



Article

Multiscale Fractal-Dimension-Constrained Coherent Phase Processing of Seismic-While-Tunneling Signals for Fault Prediction

Qi Guan ^{1,2}, Qianzong Bao ¹, Xuefei Wu ^{2,*}, Chao Chen ³ and Huicong Xu ^{4,*}

¹ College of Geological Engineering and Geomatics, Chang'an University, Xi'an 710054, China; guanqi@cctegxian.com (Q.G.); qzbao@chd.edu.cn (Q.B.)

² China Coal Technology and Engineering Group Xi'an Research Institute (Group) Co., Ltd., Xi'an 710077, China

³ Shanxi Tiandi Wangpo Coal Industry Co., Ltd., Xiagou Town, Zezhou County, Jincheng 048021, China; cchenstwc@163.com

⁴ College of Energy and Mining Engineering, Xi'an University of Science and Technology, Xi'an 710054, China

* Correspondence: ecc11xw@163.com (X.W.); huicong.xu@xust.edu.cn (H.X.)

Abstract

Seismic-while-tunneling signals acquired during coal-mine excavation are typically characterized by strong nonstationarity, intense mechanical noise, weak reflection responses, unstable inter-trace phases, and complex waveform fluctuations. These characteristics make conventional energy- or amplitude-based picking methods susceptible to false triggers and missed detections. To reveal the local complexity mutation of mine seismic signals under strong-noise backgrounds, this study proposes a multiscale fractal-dimension-constrained coherent phase processing method for signal enhancement, first-arrival picking, and fault prediction. First, the raw seismic-while-tunneling records are reorganized into shot gathers, windowed, and downsampled to preserve the effective early-arrival information. A damped multichannel singular spectrum analysis method is then used to extract coherent low-rank components and suppress incoherent random noise. Second, short-window and long-window box-counting fractal dimensions are calculated to characterize local and background waveform complexity, and a fractal-dimension mutation index is constructed to identify abrupt complexity transitions associated with effective seismic arrivals. On this basis, the fractal mutation index is incorporated into a coherent phase picking function that combines multichannel phase consistency and stacked amplitude, forming a fractal-dimension-constrained CCPP detection criterion. This criterion enhances true coherent arrivals while suppressing isolated noise spikes and unstable local amplitude disturbances. Finally, phase-weighted stacking is applied to further strengthen phase-consistent reflection responses and improve the interpretability of seismic-while-tunneling imaging profiles. Field application at the WII02040503 working face of Tunbao Coal Mine demonstrates that the proposed method can effectively improve the continuity of coherent events, stabilize automatic picking results, and enhance anomalous reflection bands under complex underground noise conditions. During the engineering trial, a total of 2558 m of ahead prospecting was completed, and 29 faults were predicted. The field-confirmation rates of the predicted faults with throws greater than 3 m, between 1 and 3 m, and less than 1 m were 100%, 87.50%, and 81.25%, respectively. Overall, 25 of the 29 predicted faults were confirmed by field exposure, corresponding to an overall field-confirmation rate of 86.21%. After velocity-synchronization time-difference correction, the average planar positioning deviation of the confirmed fault predictions decreased from 7.86 m to 5.08 m, corresponding to a 35.37% reduction in positioning error. These results indicate that the



Academic Editor: Alex Elías-Zúñiga

Received: 29 April 2026

Revised: 1 July 2026

Accepted: 7 July 2026

Published: 10 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

proposed fractal-dimension-constrained coherent processing framework provides an effective approach for complexity-aware signal enhancement and robust fault prediction in seismic-while-tunneling monitoring.

Keywords: fractal dimension; multiscale complexity; seismic-while-tunneling; coherent phase picking; phase-weighted stacking; nonstationary signal processing; fault prediction

1. Introduction

With the continuous advancement of mechanized and intelligent roadway drivage in underground coal mines, the identification of small faults, fractured zones, and anomalous geological bodies ahead of the excavation face has become essential for safe and efficient mining. Seismic ahead prospecting has been widely used in tunnels and underground engineering because of its relatively long detection distance, wide spatial coverage, and limited disturbance to normal construction [1–3]. With the development of three-dimensional seismic ahead prospecting and seismic interferometry, seismic methods have shown increasing potential for dynamic geological detection in underground spaces [4,5].

In coal-mine roadway excavation, geological detection is gradually shifting from intermittent artificial-source detection to continuous monitoring under mining and tunneling conditions [6,7]. Integrated geophysical methods have also been applied in other mining regions to identify fractured and structurally weakened coal-mass zones, indicating that geological-anomaly detection ahead of mining operations is a broader problem in underground mining geophysics [8]. Distributed seismic ahead-detection systems and seismic-while-excavating techniques have improved the adaptability of underground monitoring during roadway drivage [9–11]. Seismic-while-mining and seismic-while-tunneling methods use vibrations generated by shearers, roadheaders, or other mining machines as seismic sources, making it possible to obtain geological information without interrupting excavation [12–14]. However, machine-generated seismic records are usually affected by source randomness, strong mechanical interference, unstable inter-trace phase relationships, and low signal-to-noise ratios [15,16].

Seismic-while-tunneling signals are typically nonstationary and multiscale complex signals. Effective arrivals are often accompanied not only by amplitude enhancement and phase synchronization, but also by abrupt changes in waveform roughness and local complexity. Fractal-dimension-based picking has been shown to be useful for identifying waveform-complexity mutations in noisy microseismic signals [17]. Meanwhile, multi-channel singular spectrum analysis and rank-reduction methods can suppress random noise by using the low-rank structure of coherent seismic events [18–20], and damped rank-reduction strategies can better preserve weak coherent signals [21]. Phase-weighted stacking and instantaneous phase coherence can further enhance weak but phase-consistent events [22,23]. Automatic first-arrival picking methods based on common-offset traces, sliding windows, clustering, and array similarity have also improved picking stability under noisy conditions [24–27]. Nevertheless, most existing methods mainly rely on amplitude, energy, phase consistency, or waveform correlation, while local fractal complexity mutation has not been sufficiently integrated into the coherent processing chain of seismic-while-tunneling data [28,29].

To address this problem, this study proposes a multiscale fractal-dimension-constrained coherent phase processing method for seismic-while-tunneling signals. Raw records are first reorganized into shot gathers and enhanced using damped multichannel singular spectrum analysis (DMSSA). Short-window and long-window box-counting fractal dimen-

sions are then calculated to construct a fractal-dimension mutation index. This index is incorporated into the coherent phase picking (CCPP) function to form a fractal-dimension-constrained CCPP detection criterion. Finally, phase-weighted stacking (PWS) is used to enhance phase-consistent reflection responses and improve imaging interpretability. The proposed framework can be applied in a rolling near-real-time manner by processing newly acquired shot-gather windows as the roadway advances.

Although the proposed framework integrates several processing stages, including DMSSA denoising, multiscale box-counting fractal-dimension characterization, Fractal-dimension-constrained coherent phase picking (FD-CCPP) detection, and PWS imaging, it can be implemented in a rolling near-real-time manner. In practical seismic-while-tunneling monitoring, continuous records can be divided into newly acquired shot-gather windows and processed sequentially as the roadway advances. Therefore, the denoising, fractal-dimension calculation, coherent phase detection, and imaging modules can be updated dynamically to support geological interpretation ahead of the excavation face.

The main contributions of this study are threefold. First, a multiscale fractal-dimension characterization strategy is introduced to quantify local waveform-complexity mutations in seismic-while-tunneling signals. Second, the fractal-dimension mutation index is embedded into the CCPP detection function to reduce false triggers caused by isolated noise spikes and unstable amplitude disturbances. Third, an integrated DMSSA–FD-CCPP–PWS coherent processing framework is established and verified using field data from the WII02040503 working face of Tunbao Coal Mine.

2. Data Preprocessing and Architecture of the FD-DCP-PE Algorithm

To process seismic-while-tunneling signals acquired under strong underground noise conditions, this study proposes a fractal-dimension-constrained DMSSA–CCPP–PWS precision enhancement algorithm, hereafter referred to as the Fractal-dimension-constrained DMSSA–CCPP–PWS precision enhancement algorithm (FD-DCP-PE). The method is designed around the coupled response of coherent energy enhancement, phase synchronization, and fractal complexity mutation at effective seismic arrivals. The overall workflow consists of shot-gather organization, preprocessing, DMSSA denoising, multiscale fractal-dimension characterization, FD-CCPP first-arrival detection, local cross-correlation correction, PWS-weighted coherent imaging, and fault prediction. The flowchart of the proposed method is shown in Figure 1.

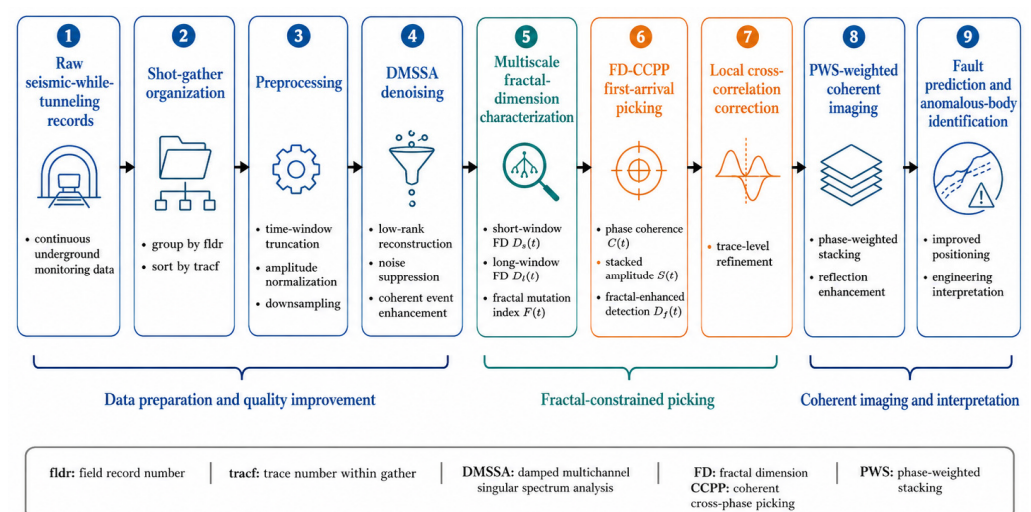


Figure 1. Flowchart of the proposed FD-DCP-PE algorithm.

