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Three-dimensional high-order total variation regularized acoustic impedance inversion for thin coal seam thickness prediction in the Yushe East Area, China

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Abstract

Conventional three-dimensional (3D) impedance inversion methods exhibit poor lateral continuity during the inversion of thin coal seams, making it difficult to effectively preserve the lateral structural characteristics of the coal seams, which in turn affects the accurate prediction of the thickness and extent of thin coal seams. To address this issue, we propose a 3D high-order total variation (TV) regularized impedance inversion method. This method introduces high-order TV regularization constraints in both the inline and crossline directions to enhance the spatial continuity of the inversion results. The inversion objective function is solved in the frequency domain using the split-Bregman method, thereby improving computational efficiency for large-scale 3D matrix operations compared to time-domain approaches. The test results of the 3D overthrust model show that the 3D high-order TV constraint can effectively improve the transverse continuity and structural retention ability of the inversion results. The practical application results on the 3D seismic data of Yushe East Exploration Area in Shanxi Province show that, compared to the model-based inversion method in STRATA, the proposed method achieves higher vertical resolution and better lateral continuity, and can clearly depict the low-impedance characteristics of the No. 15 coal seam. Based on this, the error between the predicted coal seam thickness and the well-logging interpretation thickness is less than 8.8%, indicating that the proposed method maintains good stability and predictive capability even under limited well-control conditions.

Keywords: Acoustic impedance inversion; Three-dimensional total variation regularization; High-order difference operator; Coal seam thickness prediction; Lateral continuity

1. Introduction

Thin coal seams are important targets in coalbed methane exploration and coal mining, and accurate prediction of their thickness and lateral distribution is essential for reservoir evaluation and safe production. With the growing demand for mine safety and production efficiency, coal geophysics has become increasingly important for thin-seam identification and characterization.¹ Coal seams usually exhibit relatively low acoustic impedance compared to surrounding rocks, making seismic impedance inversion an effective tool for predicting coal seams. However, due to the limited bandwidth of seismic data and the thin thickness of coal seams, conventional inversion methods often suffer from low vertical resolution and poor lateral continuity, making it difficult to accurately describe the spatial distribution of thin coal seams.^{2–4}

At present, the acoustic impedance inversion method widely used in engineering practice mainly includes the model-based inversion method and the constrained sparse pulse inversion method. Cook and Schneider⁵ first proposed the model-based acoustic impedance inversion, which provides low-frequency background and structural trends by introducing an initial impedance model, thereby ensuring inversion stability. However, in three-dimensional (3D) seismic data processing, this method is usually implemented in a trace-by-trace or line-by-line manner, and the lateral continuity of the inversion results strongly depends on the quality of the initial model. When the number of wells is limited or the initial model is inaccurate, the inversion results are prone to strong model-controlled characteristics.^{6–8} Model-based inversion has been widely applied in thin interbedded coal seam prediction, but its resolution remains limited under thin-layer conditions.⁹

To reduce the dependence on the initial model, constrained sparse spike inversion methods have been proposed. By imposing sparsity constraints on the reflection coefficients, these methods improve vertical resolution and are more suitable for thin-layer target characterization.^{10,11} Sparse spike inversion has been successfully applied in reservoir prediction and thin-layer identification¹², and related methods have also been combined with machine learning techniques to further enhance reservoir characterization capability.^{13,14} These approaches have been widely implemented in commercial software such as STRATA and JASON.^{15,16} In studies of coal seam thickness prediction and fine reservoir characterization, geostatistical inversion methods have also been widely applied.^{17,18} By introducing geostatistical constraints, such as random simulation and variogram models, these methods integrate both seismic and well data during inversion and generate multiple impedance

realizations that satisfy statistical characteristics, thereby improving the reliability of reservoir parameter prediction. In coal seam thickness prediction, geostatistical inversion can effectively describe spatial variations between wells. However, this type of method usually requires a sufficient number of wells for statistical modeling. When well control is sparse or seismic resolution is limited, prediction uncertainty increases significantly, and the computational cost is relatively high, which limits its efficiency in large-scale 3D data applications. In addition, other inversion techniques, such as MGI inversion, have also been applied to coal seam thickness prediction and have shown certain advantages under complex geological conditions.¹⁹

In addition, to improve lateral continuity, some studies have introduced spatial smoothing or other regularization constraints into the inversion process.^{20–22} Structurally constrained inversion can enhance the spatial stability of inversion results by incorporating geological structure information.²³ Total variation (TV) regularization, originally developed in the field of image processing²⁴, has been widely used in seismic inversion for its ability to preserve structural edges while suppressing noise. Nonlinear multichannel impedance inversion based on TV regularization has been shown to improve spatial stability and reduce inversion artifacts.²⁵ However, conventional first-order TV regularization tends to introduce the so-called “staircase effect,” which may oversimplify smoothly varying geological features. Previous studies in both image processing and geophysical inversion have shown that high-order TV regularization can effectively alleviate this effect by penalizing higher-order derivatives, thereby better preserving smooth variations while maintaining structural boundaries.^{26–28} Despite these improvements, most existing TV-based inversion methods are still implemented within a line-by-line framework, and the effect of true 3D spatial constraints is limited. As a result, the problem of poor lateral continuity remains, making it difficult to meet the requirements for fine characterization of thin coal seams.^{29,30} Recent studies have shown that improving the lateral stability of inversion is particularly important for thin coal-seam detection and thickness prediction under complex geological conditions.³¹

The research target of this paper is the No. 15 coal seam in the Yushe East exploration area, Shanxi Province, with an average thickness of approximately 4.5 m. The lateral development of this coal seam is relatively stable, but the number of wells is limited, necessitating accurate characterization of the spatial variation in coal seam thickness. Therefore, high requirements are imposed on the lateral continuity and vertical resolution of the inversion results. To address these challenges, this paper

proposes a 3D acoustic impedance inversion method based on high-order TV regularization. Unlike conventional approaches that perform inversion in a trace-by-trace or line-by-line manner, the proposed method directly imposes 3D spatial constraints across the full data volume, enabling simultaneous use of inter-trace correlations in both the inline and crossline directions. This method constructs a 3D high-order TV regularization constraint and integrates it into the inversion framework to enhance lateral continuity. The proposed method is validated using both synthetic models and field data and is compared to conventional impedance inversion methods. The results demonstrate that the proposed method provides clear improvements in lateral continuity and vertical resolution for thin coal-seam inversion.

2. Methodology

2.1. Model-constrained acoustic impedance inversion

The 3D seismic data s can be represented as a 3D convolutional form of wavelet w with the reflectivity volume R (Equation 1):

$$s(x, y, t) = w * R \quad (1)$$

where $*$ represents the 3D convolution operation.

