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Thin-layer weak signal enhancement based on cyclic spectrum enhancement technology

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Abstract

With the continuous growth of global energy demand, subtle reservoirs such as thin beds have become an important target for exploration and development. However, the identification accuracy of thin-layer seismic weak signals is limited by the physical resolution limit of traditional seismic exploration methods due to its small thickness, strong heterogeneity and significant interlayer interference effect. In order to solve the problem of weak signal recognition in thin layer, a method of weak signal recognition in thin layer based on cyclic spectrum enhancement technology is proposed in this paper, improving the sensitivity and accuracy of weak signal detection. The method preprocesses the original seismic data by Gauss filtering to suppress random noise while accurately preserving the main features of the signal, and then introduces even-order derivative operation, the high-frequency details of the weak signal in the thin layer are enhanced, and the reflection difference between the layers is highlighted. To mitigate the high-frequency artifacts inherently generated by high-order derivatives, a Butterworth low-pass filter is employed for directional spectral conditioning, facilitating the high-fidelity separation of the effective signal from noise. Finally, the optimal derivative order is dynamically determined through an adaptive termination criterion to prevent over-enhancement or under-enhancement. Numerical simulation and field seismic data test showed that the proposed method significantly improves the resolution of thin-layer horizons and enhances the detectability of subtle seismic signals.

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1. Introduction

With the growth of global demand for oil and gas resources, the development of conventional oil and gas reservoirs is confronted with multiple challenges, making exploration of thin and unconventional reservoirs a research hotspot. Thin reservoirs have small thickness and strong heterogeneity, and the seismic response is mostly weak reflection or low signal-to-noise ratio (SNR), especially in complex geological areas such as Tarim basin. Research from recent years found that spectral inversion can invert $\lambda/8$ thin layer, diffraction wave separation imaging can distinguish fracture-cavity body

from matrix, and generalized S-transform can enhance time-frequency feature extraction, but the algorithm is time-consuming. In practical application, thin layer weak signal identification is the key to predict sweet spot distribution of unconventional oil and gas. Luo *et al.*¹ proposed a method based on improved empirical mode decomposition, using wavelet preprocessing to reduce noise, and combining segment control and superposition technology to improve decomposition accuracy. Paksima *et al.* used synchronous compression S-transform to identify thin gas reservoirs, improving the identification accuracy.²⁻⁵ Wang *et al.*⁶ proposed a multi-channel spectral fitting (MSF) method to improve seismic resolution. Although Shearlet transform can improve resolution and weak reflection energy, attention should be paid to noise amplification when dealing with low SNR data.

In terms of seismic frequency extension technology, complementary technical support for thin-layer identification has been provided by three-dimensional layered reflectivity inversion, frequency-domain thin-layer analysis, and frequency-enhanced imaging.⁷ Deconvolution technology also has important applications in thin layer recognition. Chen *et al.*⁸ improved the vertical resolution of logging curves via wavelet transforms to predict coal and rock textures. In terms of seismic noise suppression, Yang *et al.*⁹ proposed an adaptive convolutional neural networks (CNN) for effective waveform reconstruction, while Song *et al.*¹⁰ proposed a deep convolutional autoencoder denoising neural network to effectively attenuate random noise. Cheng *et al.*¹¹ proposed a broadband wavelet deconvolution method, and Meng *et al.*¹² proposed a deconvolution approach to preserve the SNR. Furthermore, Zhou *et al.*¹³ introduced the support vector machine (SVM) method for fluid identification in thin reservoirs. Reflectivity inversion and sparse pulse deconvolution algorithms, such as those proposed by Chopra *et al.*¹⁴ and Sui *et al.*,¹⁵ have successfully bypassed traditional resolution limits. Recent advancements include frequency-dependent multi-scale networks,¹⁶ high-resolution characterization for “ahead-of-the-bit” drilling scenarios,¹⁷ and novel deep-learning-based inversion methods.¹⁸ Ge *et al.*¹⁹ demonstrated the effectiveness of modified reflectivity models for thin reservoir characterization. Additionally, Zhang *et al.*²⁰ used L1-norm sparse inversion to obtain reflection coefficients and performed clear imaging of thin interlayers. The rapid evolution of deep learning has revolutionized geophysical tasks.^{21,22} For instance, Liu *et al.*²³ adopted the generative adversarial networks (GAN) network based on the deep residual channel attention mechanism to realize seismic profile reconstruction and random noise suppression. Ni *et al.*²⁴ used CNNs to establish mapping relationships for wavelet shaping deconvolution, verifying

method reliability through thin-layer modeling. Finally, Manzoor *et al.*²⁵ inputted seismic data, 90° phase-shift data and discontinuity boundary attributes and used well high-frequency natural gamma as labels and multi-layer perceptron to predict cross-well gamma values to characterize thin reservoirs.

To enhance the recognition effect of thin layer weak signals, it is very important to increase the main frequency of the signal. Based on this understanding, this paper firstly studies the formation mechanism of thin layer weak signal through forward modeling. Especially, the influence of dominant frequency on signal strength is discussed. Then, the theory of cyclic spectrum enhancement technology is constructed, and the weak signal enhancement comparison analysis is carried out theoretically. Finally, the cyclic spectrum enhancement technology is applied to the actual data, and the actual processing effect is analyzed. In particular, it should be pointed out that thin layer weak signal identification belongs to the category of thin layer identification. Predecessors mainly identified the thickness and horizon of thin layers, usually focusing on thick thin layer signal identification. However, from the perspective of signal processing, this paper proposes a cyclic spectrum enhancement technology that can identify thin-layer extremely weak signals caused by interference effects.

2. Enhancement technique by cyclic spectrum

This paper intends to propose a weak signal enhancement method based on signal processing algorithms, especially one that can effectively enhance thin-layer weak signals. The main idea is to firstly use Gaussian filtering to initially smooth the noise, suppressing the noise while strengthening the low-frequency components of the signal. Then, the even-order derivatives of the original seismic trace are calculated to generate derivative seismic traces. Next, the even-order derivative seismic traces are superimposed onto the original seismic trace, and the smoothed seismic trace and the derivative seismic trace are subjected to cyclic superposition operations considering the adaptive loop termination condition. This process not only retains the low-frequency components but also enhances the high-frequency components, while increasing the energy of the main frequency band of the signal and broadening the frequency band width of the seismic signal. By using Butterworth low-pass filtering to handle the high-frequency interference generated by taking higher-order derivatives, the identification of thin-layer weak signals is ultimately achieved. The following sections introduce the theories including Gaussian smoothing, signal differentiation, and Butterworth low-pass filter. In

addition to giving a theoretical introduction, this paper provides an overview of practical problem to be solved, namely the enhancement of thin-layer weak signals.

2.1. Gaussian smoothing and signal derivation

Gaussian smoothing is a linear filtering method based on the Gaussian function. Its core principle is to use the weight distribution of the Gaussian function to perform weighted averaging on signals or images to achieve a smoothing effect, which is used for noise reduction, edge preservation, and multiscale analysis. Through weighted averaging, it can effectively suppress high-frequency noise and improve the quality of signals or images. Among them, the Gaussian function is the foundation of Gaussian smoothing, and its mathematical expression is as follows:

$$G(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}} \quad (1)$$

where x is the offset from the center point; σ is the standard deviation, which controls the width of the Gaussian function. By adjusting σ , the degree of smoothing can be flexibly controlled. The larger is σ , the stronger the smoothing effect will be; $G(x)$ represents the weight at position x .

The purpose of differentiating seismic signals is to extract high-frequency components and detailed information by calculating the rate of change of seismic signals, which is particularly suitable for detecting thin-layer weak signals. Additionally, the differentiation operation can also enhance the reflection wave characteristics at thin-layer interfaces, highlighting the local abrupt change points of the top and bottom interface signals of thin layers, thereby improving the resolution of thin-layer weak signals. For a continuous signal $s(t)$, its n -th order derivative is defined as follows:

$$s^{(n)}(t) = \frac{d^n s(t)}{dt^n} \quad (2)$$

where n represents the order of the derivative.