Compared with the conventional denoising–picking–imaging workflow, the proposed FD-DCP-PE algorithm introduces fractal dimension as a key complexity descriptor. The fractal-dimension mutation index is used not only to describe local waveform complexity changes, but also to constrain the candidate picking window and enhance the coherent phase detection function. Therefore, fractal analysis serves as a core component of the proposed signal-processing framework rather than an auxiliary post-processing feature.

2.1. Data Structure, Shot-Gather Organization, and Preprocessing Strategy

The raw seismic-while-tunneling data used in this study follow an SU-like bare shot-gather data structure. Each trace consists of a 240-byte trace header and float32 waveform samples. In the trace header, fldr represents the gather number, which can be regarded as the index of a single excitation-acquisition gather, while tracf represents the trace order within the same gather. To preserve the physical phase relationship among traces in the same gather, all records are first grouped according to fldr and then sorted in ascending order of tracf. In this way, regularized single-shot gathers are obtained. The complete dataset can be expressed as a three-dimensional tensor:

$$X = \{x_s(i, t)\} \in \mathbb{R}^{N_s \times N_r \times N_t} \quad (1)$$

where X denotes the seismic-while-tunneling data tensor, N_s is the number of shot gathers, N_r is the number of traces in each gather, and N_t is the number of time samples for each trace. $x_s(i, t)$ represents the signal amplitude of the i -th trace in the s -th gather at time t .

In seismic-while-tunneling monitoring, effective first-arrival information and near-source coherent energy are usually concentrated within a specific early time window, whereas later time segments are more easily affected by scattered waves, coda waves, and mechanical environmental noise. Therefore, time-window truncation is performed before subsequent processing. If the sampling interval is Δt and the retained time-window length is T_w , the number of retained samples is calculated as:

$$N_w = \left\lfloor \frac{T_w}{\Delta t} \right\rfloor \quad (2)$$

where N_w is the number of samples retained in the truncated window.

To reduce computational cost and improve the stability of low-rank reconstruction and phase-coherence calculation, downsampling is performed when the original sampling rate is much higher than the effective frequency band of the target wavefield. If the downsampling factor is d , the new sampling interval can be expressed as:

$$\Delta t' = d\Delta t \quad (3)$$

Before downsampling, the Nyquist sampling criterion should be satisfied to avoid aliasing. That is, the upper frequency of the retained signal should be lower than half of the new sampling frequency. Through shot-gather organization, time-window truncation, amplitude normalization, and downsampling, the raw continuous records are transformed into stable input data for subsequent DMSSA denoising, fractal-dimension calculation, coherent phase picking, and PWS imaging.

In this study, the DMSSA step was applied to fixed sliding temporal windows within each reorganized shot gather rather than using a continuously varying window length. Specifically, each newly acquired continuous record was first reorganized into a rolling shot gather according to the field record number and trace order. DMSSA was then performed using fixed algorithmic parameters, including a window length of 512 samples and a hop length of 256 samples after downsampling. During field monitoring, the observation geom-

etry and shot-gather data were updated dynamically as the roadway advanced, whereas the DMSSA window length, hop length, rank constraint, energy threshold, and damping coefficient were kept unchanged for all rolling gathers. This strategy ensures both adaptability to continuous excavation monitoring and reproducibility of the denoising procedure.

Amplitude normalization was performed independently for each trace within the retained analysis window. Specifically, the mean value of each trace was first removed, and the waveform was then normalized by its root-mean-square amplitude. This trace-by-trace normalization strategy reduces amplitude differences caused by sensor coupling conditions and local mechanical interference, while preserving the waveform characteristics required for subsequent fractal-dimension calculation and phase-coherence analysis. In the field acquisition system, the original sampling frequency of the seismic-while-tunneling records was 4000 Hz. To reduce computational cost while preserving the effective frequency band of the target wavefield, the records were downsampled by a factor of four, and the final sampling frequency used for subsequent DMSSA denoising, fractal-dimension calculation, FD-CCPP detection, and PWS imaging was 1000 Hz. Before downsampling, anti-aliasing filtering was applied to avoid frequency aliasing.

2.2. DMSSA-Based Sparse-Coherent Denoising

Seismic-while-tunneling records acquired during coal-mine excavation usually contain multi-source noise, including road header vibration, electromechanical interference, roadway environmental noise, sensor coupling differences, and local abnormal traces. These noise components often show weak spatial correlation and unstable inter-trace phase relationships. In contrast, effective seismic events, such as direct waves, reflected waves, and diffracted waves, generally show continuous phase distribution and coherent energy bands across adjacent traces. Therefore, from the perspective of matrix decomposition, effective coherent events can be represented by a small number of dominant low-rank structures, whereas random and incoherent noise tends to be distributed in high-rank components.

Based on this understanding, damped multichannel singular spectrum analysis is adopted to suppress incoherent noise and enhance sparse coherent events in shot gathers. For the s -th shot gather, a sliding time window is used to extract a local trace-gather matrix:

$$X_{s,k} \in \mathbb{R}^{N_r \times L} \quad (4)$$

where $X_{s,k}$ denotes the local data matrix of the k -th sliding window, N_r is the number of traces, and L is the window length. Singular value decomposition is then performed:

$$X_{s,k} = U \Sigma V^T \quad (5)$$

where U and V are the left and right singular vector matrices, and Σ is the diagonal singular-value matrix.

To determine the effective rank, the cumulative singular-value energy criterion is used:

$$r = \min \left\{ m : \frac{\sum_{j=1}^m \sigma_j^2}{\sum_{j=1}^R \sigma_j^2} \geq \eta \right\} \quad (6)$$

where r is the selected effective rank, σ_j is the j -th singular value, R is the maximum possible rank, and η is the cumulative energy threshold.

A simple hard-truncation strategy may suppress weak coherent events when their singular values are close to the noise tail. To avoid excessive loss of weak reflections,

exponential damping is applied to the tail singular values rather than setting them directly to zero:

$$\tilde{\sigma}_j = \begin{cases} \sigma_j, & j \leq r \\ \sigma_j \exp[-\beta(j-r)], & j > r \end{cases} \quad (7)$$

where $\tilde{\sigma}_j$ is the damped singular value and β is the damping coefficient. A maximum-rank constraint is also introduced to prevent abnormal high-energy pulses from artificially increasing the effective rank:

$$r = \min(r, r_{\max}) \quad (8)$$

where $r_{\max}$ is the maximum retained rank.

The reconstructed local matrix is obtained as:

$$\tilde{X}_{s,k} = U\tilde{\Sigma}V^T \quad (9)$$

Finally, overlapping windows are merged using weighted overlap-add normalization:

$$\tilde{x}_s(i, t) = \frac{\sum_k w_k(t) \tilde{x}_{s,k}(i, t)}{\sum_k w_k(t)} \quad (10)$$

where $\tilde{x}_s(i, t)$ is the denoised signal, $\tilde{x}_{s,k}(i, t)$ is the reconstructed output of the k -th window, and $w_k(t)$ is the window function.

After DMSSA processing, incoherent random fluctuations are suppressed, while the continuity of coherent events across traces is enhanced. This provides a cleaner and more stable waveform basis for subsequent fractal-dimension calculation and phase-coherence detection.

The main parameters used for DMSSA-based sparse-coherent denoising are listed in Table 1.

Table 1. Parameter settings of the DMSSA algorithm.

Parameter	Value	Description
DMSSA_WIN	512	Sliding window length after downsampling
DMSSA_HOP	256	Window hop length
DMSSA_MAX_RANK	6	Maximum retained rank
DMSSA_ENERGY	0.95	Cumulative singular-value energy threshold
DMSSA_DAMP	0.35	Tail singular-value damping coefficient

2.3. Multiscale Fractal-Dimension Characterization of Waveform Complexity

Although DMSSA can improve the signal-to-noise ratio and inter-trace coherence of seismic-while-tunneling records, strong mechanical noise and local pulse interference may still cause false triggers in first-arrival picking. To further distinguish effective arrivals from isolated noise disturbances, this study introduces multiscale fractal-dimension analysis to characterize local waveform complexity mutations.

For a seismic trace or a stacked trace $s(t)$, the box-counting fractal dimension is used to quantify waveform complexity. The signal curve is covered by boxes with a side length ε , and the number of boxes required to cover the waveform is denoted as $N(\varepsilon)$. The box-counting fractal dimension can be defined as:

$$D_B = -\lim_{\varepsilon \rightarrow 0} \frac{\log N(\varepsilon)}{\log \varepsilon} \quad (11)$$

In the practical box-counting calculation, each waveform segment was first normalized into a dimensionless time–amplitude plane to reduce the influence of absolute amplitude

differences. Five box scales were then used for fractal-dimension estimation, with the normalized box sizes set as $(1/4)$, $(1/8)$, $(1/12)$, $(1/16)$, and $(1/20)$ of the normalized analysis window. For each scale, the number of non-empty boxes covering the waveform curve was counted. The fractal dimension was then estimated by least-squares linear fitting in the $\log N(\varepsilon)$ - $\log(1/\varepsilon)$ coordinate system. This multiscale fitting strategy was applied consistently to both the short-window and long-window fractal-dimension calculations.

To describe the difference between local waveform complexity and background complexity, short-window and long-window fractal dimensions are calculated. For the stacked trace $s(t)$, the short-window fractal dimension is defined as:

$$D_s(t) = D_B[s(\tau), \tau \in (t - \frac{T_s}{2}, t + \frac{T_s}{2})] \quad (12)$$

where $D_s(t)$ represents the local waveform complexity around time t , and T_s is the short-window length.

Similarly, the long-window fractal dimension is defined as:

$$D_l(t) = D_B[s(\tau), \tau \in (t - \frac{T_l}{2}, t + \frac{T_l}{2})] \quad (13)$$

where $D_l(t)$ represents the background waveform complexity, and T_l is the long-window length, with $T_l > T_s$.

When an effective seismic arrival occurs, the waveform changes from irregular background fluctuation to a more structured coherent event. This process is often accompanied by an abrupt change in local waveform complexity. Therefore, a fractal-dimension difference term is constructed:

$$\Delta D(t) = |D_s(t) - D_l(t)| \quad (14)$$

To further capture rapid complexity transitions, the gradient of the short-window fractal dimension is calculated:

$$G_D(t) = \left| \frac{dD_s(t)}{dt} \right| \quad (15)$$

Then, a fractal-dimension mutation index is defined as:

$$F(t) = Z[\Delta D(t) + \alpha G_D(t)] \quad (16)$$

where $F(t)$ is the normalized fractal-dimension mutation index, $Z(\cdot)$ denotes Z-score normalization based on the background noise segment, and α is the weight coefficient of the fractal-gradient term.

