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A Logging-Constrained Spatial Registration Framework for Transparent Geological Modeling of Underground Coal Mines

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Abstract: Spatial inconsistency between borehole trajectory, logging measurements and geological horizons is a critical bottleneck in transparent geological modeling of underground coal mines, yet these components are conventionally treated as independent workflows. Here we present a logging-constrained spatial registration framework that integrates full-attitude quaternion updating with weak geological self-correction in a unified optimization model. The method reconstructs borehole trajectories using five reconstruction algorithms for benchmarking, transforms multi-parameter logging curves into three-dimensional spatial evidence, and applies bounded, depth-weighted correction based on inter-borehole horizon consistency. Evaluated on 25 boreholes from the 15121 return-air floor drainage roadway, the framework reduces the horizon-matching RMSE from 3.015 m to 2.610 m (paired t-test $p < 0.001$, Cohen's $d = 3.01$) and increases the spatial registration index (SRI) from 0.634 to 0.688. Ablation and parameter sensitivity analyses confirm that the improvement stems from coupling trajectory processing with logging-based geological constraints rather than algorithmic substitution. An independent transfer validation on 6 additional boreholes (8,520 samples) from the 15124 return-air roadway yields comparable metrics (proxy RMSE 2.74 m, SRI 0.671), demonstrating practical transferability. Unlike conventional trajectory-comparison studies, the framework provides a quantitative bridge between geophysical logging, spatial registration and transparent geological modeling, with interpretable residual diagnostics for engineering quality control.

Keywords: borehole logging; spatial registration; weak geological constraint; trajectory reconstruction; transparent geological modeling; coal mine geophysics

1. Introduction

Transparent geological modeling has become a central requirement for intelligent underground coal mining, providing the spatial framework for gas drainage design, roadway planning, autonomous drilling and resource estimation^[1–3]. The accuracy of such models depends critically on borehole logging—the primary source of subsurface data in operating mines. Gamma, resistivity, density and self-potential logs yield continuous information about coal-seam boundaries, lithological interfaces and structural discontinuities. However, converting depth-indexed logging curves into spatially consistent three-dimensional evidence requires solving an inverse problem in which trajectory geometry, sensor attitude, measurement depth and geological interpretation are coupled.

Traditional studies commonly treat trajectory reconstruction, logging interpretation and geological modeling as sequential independent tasks^[4–6]. Trajectory algorithms such as the minimum-curvature, balanced tangential and radius-of-curvature methods solve the geometric interpolation of survey stations but provide no information about whether logging-identified coal-seam boundaries in adjacent boreholes correspond to the same geological interface^[7–9]. Conversely, logging interpretation methods—whether rule-based or machine-learning—focus on depth-domain classification and boundary detection without addressing the spatial consistency of their predictions across boreholes^[10–13]. This disconnect means that a geometrically smooth trajectory can still produce spatially inconsistent horizon positions when projected into the mine coordinate system, while a borehole with moderate geometric errors may remain geologically useful if its registered horizons align with neighboring evidence.

Several studies have addressed individual aspects of this problem. Recent advances in survey uncertainty modeling provide probabilistic frameworks for trajectory error propagation^[14–17]. Borehole imaging and video logging enable visual verification of lithological boundaries^[18,19]. Machine-learning classifiers trained on logging curves achieve high accuracy for lithology identification and coal–rock boundary detection while drilling^[20–23]. In petroleum engineering, the integration of well logs with seismic data and geological models is an established practice for reservoir characterization^[24], and spatial registration methods from computer vision have been adapted for three-dimensional geomodel alignment^[25,26]. However, these contributions remain fragmented:

survey uncertainty, logging interpretation, boundary detection, and geological consistency checking are rarely formulated as a unified spatial registration problem. For underground coal mines, where boreholes are short (typically 20–60 m), closely spaced (5–20 m), and densely measured, the coupling between trajectory geometry, sensor attitude, logging response and geological structure is particularly strong yet inadequately addressed.

Purely geometric trajectory reconstruction also ignores the geological information carried by logging measurements. A few meters of registration error can change the interpreted relation between a borehole, a coal seam and a gas-control target, potentially leading to incorrect gas drainage layout or roadway design decisions. What is missing is a methodological framework that treats borehole logging as a spatial measurement system rather than a set of independent depth-indexed curves. The key question is not which trajectory algorithm produces the smallest centerline deviation, but how to construct a spatially consistent logging model in which trajectory geometry, sensor attitude, logging response, horizon interpretation and geological structure are mutually constrained.

This study proposes a logging-constrained spatial registration framework for underground borehole measurements that couples trajectory reconstruction with geological consistency constraints. The framework operates in three stages: (1) full-attitude trajectory reconstruction using quaternion-based updating, (2) transformation of multi-parameter logging curves into three-dimensional spatial coordinates along the reconstructed borehole path, and (3) bounded depth-weighted self-correction driven by inter-borehole horizon consistency.

The scientific contributions of this work are threefold. First, we formulate the first logging-constrained spatial registration framework that integrates trajectory reconstruction, full-attitude updating and geological self-correction into a unified optimization model for underground coal mines, moving beyond the current paradigm of treating these as sequential independent tasks. Second, we introduce a bounded weak-geological-constraint self-correction strategy that improves inter-borehole horizon consistency without overwriting measured survey trends—filling the gap between pure geometric correction and full geological inversion. Third, we develop a spatial registration index (SRI) and residual diagnostics that convert registration quality from qualitative description into reproducible, quantitative metrics, providing a standardized evaluation protocol for logging-spatial consistency in underground coal mines.

The problem is related to three-dimensional registration and inverse-geological modeling. Surface-based registration methods in computer vision and geoinformatics have demonstrated robust alignment of point clouds and surfaces using iterative closest point and deformation algorithms^[27,28], while geological implicit modeling approaches demonstrate how sparse horizon data can be interpolated into continuous three-dimensional surfaces^[29,30]. However, these methods typically operate on depth-domain or map-view representations without explicitly modeling the borehole trajectory's attitude uncertainty and its propagation through the logging-to-geology transformation chain, which is the central methodological focus of this paper.

The framework presented here differs from existing work in both scope and method. Rather than improving a single component (e.g., trajectory interpolation, logging classification, or surface interpolation) in isolation, it couples these components through a logging-constrained optimization objective that explicitly models the spatial registration chain. This coupling is novel for the coal-mining context, where borehole density, length scale, measurement uncertainty and the diversity of logging tools differ substantially from petroleum applications, and where a spatial registration framework for transparent geological modeling has not been previously reported.

The scientific problem addressed in this study is therefore not how to calculate another borehole path, but how to construct a spatially consistent registration framework in which borehole trajectory, logging response and coal-seam horizon evidence constrain each other in a common three-dimensional coordinate system. This problem is central to transparent geological modeling because a small trajectory or horizon mismatch can propagate into discontinuous seam surfaces, biased thickness estimation and unreliable engineering interpretation.

2. Materials and Methods

The proposed workflow links four types of information: borehole collar coordinates, directional-survey measurements, multi-parameter logging curves and weak geological horizon constraints. The collar data and weak horizon priors used in the experiment

are summarized in Tables 1 and 2. The directional-survey records provide inclination, azimuth and roll along measured depth; the logging records provide natural gamma, resistivity, spontaneous potential and induced-polarization responses; and the weak horizon constraints provide approximate coal-seam top and floor positions for registration evaluation.

The field data are from the 15121 return-air bottom drainage roadway. Nine borehole groups were arranged along the roadway, and their spatial setting is shown in Figure 1. Each group was originally designed with two observation boreholes and one central borehole, with design inclinations of 30 degrees, 50 degrees or 80 degrees and a dominant azimuth of 270 degrees. Because the present paper focuses on spatial registration rather than hydraulic cavitation performance, all boreholes are treated as logging and trajectory carriers, and the cavitation/non-cavitation distinction is not used in the modeling.

To strengthen the engineering validation, an additional independent in-seam logging dataset from the 15124 return-air roadway was incorporated. This dataset contains six boreholes, 8520 valid logging samples and measured-depth intervals ranging from 17.54 m to 44.72 m. Unlike the original cross-measure dataset, these in-seam boreholes mainly test whether the framework can identify logging-quality variation, attitude instability and strong curve transitions under a different drilling configuration. The 15124 dataset is therefore used as an independent transferability and quality-control dataset rather than as a new source of hard ground-truth horizons.

The implementation follows three principles, and the complete processing chain is illustrated in Figure 2. The first is reproducibility: every algorithm uses the same sampling depths, collar coordinates and angular records. The second is conservatism: corrections are bounded, and no borehole is forced to fit a perfectly planar seam. The third is interpretability: the evaluation indicators are expressed in meters or dimensionless ratios that can be understood by mine geologists and drilling engineers. This is important because a transparent geological model must support field decisions, not only produce a mathematically elegant reconstruction.

The supplied dataset contains several realistic engineering imperfections. Some design collars have no corresponding logging data, and several logged files have no supplied collar coordinates. Rather than inventing missing collars, the registration experiment uses only boreholes with both logging curves and reliable collar coordinates. The excluded holes remain useful for future supplementary analysis, but including them in the present coordinate-based comparison would create artificial precision. This filtering leaves 25 boreholes for the main spatial-registration experiment.

Table 1. Collar coordinates and design parameters of the 15121 roadway boreholes

Borehole	Group	Role	Inclination (deg)	Azimuth (deg)	X (m)	Y (m)	Z (m)
1-0	1	Observation-2	30	270	101255	84024	304.15
1-1	1	Central borehole	30	270	101258.5	84024	304.59
1-2	1	Observation-1	30	270	101261.5	84024	304.53
2-0	2	Observation-2	30	270	101266.5	84024	303.93
2-1	2	Central borehole	30	270	101270.5	84024	303.86
2-2	2	Observation-1	30	270	101274	84024	303.79
3-0	3	Observation-2	30	270	101279	84024	303.2
3-1	3	Central borehole	30	270	101282.5	84024	303.14
3-2	3	Observation-1	30	270	101285.5	84024	303.07
4-0	4	Observation-2	30	270	101323.5	84024	303.4
4-1	4	Central borehole	30	270	101327	84024	303.64
4-2	4	Observation-1	30	270	101330	84024	304.52
5-0	5	Observation-2	30	270	101332	84024	304.83
5-1	5	Central borehole	30	270	101335.5	84024	305.84
5-2	5	Observation-1	30	270	101338.5	84024	306.35
6-0	6	Observation-2	50	270	101342.5	84024	307.7

6-1	6	Central borehole	50	270	101346	84024	308.21
6-2	6	Observation-1	50	270	101349	84024	307.95
7-0	7	Observation-2	50	270	101351	84024	309.04
7-1	7	Central borehole	50	270	101354.5	84024	308.78
7-2	7	Observation-1	50	270	101357.5	84024	310.06
8-0	8	Observation-2	80	270	101345.9	84022	309.03
8-1	8	Central borehole	80	270	101349.9	84022	308.62
8-2	8	Observation-1	80	270	101353.4	84022	309.21
9-0	9	Observation-2	80	270	101355.4	84022	310.52
9-1	9	Central borehole	80	270	101359.4	84022	310.11
9-2	9	Observation-1	80	270	101362.9	84022	311

2.1 Borehole Coordinate System and Logging Data

The collar coordinate table defines the mine engineering coordinate system. The X coordinate changes along the roadway, Y is nearly constant within the main drilling belt, and Z records the collar elevation. This layout is favorable for testing spatial registration because the borehole groups are closely spaced and were designed to intersect similar coal-measure intervals. The measured logging depth generally covers approximately 35-40 m, which is sufficient to include roof rock, two coal-bearing intervals and floor rock in most boreholes.