Under the assumption of horizontally layered media, when the variation of acoustic impedance Z between adjacent sample points is smaller than the absolute impedance value, the reflectivity R can be approximated in the form of the adjacent impedance difference. By introducing the logarithmic acoustic impedance, a linear relationship between the reflectivity and the logarithmic impedance can be established as follows (Equation 2):

$$R_{i,j} = \frac{Z_{i+1,j} - Z_{i,j}}{Z_{i+1,j} + Z_{i,j}} \approx \frac{1}{2} (\ln Z_{i+1,j} - \ln Z_{i,j}) \quad (2)$$

The relationship between the seismic data s and the logarithmic impedance can be expressed as a convolutional model with a first-order vertical difference operator applied to the log-impedance (Equation 3):

$$s = WD \ln Z + n \quad (3)$$

where s denotes the seismic data, W is the wavelet convolution matrix constructed from the seismic wavelet w , D is the first-order vertical difference operator, and n represents the noise. In practical applications, the most commonly used regularization is the Tikhonov regularization. Accordingly, the objective function of

model-based acoustic impedance inversion can be written as Equation 4:

$$J(Z) = \frac{1}{2} \|s_{obs} - WD\tilde{Z}\|_F^2 + \lambda \|T(\tilde{Z} - \tilde{Z}_0)\|_2^2 \quad (4)$$

where $\|\cdot\|_F$ represents the Frobenius norm of the matrix; s_{obs} represents the observed seismic data; $\tilde{Z}$ represents the logarithmic impedance, defined as $\tilde{Z} = \ln Z$; λ is the regularization parameter; T is the Tikhonov matrix, usually taken as the first-order difference matrix. This method essentially applies an L_2 -norm constraint to impose an overall smoothing effect on the impedance model, which can weaken the boundary characteristics of geological bodies. Moreover, the lateral continuity of the inversion result strongly depends on the accuracy of the initial model. When the initial model is low-frequency, the method cannot obtain high-resolution inversion results, which limits its application to 3D fine reservoir prediction.

2.2. Three-dimensional high-order total variation regularization model

Thin-layer reservoirs such as coal seams are usually characterized by thin vertical thickness and stable lateral continuity. Therefore, in 3D acoustic impedance inversion, it is necessary to explicitly introduce spatial constraints in the lateral directions to enhance the lateral continuity of the inversion results. Conventional TV regularization imposes constraints using first-order differences in both vertical and horizontal directions. However, the first-order difference often contains amplitude-variation information of the seismic data. As shown in Figure 1B, the first-order TV model tends to suppress these variations, which may lead to the well-known staircase effect in the inversion result. Figure 1C shows the second-order difference profile. The second-order difference reflects the rate of change in amplitude rather than the amplitude itself, and it mainly appears as random noise in the profile, without containing the primary amplitude information of the seismic data. Therefore, in this study, a second-order difference operator is introduced in the lateral directions to construct the TV regularization term, thereby enhancing lateral continuity while preserving structural boundaries.

For 3D seismic data $u(x, y, t)$, there are three forms of second-order difference in the x - y plane: second-order difference along the x direction $u_{xx} = \nabla_{xx} \otimes u$, second-order difference along the y direction $u_{yy} = \nabla_{yy} \otimes u$, and mixed difference along the x - y direction $u_{xy} = u_{yx} = \nabla_{xy} \otimes u$, as shown in Figure 2.

By combining the above operators, a set of high-order lateral difference operators is constructed, enabling a more accurate representation of inter-trace correlations

in the 3D seismic volume. The combined operators can be expressed as **Equation 5**:

$$\begin{cases} \Psi_1 = \nabla_{xx} + \nabla_{yy} \\ \Psi_2 = \nabla_{xx} - \nabla_{yy} \\ \Psi_3 = 2 \cdot \nabla_{xy} \end{cases} \quad (5)$$

where Ψ_1 , Ψ_2 and Ψ_3 are the newly combined 3D difference operators. Assuming the size of the 3D seismic data is $10 \times 10 \times 10$, **Figure 3** shows the construction diagram of Ψ_1 , Ψ_2 and Ψ_3 .

Therefore, the 3D higher-order TV regularization constraint term can be expressed as **Equation 6**:

$$TV(u) = \sum_{m=1}^3 \|\Psi_m * (WD\tilde{Z})\|_2 = \sum \sqrt{(\Psi_1 * u)^2 + (\Psi_2 * u)^2 + (\Psi_3 * u)^2} \quad (6)$$

2.3. Objective function and solution method for three-dimensional acoustic impedance inversion

Under the 3D high-order TV regularization constraint, the objective function shown in **Equation 4** becomes **Equation 7**:

$$J(\tilde{Z}) = \frac{1}{2} \|s_{obs} - WD\tilde{Z}\|_F^2 + \alpha \|(\tilde{Z} - \tilde{Z}_0)\|_2^2 + \beta \sum_{m=1}^3 \|\Psi_m * (WD\tilde{Z})\|_2 \quad (7)$$

where the regularization parameters α and β control the balance between data fidelity and the strength of the high-order TV constraint. In this study, these parameters were determined empirically through a series of trial-and-error tests on a subset of the data to achieve an optimal trade-off between inversion accuracy and spatial continuity. Specifically, multiple combinations of α and β were evaluated, and the final values were selected based on quantitative metrics and visual inspection of the residuals. In general, a larger β enhances lateral smoothness but may lead to over-smoothing, whereas a smaller β may result in insufficient noise suppression.

The objective function in **Equation 7** involves 3D convolution operations, making it difficult to solve using traditional gradient-based optimization methods. Therefore, the split-Bregman method was employed to solve the inversion problem. For large 3D seismic datasets, solving the objective function in the time domain can be computationally expensive. To address this issue, the objective function is transformed into the frequency domain (**Equation 8**):

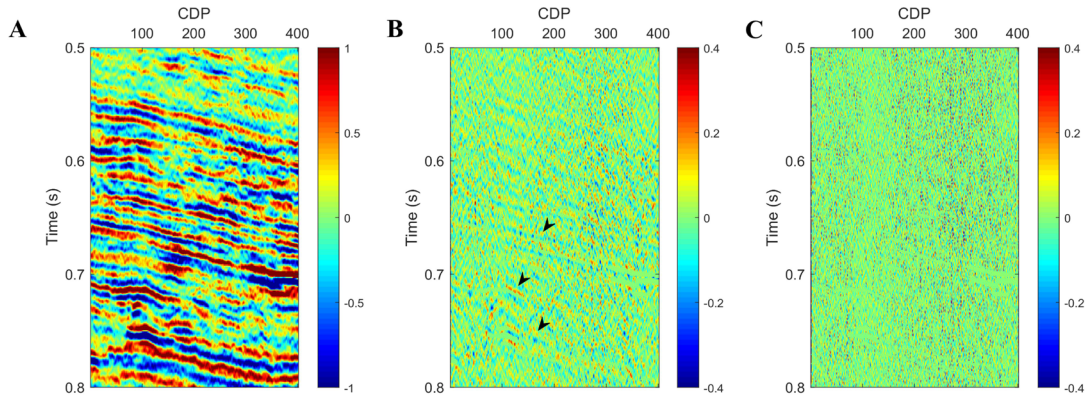


Figure 1. Seismic data and difference profiles. (A) Noisy seismic data. (B) First-order difference profile. (C) Second-order difference profile.