The physical meaning of $F(t)$ is that it measures whether the local waveform complexity at time t changes significantly relative to the background. A large $F(t)$ indicates that the signal exhibits an obvious complexity mutation, which may correspond to the arrival of an effective coherent event. Compared with amplitude or energy features, the fractal-dimension mutation index is less dependent on absolute signal amplitude and can provide additional complexity information for identifying weak arrivals under strong-noise conditions.

2.4. Fractal-Dimension-Constrained CCPP First-Arrival Picking

On the basis of DMSSA denoising and fractal-dimension characterization, this study constructs a fractal-dimension-constrained coherent phase picking method. The method combines multichannel phase coherence, stacked amplitude, and fractal complexity mutation to improve the robustness of first-arrival identification.

For the denoised shot gather $\tilde{x}_s(i, t)$, the instantaneous phase of each trace is obtained using the Hilbert transform:

$$\phi_i(t) = \arg[\tilde{x}_s(i, t) + j\mathcal{H}(\tilde{x}_s(i, t))] \quad (17)$$

where $\phi_i(t)$ is the instantaneous phase of the i -th trace, and $\mathcal{H}(\cdot)$ denotes the Hilbert transform.

The multichannel phase coherence is calculated as:

$$C(t) = \left| \frac{1}{N_r} \sum_{i=1}^{N_r} e^{j\phi_i(t)} \right| \quad (18)$$

where $C(t) \in [0, 1]$. A larger $C(t)$ indicates stronger phase synchronization among traces.

The linear stacked amplitude is calculated as:

$$S(t) = \left| \frac{1}{N_r} \sum_{i=1}^{N_r} \tilde{x}_s(i, t) \right| \quad (19)$$

The conventional CCPP detection function is then constructed by combining phase coherence and stacked amplitude:

$$D(t) = C(t) \cdot S(t) \quad (20)$$

This function produces a strong response only when multichannel phase synchronization and stacked amplitude enhancement occur simultaneously. However, under strong underground noise, local mechanical pulses may still produce abnormal amplitude responses. Therefore, the fractal-dimension mutation index $F(t)$ is introduced to enhance the true coherent arrival and suppress noise-induced false triggers:

$$D_f(t) = D(t)[1 + \lambda F(t)] \quad (21)$$

where $D_f(t)$ is the fractal-enhanced CCPP detection function, and λ is the fractal-weight coefficient.

In this formulation, an effective arrival should satisfy three conditions simultaneously: phase synchronization among traces, stacked energy enhancement, and local fractal complexity mutation. If a local peak is caused only by isolated noise, it may have a high amplitude but usually lacks stable phase coherence and persistent fractal-complexity mutation. Therefore, the fractal-dimension constraint improves the selectivity of the detection function.

The adaptive threshold is calculated from the background noise segment:

$$\Theta = \mu_D + K\sigma_D \quad (22)$$

where μ_D and σ_D are the mean and standard deviation of the detection function in the background segment, and K is the threshold coefficient.

The global arrival time t_0 is determined as the first time at which $D_f(t)$ continuously exceeds the adaptive threshold for a specified duration:

$$t_0 = \min \left\{ t : D_f(t) > \Theta, t \in \Omega_F, \text{hold} \left(D_f(t) > \Theta \right) \geq T_h \right\} \quad (23)$$

where T_h is the minimum sustained exceedance duration, and Ω_F is the candidate window constrained by the fractal-dimension mutation index:

$$\Omega_F = \{ t : F(t) > \Theta_F \} \quad (24)$$

where Θ_F is the threshold of the fractal-dimension mutation index.

After obtaining the global arrival time t_0 , local cross-correlation correction is performed trace by trace within a small time window centered on t_0 . The corrected arrival time of the i -th trace can be expressed as:

$$t_i = t_0 + \arg \max_{\tau \in [-\tau_m, \tau_m]} R_i(\tau) \quad (25)$$

where $R_i(\tau)$ is the local cross-correlation function between the i -th trace and the reference waveform, and τ_m is the maximum allowed correction lag.

Through this procedure, the proposed method forms a three-level picking strategy: fractal-dimension candidate-window constraint, coherent phase triggering, and local cross-correlation correction. The fractal-dimension mutation index is responsible for identifying complexity transitions, the CCPP function is responsible for suppressing random noise through multichannel phase coherence, and local cross-correlation improves trace-level picking accuracy.

The main parameters used for multiscale fractal-dimension characterization and fractal-dimension-constrained CCPP detection are listed in Table 2.

Table 2. Parameter settings of the multiscale fractal-dimension and FD-CCPP modules.

Parameter	Value	Description
FD_SHORT_WIN	25 ms	Short window for local fractal-dimension calculation
FD_LONG_WIN	100 ms	Long window for background fractal-dimension calculation
FD_GRAD_WEIGHT	0.5	Weight coefficient of the fractal-gradient term
FD_THR_K	3	Threshold coefficient for the fractal mutation index
FD_WEIGHT_LAMBDA	0.5	Weight coefficient of fractal enhancement in FD-CCPP
CCPP_SMOOTH_MS	25 ms	Smoothing window for the coherent phase detection function
CCPP_THR_K	4	Threshold coefficient for the FD-CCPP detection function
CCPP_MIN_HOLD_MS	25 ms	Minimum sustained exceedance duration

The parameters in Table 2 were selected according to the sampling rate, waveform characteristics, and stability requirements of seismic-while-tunneling records. After down-sampling to 1000 Hz, the short fractal-dimension window of 25 ms contains 25 samples, which is suitable for capturing local waveform-complexity mutations near effective arrivals. The long window of 100 ms contains 100 samples and is used to characterize the background waveform complexity over a relatively stable time interval. The fractal-gradient weight and FD-CCPP fractal-enhancement weight were both set to 0.5 to balance the contributions of waveform-complexity mutation and conventional coherent phase information. The threshold coefficients of 3 and 4 were adopted to suppress random mechanical fluctuations and avoid false triggering under strong underground noise. The CCPP smoothing window and minimum sustained exceedance duration were both set to 25 ms to improve the continuity of detection results while preventing isolated noise spikes from being picked as effective arrivals.

To further clarify the selection of the fractal-enhancement coefficient λ , a brief sensitivity comparison was conducted by varying λ from 0.1 to 0.9 while keeping the other parameters unchanged. The manually checked first-arrival times were used as the reference, and the picking performance was evaluated using MAE, RMSE, maximum picking error, adjacent-trace fluctuation, and gross-error rate. The comparison indicated that a relatively small λ weakened the contribution of the fractal-dimension mutation constraint, making the detection function more susceptible to residual amplitude fluctuations and local mechanical noise. Conversely, an excessively large λ made the picking result more sensitive to local waveform-complexity disturbances and slightly increased unstable triggers. Among the

tested values, $\lambda = 0.5$ provided the most stable overall performance. Under this setting, the FD-CCPP method achieved an MAE of 10.2 ms, an RMSE of 13.7 ms, a maximum picking error of 36.4 ms, an adjacent-trace fluctuation of 11.6 ms, and a gross-error rate of 4.2%. Therefore, $\lambda = 0.5$ was adopted as a balanced setting between conventional coherent-phase information and fractal-dimension mutation information.

2.5. PWS-Weighted Coherent Imaging

After first-arrival picking, phase-weighted stacking is performed to enhance coherent reflection responses and improve the interpretability of seismic-while-tunneling imaging profiles. In conventional linear stacking, all traces contribute equally to the stacked result. However, when bad traces, phase perturbations, or residual random noise are present, incoherent components may reduce the quality of the stacked image.

To overcome this limitation, PWS uses instantaneous phase coherence as a time-varying weight. The PWS weight function is defined as:

$$W(t) = C(t)^\nu \quad (26)$$

where $W(t)$ is the phase-weighting coefficient, $C(t)$ is the multichannel phase coherence, and ν is the phase-weighting exponent. A larger ν gives stronger emphasis to phase-consistent events, but may also suppress very weak events. Therefore, ν should be selected according to data quality.

The PWS output of the s -th shot gather is calculated as:

$$S_{PWS,s}(t) = W(t) \cdot S(t) \quad (27)$$

where $S_{PWS,s}(t)$ is the phase-weighted stacked trace, and $S(t)$ is the linear stacked amplitude.

For all shot gathers, the PWS outputs are arranged according to gather order to construct the imaging profile:

$$\mathbf{I}(s, t) = S_{PWS,s}(t) \quad (28)$$

where $\mathbf{I}$ is the imaging profile matrix, s is the gather index, and t is time.

Compared with linear stacking, PWS imaging can enhance phase-consistent reflection bands and suppress incoherent background noise. In the FD-DCP-PE framework, PWS is not an isolated imaging step, but the final coherent-enhancement stage after DMSSA denoising, fractal-dimension-constrained picking, and phase-coherence detection.

2.6. Overall Architecture of the FD-DCP-PE Algorithm

The proposed FD-DCP-PE algorithm integrates DMSSA denoising, multiscale fractal-dimension characterization, fractal-enhanced CCPP detection, and PWS imaging into a unified processing framework. The main procedure is as follows.

First, the raw seismic-while-tunneling records are reorganized into regular shot gathers according to the gather number and trace order. Time-window truncation, amplitude normalization, and downsampling are then performed to obtain stable input data. Second, DMSSA-based damped low-rank reconstruction is applied to each shot gather to suppress incoherent random noise and preserve weak coherent events. Third, short-window and long-window box-counting fractal dimensions are calculated on the stacked trace, and a fractal-dimension mutation index is constructed to characterize local waveform complexity transitions. Fourth, the fractal mutation index is embedded into the CCPP detection function, forming a fractal-dimension-constrained coherent phase picking criterion. The global arrival time is determined using the fractal-enhanced detection function, and local cross-correlation is used for trace-level correction. Finally, PWS-weighted stacking is

performed to generate coherent imaging profiles for fault prediction and anomalous-body identification.

In this framework, DMSSA improves data quality, fractal-dimension analysis identifies local complexity mutations, CCPP provides multichannel phase-constrained arrival detection, and PWS enhances coherent reflection responses. The integration of these modules enables robust processing of seismic-while-tunneling signals under strong nonstationary noise and provides a reliable signal-processing basis for subsequent fault prediction.