Seismic differentiation enhances reflection characteristics at thin-layer interfaces by calculating signal change rates. Physically, lower-order derivatives identify structural abruptness, while higher-order derivatives refine thin-layer characterization by capturing signal curvature and local extrema. From a spectral perspective, differentiation acts as a high-pass filter. As shown in Figure 1, the amplitude spectra of the unit impulse response derivatives demonstrate that increasing the derivative order significantly boosts high-frequency energy while suppressing low-frequency components. This non-linear frequency enhancement mechanism broadens

the bandwidth and improves vertical resolution without proportional amplification of ultra-high-frequency noise, thereby preserving the signal-to-noise ratio.

When selecting the order of derivative seismic traces, it is necessary to comprehensively consider the time shift, polarity and the balance between signal enhancement and noise suppression. From the perspective of derivative characteristics, odd-order derivation will introduce 90° phase shift, resulting in an asymmetric waveform relative to the original seismic trace. As demonstrated by the quantitative metrics in Table 1, the 1st -order derivative exhibits a phase shift of 90° and a significant zero-lag cross-correlation drop, leading to a noticeable peak time displacement. Such shifts can cause substantial positioning errors at thin-layer interfaces, making odd-order derivatives unsuitable for high-resolution thin-bed enhancement. In contrast, even-order derivatives possess zero-phase characteristics, maintaining waveform symmetry with the original trace, with only the polarity varying predictably with the order. For instance, the 2nd- and 6th-order derivatives have opposite polarities and require correction by a negative sign before superposition, whereas the 4th- and 8th-order derivatives share the same polarity.

The waveform comparison in Figure 2 and the quantitative indices in Table 1 reveal that, after polarity correction, even-order derivatives (such as 2nd and 4nd) maintain a phase shift of 0° and cross-correlation coefficients exceeding 0.95. While lower-order even derivatives are effective at preserving the overall signal trend, higher-order derivatives excel at extracting high-frequency details, albeit at the cost of amplified high-frequency noise. Therefore, this study integrates even-order derivatives with Gaussian smoothing to broaden the vertical resolution while effectively suppressing noise, thereby achieving precise characterization of thin-layer structures.

With the increase of derivative order, the ability of derivative operation to broaden the high frequency band is deteriorating; therefore, the order of cyclic superposition derivative seismic trace needs to be within a certain judgment criterion. Let S be the original seismic trace, S_n be its n -th derivative seismic trace, the dominant frequency of the n -th derivative seismic trace is denoted as D_n , and $S_n(f)$ is the spectrum of the n -th derivative seismic trace. The dominant frequency of S is as follows:

$$D_n = \frac{\int_0^\infty f S_n(f) df}{\int_0^\infty S_n(f) df} \quad (3)$$

where f in the above formula represents the frequency

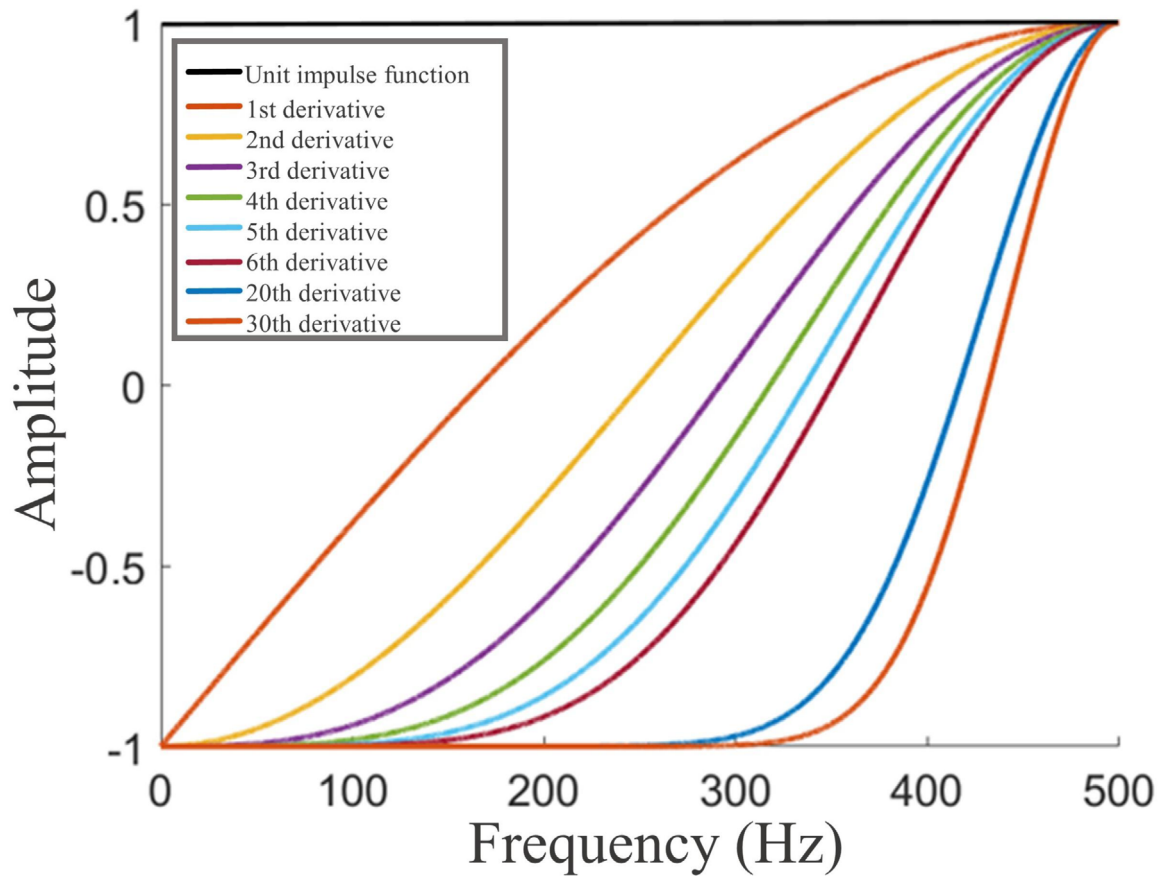


Figure 1. Unit impact function and amplitude spectrum of each derivative

Table 1. Quantitative evaluation of phase characteristics and fidelity of various derivative signals relative to the original signal

Order of derivative	Mean phase error	Correlation	Time shift (ms)
Original trace	0	1.000	0
1st derivative	90	0.052	Δt
2nd derivative	0	0.985	0
4th derivative	0	0.975	0
6th derivative	0	0.968	0

variable. Through many tests, this paper determines that the termination conditions of signal derivation are as follows:

$$\frac{D_{n+1} - D_n}{D_n - D_{n-1}} \leq \varepsilon \quad (4)$$

The parameter ε in Equation 4 acts as a critical

threshold to balance resolution enhancement against high-frequency noise amplification. To clarify the physical significance and engineering criteria for selecting ε , we conducted a sensitivity analysis by testing values of 0.1, 0.2, 0.3, and 0.4. When $\varepsilon = 0.1$, the iterative process terminates prematurely, resulting in under-enhancement that fails to resolve $\lambda/16$ thin-layer reflections. Conversely, when $\varepsilon =$