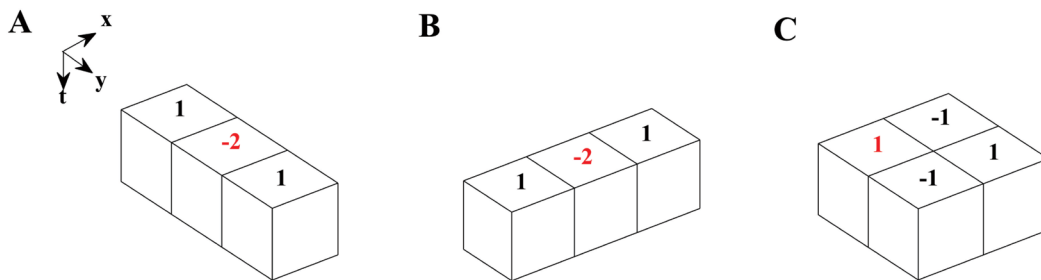


Figure 2. Three second-order difference operators on the x - y plane. (A) ∇_{xx} . (B) ∇_{yy} . (C) ∇_{xy} .

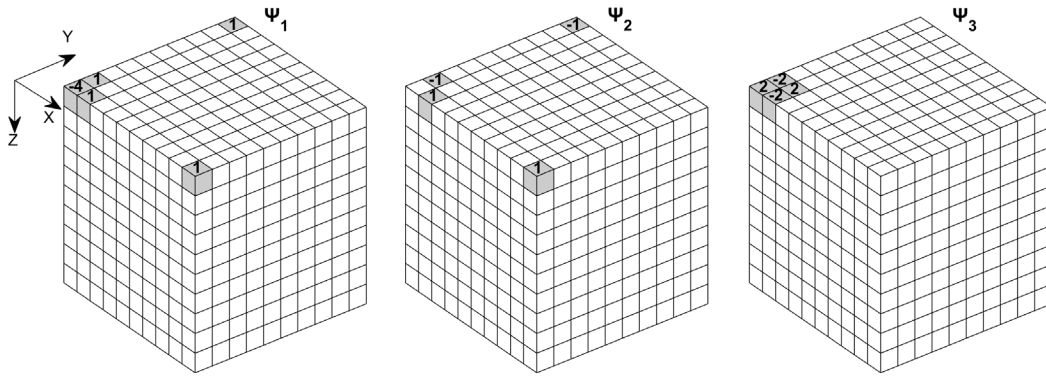


Figure 3. Schematic diagram of the construction of three combination operators

$$J(\hat{\mathbf{Z}}) = \frac{1}{2} \left\| \hat{\mathbf{S}} - \hat{\mathbf{W}} \cdot \hat{\mathbf{D}} \cdot \hat{\mathbf{Z}} \right\|_F^2 + \alpha \left\| \hat{\mathbf{Z}} - \hat{\mathbf{Z}}_0 \right\|_2^2 + \beta \sum_{m=1}^3 \left\| \hat{\Psi}_m \cdot (\hat{\mathbf{W}} \cdot \hat{\mathbf{D}} \cdot \hat{\mathbf{Z}}) \right\|_2 \quad (8)$$

The variables marked with “ $\hat{\cdot}$ ” represent their own 3D Fourier transform results, and “ $\cdot$ ” represents the dot product operation between 3D matrices. Within the split-Bregman framework, Equation 8 can be split into the following problems (Equations 9–11):

$$\hat{\mathbf{Z}}^{k+1} = \min_r \left[\frac{1}{2} \left\| \hat{\mathbf{S}} - \hat{\mathbf{W}} \cdot \hat{\mathbf{D}} \cdot \hat{\mathbf{Z}} \right\|_F^2 + \frac{\alpha}{2} \left\| \hat{\mathbf{Z}} - \hat{\mathbf{Z}}_0 \right\|_2^2 + \frac{\beta}{2} \left\| \hat{\mathbf{d}}_m^k - \hat{\Psi}_m \cdot \hat{\mathbf{W}} \cdot \hat{\mathbf{D}} \cdot \hat{\mathbf{Z}} - \hat{\mathbf{b}}_m^k \right\|_2^2 \right] \quad (9)$$

$$\hat{\mathbf{d}}_m^{k+1} = \min_{d_m} \left[\lambda \left\| \hat{\mathbf{d}}_1, \hat{\mathbf{d}}_2, \hat{\mathbf{d}}_3 \right\|_2 + \frac{\beta}{2} \sum_{m=1}^3 \left\| \hat{\mathbf{d}}_m^k - \hat{\Psi}_m \cdot \hat{\mathbf{W}} \cdot \hat{\mathbf{D}} \cdot \hat{\mathbf{Z}} - \hat{\mathbf{b}}_m^k \right\|_F^2 \right] \quad (10)$$

$$\hat{\mathbf{b}}_m^{k+1} = \hat{\mathbf{b}}_m^k - \left[\hat{\mathbf{d}}_m^{k+1} - \hat{\Psi}_m \cdot \hat{\mathbf{W}} \cdot \hat{\mathbf{D}} \cdot \hat{\mathbf{Z}}^{k+1} \right] \quad (11)$$

where d and b are intermediate variables; k is the number of iterations. Taking the derivative of Equation 9 and setting it to 0, we can simplify to obtain (Equation 12):

$$\mathbf{Z}^k = \exp \left(IFFT_{3D} \left[\frac{\alpha \hat{\mathbf{Z}}_0 + \hat{\mathbf{W}} \cdot \hat{\mathbf{D}} \cdot \hat{\mathbf{S}} + \beta \hat{\mathbf{W}} \cdot \hat{\mathbf{D}} \cdot \sum_m \{ \hat{\Psi}_m \cdot (\hat{\mathbf{d}}_m^k - \hat{\mathbf{b}}_m^k) \}}{\hat{\mathbf{W}} \cdot \hat{\mathbf{W}} \cdot \hat{\mathbf{D}} \cdot \hat{\mathbf{D}} + \alpha \mathbf{I} + \beta \hat{\mathbf{W}} \cdot \hat{\mathbf{W}} \cdot \sum_m (\hat{\Psi}_m \cdot \hat{\Psi}_m)} \right] \right) \quad (12)$$

where Z represents the desired acoustic impedance inversion result, “exp” represents the exponential operation; $IFFT_{3D}$ represents the 3D inverse Fourier transform operation; and $\mathbf{I}$ is an all-1 matrix. Equation 10 can be solved using the soft threshold constraint function (Equation 13):

$$\hat{\mathbf{d}}_m^{k+1} = FFT_{3D} \left(\max(1 - \frac{\lambda / \beta}{s^k}, 0) \cdot [\hat{\Psi}_m \cdot \hat{\mathbf{W}} \cdot \hat{\mathbf{D}} \cdot \hat{\mathbf{Z}}^{k+1} + \hat{\mathbf{b}}_m^k] \right) \quad (13)$$

$$\text{where } s^k = \sqrt{\sum_{m=1}^3 \left(\hat{\Psi}_m \cdot (\hat{\mathbf{W}} \cdot \hat{\mathbf{D}} \cdot \hat{\mathbf{Z}}^{k+1}) + \hat{\mathbf{b}}_m^k \right)^2}.$$