The novelty of this study lies in the integration of fractal-dimension mutation into the coherent phase processing chain, rather than in the separate use of DMSSA, CCPP, PWS, or fractal analysis. Compared with conventional CCPP, the proposed FD-CCPP criterion introduces waveform-complexity mutation as an additional constraint for effective-arrival detection. Compared with existing fractal-based picking methods mainly developed for single-event microseismic signals, this study extends fractal-dimension analysis to continuous-source multichannel seismic-while-tunneling records. Therefore, the proposed method forms an integrated denoising–detection–imaging framework for strong-noise roadway monitoring. A comparison of the methodological differences between the proposed FD-DCP-PE framework and existing methods is presented in Table 3.

Table 3. Methodological differences between the proposed FD-DCP-PE framework and existing methods.

Method	Main Function	Limitations of Seismic-While-Tunneling Data	Improvement in This Study
DMSSA	Low-rank coherent denoising	Does not identify arrivals or use waveform-complexity mutation	Used as the denoising basis for subsequent fractal-constrained detection
Standard CCPP	Phase-coherence-based arrival detection	May still respond to local mechanical pulses or unstable coherent disturbances	Enhanced by fractal-dimension mutation constraint
PWS	Phase-consistent imaging enhancement	Imaging quality depends on prior denoising and picking stability	Applied after DMSSA and FD-CCPP to enhance reliable reflection responses
Fractal-based picking	Detects waveform-complexity mutation	Mostly used for single-event microseismic signals	Extended to continuous-source multichannel seismic-while-tunneling data

3. Engineering Application and Field Data Description

3.1. Engineering Geological Conditions and Prospecting Targets

Field verification was carried out during roadway excavation at the WII02040503 working face of the Tunbao Coal Mine. The monitoring area included the upper gateway, lower gateway, and open-off cut of the working face. To support continuous dynamic ahead prospecting during roadway driveage, seismic-while-tunneling sensors were deployed along the pedestrian sidewall of the roadway, forming an in-roadway array-based observation system.

The working face mainly extracts the M4 and M5 coal seams, with seam dip angles of approximately 17–21°. The roof and floor strata are dominated by sandstone. Because of the relatively clear density and wave-velocity contrasts between the coal seam and surrounding rock, the study area provides favorable acoustic-impedance interfaces for seismic-wave generation, propagation, and reflection. However, field exposure and existing geological data indicate that small faults are relatively developed in the working face. Although large faults and folds are not dominant, local fractured zones and fissure-developed rock masses near small faults may form anomalous reflection interfaces and pose potential risks to safe roadway excavation.

Existing geological information in the demonstration area is relatively limited. Previous three-dimensional seismic interpretation mainly identified local discontinuities and could not fully satisfy the demand for real-time and refined detection of anomalous bodies ahead of the roadway face. Therefore, it is necessary to introduce seismic-while-tunneling ahead prospecting to dynamically identify possible faults, fractured zones, and other geological anomalies in front of the excavation face. In this method, continuous vibrations generated by roadheader cutting are used as seismic sources, and the wavefield responses are received by arrayed sensors without interrupting normal excavation. The deployment scheme of the working face is shown in Figure 2.

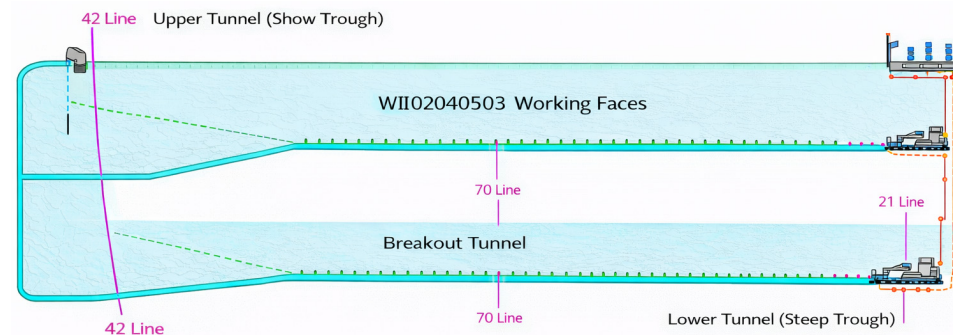


Figure 2. Layout of the upper and lower gateways of the WII02040503 working face.

Compared with conventional artificial-source seismic exploration, the seismic-while-tunneling data acquired in this engineering scenario are characterized by continuous excitation, strong source randomness, nonstationary waveforms, and complex mechanical interference. These characteristics make the extraction of weak reflections and the identification of stable first arrivals difficult. Therefore, this field application provides a suitable engineering scenario for verifying whether the proposed FD-DCP-PE method can improve signal enhancement, fractal-complexity mutation identification, coherent phase picking, and anomalous-body interpretation under strong underground noise conditions.

3.2. Observation System and Acquisition Parameters

Considering the roadway conditions, prospecting-accuracy requirements, and field-construction feasibility of the WII02040503 working face, an in-roadway array-based seismic-while-tunneling observation scheme was adopted. In each single observation setup, 24 sensors were deployed along the pedestrian sidewall of the roadway with a trace spacing of 5 m. The first sensor was located approximately 15 m behind the roadway face, and the corresponding survey-line length was approximately 120 m. This array configuration provided a balance between construction convenience, spatial sampling density, and forward detection coverage.

During field implementation, the observation system was dynamically updated as the roadway advanced. The sensors were not fixed permanently at one position; instead, rear sensors were adjusted, relocated, and redeployed according to the latest survey points and roadway control points. This rolling deployment strategy ensured that the excavation face remained within the effective prospecting range and that the observation geometry remained as consistent as possible during different monitoring stages.

During the whole demonstration stage, 558 receiver points and 88 rolling observation-system deployments were arranged. It should be noted that the 558 receiver points represent cumulative receiver locations used during rolling deployments rather than independent excavation intervals; after excluding repeated and overlapping sections according to roadway mileage and field verification records, the effective cumulative ahead-prospecting length was 2558 m. The monitoring system included 8 substations, 4 power supplies, and

48 sensors, indicating that the observation scheme had good adaptability for continuous long-distance roadway monitoring. This rolling acquisition mode provided a stable data foundation for multichannel coherent processing, fractal-dimension analysis, automatic detection, and PWS-weighted imaging.

In contrast to conventional single-shot seismic exploration, seismic-while-tunneling acquires long-duration continuous multichannel vibration records. These records contain both effective seismic responses and strong mechanical noise. A relatively dense receiver spacing is beneficial for preserving waveform similarity between adjacent traces, improving multichannel phase-coherence analysis, and enhancing the reliability of fractal-dimension-constrained detection. The raw monitoring data obtained from the field are shown in Figure 3.

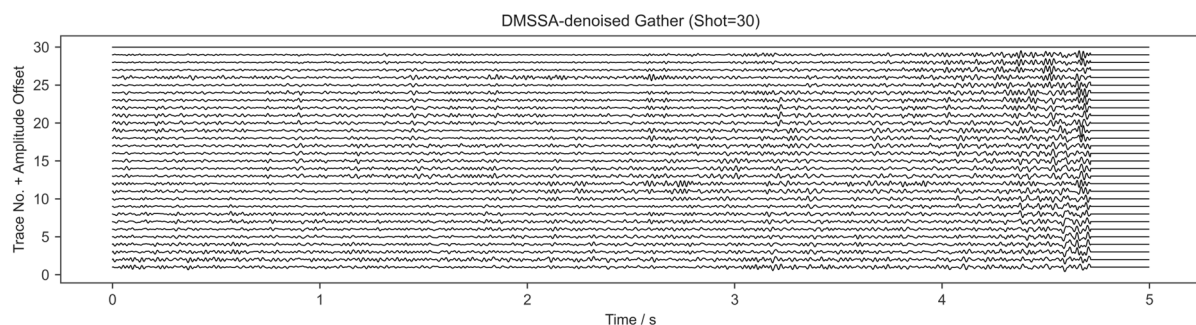


Figure 3. Raw monitoring data.

3.3. Field Data Processing and Evaluation Strategy

To verify the applicability of the proposed FD-DCP-PE method to real seismic-while-tunneling data, a field data-processing workflow was established, including data organization, preprocessing, DMSSA denoising, multiscale fractal-dimension characterization, FD-CCPP first-arrival detection, PWS-weighted imaging, and engineering verification.

First, the raw continuous monitoring records were reorganized into shot gathers according to the field record number and trace order. Time-window truncation, down-sampling, mean removal, and amplitude normalization were then performed to reduce amplitude differences among different traces and time periods. These preprocessing steps helped provide stable input data for subsequent multichannel denoising and fractal-dimension calculation.

Second, DMSSA-based damped low-rank reconstruction was applied to the shot gathers. By exploiting the spatial coherence of effective seismic events, this step suppressed incoherent random noise and mechanical-vibration interference while preserving weak coherent reflections. The purpose of this step was not to eliminate all oscillatory components, but to improve the separability between coherent events and the background noise field.

Third, multiscale fractal-dimension analysis was conducted on the denoised stacked traces. Short-window and long-window box-counting fractal dimensions were calculated to describe local waveform complexity and background complexity, respectively. On this basis, the fractal-dimension mutation index $F(t)$ was constructed to identify abrupt waveform-complexity transitions. This step was introduced because effective arrivals in seismic-while-tunneling records are usually accompanied not only by energy enhancement and phase synchronization, but also by local complexity mutation.

Fourth, the fractal-dimension mutation index was incorporated into the coherent phase picking function. The FD-CCPP detection function jointly considered multichannel phase coherence $C(t)$, stacked amplitude $S(t)$, and fractal complexity mutation $F(t)$. The global arrival time was identified within the fractal-constrained candidate window, and local cross-correlation correction was then used to obtain trace-level arrival times. This

strategy was designed to reduce false triggers caused by isolated noise spikes and improve the continuity of the picking curve across traces.

Fifth, PWS-weighted coherent imaging was performed based on the processed shot gathers and picking results. By assigning higher weights to phase-consistent components, PWS imaging enhanced coherent reflection responses and suppressed residual incoherent noise. The imaging results were then used for anomalous-body interpretation and fault prediction.