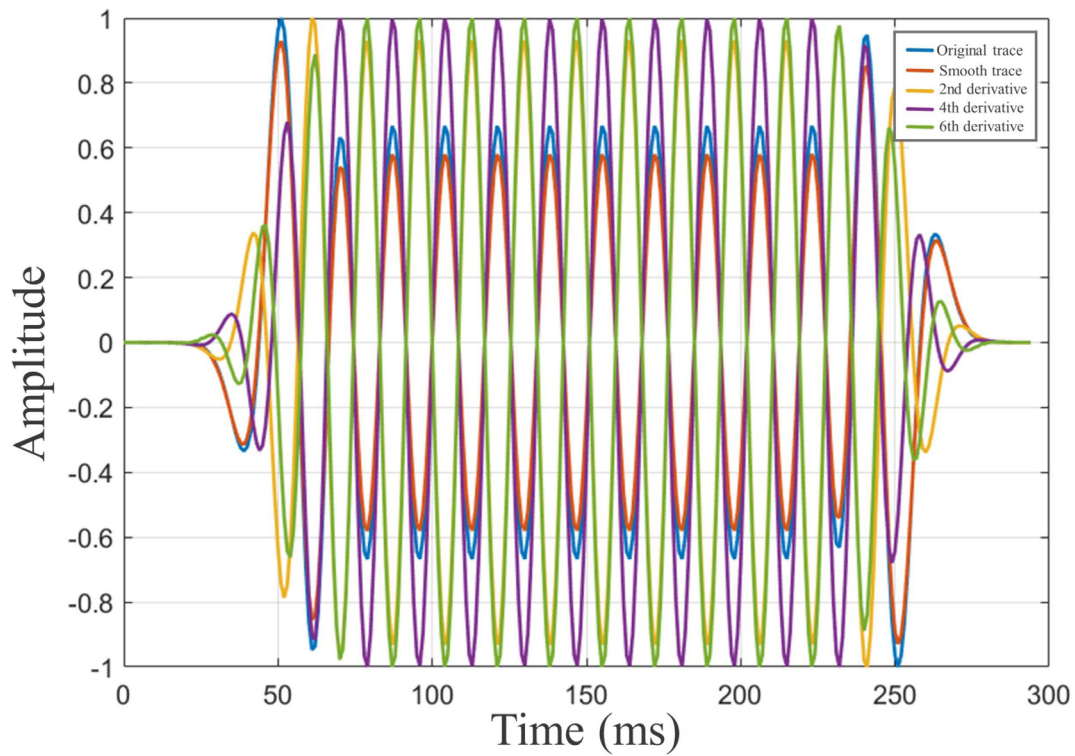


Figure 2. Original trace and derivative seismic trace of each order

0.4, excessive derivative orders lead to over-enhancement and the emergence of high-frequency artifacts. From an engineering perspective, the selection of ε is inversely related to the SNR of the raw data; lower-SNR records require a larger tolerance to ensure operator stability. Based on these comprehensive tests, this paper determines that the optimal range for the termination parameter ε is 0.2–0.3, which ensures maximum resolution improvement while strictly maintaining signal fidelity.

2.2. Cyclic spectrum enhancement technique

After high-order derivation operation, more high-frequency noise and numerical instability will be introduced. In this paper, Butterworth low-pass filter is selected to remove high-frequency noise interference. The characteristic of Butterworth low-pass filter is that the frequency response is flat in the passband, but the frequency value gradually decreases in the stopband. The mathematical formula of Butterworth low-pass filter is as follows:

$$H(s) = \frac{1}{\sqrt{1 + \left(\frac{s}{\omega_c}\right)^{2n}}} \quad (5)$$

where $H(s)$ is the transfer function of the filter, ω_c is the cut-off frequency, and n is the order of the filter. In the process of designing Butterworth low-pass filters, the Butter function is used to determine the order and cut-off frequency of the filter to meet the predetermined performance indicators of the filter.

The SNR estimation of the low-pass filtered seismic traces is carried out to verify the accuracy of the derivative order selected in **Equation 4**. Generally speaking, the SNR of the filtered signal gradually decreases, because the higher the derivative order, the more serious the high-frequency interference will be, which will reduce the SNR of the filtered signal as a whole. After filtering the seismic trace, the SNR of the signal is in a constant stage, which indicates that further derivation and denoising can no longer improve the vertical resolution of the thin interlayer. At this time, the derivation order is the cyclic superposition termination order. The algorithm expression of the cyclic spectrum enhancement technology constructed in this paper is as follows:

$$S' = \text{Butter}(\text{Nor}(S) + \text{Gao}(\text{Nor}(S))) - \sum_{i=2}^{k=4m-2} R_k(\text{Nor}(S^{(i)})) + \sum_{j=4}^{b=4n} R_b(\text{Nor}(S^{(j)})) \quad (6)$$

where Nor means normalization of the signal, and normalization before and after processing can avoid incomplete display of the results due to the difference of data magnitude; Gao represents Gaussian smoothing, and $S^{(i)}$ represents the i -order derivative of the signal respectively; R represents the difference threshold of calculating the derivative seismic trace, and k is the order after the cycle termination condition is determined, which needs to be cyclically superimposed on the seismic trace by adding a negative sign; b is the order of the largest integer multiple of 4 derivative seismic trace under this condition. Let $k = 4m - 2$, $b = 4n$, find m and n and then cyclically superimpose them to the original seismic trace. Butter means Butterworth low-pass filtering of high-frequency noise, and S' is the processed normalized seismic trace.

The specific algorithm flowchart of the cyclic spectrum enhancement technology represented by Equation 6 is shown in Figure 3.

3. Comparative analysis of different high frequency interference removal methods

To validate the low-frequency filtering performance of the Butterworth filter selected in Equation 6, this study compares the proposed approach against Complete Ensemble Empirical Mode Decomposition (CEEMD), a robust adaptive signal processing technique.²⁶ While both adaptive processing and traditional filtering are staples of digital signal processing, CEEMD provides a high-fidelity benchmark for denoising. Based on the cyclic superposition constraints in Equation 4, the Butterworth low-pass filter was configured to the 8th order to effectively eliminate high-frequency interference.

The denoising performance of CEEMD and the Butterworth low-pass filter was evaluated using single-channel seismic records with thin-layer thicknesses of $\lambda/8$ (Figure 4) and $\lambda/16$ (Figure 5). As illustrated, CEEMD results in significant amplitude attenuation in strong-signal regions and fails to effectively enhance weak reflections, particularly in the thinner $\lambda/16$ layer where residual noise and event dislocations are prominent (Figure 5a).

Conversely, the Butterworth filter, applied to high-order derivative traces, effectively suppresses high-frequency noise while preserving strong-signal amplitudes. It significantly improves the resolution of thin-layer horizons with 0.02 ms dislocation, as confirmed by the enlarged views. These comparisons demonstrate that for high-order derivative-induced noise, the Butterworth filter offers superior denoising stability and SNR over CEEMD.

Analysis indicates that derivative operations beyond the 8th order primarily amplify high-frequency noise rather

than effective signals. While CEEMD-based denoising fails to enhance weak interlayer reflections and even attenuates strong-signal amplitudes, the proposed Butterworth filtering approach effectively suppresses derivative-induced noise while preserving strong signals and enhancing weak interlayer reflections.

Spectral analysis (Figure 6) confirms these advantages. For thin layers of $\lambda/8$ and $\lambda/16$, the cyclic spectrum enhancement significantly broadens the bandwidth and increases the dominant frequency. The rightward shift of low-frequency components and the boost in high-frequency content demonstrate the method's ability to improve resolution and restore subtle interlayer horizons. By expanding the high-frequency range while maintaining low-frequency integrity, the proposed technique effectively enhances seismic signal interpretability.

In order to demonstrate the effect of different signal processing methods on 2D seismic profiles, CEEMD and Butterworth low-pass filter are used to process 2D seismic records of 5 m ($\lambda/8$) thin layer weak signals, respectively. The processed seismic record is shown in Figure 7. It can be clearly seen that in the two-dimensional seismic record processed by Butterworth low-pass filter, the enhancement effect of thin layer weak signal area is more significant. This shows that using Butterworth low-pass filter can reduce the loss of thin layer weak signal to a greater extent, while retaining more high-frequency information.

Through the analysis of the processing effect of single-channel and two-dimensional seismic profiles above, it is proved that the noise suppression after weak signal enhancement by Butterworth low-pass filter is effective.

4. Numerical experiments

4.1. Single-channel seismic record

In order to verify the effect of cyclic spectrum enhancement technology on weak signal detection, single-channel seismic records with single layer thickness of 40 m and 5 m ($\lambda/8$) were simulated and enhanced. Figure 8 shows that the amplitude of the original seismic trace of 40 m is compensated to some extent after the cyclic spectrum is enhanced, and the degree of compensation for strong signals is low, indicating that this technology can enhance weak signals in thin layers without affecting the energy of strong signals in thick layers.