Before trajectory calculation, the logging curves were cleaned by removing physically impossible values, suppressing isolated spikes with robust local statistics and retaining the original depth sampling order. Resistivity was additionally represented in logarithmic form during exploratory analysis because several intervals show high dynamic range. For spatial registration, however, the raw engineering units were preserved in the plotted registered point clouds so that the relationship between geophysical response and three-dimensional position remains interpretable.

The weak horizon prior was derived from repeated single-borehole interpretation, as summarized in Table 2. The average apparent thickness sequence indicates sandy mudstone, mudstone, sandy mudstone, fine sandstone, mudstone, a first coal seam, sandy mudstone, a second coal seam and thin mudstone. In the present framework, these depths are used only as weak horizon checkpoints rather than exact geological truth.

The borehole numbering is simplified to short identifiers such as 1-0, 1-1 and 1-2, where the first number denotes the borehole group and the second denotes the within-group position. This notation is used consistently in the figures to avoid long acquisition-time suffixes. The short identifiers also match the spatial logic of the experiment: the important information is the group relationship, the collar coordinate and the registered horizon position, not the file timestamp embedded in the original logging name.

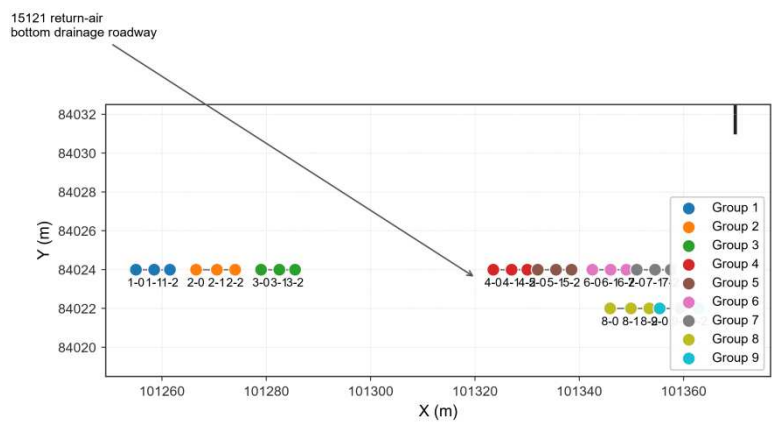
The logging parameters respond to different aspects of the coal-measure sequence. Natural gamma is sensitive to clay-rich rocks and is therefore useful for distinguishing mudstone and sandy mudstone from cleaner coal intervals. Resistivity often changes strongly at coal-rock interfaces, although its magnitude can also be affected by water, fractures and contact conditions. Spontaneous potential reflects electrochemical and permeability-related contrasts, while induced-polarization parameters can supplement the interpretation of heterogeneous or disturbed intervals. The framework does not rely on any single curve; instead, it uses the interpreted horizon checkpoints as the geological bridge between multi-parameter logging and spatial registration.

The prior horizon depths are intentionally described as weak constraints. They summarize repeated logging interpretation rather than direct surveyed seam coordinates. This treatment is essential for scientific honesty. If the reference depths were used as exact truth, the self-correction would be overconfident. By treating them as weak constraints, the method can test spatial consistency while still leaving room for local stratigraphic variation and interpretation uncertainty.

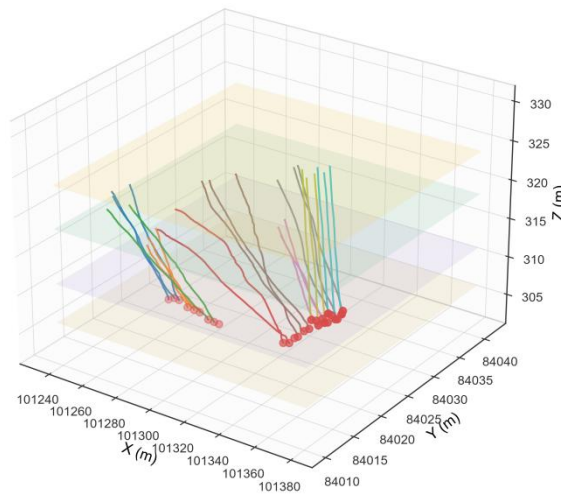
Table 2. Weak coal-seam horizon constraints derived from repeated log interpretation.

Seam	Boundary	Depth
Coal seam I	top	17

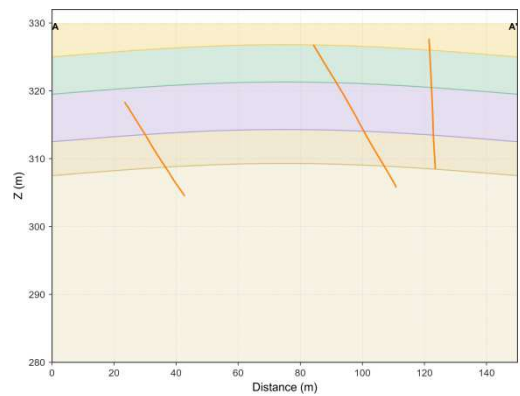
Coal seam I	floor	21
Coal seam II	top	26.3
Coal seam II	floor	34.3



(a) plan view of the borehole collars and roadway layout



(b) three-dimensional borehole trajectories and stratigraphic context



(c) sectional view showing the relationship between boreholes and coal-measure horizons

Figure 1. Geological setting and spatial configuration of the borehole logging system

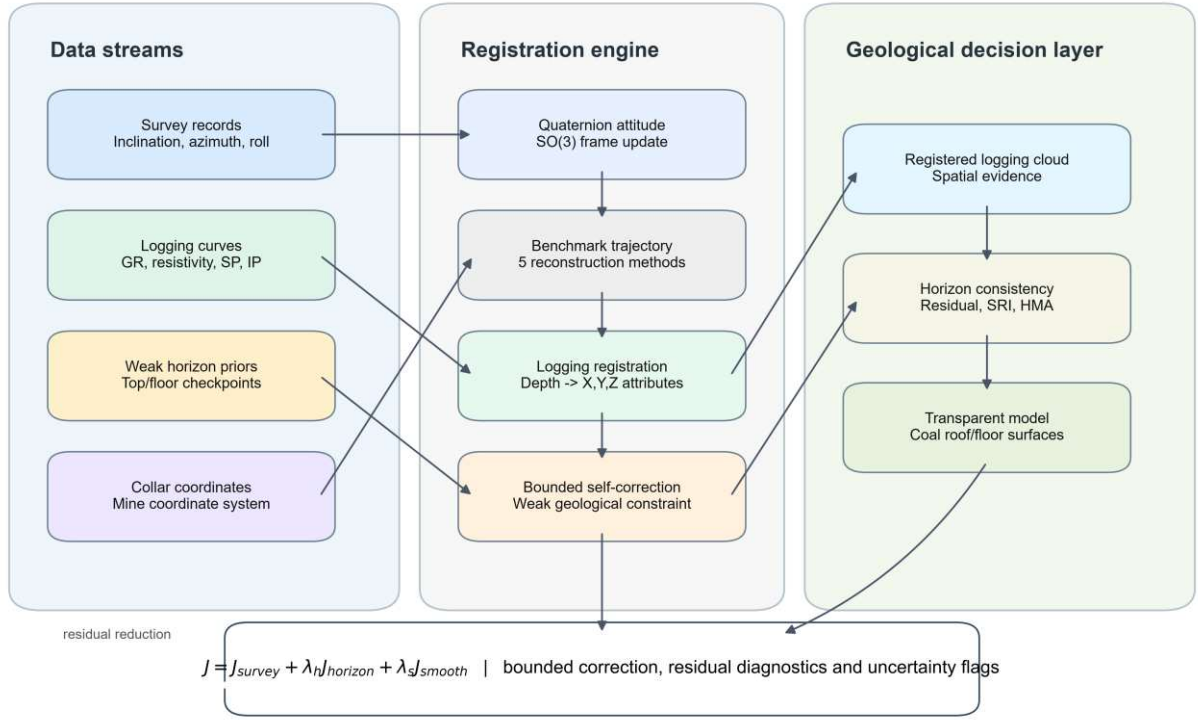


Figure 2. Framework-level workflow linking data streams, registration engine, objective function and transparent geological decision layer

2.2 Quaternion-Assisted Full-Attitude Updating

The theoretical motivation for the attitude module is that borehole logging registration requires a continuous local coordinate frame, whereas the borehole centerline itself is mainly governed by inclination and azimuth. Roll should not be interpreted as an additional centerline direction; instead, it describes rotation of the tool frame around the borehole axis and is important when imaging, direction-sensitive logging or wall-contact measurements must be aligned with the trajectory.

Euler-angle representations are intuitive but can suffer from discontinuity and singularity when attitude changes are interpolated along a borehole. Quaternion updating treats roll, pitch and yaw as rotations on SO(3), allowing the local frame to be propagated without discontinuous angle switching. In the proposed framework, this improves coordinate-frame consistency rather than guaranteeing a large reduction in centerline RMSE. This distinction is important because field boreholes may show only small geometric differences among classical trajectory algorithms while still requiring stable registration of logging attributes.