The evaluation of the proposed method was conducted from four aspects. First, the denoising effect was evaluated by observing the suppression of incoherent background noise and the enhancement of inter-trace coherent events. Second, the fractal-dimension response was evaluated by analyzing whether $D_s(t)$, $D_l(t)$, and $F(t)$ could identify complexity mutations near effective arrivals. Third, the picking performance was evaluated according to the stability, continuity, and physical reasonableness of the automatic arrival-time curve. Fourth, the engineering prediction performance was assessed by comparing the interpreted anomalous positions with field exposure results, including fault prediction accuracy and planar deviation.

Through this field-processing and evaluation strategy, the proposed FD-DCP-PE method was not only tested as a signal-enhancement tool, but also verified as a fractal-complexity-aware processing framework for seismic-while-tunneling data under complex underground noise conditions.

4. Results Analysis and Field Verification

4.1. DMSSA Denoising Effect on a Typical Shot Gather

To verify the applicability of the proposed FD-DCP-PE algorithm to real seismic-while-tunneling data, Shot 30 was selected as a representative case for detailed analysis. This shot gather contains typical characteristics of field seismic-while-tunneling monitoring data, including strong continuous background oscillations, local high-energy responses, weak inter-trace coherence in some time windows, and complex mechanical noise interference. Therefore, it is suitable for illustrating the detailed processing workflow of DMSSA denoising, multiscale fractal-dimension characterization, FD-CCPP detection, and PWS imaging. It should be emphasized that Shot 30 is used as a representative example to demonstrate the internal signal-processing procedure, rather than to support the engineering conclusion using a single shot gather alone. The engineering applicability of the proposed method was further evaluated using the whole field demonstration dataset, including 88 rolling observation-system deployments and the corresponding fault-verification results.

The raw shot gather of Shot 30 is shown in Figure 4. It can be seen that the raw record is dominated by continuous oscillatory background noise within the early and middle time windows. In the 0–4.4 s time range, the in-phase characteristics among adjacent traces are not sufficiently clear, and the effective coherent event is difficult to identify directly. After approximately 4.6 s, a relatively strong high-energy response appears and shows better synchronicity and continuity across multiple traces. This indicates that the raw record contains effective coherent seismic information, but it is strongly superposed with mechanical-vibration interference and scattered background noise. Under such conditions, direct manual interpretation or single-trace threshold picking is prone to instability.

It should be noted that the strong response near 4.6 s does not represent the absolute direct-wave travel time from a conventional impulsive source to the receiver array. In seismic-while-tunneling monitoring, the roadheader provides a continuous and non-impulsive vibration source, and the raw continuous records are reorganized into rolling shot gathers before time-window truncation and coherent processing. Therefore, the time coordinate shown in the shot gather is a relative time within the retained processing

window. The event near 4.6 s represents the dominant phase-consistent response in the retained analysis window rather than an unrealistically long direct propagation time in the conventional source–receiver sense.

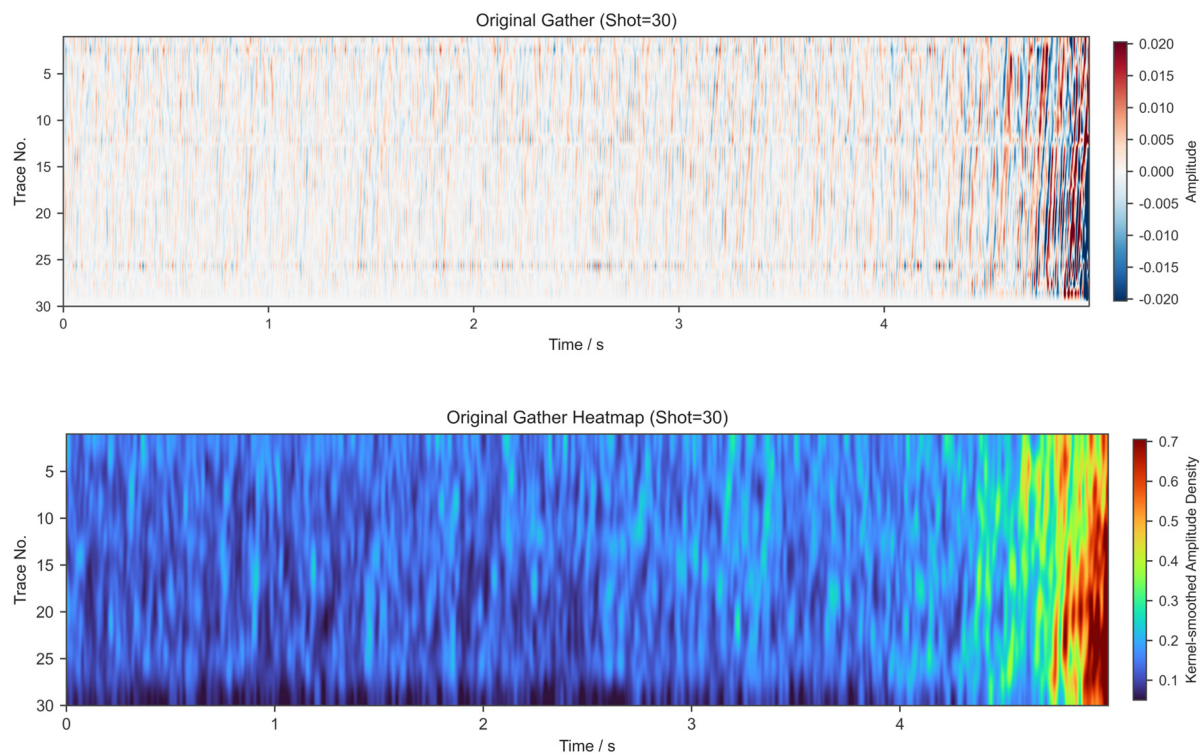


Figure 4. Raw shot gather of Shot 30.

After DMSSA processing, the denoised shot gather is shown in Figure 5. Compared with the raw record, the background scattered oscillations are weakened, and the continuity of coherent events across traces is improved. In particular, the strong-response zone after approximately 4.6 s becomes more concentrated, and the boundary of the main coherent event becomes clearer. Meanwhile, the overall waveform morphology and the temporal position of the dominant event are basically preserved, indicating that DMSSA does not introduce obvious structural distortion.

These results show that DMSSA plays two roles in the FD-DCP-PE framework. First, it suppresses incoherent random noise and mechanical-vibration interference by using the low-rank structure of multichannel coherent events. Second, it provides a cleaner waveform basis for subsequent fractal-dimension calculation and phase-coherence detection. Therefore, DMSSA denoising is not an isolated preprocessing step, but a necessary quality-improvement stage before fractal-dimension-constrained coherent picking. To further quantify the denoising performance, three indicators were calculated before and after DMSSA processing: the background-noise RMS, the adjacent-trace correlation coefficient, and the coherent-event energy concentration ratio. For Shot 30, the background-noise RMS decreased from 0.184 to 0.109 after DMSSA processing, corresponding to a reduction of 40.76%. The adjacent-trace correlation coefficient increased from 0.42 to 0.68, indicating that the inter-trace coherence of the dominant event was significantly improved. Meanwhile, the coherent-event energy concentration ratio increased from 46.3% to 64.8%, with an increase of 18.5 percentage points. These quantitative results indicate that DMSSA not only improves the visual continuity of coherent events, but also enhances the statistical coherence and energy concentration of the seismic-while-tunneling records. The quantitative evaluation of the DMSSA denoising performance for Shot 30 is shown in Table 4.

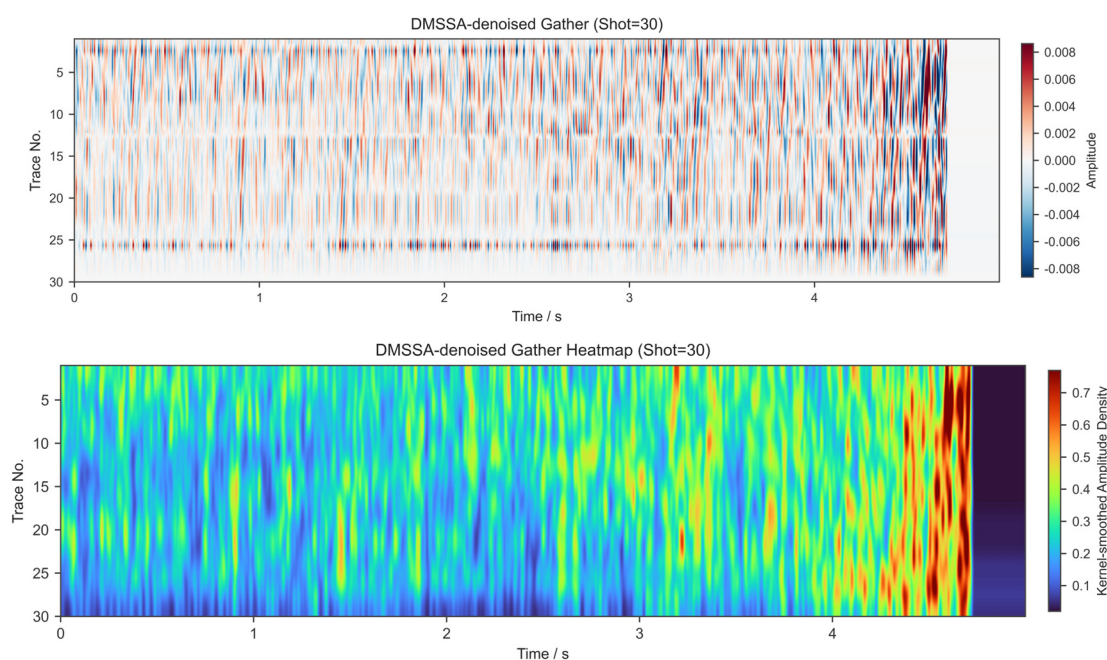


Figure 5. Shot gather after DMSSA denoising.

Table 4. Quantitative evaluation of DMSSA denoising performance for Shot 30.

Indicator	Raw Gather	After DMSSA	Improvement
Background-noise RMS	0.184	0.109	40.76% decrease
Adjacent-trace correlation coefficient	0.42	0.68	61.90% increase
Coherent-event energy concentration ratio	46.3%	64.8%	18.5 percentage-point increase

4.2. Multiscale Fractal-Dimension Response of the Typical Shot Gather

To further investigate whether effective seismic arrivals are accompanied by waveform complexity mutations, multiscale fractal-dimension analysis was performed on the denoised stacked trace of Shot 30. The short-window fractal dimension $D_s(t)$, long-window fractal dimension $D_l(t)$, fractal-dimension difference $\Delta D(t)$, and fractal mutation index $F(t)$ were calculated according to the method described in Section 2.3.