3. Algorithm verification

To evaluate the effectiveness of the proposed method, a 3D overthrust model was constructed for algorithm testing (Figure 4A). The model exhibited clear horizontal structural changes and local fracture and thin-layer characteristics, which could be used to test the inversion method’s ability to portray spatial continuity under complex structural conditions. The original impedance model was smoothed using a low-pass filter to generate the initial low-frequency model required for inversion (Figure 4B). The corresponding 3D synthetic seismic record was generated using a convolution model, and 20% Gaussian random noise was added to the seismic record to simulate noise interference in the actual data. The obtained seismic data is shown in Figure 5. To analyze the impact of different dimensional constraints on the inversion results, we used the one-dimensional trace-by-trace inversion method, the two-dimensional line-by-line inversion method, and the proposed method. Among them, the one-dimensional trace-by-trace inversion method only introduced L_1 -norm constraints in the time direction, and each trace was independent of each other and did not contain any horizontal constraint information; the two-dimensional line-by-line inversion method inverted on a single measurement line, and introduced horizontal second-order TV regularization constraints in the line direction, so as to enhance the continuity of the inline direction, but there remained no mutual constraints between different measurement lines.

Figure 6 shows the acoustic impedance inversion results of the three methods and the corresponding residual profile comparison. From the inversion results, the one-dimensional trace-by-trace inversion (Figure 6A) showed clear “string-shaped” characteristics horizontally, with large amplitude variations between traces, reflecting strong randomness. This is due to the lack of horizontal constraints in the independent solution of each trace inversion, which prevents effective suppression of noise and inversion errors in space.

The two-dimensional line-by-line inversion (Figure 6C) showed improved continuity along the main inline direction compared to the one-dimensional approach, indicating that introducing lateral constraints along the line direction enhanced inversion stability. However, significant “vertical streaks” remain in the crossline direction, demonstrating that line-by-line inversion can

only ensure continuity along a single direction and is insufficient to preserve 3D spatial consistency.

In contrast, the proposed method produced results (Figure 6E) that more closely match the true model. Within the overthrust structural region, impedance interfaces maintained good lateral continuity, structural boundaries were clear, and the overall inversion result was smoother and more stable. This improvement is attributed to the high-order TV regularization applied simultaneously in both horizontal directions, which effectively exploits the spatial correlation between traces and significantly suppresses the lateral propagation of random noise and inversion errors.

Examining the original impedance model in Figure 4A, an obvious fault structure was evident at the position indicated by the black arrow. Both the one-dimensional and two-dimensional inversion methods failed to accurately recover the spatial position and boundary geometry of this

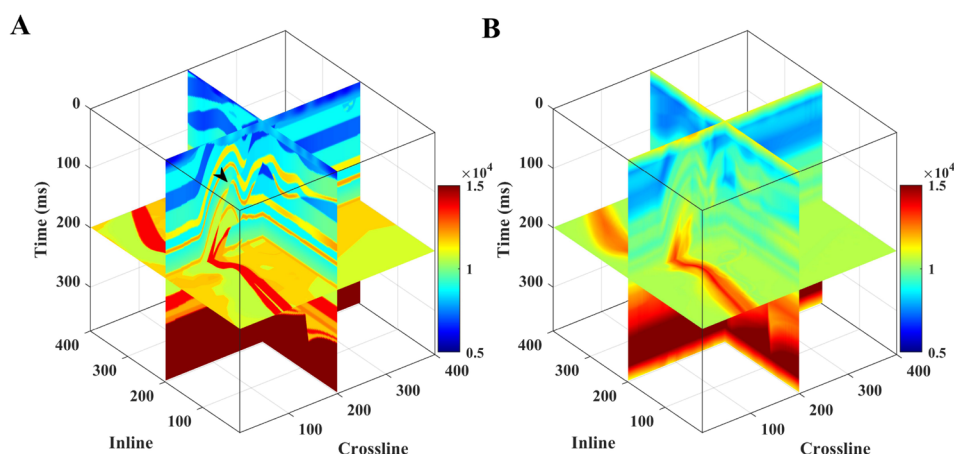


Figure 4. The overthrust model. (A) Three-dimensional overthrust impedance model. (B) Smoothed initial impedance model.

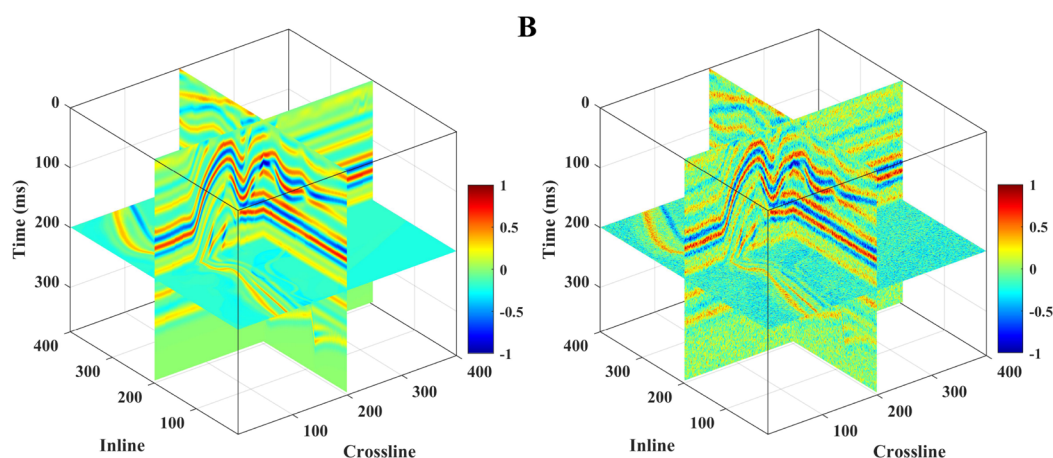


Figure 5. The seismic data. (A) Noise-free seismic data. (B) Noisy seismic data.

structure, showing varying degrees of displacement and blurring near the fault. In contrast, the proposed method reconstructed the fault geometry with high fidelity, and the fault position closely matched the true model, demonstrating the clear advantage of incorporating 3D spatial constraints in complex structural characterization.

Analysis of the residual profile further confirmed these observations. The residuals of the one- and two-dimensional inversions (Figure 6B and 6D) showed clear layered reflections and boundary features, indicating that the inversion results do not fully fit the seismic data. Moreover, the residuals exhibited lateral striping, reflecting strong spatial inconsistencies during inversion. In comparison, the residual section of the proposed method (Figure 6F) contained almost no continuous reflection features, indicating that the 3D high-order TV regularization can maintain data fitting accuracy while substantially improving the stability and spatial consistency of the inversion results.