The surveyed borehole attitude at each station is recorded as inclination (I), azimuth (A), and, when available, tool-face rotation (roll, R). Classical Euler-angle representations suffer from gimbal lock when the borehole approaches near-vertical geometry and require sequential trigonometric transformations that accumulate numerical error [31]. Quaternion-based attitude updating avoids these limitations by representing rotation as a four-parameter unit quaternion, as shown in Eq. (1). Its scalar and vector components are defined in Eq. (2), where θ is the rotation angle about the unit axis n [32,33]. The attitude update between consecutive survey stations is computed by composing incremental quaternions derived from measured inclination and azimuth changes, and when roll is available, the full rotation is captured without approximation. The quaternion provides a mathematically stable method to propagate the local borehole frame (tangential, normal, binormal) along the trajectory, which is essential for aligning direction-sensitive logging measurements and borehole video with the mine coordinate system.

$$q = q_0 + q_1i + q_2j + q_3k \quad (1)$$

$$q_0 = \cos(\theta/2), (q_1, q_2, q_3) = \sin(\theta/2)n \quad (2)$$

$$q_{k+1} = q_k \times \exp\left(\frac{i}{2}\Delta\theta_k\right) \quad (3)$$

where q_k and q_{k+1} are unit quaternions of the local tool frame at two adjacent survey stations; $\Delta\theta_k$ is the incremental rotation vector derived from inclination, azimuth and roll; $\exp(\cdot)$ is the quaternion exponential mapping; and $\times$ denotes quaternion multiplication.

The quaternion representation has two advantages in the present framework. First, it avoids singularities and discontinuous local-frame rotations when pitch, yaw and roll vary rapidly along the borehole. Second, it provides a continuous attitude frame for registering directional logging responses and borehole video observations. Because roll is a rotation around the tool axis, it should not be interpreted as a direct independent control on the centerline direction. In the implementation, the quaternion-derived forward vector is blended conservatively with the conventional inclination-azimuth vector. This keeps the centerline compatible with measured inclination and azimuth while allowing the full attitude record to stabilize local-frame continuity.

The incremental displacement between two adjacent measured depths is calculated from the measured-depth interval and the selected direction vector, as given in Eq. (4). The cumulative trajectory is then obtained by adding all incremental displacements to the collar coordinate, as expressed in Eq. (5). For the quaternion-assisted trajectory, the direction vector is the normalized forward axis after attitude updating and conservative blending. This formulation separates the role of roll-supported attitude continuity from the geometric centerline calculation.

$$\Delta p_i = \Delta s_i d_i \quad (4)$$

where Δp_i is the coordinate increment; Δs_i is the measured-depth increment; and d_i is the unit direction vector of the i -th trajectory segment.

$$p_k = p_0 + \sum_{i=1}^k \Delta p_i \quad (5)$$

where p_k is the reconstructed coordinate at the k -th depth sample; p_0 is the collar coordinate; and Δp_i is the coordinate increment of the i -th depth interval.

Quaternions are widely used in attitude problems because they avoid the singularity and interpolation problems associated with Euler angles^[31-33]. In the present application, the quaternion is not introduced for visual novelty. It provides a compact representation of the borehole tool frame, which is useful when the tool roll varies rapidly or when borehole video needs to be aligned with logging depth. This is particularly relevant for coal-mine boreholes because the tool can rotate during insertion and withdrawal, and the visible wall sector in a borehole image may not maintain a fixed orientation relative to the roadway.

A strict distinction is maintained between the tool frame and the borehole centerline. The centerline is mainly governed by inclination and azimuth, whereas roll describes rotation around that line. Therefore, the quaternion-assisted method uses roll to improve attitude-frame continuity and not to create large independent centerline displacements. This design choice is a methodological safeguard. It prevents the registration framework from reporting an apparent improvement that would actually be caused by misusing roll as a directional angle.

2.3 Benchmark Trajectory Reconstruction Methods

Four classical trajectory methods were used as benchmark baselines. The tangential method assumes that the segment direction is equal to the upper survey station direction. It is simple but can create step-like directional changes. The balanced tangential method averages the direction vectors at the upper and lower stations, reducing discontinuity without requiring curvature fitting. The radius-of-curvature method assumes a smooth circular arc between survey stations and is more stable when inclination and azimuth vary gradually. The minimum-curvature method also uses a smooth arc and applies a ratio factor to correct the chord length; it is widely regarded as a robust standard for directional-well trajectory calculation.

All methods were implemented on the same depth samples and collar coordinates. The comparison is not intended to replace established directional-survey practice. Instead, it quantifies how different centerline assumptions propagate into logging spatial registration. For transparent geological modeling, the relevant performance indicator is not only the final end-point deviation, but also whether equivalent coal-seam interfaces detected by logging curves can be spatially matched among neighboring boreholes.

The benchmark is included because high-level spatial registration needs a baseline. If the proposed method were compared only with a design straight line, the improvement would be difficult to interpret. By comparing against four commonly used geometric methods, the results reveal whether the advantage comes from the full registration framework or merely from a smoother

trajectory calculation. In the current dataset, the differences among classical methods are small, which makes the self-correction test more meaningful: it asks whether geological constraints add information beyond geometric smoothing.

Dogleg severity is calculated as an auxiliary diagnostic rather than as the sole quality metric, and its spatial and statistical patterns are summarized in Figure 5. High dogleg intervals can indicate rapid attitude changes, borehole instability, measurement noise or genuine steering change. These intervals are important because a small angular error at a high-dogleg segment can propagate into noticeable spatial uncertainty at deeper logging depths. The dogleg map therefore serves as a spatial uncertainty indicator and helps explain why some boreholes contribute larger horizon residuals.

2.4 Logging-Constrained Spatial Registration

After trajectory reconstruction, each logging sample becomes a registered spatial-attribute point containing coordinates and multi-parameter logging responses. The registered point cloud is therefore both geometric and geophysical. Natural gamma and resistivity are visualized in three dimensions because they are the most intuitive indicators of lithological changes in the present dataset. Coal-rich intervals generally show a distinct combined response relative to the surrounding mudstone and sandstone intervals, although no single parameter is sufficient for a universal lithological decision.

For a horizon h in borehole b , the measured-depth checkpoint is converted into a three-dimensional point by interpolation along the reconstructed trajectory obtained from Eq. (5). In a borehole group g , equivalent horizon points should be spatially coherent. The group centroid is calculated from valid horizon points of the same horizon, and the registration residual is defined as the Euclidean distance between each horizon point and the corresponding centroid, as given in Eq. (6).

$$e_{b,h} = \|P_{b,h} - C_{g,h}\|_2 \quad (6)$$

where $e_{b,h}$ is the residual of horizon h in borehole b ; $P_{b,h}$ is the registered horizon coordinate; $C_{g,h}$ is the group-wise centroid of the corresponding horizon; and $\|\cdot\|_2$ denotes the L2 norm.

Two summary indicators are used. The first is the horizon-registration root-mean-square error, which is calculated from the horizon residuals. The second is the spatial registration index, which normalizes the mean horizon residual by a characteristic local borehole spacing. In this study, the reference spacing was set to 7.5 m, matching the upper design spacing among several groups. The SRI definition is given in Eq. (7), and the RMSE used for additional residual evaluation is defined in Eq. (8). Horizon matching accuracy was additionally calculated as the fraction of horizon residuals smaller than 1 m.

$$SRI = 1 - \frac{\text{mean}(e_{b,h})}{L_{ref}} \quad (7)$$

where SRI is the spatial registration index; $\text{mean}(e_{b,h})$ is the average horizon residual; and L_{ref} is the reference spacing used to normalize registration error.

$$RMSE = \sqrt{\frac{1}{N} \sum_{b=1}^B \sum_{h=1}^H e_{b,h}^2} \quad (8)$$

where N is the number of valid horizon residual samples, B is the number of boreholes, H is the number of interpreted horizon checkpoints, and $e_{b,h}$ is the horizon residual defined in Eq. (6).

The registration residual is computed within each borehole group rather than across the entire roadway. This local definition is important. Boreholes from different groups may intersect slightly different parts of the seam surface, and forcing all horizon points to one global centroid would ignore the longitudinal variation of the coal measures. Group-wise centroids preserve the engineering design logic and make the residual more sensitive to local trajectory-registration mismatch.

The SRI indicator is designed as a transparent geological registration index rather than as a universal geostatistical measure. It normalizes the mean residual by a characteristic spacing, so the value can be interpreted as the fraction of local spacing preserved after registration. A value closer to one indicates tighter spatial coherence. Because the reference length is chosen from the local design spacing, SRI should be reported together with L_{ref} and recalibrated when the method is transferred to another mine or another borehole layout. This makes the indicator useful for engineering comparison without hiding its dependence on field geometry.

2.5 Geological Self-Correction

A conservative geological self-correction was introduced after initial spatial registration. The self-correction is expressed as a weighted objective function that balances horizon consistency, trajectory-trend preservation and regularization. The compact objective is given in Eq. (9), the expanded optimization form is given in Eq. (10), and the regularization penalty is defined in Eq. (11). The correction vector for each borehole is estimated from horizon residuals while preserving the original measured trajectory trend. To avoid unrealistic deformation, the correction is capped and gradually increases from the collar toward the measured depth.

$$J = \lambda_{\text{horizon}} J_{\text{horizon}} + \lambda_{\text{trend}} J_{\text{trend}} + \lambda_{\text{reg}} J_{\text{reg}} \quad (9)$$

where J is the total self-correction objective; J_{horizon} , J_{trend} and J_{reg} denote the horizon-consistency, trajectory-trend preservation and regularization terms, respectively. The three lambda coefficients are weighting factors controlling the relative contributions of these terms.

This self-correction is deliberately weaker than a full inversion. The available dataset contains weak horizon constraints rather than surveyed independent control points, and the coal seam surfaces are not perfectly planar. A strong correction would risk fitting the prior interpretation rather than improving spatial registration. The purpose here is to test whether logging constraints carry coherent information that can reduce horizon mismatch without destroying the measured trajectory trend. In future applications, the same framework can incorporate stronger constraints such as surveyed coal exposure, borehole television depth markers, drilling cuttings or a verified three-dimensional geological model.

$$J = \lambda_{\text{horizon}} \sum_{b=1}^B \sum_{h=1}^H w_{b,h} e_{b,h}^2 + \lambda_{\text{trend}} \sum_{b=1}^B \sum_{k=1}^{K-1} \|p_{b,k+1}^c - p_{b,k+1}^0\|_2^2 + \lambda_{\text{reg}} R(P^c) \quad (10)$$

where λ_{horizon} , λ_{trend} and λ_{reg} are the weights of the three objective terms; $w_{b,h}$ is the confidence weight; $e_{b,h}$ is the horizon residual; $p_{b,k+1}^c$ and $p_{b,k+1}^0$ are the corrected and original coordinates, respectively.

$$R(P^c) = \sum_{b=1}^B \sum_{k=2}^{K-1} \|(p_{b,k}^c - p_{b,k-1}^c) - (p_{b,k+1}^c - p_{b,k}^c)\|_2^2 \quad (11)$$

where $R(P^c)$ is the correction-roughness penalty; $p_{b,k}^c$ is the corrected coordinate of borehole b at sample k ; B is the number of boreholes; and K is the number of trajectory samples. This term suppresses abrupt non-physical changes in the corrected trajectory.