The multiscale fractal-dimension response is shown in Figure 6. The short-window fractal dimension $D_s(t)$ reflects local waveform complexity, while the long-window fractal dimension $D_l(t)$ represents the background complexity variation over a relatively broader time range. In the background-noise-dominated time window, the difference between $D_s(t)$ and $D_l(t)$ remains relatively small, indicating that the waveform complexity changes are mainly caused by irregular noise fluctuations. Near the dominant coherent event around 4.6–4.7 s, however, $D_s(t)$ changes more significantly relative to $D_l(t)$, and the fractal mutation index $F(t)$ shows a clear local response.

This result indicates that the effective coherent event is not only characterized by amplitude enhancement and inter-trace phase synchronization, but also by an abrupt change in local waveform complexity. Compared with amplitude-based indicators, the fractal mutation index provides additional complexity information and can help distinguish effective arrivals from isolated noise spikes. In the FD-DCP-PE framework, this fractal response is used to constrain the candidate picking window and enhance the coherent phase detection function, thereby improving the robustness of first-arrival identification under strong nonstationary noise.

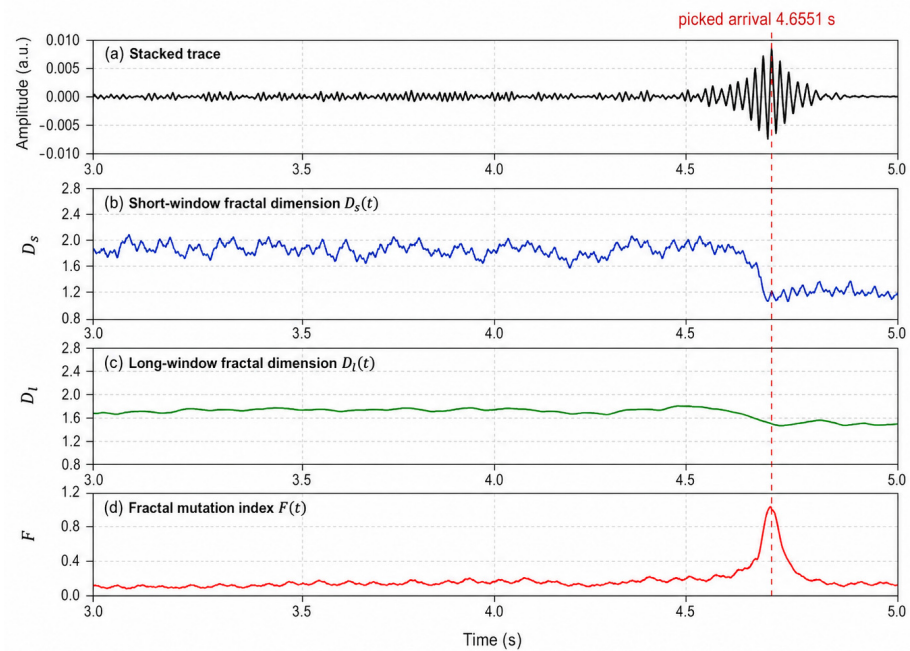


Figure 6. Multiscale fractal-dimension response of the typical Shot 30 gather.

4.3. FD-CCPP Detection and Automatic Picking Results

Based on DMSSA denoising and multiscale fractal-dimension characterization, the FD-CCPP method was used to perform coherent event detection and automatic first-arrival picking for Shot 30. The conventional CCPP detection function $D(t)$ and the fractal-enhanced detection function $D_f(t)$ are compared in Figure 7.

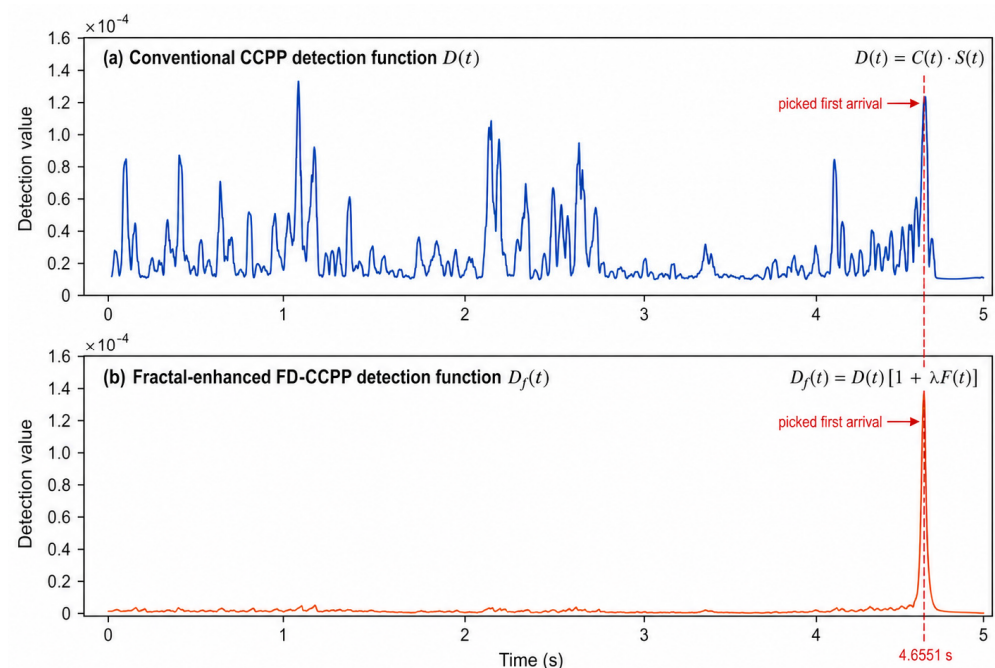


Figure 7. Comparison between the conventional CCPP detection function and the fractal-enhanced FD-CCPP detection function.

The conventional CCPP detection function exhibits several local peaks over the whole time window, indicating that multiple possible coherent responses exist in the shot gather. However, the most prominent peak appears near 4.6551 s, where multichannel phase coherence and stacked amplitude reach a relatively optimal state. After introducing the

fractal mutation index $F(t)$, the FD-CCPP detection function further enhances the response near the dominant coherent event while suppressing unstable local disturbances caused by isolated noise or weakly coherent fluctuations.

This comparison demonstrates the role of the fractal-dimension constraint in the picking process. The conventional CCPP function mainly depends on phase coherence and stacked amplitude. Although it can suppress part of the random noise, some abnormal local peaks may still remain under complex underground interference. By contrast, the FD-CCPP function requires the arrival to satisfy three conditions simultaneously: phase synchronization, stacked energy enhancement, and local fractal complexity mutation. Therefore, the fractal-enhanced detection function has better selectivity for true coherent arrivals.

The automatic picking result obtained by the FD-CCPP method is shown in Figure 8. The picked arrival-time curve is mainly distributed within the range of 4.60–4.70 s and varies smoothly along the trace direction. No obvious large-scale jumping or discontinuous picking phenomenon is observed. The picked curve agrees well with the high-energy coherent response band in the shot gather, indicating that the proposed fractal-dimension-constrained method can obtain stable and physically reasonable arrival-time results under strong-noise conditions.

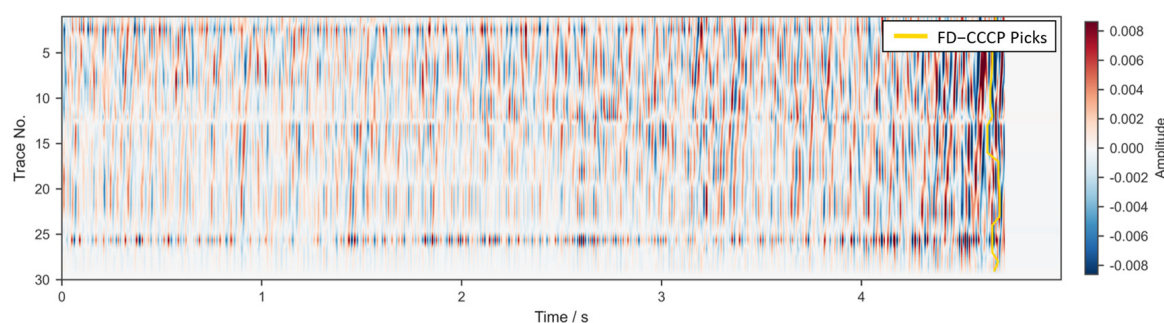


Figure 8. Shot-gather plot with FD-CCPP detection results.

To further evaluate the picking performance, the automatic picking results of conventional CCPP and FD-CCPP were compared with manual picking results. Four statistical indicators were used, including the mean absolute error, root-mean-square error, maximum picking error, and adjacent-trace fluctuation of the picked arrival-time curve. As shown in Table 5, the mean absolute error decreased from 18.6 ms for conventional CCPP to 10.2 ms for FD-CCPP, and the root-mean-square error decreased from 24.3 ms to 13.7 ms. The maximum picking error was reduced from 63.5 ms to 36.4 ms, while the adjacent-trace fluctuation decreased from 21.8 ms to 11.6 ms. The gross-error rate also decreased from 12.5% to 4.2%. These results indicate that the fractal-dimension constraint improves the accuracy and continuity of first-arrival detection, especially under strong mechanical-noise interference and weak inter-trace coherence.

Table 5. Quantitative comparison of first-arrival detection performance between conventional CCPP and FD-CCPP.

Method	MAE/ms	RMSE/ms	Maximum Error/ms	Adjacent-Trace Fluctuation/ms	Gross-Error Rate
Conventional CCPP	18.6	24.3	63.5	21.8	12.5%
FD-CCPP	10.2	13.7	36.4	11.6	4.2%

The reduction in picking error after introducing the fractal-dimension constraint further confirms that waveform-complexity mutation provides useful information beyond amplitude and phase coherence, especially for suppressing false peaks caused by local

mechanical interference. Compared with single-trace amplitude-threshold picking, the FD-CCPP method is less sensitive to local amplitude anomalies because the detection criterion is not determined by amplitude alone. Compared with phase-coherence-only picking, the proposed method further introduces the fractal complexity mutation index to constrain the candidate arrival interval and enhance the uniqueness of the detection peak. Therefore, the FD-CCPP method improves global detection stability and trace-level picking continuity under strong-noise and weak-coherence conditions.