Figure 9 shows the waveforms of 5 m ($\lambda/8$) original seismic trace and cyclic spectrum enhancement trace. Based on the adaptive cycle stop criterion, even-order seismic guide traces are linearly superimposed to obtain enhanced tracks. The amplitude of the visible strong signal is basically consistent with that of the original track, while

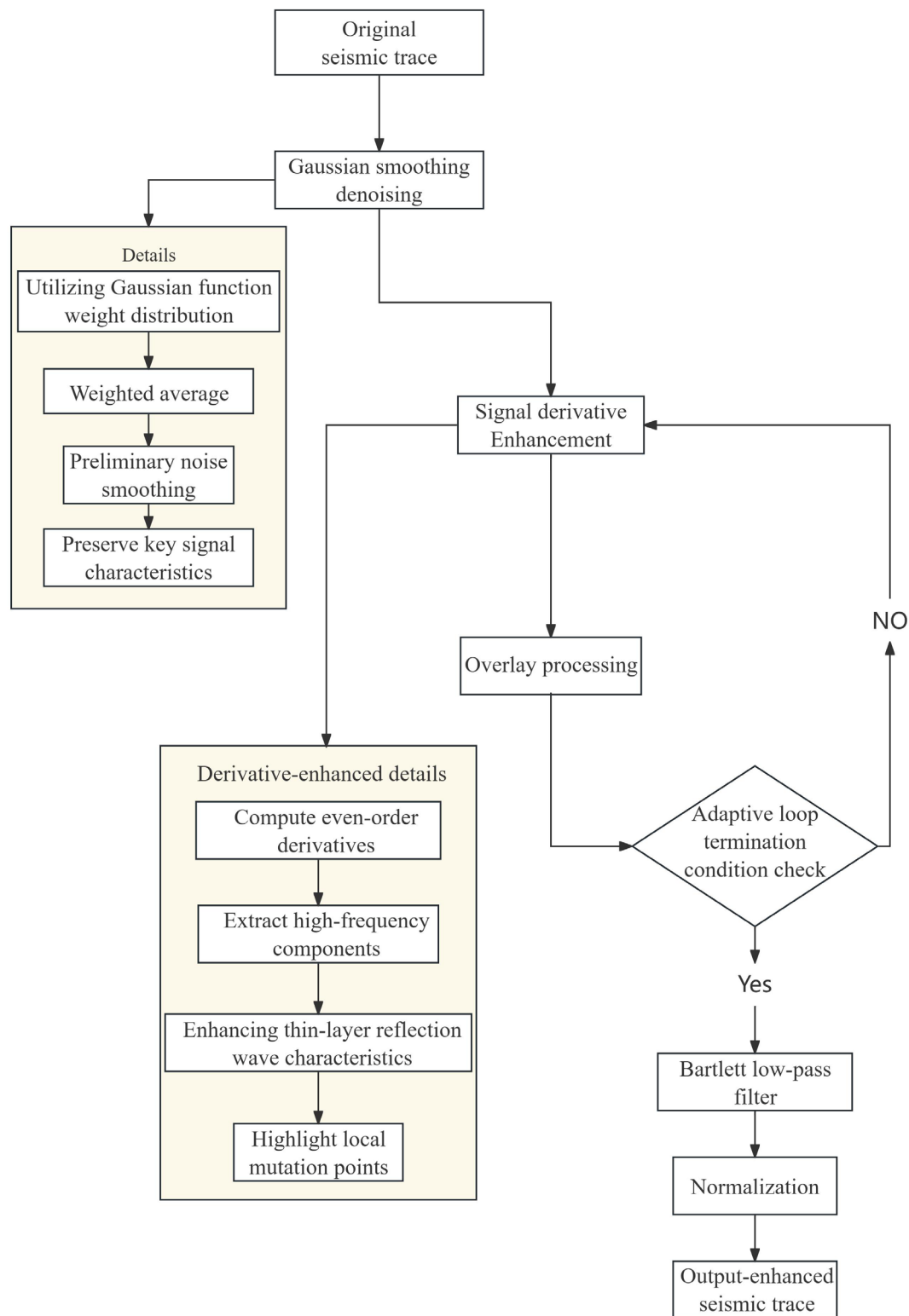


Figure 3. Flow chart of cyclic spectrum enhancement technology

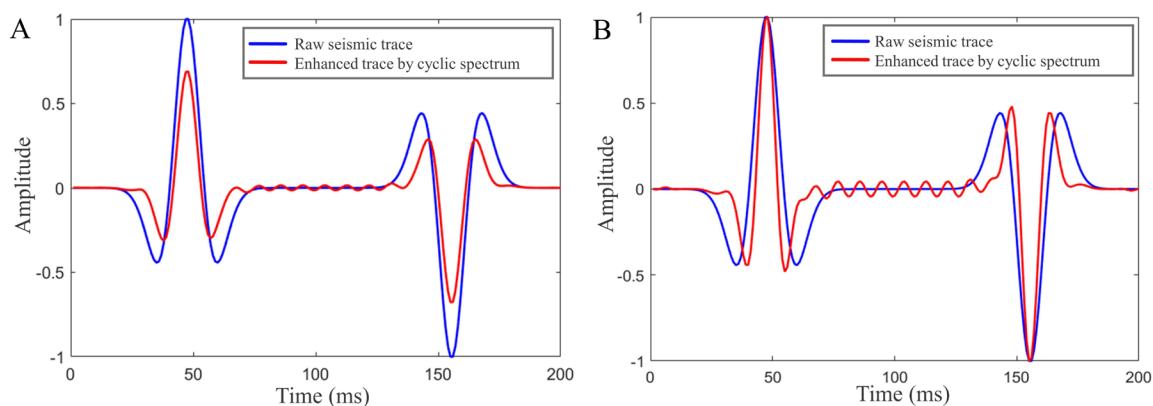


Figure 4. Comparison of waveforms processed by different denoising methods of $\lambda/8$ thin-layer. (A) Denoising results of Complete Ensemble Empirical Mode Decomposition (CEEMD) method; (B) Butterworth filter denoising results.

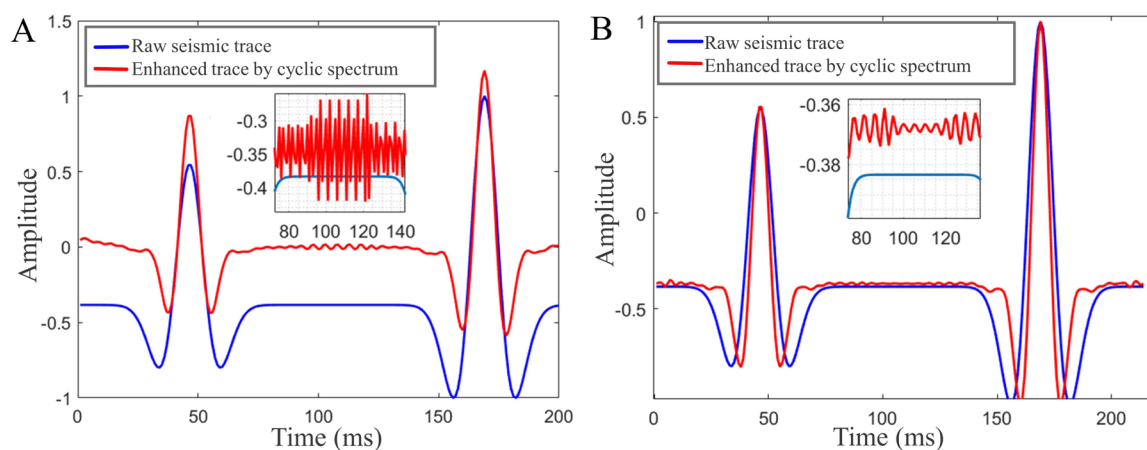


Figure 5. Comparison of waveforms processed by different denoising methods of $\lambda/16$ thin-layer. (A) Denoising results of Complete Ensemble Empirical Mode Decomposition (CEEMD) method; (B) Butterworth filter denoising results.

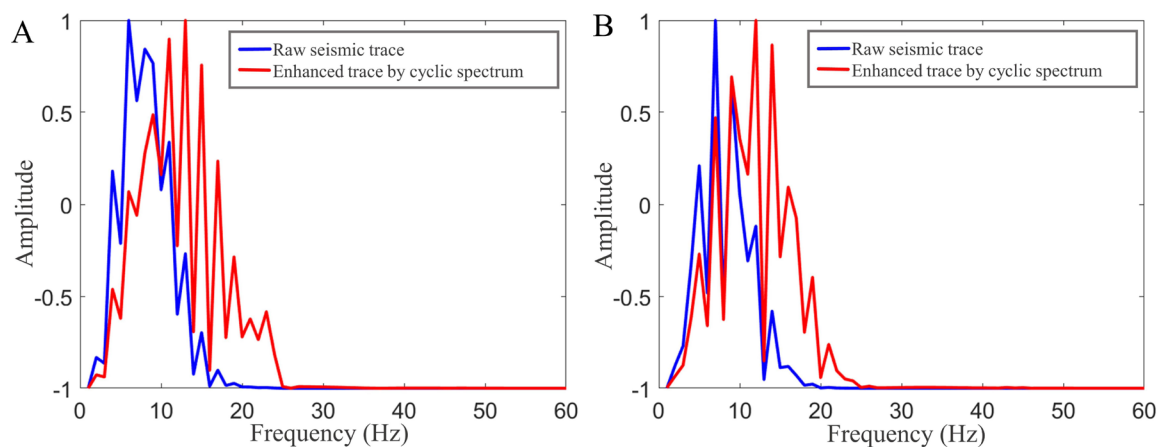


Figure 6. Comparison of amplitude spectra of two kinds of thin interlayer treatment. (a) $\lambda/8$; (b) $\lambda/16$.