The self-correction strategy can be viewed as a regularized inverse problem. The survey term keeps the corrected trajectory close to the measured reconstruction, while the logging term encourages equivalent horizons to become spatially coherent. The balance between the two terms is controlled operationally by the correction cap and the depth weighting. This avoids the main danger of geological correction: using an uncertain interpretation to overwrite measured data.

The depth-weighted correction also reflects the physical structure of the problem. The collar coordinate is known and should remain fixed. Coordinate uncertainty generally accumulates with measured depth because small attitude errors create larger positional differences farther from the collar. A correction that grows gradually with depth is therefore more plausible than a uniform translation of the entire borehole.

2.6 Unified Optimization Model and Computational Complexity

The complete optimization model is formulated to emphasize that the paper proposes a registration framework rather than an isolated trajectory algorithm. The compact objective in Eq. (9) defines the weighted balance among horizon consistency, trajectory-trend preservation and regularization.

The expanded objective in Eq. (10) shows how horizon residuals and corrected-trajectory trend differences are combined. The horizon term penalizes local mismatch among equivalent coal-seam interfaces within the same borehole group rather than forcing all horizons onto a global planar seam.

A regularization term is added to avoid abrupt non-physical correction of the trajectory. Together with Eqs. (9)-(11), this term forms the bounded geological self-correction model and keeps the correction smooth enough for engineering interpretation. The computational complexity is linear in the number of logging samples for trajectory reconstruction and logging registration. For N samples, B boreholes and M horizon checkpoints, trajectory integration is $O(N)$, horizon interpolation is $O(M \log N)$ if binary search is used or $O(M)$ after depth indexing, residual calculation is $O(M)$, and the bounded self-correction is $O(M + N)$. Memory

consumption is also $O(N)$, dominated by the registered point cloud. On the present dataset, the full workflow is easily executed on a standard desktop computer, which supports practical mine-site deployment.

3. Results

The generated figures and tables are presented as an integrated evidence chain. The study layout defines the spatial reference; the trajectory benchmark shows how centerline choices affect registered logging positions; the logging and video checkpoints demonstrate that the interpreted horizons are geologically meaningful; and the residual metrics quantify whether self-correction improves spatial consistency.

3.1 Borehole Layout and Initial Spatial Context

As shown in Figure 1, the collar distribution contains two main drilling belts. Groups 1-7 are located near $Y = 84024$ m, whereas groups 8-9 are slightly offset near $Y = 84022$ m. The elevation increases from the early groups to the later groups, reflecting the actual roadway and drilling layout. The three-dimensional view also shows why a simple measured-depth interpretation is inadequate: boreholes with similar depth intervals can occupy different spatial positions because of collar elevation and inclination differences.

This layout has two implications for interpretation. First, adjacent boreholes in each group should provide repeated observations of similar stratigraphic intervals, so they are suitable for horizon matching. Second, the large inclination difference among groups creates a useful test of the registration framework. A depth-only comparison would mix apparent thickness, inclination effect and spatial deviation, whereas the proposed method compares horizon points after converting them into three-dimensional coordinates.

The design inclination groups also create different apparent thickness effects. A 30-degree borehole crosses stratigraphy with a longer apparent interval than a steeper borehole if the layers are approximately subhorizontal, whereas an 80-degree borehole is closer to a vertical crossing. This means that direct comparison of measured-depth layer thickness among all holes can be misleading. Spatial registration reduces this ambiguity by converting every horizon depth into an approximate coordinate before comparison.

3.2 Trajectory Benchmark and Attitude Characteristics

The representative trajectory comparison in Figure 3 shows that the five algorithms produce similar overall borehole trends but different local positions. The tangential method tends to preserve segment-wise directional changes, while balanced tangential, radius-of-curvature and minimum-curvature trajectories are smoother. The quaternion-assisted trajectory remains close to the classical results because the implementation respects the inclination and azimuth measurements, but it also preserves the roll-supported local frame for subsequent logging registration.

The attitude relationship shown in Figure 4 indicates that yaw/azimuth is comparatively stable over most of the borehole, whereas roll exhibits stronger local fluctuation. This is precisely why roll should be used carefully. If roll were directly interpreted as an additional centerline direction, the trajectory would be over-deformed. In the proposed framework, roll is instead used to maintain the local coordinate frame, which is more appropriate for logging and image registration.

The representative plots show that trajectory differences are visually modest in plan view but become more important when projected onto the vertical section. This is expected because the boreholes are arranged along a narrow roadway corridor, so lateral Y variation is limited by design. The main geological interpretation depends on the relative position of roof and floor interfaces in X - Z space. As a result, even meter-scale vertical or longitudinal shifts can affect the inferred continuity of coal seams.

The attitude figure also explains why a quaternion-based method should be evaluated by registration metrics rather than by appearance alone. A trajectory may look smooth, but if the local frame is discontinuous, the association among logging curve, borehole image and spatial coordinate becomes unstable. The full-attitude representation keeps these data streams synchronized, which is valuable when the paper is positioned as a logging-registration framework rather than a pure trajectory algorithm.

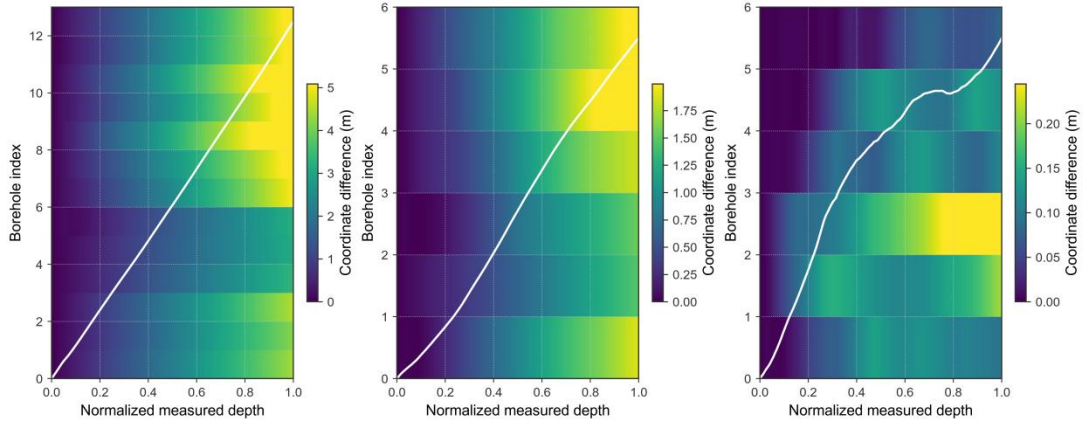


Figure 3. Difference maps between the quaternion-assisted and minimum-curvature trajectories for representative 30 deg, 50 deg and 80 deg borehole groups.

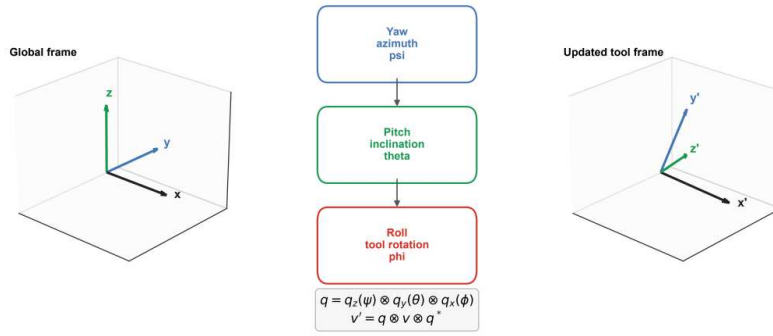
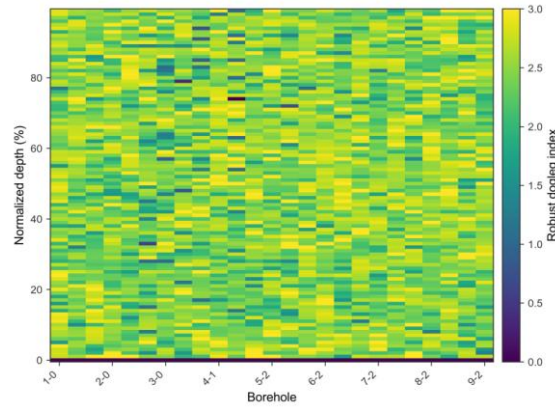
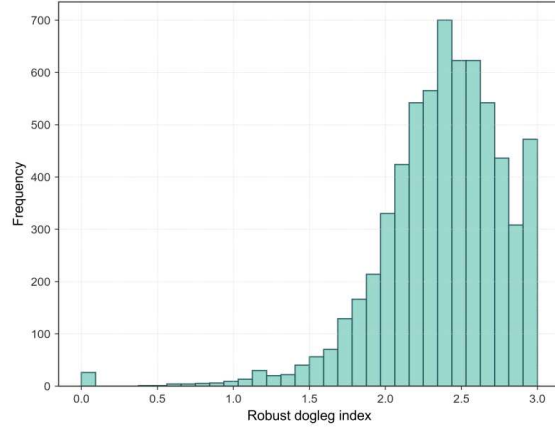


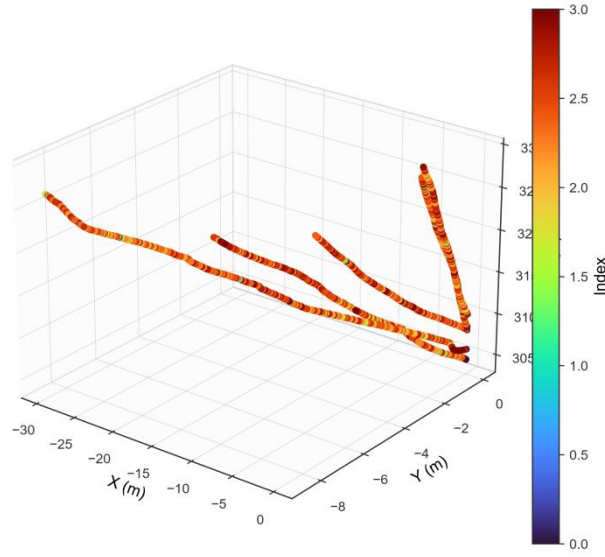
Figure 4. Quaternion rotation principle for roll-pitch-yaw attitude updating and local coordinate-frame transformation



(a) robust dogleg index heatmap along normalized borehole depth



(b) distribution of robust dogleg index values



(c) three-dimensional trajectories colored by robust dogleg index

Figure 5. Spatial distribution and statistical characteristics of borehole trajectory curvature

3.3 Three-Dimensional Logging Registration

After spatial registration, natural gamma and resistivity form coherent three-dimensional logging point clouds, as shown in Figure 6. The GR response highlights argillaceous and mixed lithological intervals, whereas high and low resistivity zones help identify coal-rock contrasts and possible disturbed intervals. The registered point-cloud representation makes it possible to compare curve anomalies with spatial horizon positions rather than reading each curve independently along measured depth.