In addition, the root mean square error (RMSE) and the correlation coefficient (CC) for different methods were compared to provide a quantitative assessment of their performance. The RMSE and CC are defined as Equation 14:

$$\text{RMSE} = \sqrt{\frac{1}{N \times M \times P} \|Z^{\text{inv}} - Z^{\text{true}}\|_2^2},$$

$$\text{CC} = \frac{|Z^{\text{inv}} - \bar{Z}^{\text{inv}}|_1 \cdot |Z^{\text{true}} - \bar{Z}^{\text{true}}|_1}{\sqrt{\|Z^{\text{inv}} - \bar{Z}^{\text{inv}}\|_2^2 \cdot \|Z^{\text{true}} - \bar{Z}^{\text{true}}\|_2^2}} \quad (14)$$

where Z_i^{inv} and Z_i^{true} denote the inverted and true impedance values, respectively; $\bar{Z}^{\text{inv}}$ and $\bar{Z}^{\text{true}}$ represent their corresponding mean values; N , M , and P denote the number of sampling points, traces, and inlines of the 3D seismic data, respectively. A smaller RMSE indicates that the inversion result is closer to the true impedance, whereas the CC ranges from -1 to 1 , with values closer to 1 indicating a higher similarity between the inverted and true impedance.

As shown in Table 1, the proposed method yields the lowest RMSE and the highest CC, demonstrating superior inversion accuracy and better consistency with the reference data compared to other methods.

4. Practical applications

4.1. Overview of the study area

The study area is located in the eastern part of Yushe County, Jinzhong City, Shanxi Province, within the central-western portion of the Yushe East exploration block in the northeastern Qinshui Basin.³² The 3D seismic data used in this study cover an area of approximately 10 km². The area lies in the western foothills of the Taihang Mountains and is characterized by eroded, dissected mid-mountain terrain with pronounced topographic relief and well-developed valleys. The overall topography is higher in the central region and lower on both sides, with elevations ranging from 1,220 to 1,380 m and a relative relief of about 150 m. The surface is predominantly bedrock, locally overlain by thin loess layers. Such complex terrain can affect the quality of seismic data and the lateral continuity of inversion results, placing higher demands on the stability of acoustic impedance inversion methods.

Structurally, the study area lies within the gentle fold belt of the Qinshui Basin, dominated by northeast-trending strata with relatively low dip angles and minor faulting. The overall structural conditions are relatively stable, favoring the preservation and lateral continuity of coal seams. The basin interior is characterized by short-axis folds and predominantly small-scale normal faults, indicating weak overall deformation. The stratigraphic sequence in the area is relatively complete, comprising, from bottom to top, the Precambrian, Paleozoic, Mesozoic, and Cenozoic sediments, with the Carboniferous–Permian coal-bearing strata being the main target. These coal-bearing units consist primarily of interbedded sandstones, mudstones, and coal layers, representing a marine–continental transitional depositional system. Coal seams generally exhibit stable lateral continuity, although local variations in thickness are observed.

The target layer for this study is the No. 15 coal seam, which is laterally continuous across the area but exhibits

Table 1. Comparison of quantitative indicators for different inversion results

Indicator	One-dimensional trace-by-trace method	Two-dimensional line-by-line method	The proposed method
CC	0.9731	0.9802	0.9980
RMSE	628.8129	538.2387	170.1518

Abbreviations: CC: Correlation coefficient; RMSE: Root mean square error.

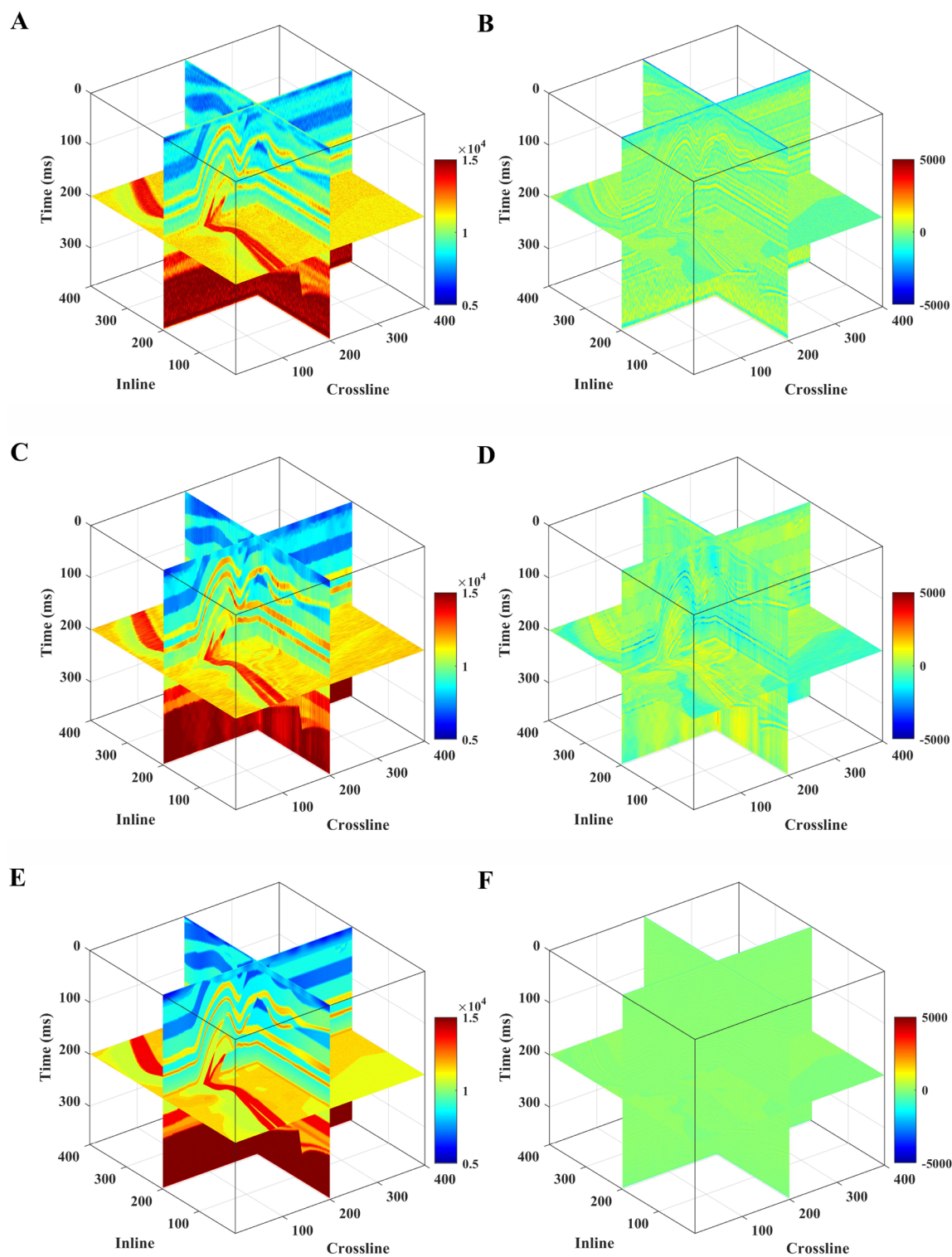


Figure 6. Inversion results and residual profiles of each method

some heterogeneity due to sedimentary and structural influences. The seam is relatively thin in the vertical direction, placing high demands on the lateral stability and vertical resolution of seismic inversion results. Given the limited well control in the study area, accurately characterizing lateral variations in coal thickness is challenging based solely on wells. Therefore, high-resolution 3D acoustic impedance inversion using seismic data is necessary to improve the reliability of coal seam spatial distribution predictions.