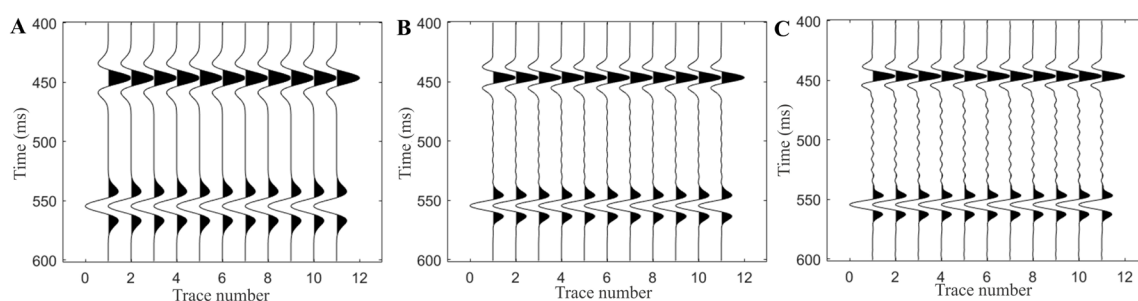


Figure 7. Comparison of seismic records processed by different denoising methods. (A) Raw seismic records; (B) CEEMD; (C) Butterworth filter.

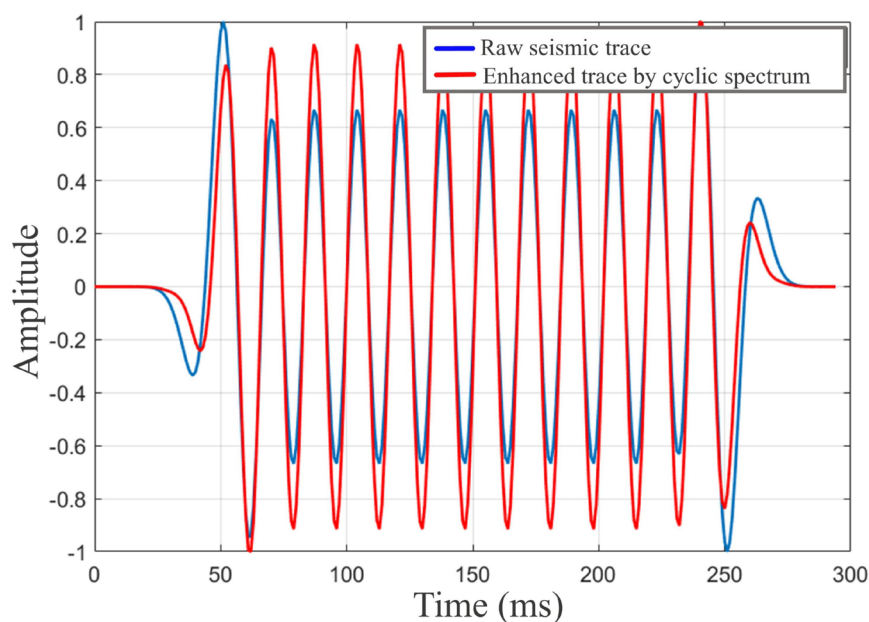


Figure 8. Thick layer numerical seismic traces and derivative seismic traces

the thin interlayer weak signal is enhanced from very weak to visible to the naked eye, which shows that this technology can enhance the thin interlayer weak signal and make it accurately recognized.

4.2. Two-dimensional seismic record

The two-dimensional thin interbedded seismic records of 40 m, 10 m and 5 m were subjected to cyclic spectrum enhancement, and the results are shown in Figure 10. It can be seen from the comparison chart before (Figure 10a) and after (Figure 10b) processing 40 m (1λ) record that the amplitude of strong reflection signal has not changed, indicating that this technology has no enhancement effect on thick layer strong seismic reflection signal. The amplitude of the 10 m ($\lambda/4$) original record (Figure 10c) increased after processing (Figure 10d), showing that the proposed method can enhance the moderate intensity

signal. After 5 m ($\lambda/8$) original recording (Figure 10e) is processed (Figure 10f), the amplitude of the original weak signal near zero is significantly improved. To sum up, cyclic spectrum enhancement technology can compensate the amplitude of weak signals and extremely weak signals without losing strong signals, and the enhancement effect becomes more obvious as the thickness of the thin layer decreases.

5. Field data

Two-dimensional seismic data from an onshore exploration area in Jizhong, North China Plain, were used as the study dataset. The area lies within the tectonic transition zone of the western margin of Bohai Bay Basin, and has typical thin-layer geological characteristics of sandstone and mudstone. Numerous thin-layer structures are present, accompanied by pronounced weak-signal

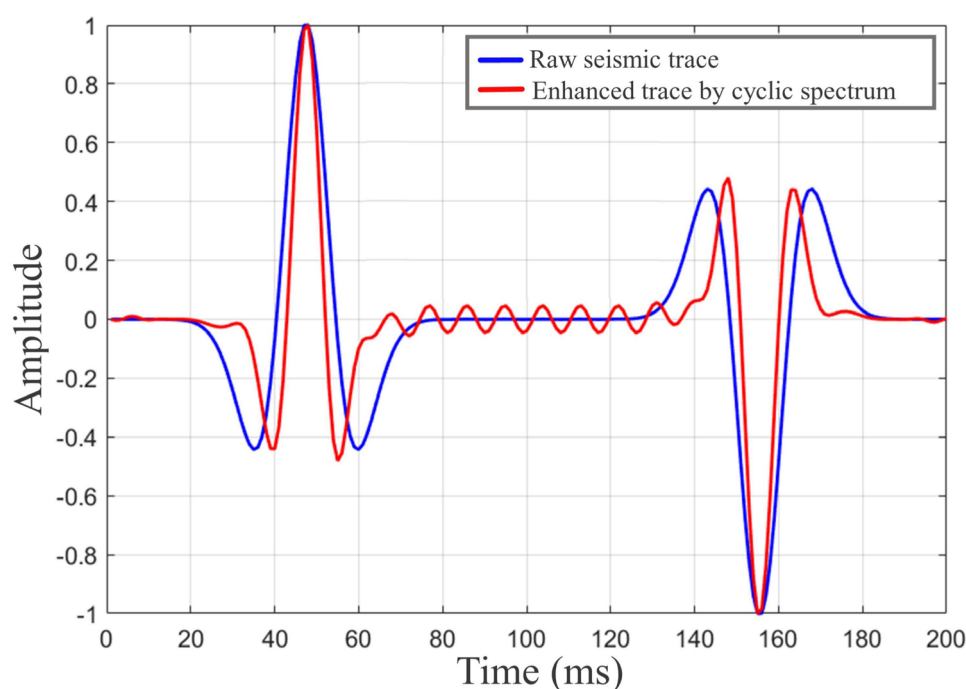


Figure 9. Thin layer numerical seismic traces and derivative seismic traces

characteristics, making this dataset particularly well suited for investigating identification of thin-layer weak signals. The length of each data in the experimental section is 3,000 sampling points, and the sampling rate is set to 1 ms, which contains 571 seismic data. In this paper, the classic thin-layer weak signal identification technology is compared experimentally through a predictive deconvolution method. Figure 11 shows the actual seismic record data. 1–100 thin-layer seismic records with actual data and a seismic record length of 2,000–2,200ms are selected for processing (as shown in the red box), and the amplitude spectrum, f-k spectrum and local similarity of the weak signal enhancement of the actual seismic data are analyzed.

Based on Figure 12a, the continuity of the in-phase axis of the seismic data before processing is poor, and there are many weak signals between layers. The results processed by the prediction deconvolution method are shown in the figure. The continuity of the in-phase axis of the processed seismic data is poor, and some strong signals are weakened, only part of the weak signals between layers are enhanced, and the extremely weak signals between layers have no enhancement effect. The seismic data processed by this method is shown in Figure 12c. The continuity of the in-phase axis at the arrow-indicated position is improved, and the weak signal between thin layers are markedly enhanced.