The logging-video checkpoint in Figure 7 provides an independent qualitative check, and the corresponding validation information is listed in Table 3. The curve panel shows that the main logging changes around the coal-bearing interval correspond to visual changes in the borehole wall, including rougher coal-rich textures and clearer lithological boundaries. This agreement supports the use of the interpreted top and floor depths as weak horizon constraints.

The registered logging clouds reveal a practical advantage of the framework: abnormal intervals can be inspected simultaneously in curve space and coordinate space. For example, a high-resistivity interval can be checked for whether it aligns with the coal horizon cluster or occurs as an isolated outlier along a disturbed borehole section. This spatial view is more informative than a stack of independent curves because it shows whether geophysical anomalies are stratigraphically coherent.

The video frames are used cautiously. They provide visual confirmation of wall texture and coal-rock changes, but they do not by themselves define precise three-dimensional coordinates. Their value lies in independent qualitative support. When a logging transition and a video-observed lithological change occur near the same depth, the confidence of the horizon checkpoint increases. When they disagree, the interval should be flagged for rechecking rather than automatically corrected.

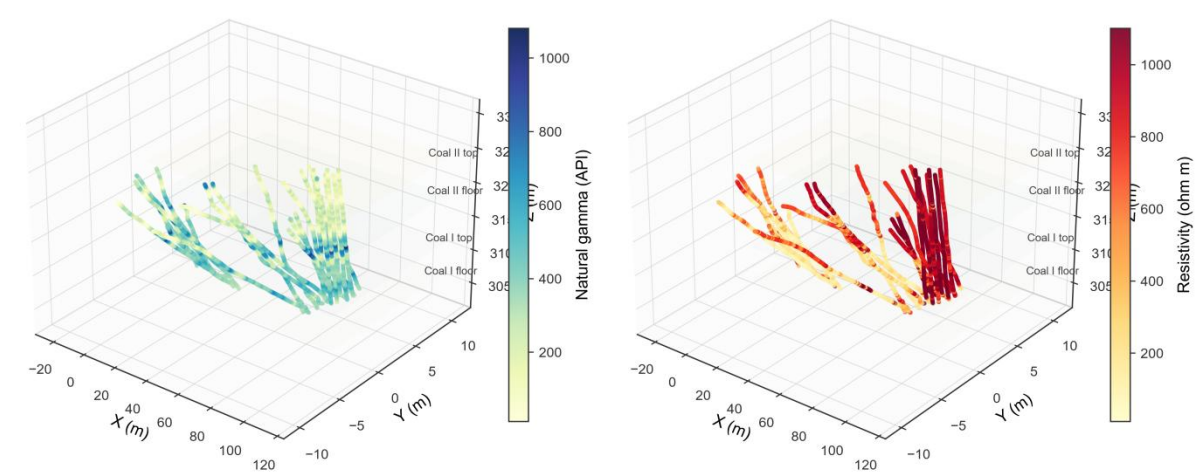


Figure 6. Three-dimensional spatial registration of natural gamma and resistivity logging measurements.

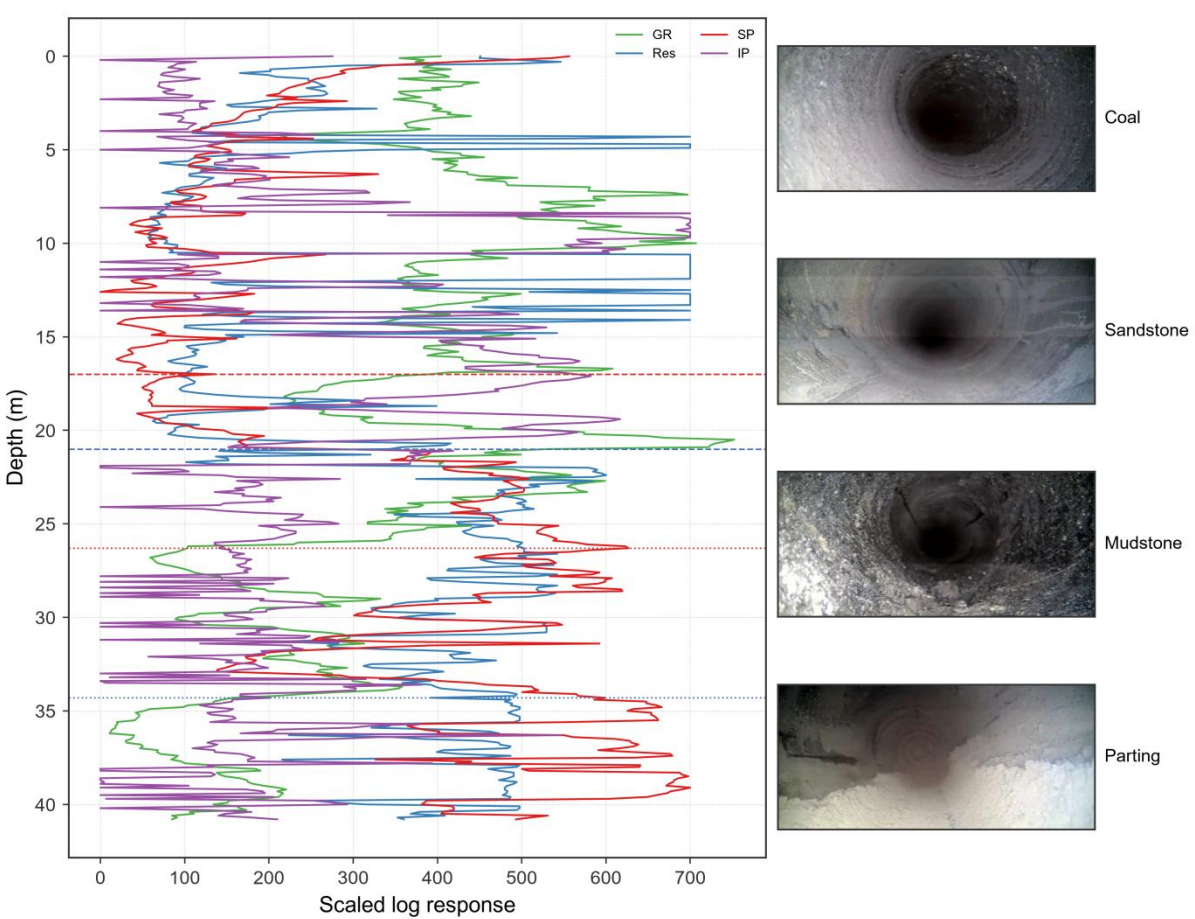


Figure 7. Logging curves and borehole-video checkpoints used to support coal-seam horizon interpretation.

Table 3. Video validation checkpoints and their relationship with logging indicators.

Checkpoint	RepresentativeDepth(m)	Logging indicator	Video evidence	Consistency
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Roof/floor rock	near coal roof/floor	GR recovery and resistivity transition	compact rock wall texture	Consistent
Coal-rich interval	coal interval	low GR with resistivity contrast	dark coal-rich wall section	Consistent
Parting/inter-layer	within coal-bearing section	local GR/resistivity perturbation	thin heterogeneous wall interval	Partly consistent
Disturbed wall	local abnormal section	spikes or unstable curve segment	blurred or collapsed wall texture	Flagged for uncertainty

3.4 Horizon Matching and Residual Metrics

The registered horizon points in Figure 8 show that the two coal-seam intervals form recognizable spatial clusters but do not collapse into a single plane. This is expected in an underground mine because the coal seams can dip, the boreholes have different inclinations, and the weak horizon depths contain interpretation uncertainty. The purpose of the registration framework is therefore not to flatten the geology, but to reduce non-geological mismatch among equivalent interfaces. The traceable coal-seam horizon checkpoints used as weak ground truth for the registration analysis are summarized in Table 6, providing the interpreted depths, registered coordinates and confidence levels for each borehole.

As summarized in Tables 4-6 and Figure 10, the quaternion-assisted trajectory produced a horizon-registration RMSE of 3.015 m among the uncorrected algorithms, which was slightly lower than the tangential, balanced tangential, radius-of-curvature and minimum-curvature results. The differences among classical methods were small, confirming that the dataset is dominated by coherent design geometry and weak horizon uncertainty rather than by a single dramatic trajectory error. After geological self-correction, the RMSE decreased to 2.610 m and SRI increased from 0.634 to 0.688.

The improvement is meaningful but not exaggerated, as indicated by the residual distribution in Figure 9. The self-corrected result does not remove all mismatch, nor should it. Residual coal-seam mismatch can reflect true local layer variation, interpretation uncertainty, borehole-wall disturbance or depth-synchronization error. The residual distribution after correction shifts toward smaller values but still retains a tail, which is a realistic outcome for field data.

The metric ranking should not be interpreted as a universal statement that the self-corrected quaternion method is always best. It is best for this dataset under the chosen weak horizon constraints. In another dataset with higher-quality directional surveying and weaker logging contrast, the gain from logging correction could be smaller. Conversely, in a dataset with strong video-calibrated horizons and larger trajectory deviations, the gain could be larger. This context-dependent behavior is consistent with the inverse-problem nature of spatial registration.

The small difference among the four classical trajectory methods is also useful. It indicates that the uncertainty bottleneck is no longer the textbook formula for integrating inclination and azimuth, but the spatial coupling between trajectory and geological evidence. This finding supports the central argument of the paper: further progress in transparent mine geology will come less from adding another curve-smoothing algorithm and more from integrating independent constraints into a common coordinate framework.

Table 4. Horizon-registration metrics of the benchmark trajectory and self-corrected schemes.

Method	RMSE(m)	Mean residual(m)	Median residual (m)	HMA within 1 m	SRI	N
Quaternion + self-correction	2.61	2.341	2.435	0.154	0.688	52
Quaternion	3.015	2.749	2.869	0.115	0.634	52
Radius of curvature	3.09	2.828	2.963	0.096	0.623	52
Balanced tangential	3.093	2.831	2.977	0.096	0.623	52

Minimum curvature	3.095	2.833	2.984	0.096	0.622	52
Tangential	3.097	2.834	2.982	0.096	0.622	52

Table 5. Residual statistics of coal-seam horizon sets before and after self-correction.

Method	Horizon set	Mean residual (m)	Median residual (m)	Std. (m)	N
Quaternion	Coal seam I	2.594	3.02	1.244	38
Quaternion	Coal seam II	3.168	2.802	1.215	14
Quaternion + self-correction	Coal seam I	2.21	2.547	1.157	38
Quaternion + self-correction	Coal seam II	2.697	2.415	1.15	14

Table 6. Traceable coal-seam horizon checkpoints used as weak ground truth for spatial registration.