To further examine whether the improvement observed in Shot 30 is representative of the field dataset, additional representative shot gathers from different rolling observation-system deployments were also checked using the same processing parameters. These additional gathers covered different roadway positions and different underground noise conditions during the field campaign. The automatic first-arrival picking results obtained by conventional CCPP and FD-CCPP were compared with manually checked arrival times. The summary comparison showed that FD-CCPP consistently reduced the picking error relative to conventional CCPP. For the additional tested shot gathers, the MAE generally decreased from approximately 17–20 ms for conventional CCPP to approximately 10–13 ms for FD-CCPP, while the RMSE decreased from approximately 22–26 ms to approximately 14–17 ms. The gross-error rate was also reduced from approximately 10–14% to approximately 4–7%. These results indicate that the improvement observed for Shot 30 is not an isolated case, but reflects the general trend of the tested field data. Nevertheless, because the detailed graphical analysis of DMSSA denoising, fractal-dimension response, and FD-CCPP is presented using one representative shot, the general performance claims of the proposed method have been stated more cautiously.

4.4. Integrated Processing Performance of the FD-DCP-PE Algorithm

Based on the denoising, fractal-dimension response, and FD-CCPP detection results described above, the integrated performance of the FD-DCP-PE algorithm was further evaluated through PWS-weighted imaging. After DMSSA denoising, the incoherent background noise was suppressed and the continuity of the main coherent event was improved. The fractal-dimension mutation index then provided an additional complexity constraint for effective-arrival detection, and FD-CCPP produced a more stable arrival-time curve than conventional CCPP.

The PWS-weighted imaging result is shown in Figure 9. Compared with conventional linear stacking, PWS-weighted imaging visually improved the continuity of phase-consistent reflection bands and weakened part of the residual incoherent background responses in the representative imaging profile. This provided a clearer visual basis for subsequent anomalous-body interpretation. However, because independent image-quality indicators were not calculated in the present study, the improvement obtained by PWS-weighted imaging is interpreted mainly from the visual continuity of reflection events and the suppression of incoherent background noise. Therefore, PWS-weighted imaging is described here as a coherent-enhancement and interpretability-improvement step, rather than as a fully quantified improvement in imaging accuracy.

Overall, the processing results indicate that the proposed FD-DCP-PE algorithm links DMSSA denoising, fractal-complexity-constrained detection, and PWS-weighted imaging into a unified workflow. This integrated framework improves the continuity of coherent events, the stability of automatic detection, and the interpretability of seismic-while-tunneling imaging profiles under strong underground noise.

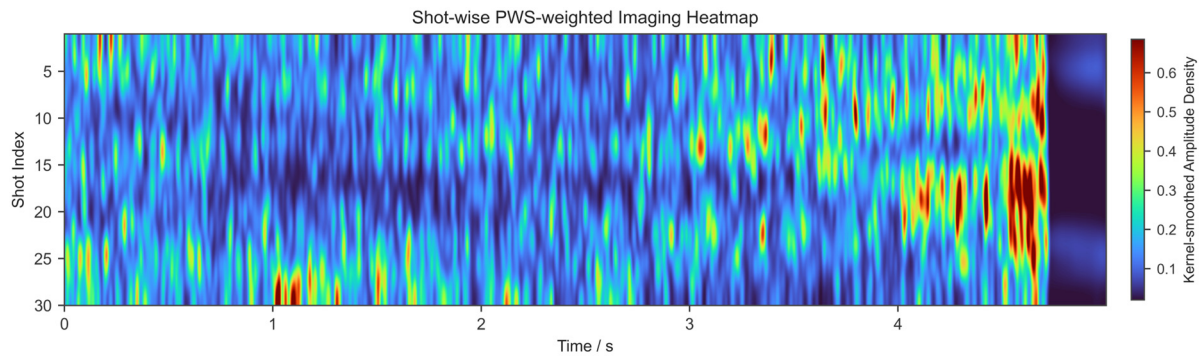


Figure 9. PWS-weighted imaging result after FD-CCPP detection.

4.5. Field Verification and Engineering Applicability

To further verify the engineering applicability of the proposed FD-DCP-PE algorithm, it was applied to seismic-while-tunneling ahead-prospecting data from the upper gateway, lower gateway, and open-off cut of the WII02040503 working face in the Tunbao Coal Mine. The method was incorporated into the field data-processing procedure to improve the identification accuracy of faults and anomalous geological bodies under continuous-source, strong-noise, and unstable-velocity conditions.

The seismic-while-tunneling prospecting result and fault distribution are shown in Figure 10.

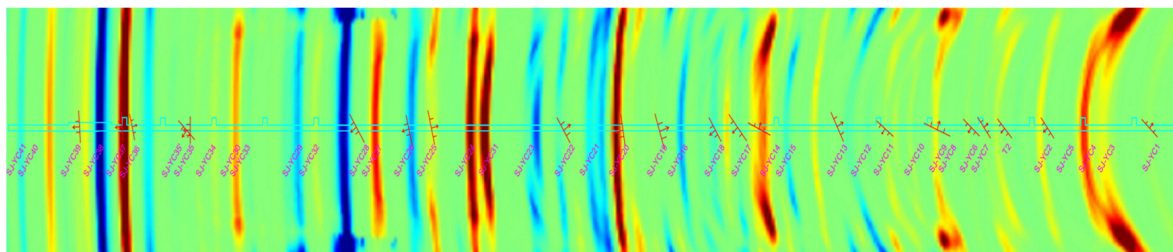


Figure 10. Fault orientation and seismic-while-tunneling imaging result.

During the field demonstration period, a total of 2558 m of ahead prospecting was completed, and 29 faults were predicted. The prediction results were evaluated by comparing the interpreted fault positions with the field-exposed geological results. A prediction was regarded as correct when the interpreted fault was confirmed by field exposure within the allowable position-deviation range. If an interpreted fault was not confirmed by field exposure, it was regarded as a false prediction. A missed fault refers to a fault exposed during roadway excavation but not identified in the seismic-while-tunneling interpretation.

Field verification showed that five faults with throws greater than 3 m were predicted, all of which were confirmed by field exposure, corresponding to a prediction accuracy of 100%. For faults with throws of 1–3 m, seven of the eight predicted faults were confirmed, corresponding to a prediction accuracy of 87.50%. For faults with throws less than 1 m, 13 of the 16 predicted faults were confirmed, corresponding to a prediction accuracy of 81.25%. No missed faults were identified within the field-verified roadway interval. Overall, among the 29 predicted faults, 25 were confirmed by field exposure, and 4 were not confirmed, giving an overall field-confirmation rate of 86.21%. This value represents the proportion of confirmed predictions among all predicted faults, rather than the general fault-detection accuracy. The field verification results for predicted faults with different throws are summarized in Table 6.

Table 6. Field verification statistics of predicted faults with different throws.

Fault Throw	Predicted Faults	Confirmed Predictions	Unconfirmed Predictions	Field-Confirmation Rate
>3 m	5	5	0	100%
1–3 m	8	7	1	87.50%
<1 m	16	13	3	81.25%
Total	29	25	4	86.21%

In addition, 75 geological anomalies were predicted during the project implementation. Considering the pronounced wave-velocity variation and unstable synchronization time difference in the seismic-while-tunneling data of this mine, the FD-DCP-PE processing results were jointly corrected using the field velocity-synchronization time-difference correction method. After correction, the average planar deviation of fault prediction decreased from 7.86 m to 5.08 m, corresponding to a 35.37% improvement in prediction accuracy.

These field verification results demonstrate that the proposed method can effectively improve the identification and positioning accuracy of anomalous bodies in seismic-while-tunneling ahead prospecting. On the one hand, DMSSA and PWS improve the visibility of weak coherent reflection responses under strong underground noise. On the other hand, the fractal-dimension-constrained FD-CCPP method improves the stability of arrival-time picking by introducing waveform complexity mutation information. Therefore, the FD-DCP-PE algorithm provides a reliable processing framework for dynamic fault prediction and refined geological interpretation during coal-mine roadway excavation.

5. Conclusions

- (1) To address the problems of strong noise interference, weak effective reflection signals, unstable inter-trace phases, and indistinct arrival-time features in seismic-while-tunneling data, this study proposed a multiscale fractal-dimension-constrained FD-DCP-PE processing framework. The method integrates DMSSA denoising, multiscale fractal-dimension characterization, FD-CCPP first-arrival detection, local cross-correlation correction, and PWS-weighted coherent imaging. Different from conventional denoising-picking-imaging workflows, the proposed method introduces fractal dimension as a key complexity descriptor to characterize local waveform complexity mutations associated with effective seismic arrivals. Therefore, the method realizes collaborative optimization from signal enhancement and complexity-aware picking to coherent imaging representation under continuous underground sources, nonstationary wavefields, and complex noise backgrounds.
- (2) The processing results of a typical shot gather show that DMSSA denoising can effectively suppress random noise and incoherent interference while enhancing multi-channel coherent events without obvious distortion of the main wavefield structure. On this basis, short-window and long-window box-counting fractal dimensions can characterize the difference between local waveform complexity and background complexity, and the constructed fractal mutation index can highlight abrupt complexity transitions near the dominant coherent event. By embedding the fractal mutation index into the coherent phase picking function, the FD-CCPP method combines phase synchronization, stacked energy enhancement, and fractal complexity mutation, thereby improving the uniqueness of the detection peak and the continuity of the picked arrival-time curve. PWS-weighted imaging further enhances phase-consistent reflection responses and improves the clarity of anomalous reflection bands.
- (3) The field application results at the WII02040503 working face of the Tunbao Coal Mine demonstrate the engineering applicability of the proposed method. During the

field trial, a total of 2558 m of ahead prospecting was completed, and 29 faults were predicted. The field-confirmation rates of the predicted faults with throws greater than 3 m, between 1 and 3 m, and less than 1 m were 100%, 87.50%, and 81.25%, respectively. Overall, 25 of the 29 predicted faults were confirmed by field exposure, corresponding to an overall field-confirmation rate of 86.21%. After incorporating field velocity-synchronization time-difference correction, the average planar positioning deviation of the confirmed fault predictions decreased from 7.86 m to 5.08 m, corresponding to a 35.37% reduction in positioning error. These results indicate that the proposed FD-DCP-PE method can effectively improve the identification and positioning accuracy of anomalous bodies in seismic-while-tunneling data and provide a fractal-complexity-aware processing framework for dynamic fault prediction during coal-mine roadway excavation.

