectiveness and signal fidelity.

4. Discussion

4.1. Theoretical advances beyond empirical Fourier decomposition

The AEFD method builds directly upon the EFD framework by Zhou *et al.* [18], inheriting its core philosophy of ASS based on Fourier spectrum extrema. Both methods operate in the frequency domain and construct zero-phase filter banks without predefined basis functions. However, AEFD introduces two critical advances: (i) an adaptive band number criterion (Equation 5) that ensures consistent physical interpretability across varying sampling rates, preventing over- or under-segmentation; and (ii) the Gini coefficient-based adaptive threshold (Equation 9) that enables fully automated component screening, eliminating EFD's reliance on manual inspection.

4.2. Theoretical affinities with modal decomposition methods

Beyond its EFD lineage, AEFD shares fundamental behaviors with established methods. Both VMD and AEFD implement frequency-domain filtering, yielding comparable results for clean signals with well-separated spectral peaks. However, VMD's fixed bandwidth constraints may merge adjacent peaks under noisy conditions, whereas AEFD's adaptive boundaries preserve resolution. Similarly, EMD and AEFD both pursue data-driven decomposition without prior models—EMD through time-domain sifting, whereas AEFD through frequency-domain segmentation. Both face noise-induced feature confusion: EMD suffers mode mixing from spurious extrema; AEFD is affected by spectral distortion induced by periodic noise. The RSM preprocessing in ASS addresses this shared vulnerability through deterministic subspace projection, analogous to EEMD's stochastic ensemble averaging but with deterministic guarantees.

4.3. Limitations and future directions

The proposed method's primary boundary lies in ultra-low SNR conditions (below approximately -26 dB), where signal sparsity characteristics diminish and Gini coefficient discrimination becomes unreliable. Additionally, while validated against periodic and Gaussian noise, robustness against impulsive noise remains unverified due to its sparsity similarity to effective signals.

Future work should focus on: (i) integrating deep learning for enhanced ultra-low SNR detection; (ii) developing robust strategies for impulsive and non-stationary noise; and (iii) validating across diverse scenarios (e.g., natural seismicity, mining microseismicity) to establish the boundaries of generalization.

5. Conclusion

This study addresses the challenges of severe background noise interference, low SNR, and difficulties in real-time processing of microseismic monitoring data. An ASS-based method for microseismic signal extraction is proposed, with the following main achievements:

- (i) RSM was employed to construct a periodic subspace projection, effectively identifying and removing periodic noise such as power frequency interference and mechanical vibrations from microseismic data. This avoids interference from discrete spectral peaks in subsequent frequency band segmentation, providing a clean spectral foundation for further processing.
- (ii) An adaptive frequency band number determination criterion based on the sampling rate was established, using the characteristic frequency bandwidth unit of microseismic signals for spectral segmentation. This overcomes the limitation of fixed frequency band numbers in traditional EFD. By optimizing frequency band boundaries in conjunction with spectral maxima, the segmentation accuracy and adaptability to signals are improved.
- (iii) The Gini coefficient was introduced as a measure of component sparsity, and an adaptive threshold screening criterion based on statistical distribution was established. This enables automatic discrimination and reconstruction of noise components and effective signal components, avoiding the subjectivity of manual judgment and enhancing the level of automation of the method.
- (iv) For real-time application scenarios such as fracturing monitoring, a unified filtering method based on statistically overlapping frequency bands is proposed. By determining a common effective frequency band through preliminary multi-channel data analysis,

rapid band-pass filtering of subsequent data is achieved. This significantly improves computational efficiency while ensuring processing consistency, with a total processing efficiency improvement of up to 72%.

The method proposed in this study is primarily designed for microseismic monitoring data in hydraulic fracturing. Its applicability to different scenarios, such as natural earthquakes, mine microseismicity, and geothermal development, requires further validation with more measured data. Additionally, its effectiveness in suppressing non-periodic narrowband noise (e.g., environmental interference at specific frequencies) warrants further testing.

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Conflict of interest

The authors have no conflicts to disclose.

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Availability of data

Data supporting the findings of this study are available from the corresponding author upon reasonable request.

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