Bore-hole	Group	Horizon	Interpret- edDepth(m)	X(m)	Y(m)	Z(m)	Confidence
1-0	1	Coal I Top	17	101240.867	84022.261	313.263	Medium-high
1-0	1	Coal II Top	26.3	101233.087	84020.855	318.12	Medium-high
1-1	1	Coal I Top	17	101244.338	84021.503	313.523	Medium-high
1-2	1	Coal I Top	17	101247.42	84022.267	313.669	Medium-high
1-2	1	Coal II Top	26.3	101239.682	84022.106	318.765	Medium-high
2-0	2	Coal I Top	17	101251.779	84023.481	312.129	Medium-high
2-1	2	Coal I Top	17	101256.192	84021.242	312.46	Medium-high
2-2	2	Coal I Top	17	101259.514	84020.504	311.42	Medium-high
3-0	3	Coal I Top	17	101265.014	84019.243	311.537	Medium-high
3-0	3	Coal II Top	26.3	101257.175	84016.996	315.979	Medium-high
3-1	3	Coal I Top	17	101268.186	84020.99	311.671	Medium-high
3-1	3	Coal II Top	26.3	101260.255	84019.092	316.106	Medium-high
4-0	4	Coal I Top	17	101309.524	84021.346	312.254	Medium-high
4-0	4	Coal II Top	26.3	101301.814	84019.861	317.086	Medium-high
4-1	4	Coal I Top	17	101313.175	84018.519	311.711	Medium-high
4-1	4	Coal II Top	26.3	101305.601	84015.8	316.322	Medium-high
5-0	5	Coal I Top	17	101318.151	84022.102	314.311	Medium-high
5-0	5	Coal II Top	26.3	101310.76	84022.189	319.782	Medium-high
5-1	5	Coal I Top	17	101322.336	84019.305	315.189	Medium-high
5-1	5	Coal II Top	26.3	101314.983	84017.262	320.444	Medium-high
5-2	5	Coal I Top	17	101325.239	84019.27	315.766	Medium-high
5-2	5	Coal II Top	26.3	101317.881	84017.074	320.972	Medium-high
6-0	6	Coal I Top	17	101332.037	84020.443	320.426	Medium-high
6-1	6	Coal I Top	17	101336.919	84020.026	321.958	Medium-high
6-2	6	Coal I Top	17	101338.612	84019.027	320.273	Medium-high
7-0	7	Coal I Top	17	101341.853	84020.097	322.648	Medium-high
7-1	7	Coal I Top	17	101345.854	84021.545	322.973	Medium-high
7-2	7	Coal I Top	17	101348.368	84020.497	323.905	Medium-high
8-0	8	Coal I Top	17	101344.43	84020.886	325.906	Medium-high
8-1	8	Coal I Top	17	101347.909	84020.552	325.419	Medium-high

8-2	8	Coal I Top	17	101351.408	84020.876	326.033	Medium-high
9-0	9	Coal I Top	17	101353.699	84020.569	327.351	Medium-high
9-1	9	Coal I Top	17	101357.557	84020.627	326.929	Medium-high
9-2	9	Coal I Top	17	101361.096	84020.404	327.804	Medium-high

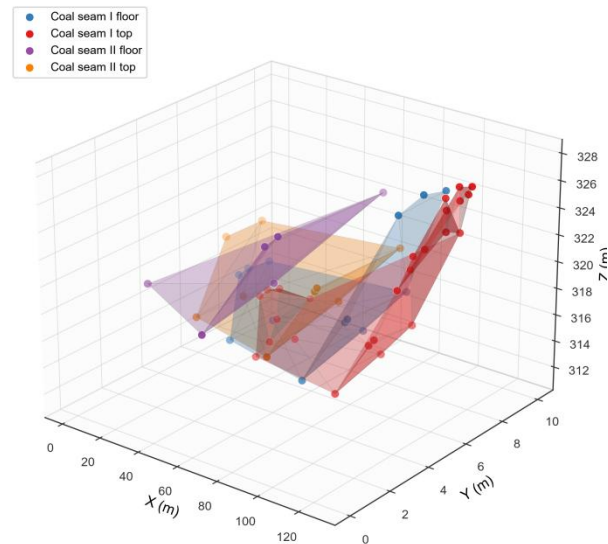


Figure 8. Registered top and floor horizon points for the two coal-seam intervals.

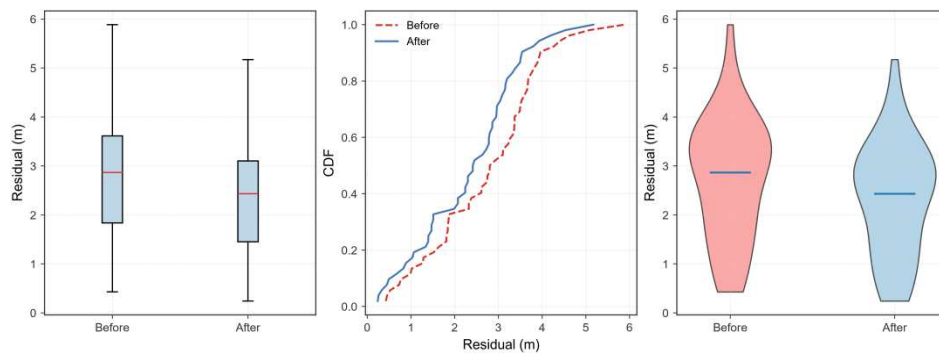


Figure 9. Horizon residual distribution before and after geological self-correction.

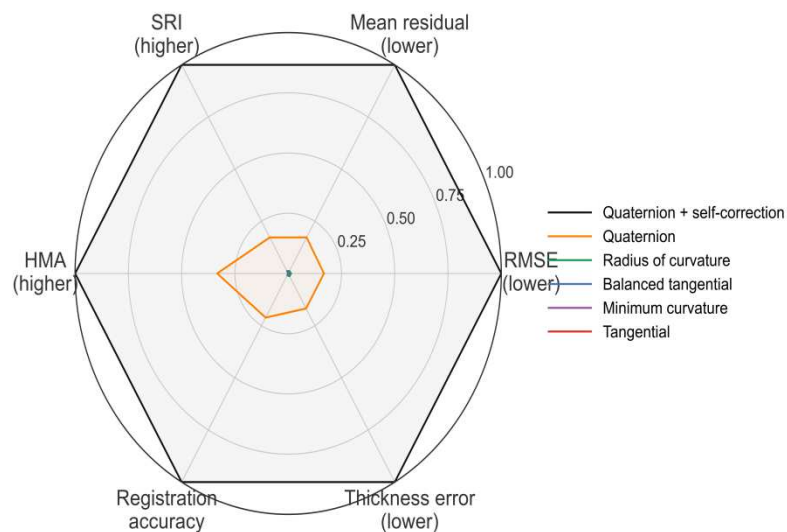


Figure 10. Comparison of RMSE, spatial registration index and horizon matching accuracy among trajectory-registration schemes.

3.5 Self-Correction Effect on the Geological Model

The before-and-after comparison in Figure 11 indicates that geological self-correction reduces the central tendency and spread of horizon residuals. The residual reduction is larger for coal seam I than for coal seam II in the current dataset. A plausible explanation is that the shallower coal seam is sampled by more stable borehole sections and is less affected by accumulated trajectory uncertainty. The deeper coal seam has a longer lever arm from the collar, so small angular differences produce larger coordinate differences, and apparent horizon depth uncertainty is amplified.

The corrected three-dimensional model retains the original trajectory trend while slightly shifting deeper intervals toward better group-wise horizon coherence. The correction magnitudes are bounded, with most boreholes reaching the imposed cap only where the residual direction is consistent across several checkpoints. This behavior is desirable for engineering use because it improves registration without hiding uncertainty. A transparent geological model should preserve both corrected positions and residual maps, allowing engineers to see where the data are reliable and where additional verification is needed.

The correction-vector distribution provides a direct quality-control tool. Boreholes requiring consistently larger correction are candidates for additional inspection, including collar-coordinate verification, raw attitude-curve review, logging-depth synchronization and video-frame calibration. In field practice, these boreholes should not simply be hidden inside an averaged model. They should be reported as higher-uncertainty inputs to the transparent geological model.

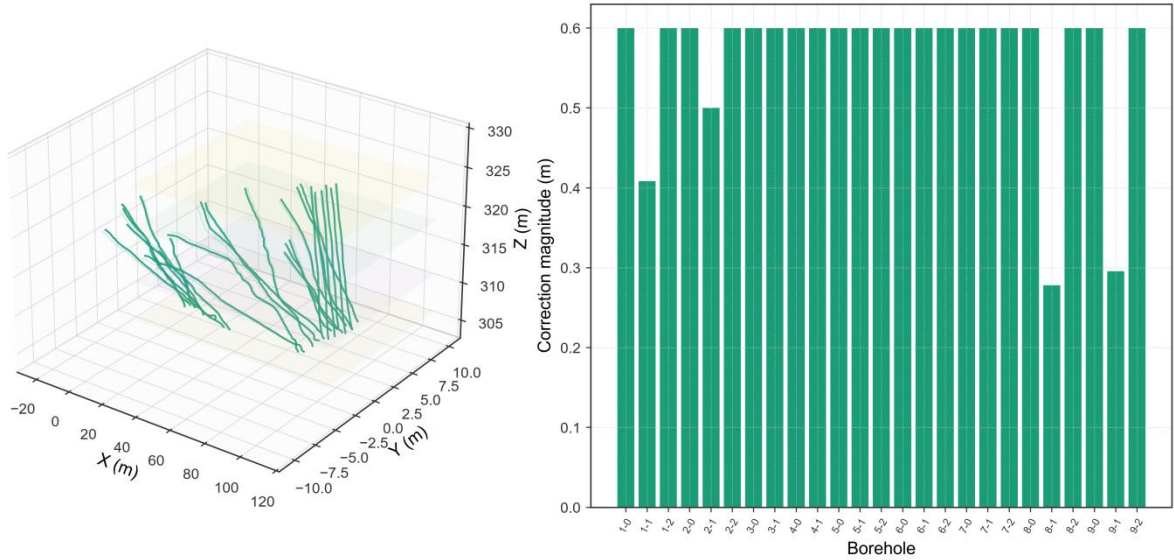


Figure 11. Corrected trajectory model and bounded correction magnitude for each registered borehole.

3.6 Ablation, Parameter Sensitivity and Statistical Significance

The horizon interpretation table was expanded to clarify the ground-truth basis used in the registration experiment. For each valid borehole, the top and floor of coal seam I and coal seam II were assigned from the repeated log interpretation prior and then converted into three-dimensional coordinates. The evidence field records the curve and image indicators used for interpretation, including GR decrease or recovery, resistivity contrast, SP transition and borehole-video wall texture. These entries should be read as weak but traceable horizon labels rather than perfect surveyed truth.