After the actual seismic data is processed by cyclic

spectrum enhancement technology, the local similarity analysis is carried out on the two-dimensional seismic profile. The closer the color is to the yellow part on the color scale, the higher the similarity between the representative and the original data, and the closer the color scale is to the blue part on the lower color scale, the lower the similarity with the original data. The local similarity diagram of the actual seismic data processed by the predictive deconvolution method is shown in Figure 13a. Based on the diagram, it can be seen that the region with similarity coefficient close to zero appears in the strong reflection horizon (shown by the red arrow), indicating that the predictive deconvolution technology cannot guarantee the fidelity of the algorithm to the original data when processing strong signals. The local similarity diagram of this method is shown in Figure 13b, in which the weak signal enhancement region has good similarity with the original data.

The f-k spectrum of the original seismic data and the actual seismic data processed by different methods is shown in Figure 14. In the f-k spectrum, brighter colors indicate higher frequency values, greater energy concentration, and stronger effective signals. It can be seen from Figure 14b and 14c that the energy of the seismic data processed by the predictive deconvolution method and the method reported in this paper is concentrated, but the energy points in the f-k spectrum obtained by the

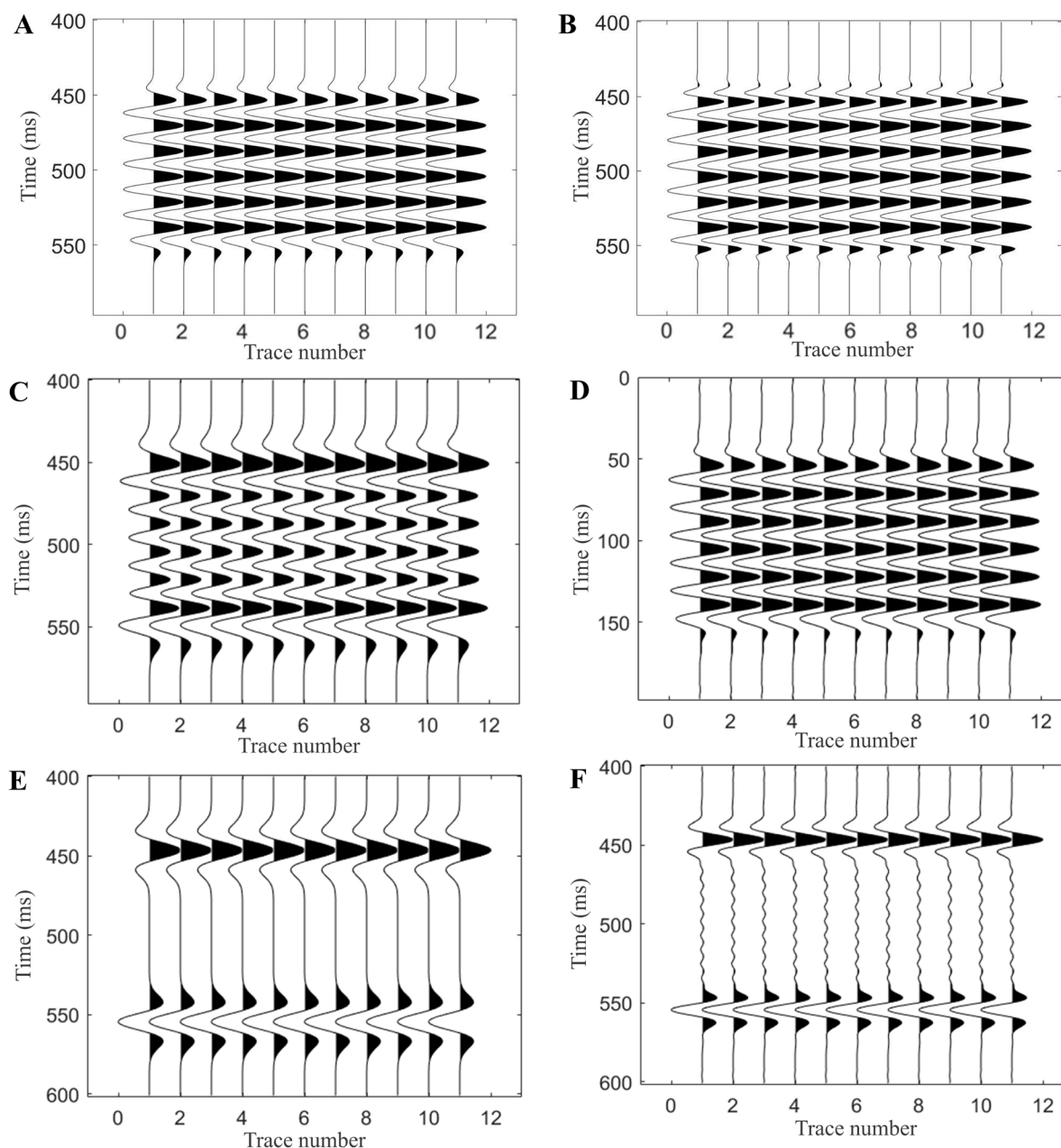


Figure 10. Comparison of effects before and after mutual recognition of different thicknesses. (A) 1λ original record; (B) post-process 1λ layers; (C) $\lambda/4$ original records; (D) post-process $\lambda/4$ layers; (E) $\lambda/8$ original records; (F) post-process $\lambda/8$ layers.

predictive deconvolution method are more scattered, and the randomly distributed energy points usually represent noise. The energy of f-k spectrum of this method is more concentrated, and the brightness of the effective signal is higher, indicating enhanced effective signal, but there are also scattered energy points that are unevenly distributed, suggesting the necessity of further algorithm optimization for removing high frequency interference.

Figure 15 shows the amplitude spectrum analysis of the two-dimensional seismic profiles before and after treatment. Compared with the predictive deconvolution method, the method in this paper has a better enhancement effect on weak signals, along with wider frequency band of the enhanced signal and better compensation effect in both low- and high-frequency directions, indicating that the method yields a better enhancement effect on weak

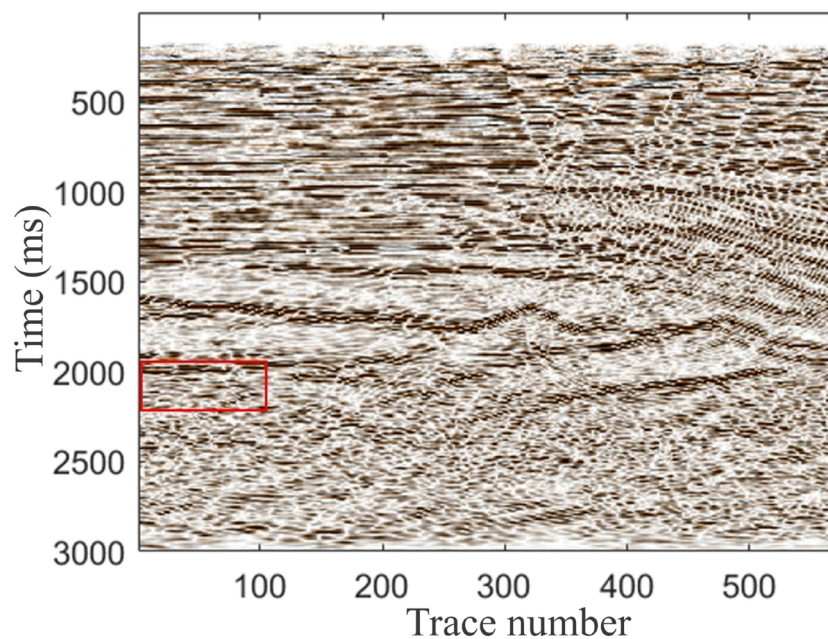


Figure 11. Sectional view of field data

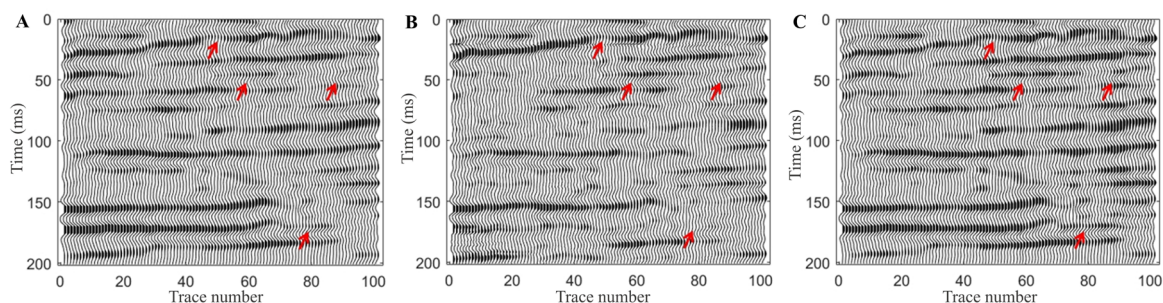


Figure 12. Different methods of processing cross-section enlargement effect. (A) Raw seismic data; (B) a predictive deconvolution method; (C) method reported in this paper.