4.2. Rock physical characteristics

To analyze the petrophysical characteristics of the target coal seam, a cross-plot analysis of well-log data was performed. The results (Figure 7) indicate that the target coal seam (black) exhibited distinct rock-physics properties compared to the surrounding strata (purple). According to the cross-plot analysis, the coal seam was characterized by relatively low P-wave velocity, low density, and low acoustic impedance. Specifically, the P-wave velocity is generally less than 2,400 m/s, the density is less than 1.5 g/cm³, and the acoustic impedance is less than 5,000 (m/s)·(g/cc). These features clearly distinguish the coal seam from the surrounding rocks and provide a reliable basis for identifying it using impedance inversion.

4.3. Analysis of acoustic impedance inversion results

To evaluate the practical performance of the proposed method, we use a model-based multi-channel acoustic impedance inversion module implemented in commercial software STRATA (7.1, CGG GeoSoftware, France) as a reference. The 3D seismic data are shown in Figure 8A. Acoustic impedance curves were first calculated from well-log data. Low-pass filtering was then applied to the well-derived impedance curves to extract the low-

frequency trend. Subsequently, horizon-constrained inter-well interpolation was performed to construct a 3D low-frequency acoustic impedance model (Figure 8B).

Figure 9 compares 3D inversion results obtained from the two methods. Black arrows indicate the target No.15 coal seam. Overall, STRATA inversion results exhibit relatively low vertical resolution. Consequently, the top and bottom interfaces of the coal seam appeared ambiguous, and recovery of high-frequency components was limited. In contrast, the proposed method significantly enhanced vertical resolution. Interlayer interfaces became clearer, while thin-layer structures were delineated more accurately. Moreover, detailed variations of reservoir properties were better represented.

Figure 10 shows the inversion profile at inline #295, which passes through the well location. Impedance values derived from STRATA inversion were generally overestimated, and the target coal seam showed poor lateral continuity. Noticeable smoothing also appeared in thin-layer zones near the well. As a result, sensitivity to local high- and low-impedance variations remained limited, leading to inaccurate delineation of reservoir boundaries. In comparison, inversion results produced by the proposed method matched well-log curves more closely. High-frequency impedance variations near well-controlled locations were effectively recovered. Furthermore, coal seam interfaces appeared clearer, and both vertical resolution and lateral continuity were substantially improved.

For further comparison, inversion results at inline #485 were examined. This line lies far from the well location, and inversion constraints mainly relied on seismic data and the low-frequency model (Figure 11). Under this condition, STRATA inversion was strongly dominated

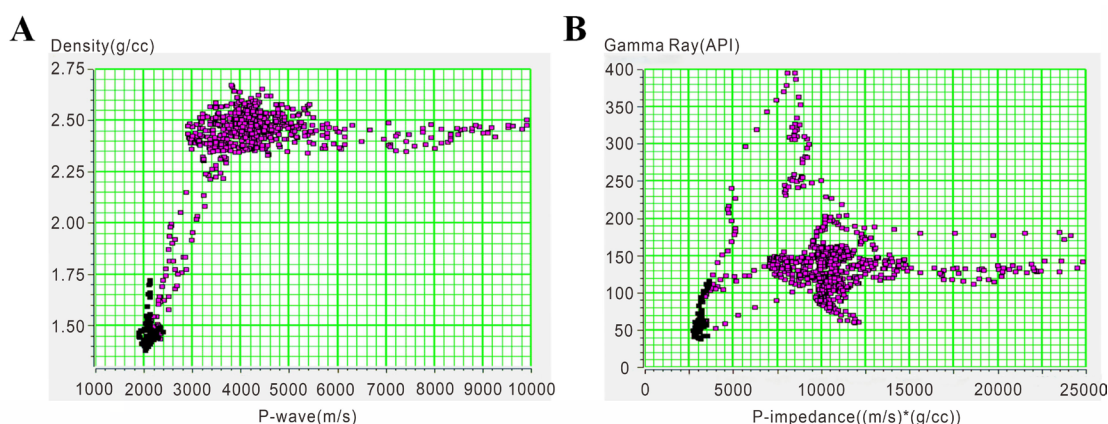


Figure 7. Cross-plot analysis. (A) Density-P wave. (B) Gamma-Ray-impedance.

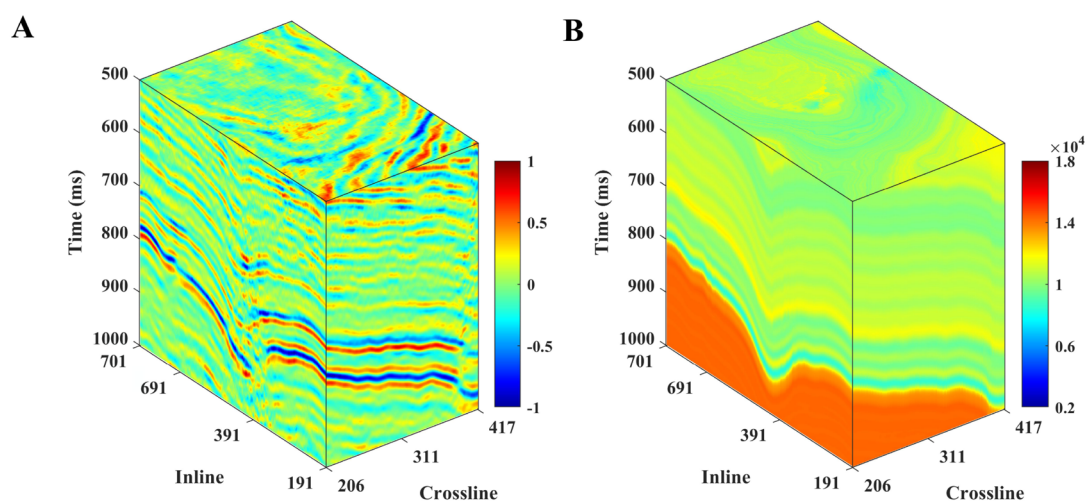


Figure 8. The field data. (A) Three-dimensional field seismic data. (B) Low-frequency impedance model.