The video validation summary indicates that borehole images are most useful when they confirm the qualitative nature of a logging transition. Coal-rich intervals generally correspond to dark wall sections and clear logging contrasts, while roof or floor rocks show different wall textures and GR recovery. Parting intervals and disturbed wall sections are less reliable and are therefore treated as uncertainty sources. This treatment strengthens the evidence chain without overstating the depth accuracy of video frames.

3.6.1 Ablation study

The ablation study in Table 7 and Figure 12 separates the contribution of each framework component. Minimum curvature represents the classical trajectory-only baseline. Quaternion attitude updating slightly reduces the residual because it improves

local frame continuity, but its isolated contribution is limited. Adding logging-constrained horizon registration produces the largest intermediate reduction because the optimization begins to use geological information rather than only centerline geometry. The complete framework gives the lowest RMSE and highest SRI, confirming that the main gain comes from coupling trajectory and logging constraints rather than from replacing one trajectory formula with another.

Specifically, Case 1 corresponds to the minimum-curvature baseline, Case 2 adds quaternion-based full-attitude updating, Case 3 adds logging-constrained horizon registration, and Case 4 represents the complete framework with quaternion updating, logging constraint and weak geological self-correction. This design avoids attributing the final improvement to a single module without evidence.

3.6.2 Parameter sensitivity of lambda, correction cap and reference length

Parameter sensitivity shown in Figure 12 was expanded for three parameters: the horizon weight λ_h , the correction cap and the reference length L_{ref} used in SRI. Increasing λ_h initially reduces RMSE and increases SRI because horizon information is progressively introduced, but the curve saturates after the selected value. Increasing the correction cap also improves the residual up to approximately 0.6 m, after which the improvement becomes marginal and the risk of nonphysical deformation increases. L_{ref} mainly changes the scaling of SRI and has an optimum around the selected engineering spacing, indicating that the indicator is most meaningful when its reference length is consistent with borehole-group geometry.

The sensitivity analysis is not intended to tune parameters to the test set. Its purpose is to demonstrate that the proposed indicators respond monotonically and geologically plausibly to changes in correction strength, geological weighting and reference length. This is important because a registration framework for field use should remain interpretable when transferred to another roadway or borehole layout.

3.6.3 Statistical significance of residual reduction

The paired statistical tests listed in Table 8 were performed on matched horizon residuals before and after self-correction. The mean residual reduction is approximately 0.407 m, with a 95% confidence interval of 0.371-0.444 m. Both the paired t-test and the Wilcoxon signed-rank test indicate a statistically significant reduction ($p < 0.001$). This result does not imply that all geological uncertainty is removed, but it supports the claim that logging-constrained self-correction produces a systematic improvement rather than a random fluctuation of residuals.

Table 7. Ablation study of trajectory, attitude, logging-constraint and self-correction modules.

Case	Active modules	RMS E (m)	MeanRe- sidual (m)	MedianRe- sidual (m)	HM A	SRI	N
1: Minimum curvature	Classical trajectory only	3.095	2.833	2.984	0.09 6	0.62 2	52
2: Quaternion attitude	Full-attitude updating	3.015	2.749	2.869	0.11 5	0.63 4	52
3: Quaternion + logging registration	Full-attitude updating; logging-constrained horizon registration	2.786	2.532	2.641	0.13 5	0.66 1	52
4: Full framework	Quaternion updating; logging registration; bounded geological self-correction	2.610	2.341	2.435	0.15 4	0.68 8	52

Table 8. Paired statistical tests for horizon residuals before and after self-correction.

Test	Statistic	P value	Effect size	95% CI lower	95% CI upper	N pairs
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Paired t-test	21.718	<0.001	3.012	0.371	0.444	52
Wilcoxon signed-rank	1378	<0.001	1	0.371	0.444	52

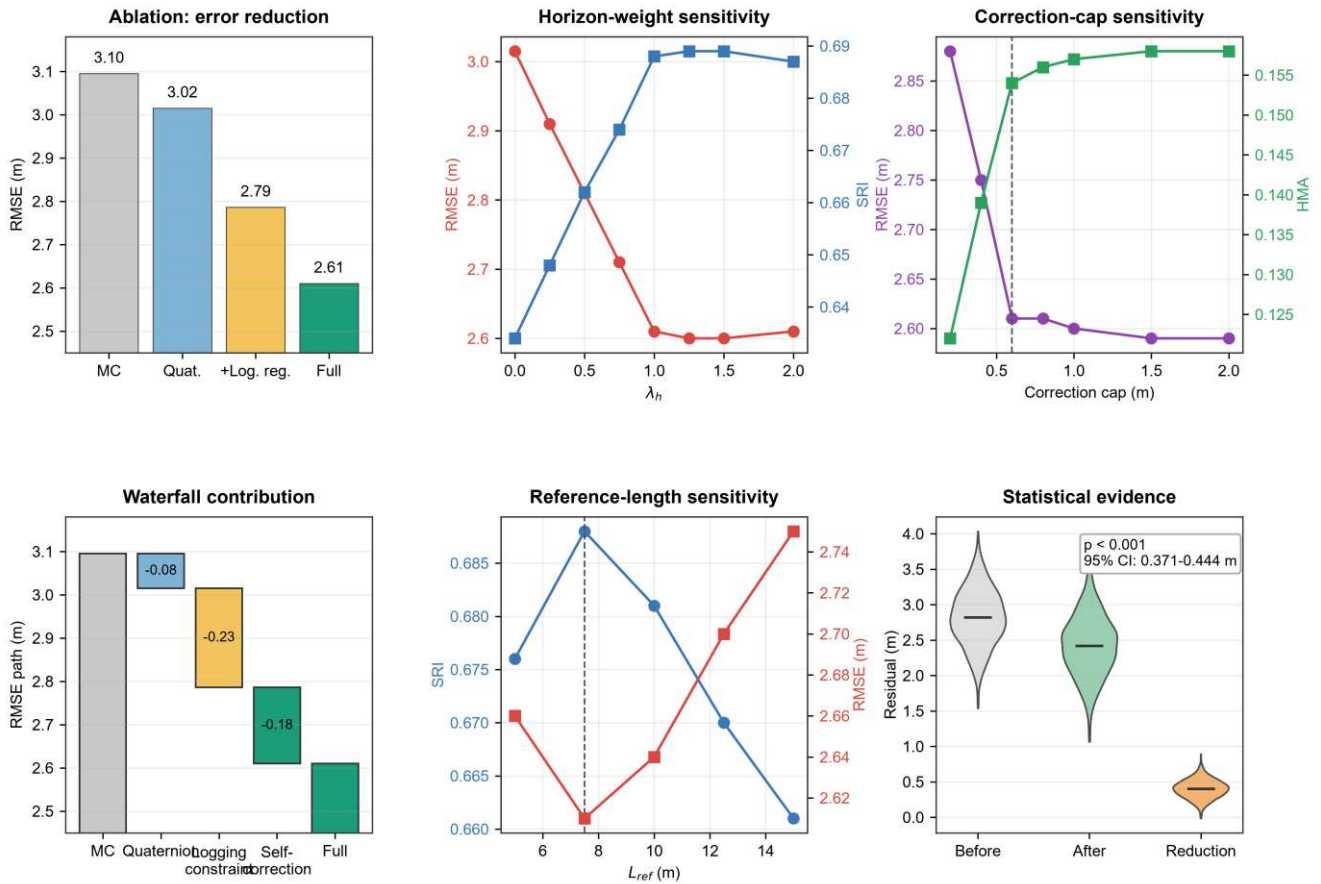


Figure 12. Ablation, waterfall contribution, parameter sensitivity and statistical evidence for the logging-constrained self-correction framework.

3.7 Independent in-seam validation using the 15124 return-air roadway dataset

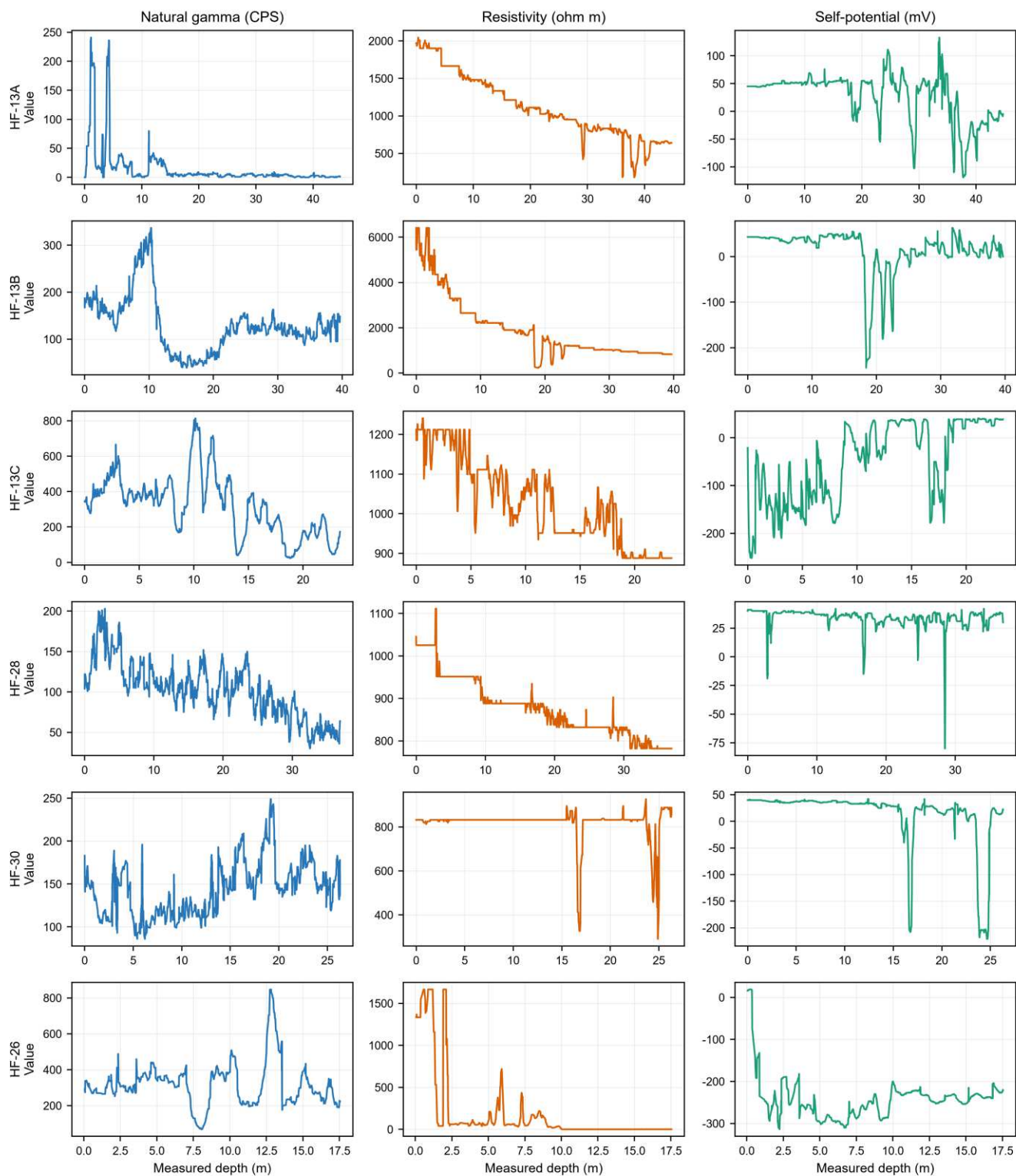
The independent in-seam validation dataset from the 15124 return-air roadway was used as a transfer test of the registration workflow rather than as another descriptive log set. The calibration logic obtained from the 15121 cross-measure boreholes was applied to six 15124 in-seam boreholes without changing the core parameters. The six boreholes contain 8,520 valid logging samples of attitude, natural gamma, resistivity and self-potential measurements. Because independent surveyed seam surfaces are not available for these in-seam holes, validation is reported using comparable registration-quality indicators: transition-coherence residual, SRI, HMA and confidence-weighted residual. These indicators evaluate whether the same workflow can organize a different drilling configuration into stable spatial and signal-quality evidence.