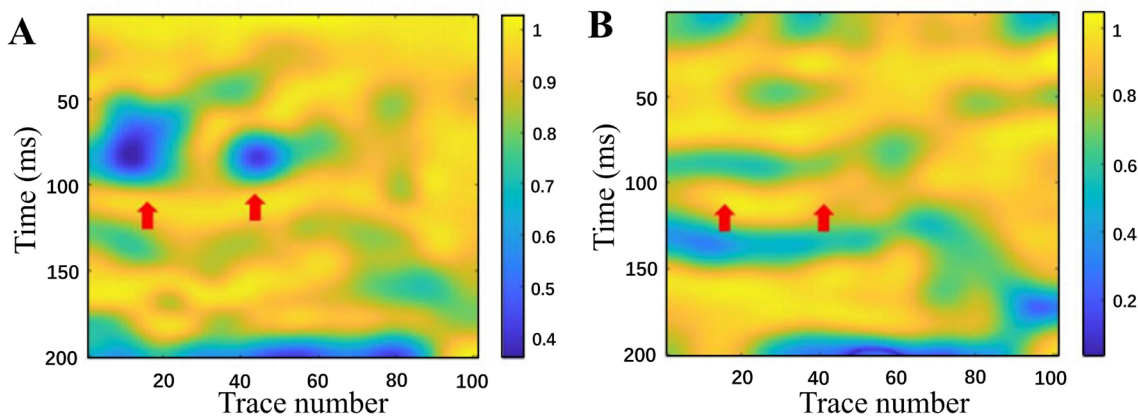


Figure 13. Local similarity diagram between data processed by different methods and original data. (A) A predictive deconvolution method; (B) method reported in this paper.

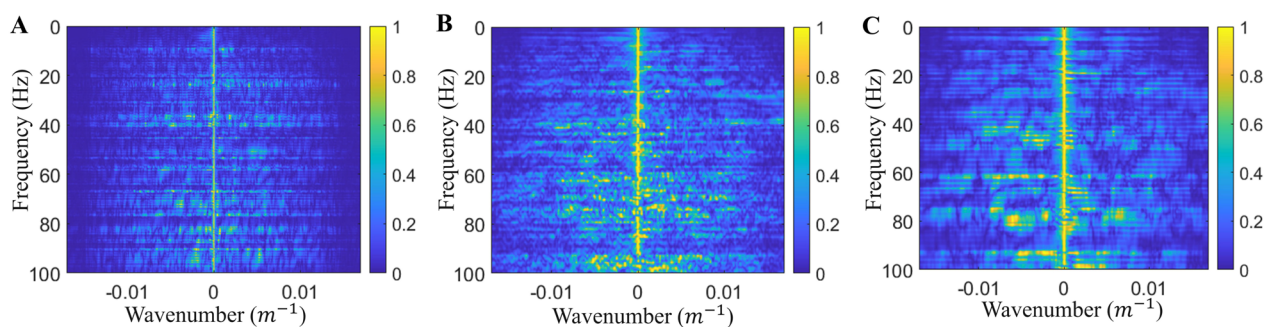


Figure 14. f-k spectra of different methods. (A) The original number of earthquakes; (B) predicting deconvolution; (C) Methods herein.

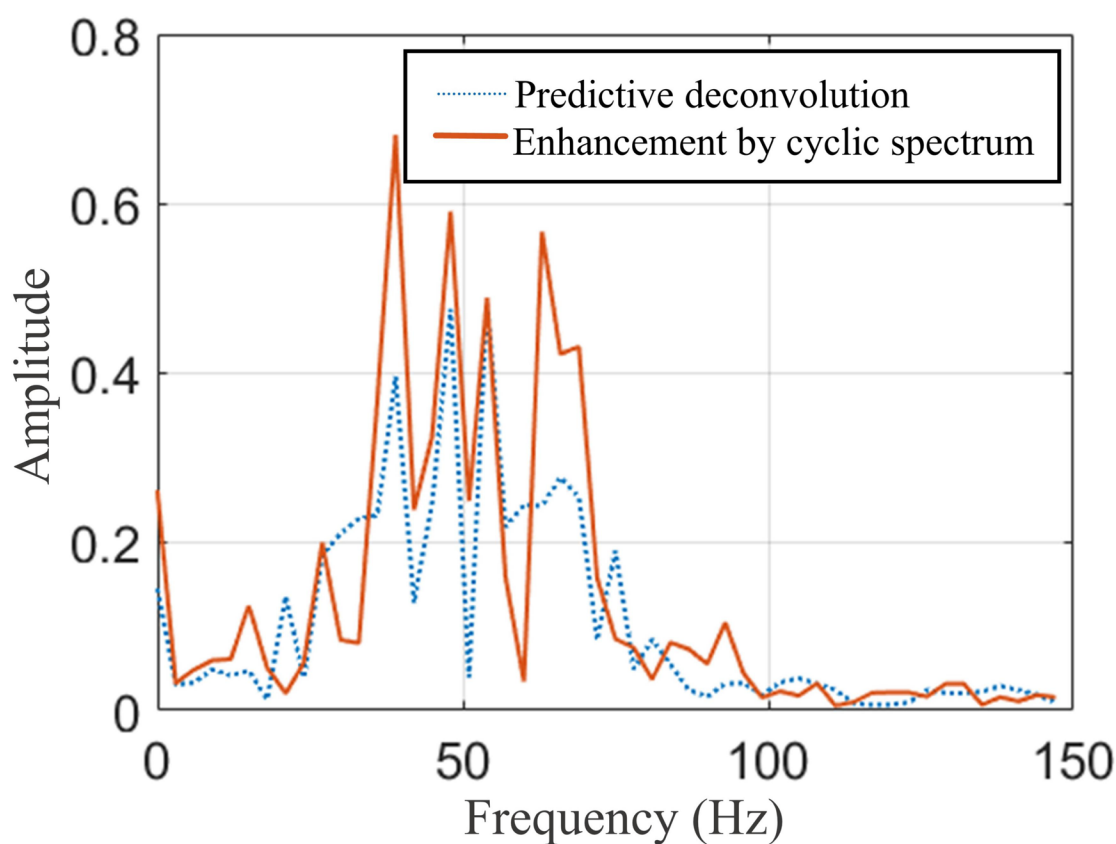


Figure 15. Post-processing profile amplitude spectra of predictive deconvolution and enhancement by cyclic spectrum

signals.

By applying the proposed method to the actual seismic data of Suning–Dawangzhuang area where thin layer development is extremely significant in Northern China, the accuracy of cyclic spectrum enhancement technology in thin layer recognition is verified by comparing the results before and after the processing of through-well seismic profiles. There are many layers of thin sandstone

with a thickness of 3–5 m in this research area. Because of the delicate lithology of the thin sandstone layer, the wave impedance difference between the upper and lower strata is relatively small, and the interference between the thin sandstone layers makes its seismic reflection signal relatively weak. Figure 16a shows the original seismic profile, while Figure 16b presents the processed seismic profile. Some in-phase axes are added to the seismic profile

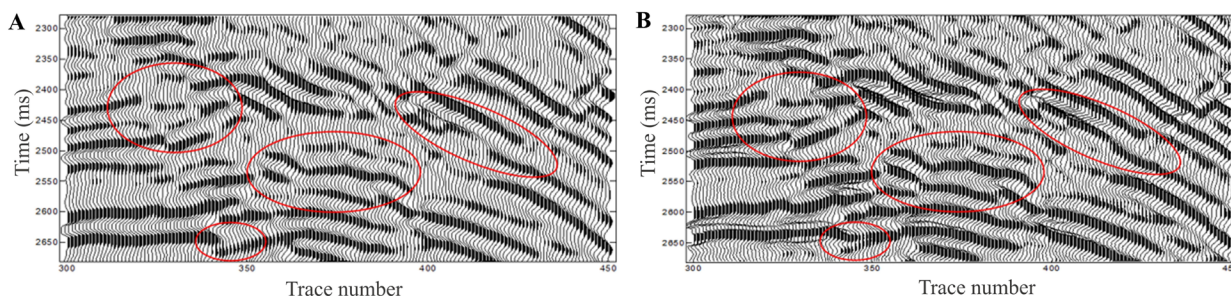


Figure 16. Comparison of seismic profiles before and after processing. (A) Original seismic data; (B) post-processing seismic profile.

processed by cyclic spectrum enhancement technology; the continuity of in-phase axes shows improvements, and the reflected signal becomes effectively enhanced.