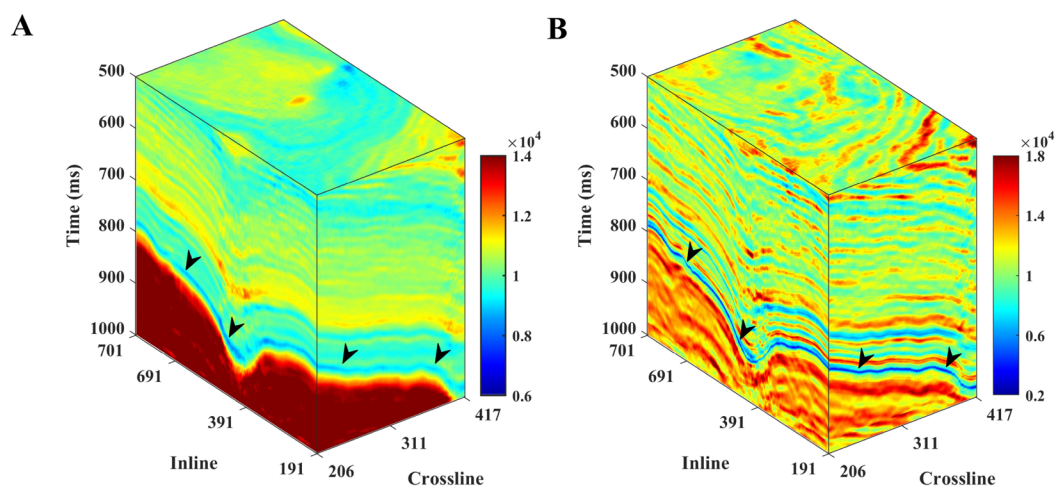


Figure 9. Comparison of inversion results. (A) Result from STRATA inversion. (B) Result from the proposed method.

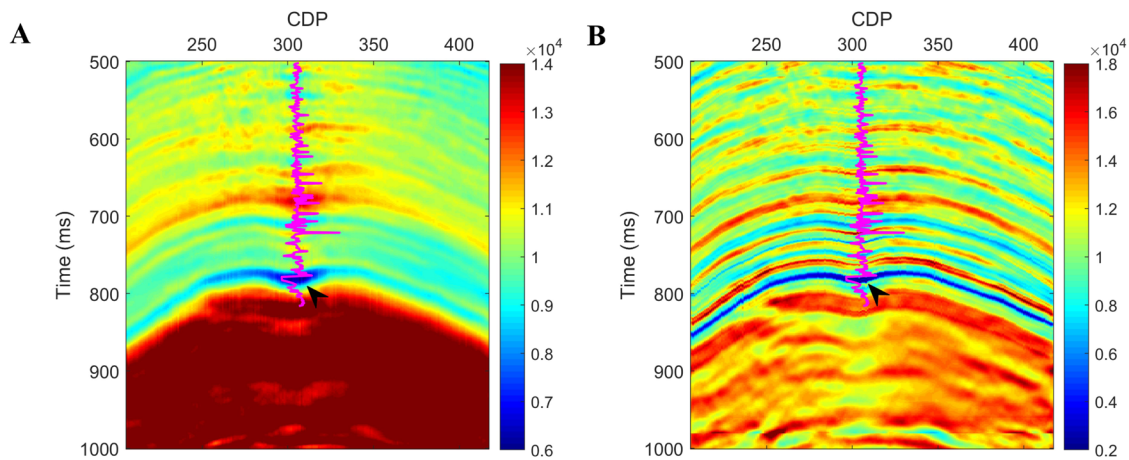


Figure 10. Inversion profile at inline #295. (A) Result from STRATA inversion. (B) Result from the proposed method.

by the low-frequency model. Consequently, structural smoothing became evident, impedance interfaces showed poor continuity, thin-layer features remained unclear, and contrasts between high- and low-impedance zones were weak. These limitations hindered the accurate characterization of the coal seam and adjacent strata. In contrast, the proposed method successfully recovered the low-impedance anomaly associated with the target coal seam. Coal seam interfaces were delineated with good lateral continuity, and predicted results agreed with regional geological understanding. These observations demonstrate that the proposed method maintained stable performance and reliable predictive capability even under weakly constrained conditions.

4.4. Coal seam thickness prediction

Preliminary cross-plot analysis indicated that the acoustic impedance of the target coal seam was lower than 5,000 (m/s)·(g/cm³). However, the STRATA inversion results generally show higher impedance values, with notable discrepancies relative to the coal-seam impedance inferred from well-log data. This mismatch obscured the low-impedance characteristics of the coal seam, making it difficult to accurately identify the roof and floor interfaces and, consequently, to reliably estimate coal seam thickness.

Figure 12 presents the coal seam thickness prediction results obtained using the two methods. The proposed method yielded a relatively stable thickness distribution

within the target area, with values mainly ranging from 3 m to 6.5 m. Relatively thick and laterally continuous coal seams were developed in the northwestern and southern parts of the study area, which were favorable for coalbed methane exploitation. In contrast, the thickness predicted by the STRATA inversion was generally underestimated and showed poor lateral continuity, making it difficult to effectively identify the stable distribution of the coal seam.

Table 2 compares the predicted coal seam thicknesses at five wells with those interpreted from well logs. The results obtained by the proposed method agreed well with the logging interpretations, with absolute errors less than 0.5 m. In addition, the predicted coal seam thickness away from the well locations varied smoothly without unreasonable abrupt changes.

The dominant frequency of the seismic data used in this study was approximately 35 Hz. No explicit spectral broadening or resolution enhancement processing was applied beyond standard preprocessing procedures. Based on this frequency, the theoretical vertical resolution of seismic data was approximately 8 m. It should be noted that the high accuracy of thickness prediction (errors < 0.5 m) does not rely solely on intrinsic seismic resolution, but also on the integration of well constraints and high-order TV regularization, which enhances the continuity and stability of the inversion results. As a result, the proposed method provided reliable thickness estimates even for thin coal seams.

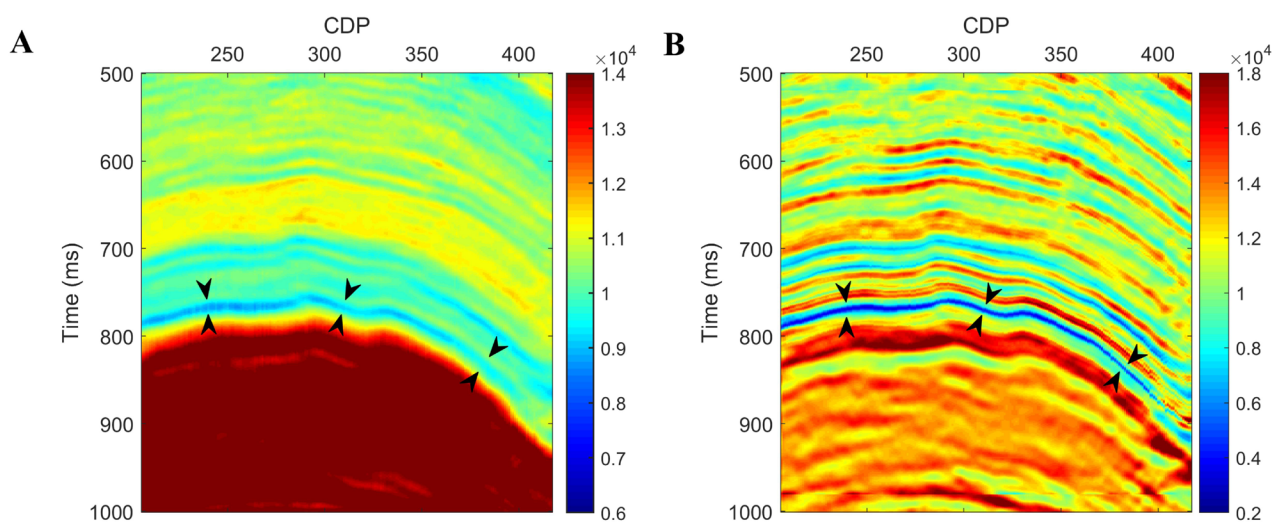


Figure 11. Inversion profile at inline #485. (A) Result from STRATA inversion. (B) Result from the proposed method.