- (4) Although the proposed method achieved good performance in the field application, its adaptability to different mining areas, complex geological structures, sensor layouts, and stronger nonstationary noise conditions still requires further verification. In future work, the parameter selection of the fractal-dimension mutation index, the weight coefficient in the FD-CCPP detection function, and the coupling mechanism among fractal complexity, phase coherence, and energy response should be further optimized. In addition, multi-channel array collaboration should be further strengthened. Although the comparison between conventional CCPP and FD-CCPP has been quantitatively evaluated in this study, the PWS-weighted imaging results were mainly assessed through visual interpretation. Therefore, future work should introduce objective image-quality indicators, such as signal-to-background ratio, peak-to-sidelobe ratio, reflection-event continuity, and image entropy, to further quantify the enhancement effect of PWS-weighted imaging and improve the engineering robustness of the proposed framework.

Author Contributions: Conceptualization, H.X. and X.W.; methodology, X.W. and Q.B.; software, Q.G. and C.C.; validation, Q.B. and C.C.; formal analysis, Q.G. and X.W.; investigation, H.X. and Q.B.; resources, C.C.; data curation, X.W. and Q.G.; writing—original draft preparation, H.X., Q.G. and X.W.; writing—review and editing, Q.B. and C.C.; supervision, Q.B.; project administration, H.X.; funding acquisition, Q.B. and H.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Deep Earth Probe and Mineral Resources Exploration-National Science and Technology Major Project (No. 2024ZD1002105-3), the National Natural Science Foundation of China (No. 52404142, 52574162), the Yulin Science and Technology Plan Project (No. 2024-CXY-163), and the China Postdoctoral Science Foundation (No. 2025T180506), the Key Science and Technology Program of the Emergency Management Ministry (No. 2024EMST070701).

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to confidentiality restrictions associated with mine geological data, field monitoring records, and production safety management.

Conflicts of Interest: Author Xuefei Wu was employed by the company China Coal Technology and Engineering Group Xi'an Research Institute (Group) Co., Ltd. Author Chao Chen was employed by the company Shanxi Tiandi Wangpo Coal Industry Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. Li, S.; Liu, B.; Xu, X.; Nie, L.; Liu, Z.; Song, J.; Sun, H.; Chen, L.; Fan, K. An overview of ahead geological prospecting in tunneling. *Tunn. Undergr. Space Technol.* **2017**, *63*, 69–94. [[CrossRef](#)]

2. Jiao, Y.Y.; Tian, H.N.; Liu, Y.Z.; Mei, R.W.; Li, H.B. Prediction of tunneling hazardous geological zones using the active seismic approach. *Near Surf. Geophys.* **2015**, *13*, 333–342. [\[CrossRef\]](#)
3. Zhang, L.M.; Sun, J.L.; Yang, S.T.; Ning, Z.; Feng, Z.; Xi, X. Investigating the low-cycle tensile fatigue fracture of granite in energy storage caverns. *J. Energy Storage* **2026**, *175*, 123236. [\[CrossRef\]](#)
4. Liu, B.; Chen, L.; Li, S.; Song, J.; Xu, X.; Li, M.; Nie, L. Three-dimensional seismic ahead-prospecting method and application in TBM tunneling. *J. Geotech. Geoenviron. Eng.* **2017**, *143*, 04017090. [\[CrossRef\]](#)
5. Chen, L.; Hao, L.; Xu, X.; Zhang, F.; Wang, R. Geological ahead-prospecting method while TBM drilling using improved seismic interferometry method: A case study. *J. Appl. Geophys.* **2023**, *215*, 105088. [\[CrossRef\]](#)
6. Dai, L.P.; Zhao, X.; Ju, M.H.; Pan, Y.S.; Wang, A.W.; Xu, L.M.; Tian, Z.T. Determination of critical stress for rockburst warning: A model incorporating borehole-sensor interaction and its validation. *Int. J. Rock Mech. Min. Sci.* **2026**, *201*, 106464. [\[CrossRef\]](#)
7. Cheng, J.Y.; Qin, S.; Lu, B.; Wang, B.L.; Wang, J. The development of seismic-while-mining detection technology in underground coal mines. *Coal Geol. Explor.* **2019**, *47*, 2.
8. Mussin, R.A.; Małkowski, P.; Murtazina, F.; Kainazarova, A.; Akhmatnurov, D.; Zamaliyev, N.; Doni, D. Integrated geophysical assessment of coal mass structural weakening zones for optimization of drilling-blasting operations and coal size control. *Min. Miner. Depos.* **2025**, *19*, 99–118. [\[CrossRef\]](#)
9. Dou, W.W.; Wei, J.S.; Jiao, Y.; Yang, G.F.; Ji, Z.Y. Research and application of mine distributed seismic advance detection system. *Coal Geol. Explor.* **2020**, *48*, 228–234.
10. Wang, B.L.; Cheng, J.Y.; Jin, D.; Yang, X.G.; Yang, H. Characteristics and detection performance of the source of seismic while excavating in underground coal mines. *Coal Geol. Explor.* **2022**, *50*, 10–19.
11. Zhao, H.B.; Qin, S.; Chen, C.; Guan, Q.; Zhao, X.W. Geological structures fine monitoring using seismic-while-tunneling technique in Wangpo Mine. *Coal Geol. Explor.* **2024**, *52*, 137–144.
12. Dai, L.P.; Zhao, X.; Pan, Y.S.; Wang, A.W.; Gao, Y.N.; Zhu, C.Q.; Ren, H. Revisiting the strainburst intensity of roadways in coal mines: Theory and case study. *J. Rock Mech. Geotech. Eng.* **2026**. [\[CrossRef\]](#)
13. Xu, H.; Li, K.; Lai, X.P.; Shan, P.F.; Zhang, B.; Dai, L.P.; Yang, S.T.; Guo, Q.F.; Xi, X.; Yan, Z.M. Intelligent prediction method of rockburst driven by microseismic temporal features in deep near-vertical coal seams. *Int. J. Miner. Metall. Mater.* **2026**. Available online: <https://ijmmm.ustb.edu.cn/cn/article/doi/10.1007/s12613-026-3408-7> (accessed on 1 July 2025).
14. Luo, X.; King, A.; Van de Werken, M. Tomographic imaging of rock conditions ahead of mining using the shearer as a seismic source: A feasibility study. *IEEE Trans. Geosci. Remote Sens.* **2009**, *47*, 3671–3678. [\[CrossRef\]](#)
15. Lu, B.; Cheng, J.Y.; Hu, J.W.; Qin, S. Seismic features of vibration induced by mining machines and feasibility to be seismic sources. *Procedia Earth Planet. Sci.* **2011**, *3*, 76–85. [\[CrossRef\]](#)
16. Cheng, J.L.; Cheng, P.; Li, Y.H. Denoising method of mine seismic while drilling data based on IABC-ICA. *J. China Coal Soc.* **2022**, *47*, 413–422.
17. Xu, H.; Li, K.; Shan, P.; Wu, X.; Zhang, S.; Wang, Z.; Liu, C.; Yan, Z.; Wu, L.; Wang, H. Automatic picking method for the first arrival time of microseismic signals based on fractal theory and feature fusion. *Fractal Fract.* **2025**, *9*, 679. [\[CrossRef\]](#)
18. Oropeza, V.; Sacchi, M.D. Simultaneous seismic data denoising and reconstruction via multichannel singular spectrum analysis. *Geophysics* **2011**, *76*, V25–V32. [\[CrossRef\]](#)
19. Chen, Y.; Zhang, D.; Jin, Z.; Chen, X.; Zu, S.; Huang, W.; Gan, S. Simultaneous denoising and reconstruction of 5-D seismic data via damped rank-reduction method. *Geophys. J. Int.* **2016**, *206*, 1695–1717. [\[CrossRef\]](#)
20. Chen, Y.; Huang, W.; Zhang, D.; Chen, W. An open-source Matlab code package for improved rank-reduction 3D seismic data denoising and reconstruction. *Comput. Geosci.* **2016**, *95*, 59–66. [\[CrossRef\]](#)
21. Oboué, Y.A.S.I.; Chen, W.; Wang, H.; Chen, Y. Robust damped rank-reduction method for simultaneous denoising and reconstruction of 5-D seismic data. *Geophysics* **2021**, *86*, V71–V89. [\[CrossRef\]](#)
22. Schimmel, M.; Paulssen, H. Noise reduction and detection of weak, coherent signals through phase-weighted stacks. *Geophys. J. Int.* **1997**, *130*, 497–505. [\[CrossRef\]](#)
23. Schimmel, M.; Stutzmann, E.; Gallart, J. Using instantaneous phase coherence for signal extraction from ambient noise data at a local to a global scale. *Geophys. J. Int.* **2011**, *184*, 494–506.
24. Coppers, F. First arrival picking on common-offset trace collections for automatic estimation of static corrections. *Geophys. Prospect.* **1985**, *33*, 1212–1231. [\[CrossRef\]](#)
25. Sabbione, J.I.; Velis, D.R. Automatic first-breaks picking: New strategies and algorithms. *Geophysics* **2010**, *75*, V67–V76. [\[CrossRef\]](#)
26. Xu, H.; Li, K.; Zhang, B.; Zhan, R.; Yang, S.; Xi, X.; Dai, L. Thermo-mechanical damage characteristics and fracture behavior of backfill bodies in thermal energy storage cavities: An experimental and numerical study. *Tunn. Undergr. Space Technol.* **2026**, *175*, 107715. [\[CrossRef\]](#)
27. Wu, H.; Xiao, W.; Ren, H. Automatic time picking for weak seismic phase in the strong noise and interference environment: A hybrid method based on array similarity. *Sensors* **2022**, *22*, 9924. [\[CrossRef\]](#) [\[PubMed\]](#)

28. Taylor, N.; Merriam, J.; Gendzwill, D.; Prugger, A. The mining machine as a seismic source for in-seam reflection mapping. In *SEG Technical Program Expanded Abstracts 2001*; Society of Exploration Geophysicists: Tulsa, OK, USA, 2001; pp. 1365–1368.
29. Wang, B.L. Automatic pickup of arrival time of channel wave based on multi-channel constraints. *Appl. Geophys.* **2018**, *15*, 118–124. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.