Through the comparison of well-passing seismic profiles, the seismic reflection characteristics can be accurately matched with the actual drilling data (covering lithology, logging curves, oil and gas horizons). This process can not only effectively verify the reliability of seismic processing results, but also establish an accurate time-depth conversion relationship, thus verifying the accuracy of this method in structural interpretation and reservoir prediction. A comparison of the post-processing well-tie seismic profiles presented in Figure 17a and 17b revealed that the weak signals are significantly enhanced after the application of cyclic spectrum enhancement technology, along with substantial improvements in the continuity of the in-phase axis (as shown in the area marked by red circle) and enhanced clarity of the horizon information.

Figure 17 shows the macroscopic characteristics before and after well-tie profile processing, while Figure 18 (partial enlarged view of the red box area) reveals the significant advantages of this method in detail restoration. A comparison of results presented in Figure 18a and 18b indicated effective restoration of the amplitude characteristics of the reflected signal with weak energy and submerged in background noise in the original profile

following processing using this method. Especially in the area marked by the red box in the figure, the original fuzzy weak reflection in-phase axis becomes clearer and sharper, and the background clutter is effectively suppressed. In the original section, some of the in-phase axes are intermittent and distorted, posing challenges in horizon tracking. After treatment, these breakpoints have been effectively bridged, the lateral continuity of the in-phase axis has been greatly improved, and the characteristics of the wave group become smoother and more natural, showing a good compliance with the stratigraphic deposition law. Integrated with the logging lithology column and curves shown in the center, the correspondence between the processed seismic waveform and the drilling layered interface is markedly improved. At the strong reflection horizon in the middle of Figure 18b, the enhanced wave group aligns closely with the key lithologic interface (yellow filling part) indicated by the logging data. This agreement confirms that this method enhances resolution while preserving the fidelity of the geological structure. This result strongly proves that the method utilized in this study can effectively mine the hidden information in seismic data, improve the resolution of the profile, and ensure high reliability of geological interpretation, which is of great value to address problems surrounding thin layer identification in complex structural areas.

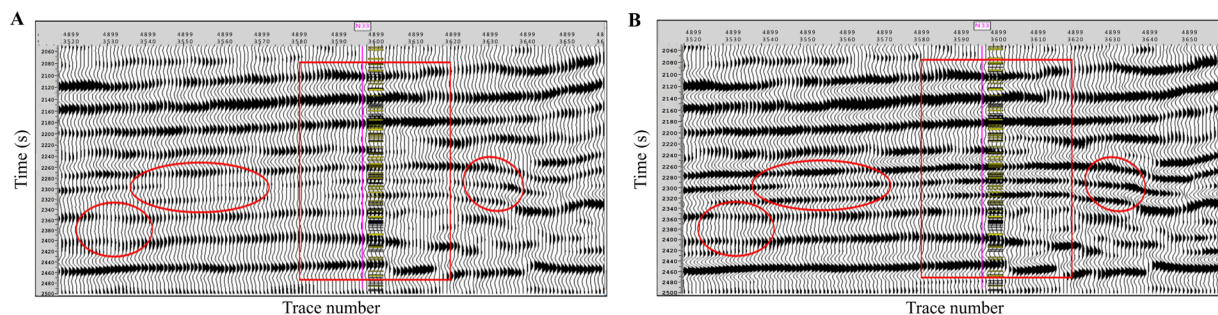


Figure 17. Comparison of seismic profiles before and after processing. (A) Original seismic data; (B) post-processing seismic profile.

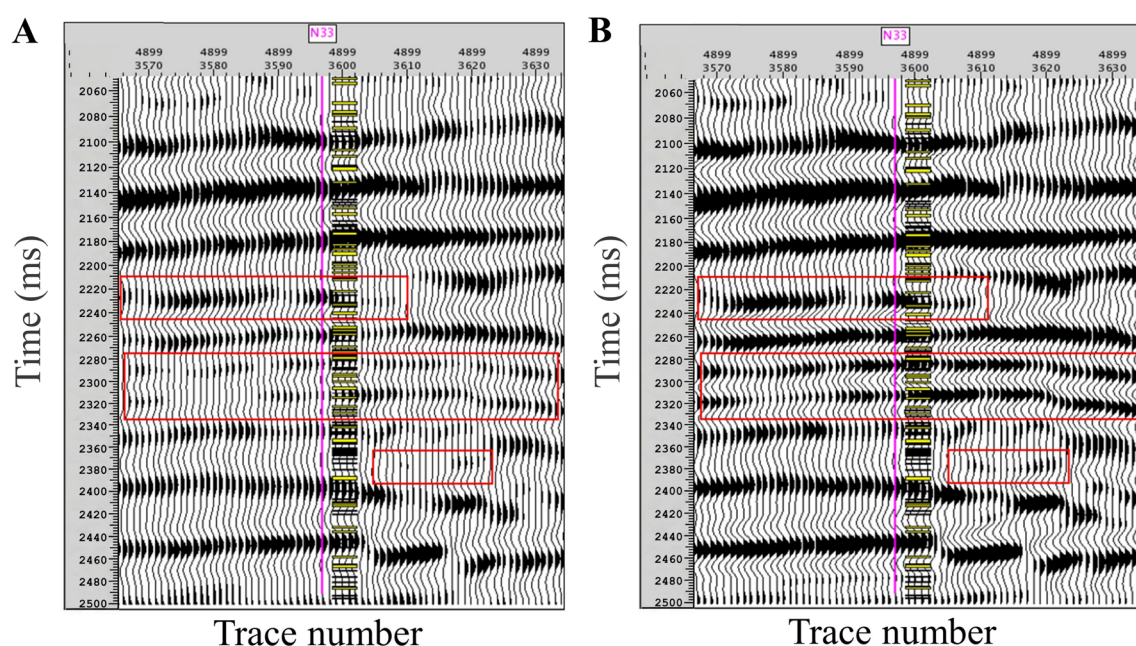


Figure 18. Enlarged comparison diagram of well-tie seismic profile. (A) Original seismic profile; (B) post-processing seismic profile.

6. Conclusion

In this paper, a cyclic spectrum enhancement technique is proposed to resolve weak reflections obscured by thin-layer interference. This methodology integrates Gaussian smoothing, derivative enhancement, and adaptive spectral conditioning to significantly improve the detectability of subtle seismic signals. Model tests and field data processing demonstrate that while the method maintains stability for thicker formations, it demonstrates exceptional performance in resolving weak signals at the tuning thickness ($\lambda/4$) and even extremely weak signals at $\lambda/8$, while maintaining high data fidelity and horizon consistency. However, the proposed technology struggles with several imitations in its application. For ultra-thin layers approaching the $\lambda/32$ limit, destructive interference becomes so pronounced that the effective signal spectrum is largely masked by the wavelet sidelobes, potentially leading to resolution instability or spurious events. Furthermore, beneath strong shielding layers (such as thick salt or basalt), severe energy attenuation and multiple-wave interference significantly reduce the SNR, thereby limiting the method's ability to recover weak deep-seated reflections. Future work will focus on integrating this technique with deep learning architectures to achieve adaptive parameter optimization and intelligent signal identification. By incorporating physics-informed neural networks, we aim to extend the method's applicability to ultra-deep, ultra-thin reservoirs and complex formations

such as shale and tight gas, thereby facilitating high-precision sweet-spot prediction in challenging geological settings.

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Conflict of interest

All authors declare no conflicts of interest.

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Availability of data

Data are available from the corresponding author upon reasonable request.

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