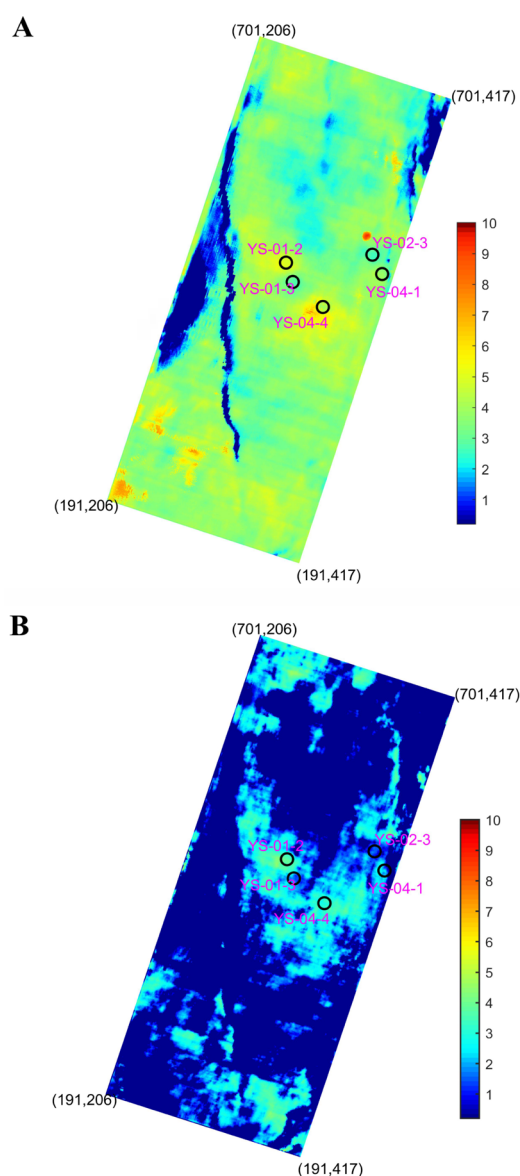


Figure 12. Predicted thickness of the target coal seam. (A) The proposed method; (B) STRATA inversion.

5. Discussion

The proposed method applies high-order TV constraints simultaneously in both the inline and crossline directions, allowing direct inversion of the entire 3D seismic volume without trace-by-trace or line-by-line processing. This strategy strengthens the spatial correlation within the seismic cube and improves the lateral stability of the inversion results. The high-order difference operator preserves structural boundaries while maintaining strong robustness to noise. In addition, the method shows reduced dependence on the initial model, enabling more reliable

impedance estimation under limited well constraints. These characteristics are consistent with the requirements for predicting thin coal seam thickness.

Although the proposed 3D high-order TV-regularized inversion method shows clear advantages in improving lateral continuity and vertical resolution, several limitations should be noted. First, the inversion result is sensitive to the selection of regularization parameters. The weights of the high-order TV constraint and the data misfit term (α and β) need to be determined through empirical testing. In general, larger regularization parameters promote smoothness but can lead to over-smoothing, whereas smaller values preserve fine-scale features but can introduce noise. In practice, parameter selection is performed stepwise. Specifically, α , which controls data fidelity, is first adjusted to ensure that the reconstructed data match the observed seismic data with an acceptable residual level. Then, β , which controls the strength of the high-order TV constraint, is gradually increased to improve lateral continuity while monitoring the preservation of structural details. The optimal parameter combination is selected by jointly considering quantitative metrics (e.g., RMSE and CC) and visual assessment of inversion results.

Second, the introduction of 3D spatial constraints increases the computational complexity of the inversion process. Compared to conventional trace-by-trace or line-by-line inversion methods, the proposed method requires solving the objective function over the entire 3-D seismic volume. Although the split-Bregman algorithm and frequency-domain solution are used to improve computational efficiency, the computational cost remains higher, especially for large-scale 3D seismic datasets.

Third, the high-order TV regularization enhances lateral continuity by suppressing rapid spatial variations, which may otherwise lead to excessive smoothing in areas with complex geological structures, such as fault zones or strongly heterogeneous strata. In these cases, small-scale structural details may be partially weakened, and additional structural constraints or adaptive regularization strategies may be required.

Future work should focus on developing adaptive regularization-parameter selection methods that incorporate structural or geological constraints and combine intelligent inversion techniques to further enhance the method's applicability to complex reservoirs and thin-layer prediction problems.

6. Conclusion

To overcome poor lateral continuity and strong dependence on initial models in conventional impedance inversion for

Table 2. Comparison of log-interpreted and predicted thicknesses of the target coal seam

Well	Well logging interpretation thickness (m)	Predicted thickness (m)		Absolute error (m)	Percentage of relative error
		STRATA	The proposed method		
YS01-2	4.21	3.762	4.258	0.048	1.14%
YS01-3	4.22	2.153	4.319	0.099	2.35%
YS02-3	4.15	1.765	3.955	-0.195	4.70%
YS04-1	5.28	2.688	4.816	-0.464	8.79%
YS04-4	4.62	3.216	4.425	-0.195	4.22%

3D seismic data, a 3D impedance inversion method based on high-order TV regularization is proposed. High-order difference operators were introduced in both horizontal directions to construct spatial TV constraints, allowing global regularization of the entire seismic volume and better utilization of trace-to-trace correlations. Synthetic tests showed that the proposed method significantly improved lateral continuity while preserving structural boundaries and accurately recovered impedance in structurally complex areas, demonstrating the effectiveness of 3D spatial constraints.

Application to 3D seismic data from the Yushe East exploration area, compared to model-based inversion in STRATA, the proposed method provided higher vertical resolution, better lateral continuity, and more clearly revealed the low-impedance characteristics of the No. 15 coal seam. Coal seam thickness prediction based on the inversion results shows a stable distribution, with errors less than 0.5 m compared to well interpretations, even in areas far from wells. The results indicate that the proposed method can achieve reliable characterization of thin coal seams. It is particularly effective in scenarios with limited well control and relatively high noise levels, where enhanced spatial continuity and noise suppression are critical for improving inversion stability and thin-layer prediction accuracy.

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Conflict of interest

Yaju Hao is an Early Career Editorial Board Member of this journal, but was not in any way involved in the editorial and peer-review process conducted for this paper, directly or indirectly. The authors declare no potential conflict of interest.

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Availability of data

Data are available from the corresponding author upon reasonable request.

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