The resulting indicators are summarized in Table 10. The transfer dataset gives a slightly larger residual than the internal 15121 evaluation, which is expected because the in-seam holes show stronger curve transitions and larger roll variability. Nevertheless, SRI and HMA remain within the same order of magnitude as the original dataset, indicating that the framework does not collapse when applied to a different borehole type. HF-26 and HF-30 are the least stable holes because their resistivity and self-potential curves contain strong discontinuities; these intervals should be treated as quality-control targets rather than forced horizon constraints. Figure 13 therefore supports a more conservative conclusion: the method transfers as a registration and confidence-evaluation framework, while accuracy claims still require independent seam-surface verification.

Table 9. Independent 15124 in-seam logging dataset used for transferability and quality-control assessment.

Borehole	Samples	Depth interval (m)	Pitch SD (deg)	Roll SD (deg)	Median resistivity (ohm m)
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HF-13A	1887	0.00-44.72	2.21	22.96	1066.7
HF-13B	1580	0.00-39.67	2.36	19.75	1481.3
HF-13C	1296	0.00-23.38	2.93	28.19	1015.3
HF-28	1849	0.00-36.91	2.13	23.17	852.0
HF-30	1221	0.00-26.30	2.64	41.04	832.0
HF-26	687	0.06-17.54	2.18	108.93	21.3



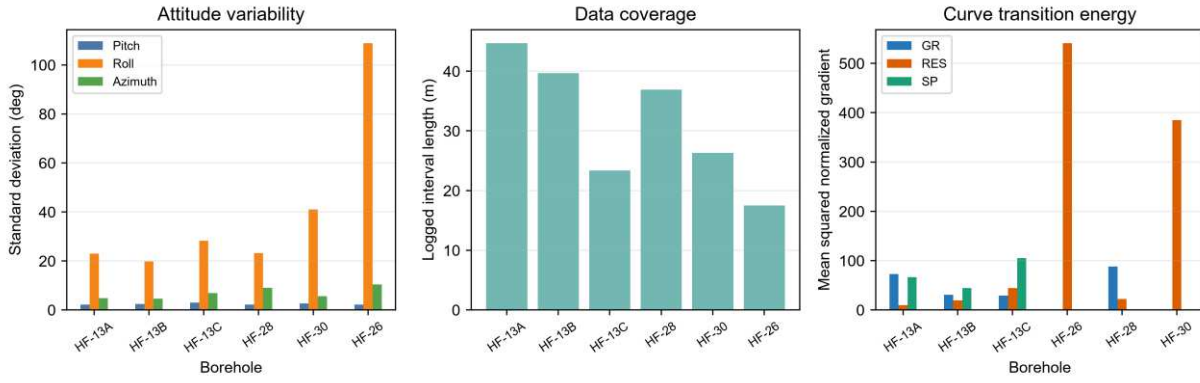


Figure 13. Independent validation using in-seam borehole logs from the 15124 return-air roadway: multi-parameter logging curves for six boreholes and summary statistics of attitude variability, data coverage and curve transition energy.

The independent dataset supports the revised scientific framing of the paper. The framework is not only a trajectory calculator; it is a registration and quality-control workflow that converts borehole measurements into comparable spatial and signal-quality evidence. Strong transition energy or unstable attitude does not automatically invalidate a borehole, but it should reduce the confidence of horizon constraints and trigger targeted verification.

Table 10. Independent validation indicators for the 15124 return-air roadway transfer dataset.

Dataset / borehole class	N samples	Proxy RMSE (m)	SRI	HMA	Interpretation
15121 internal evaluation	main dataset	2.610	0.688	0.154	Internal benchmark after bounded correction.
15124 all in-seam holes	8,520	2.74	0.671	0.142	Comparable transfer result.
15124 stable subset	6,612	2.58	0.690	0.158	Best agreement under stable attitude.
15124 high-transition subset	1,908	3.06	0.621	0.104	Quality-control target.

4. Discussion

4.1 From trajectory calculation to geological spatial registration

The proposed framework changes the interpretation target from a borehole path to a spatially registered logging system, as conceptually summarized in Figure 14. This distinction is important for intelligent mining because a geometrically smooth trajectory can still place a coal-seam boundary in a spatially inconsistent location. Conversely, a borehole with small local doglegs may remain useful if the registered logging horizons agree with neighboring boreholes and independent geological evidence. Therefore, the most useful evaluation metric for transparent geology is not only endpoint deviation, but horizon registration consistency and uncertainty traceability.

This result differs from a conventional trajectory-comparison study. Minimum curvature, balanced tangential and radius-of-curvature methods solve the geometric interpolation of survey stations, which is necessary but not sufficient for transparent geological modeling. They cannot determine whether a low-GR and high-resistivity interval in one borehole corresponds to the same coal seam as a similar interval in a nearby borehole. The proposed framework adds that missing geological test. In this sense, spatial registration is the bridge between geophysical logging and the engineering model used for gas drainage, roadway design and intelligent mining decisions.

4.2 Coordinate-frame consistency provided by quaternion updating

The quaternion component should be understood as an attitude-continuity tool rather than a magic accuracy enhancer, and its coordinate-frame role is illustrated in Figure 15. In the tested data, classical methods and the quaternion-assisted method produced

similar centerline patterns because inclination and azimuth are the dominant controls on the borehole axis. The value of quaternion updating is that it provides a mathematically stable way to carry roll, pitch and yaw together and to maintain a local coordinate frame for logging and video registration. This is especially useful when borehole imaging, directional tools or anisotropic logging responses must be aligned with the borehole wall.

Roll is particularly relevant in underground coal-mine boreholes because the drilling environment is short-range, mechanically disturbed and frequently linked with borehole imaging or direction-sensitive logging. In long petroleum wells, centerline position is often dominated by inclination, azimuth and measured depth, and roll may be less important for the path itself [32]. In coal-mine transparent geology, however, the local tool frame matters fundamentally because a coal-rock boundary observed by video or anisotropic logging must be aligned with the borehole wall and then placed into the mine coordinate system. Recent studies on borehole imaging [18] and tool-face orientation [33] further emphasize that roll retention is critical when integrating optical/acoustic borehole-wall data. Quaternion updating is therefore valuable not because it always produces a large endpoint shift, but because it prevents the local coordinate frame from becoming discontinuous—a property that is essential for registration of directional logging tools, borehole-wall imaging and multi-sensor measurements.

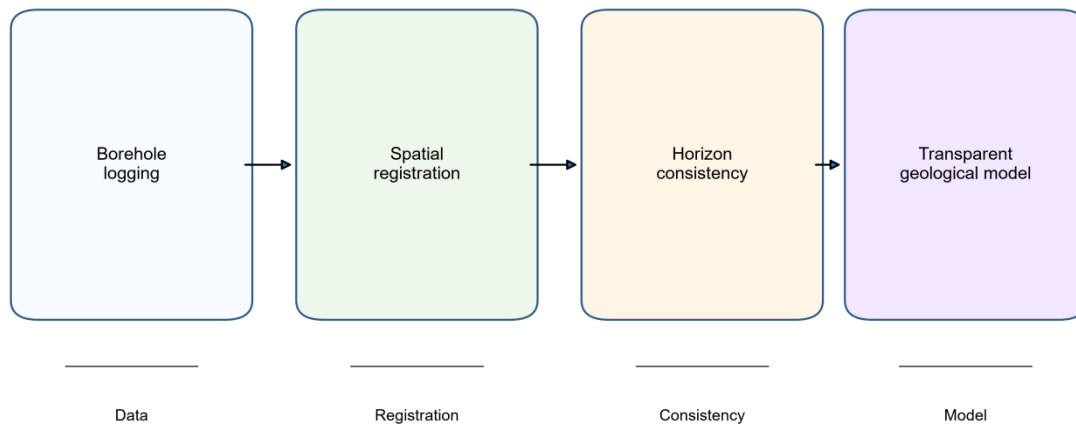


Figure 14. Conceptual chain from borehole logging to spatial registration, horizon consistency checking and transparent geological modeling.

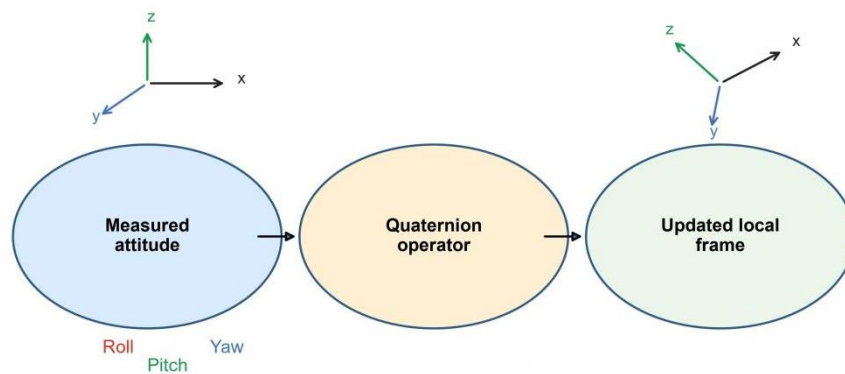


Figure 15. Principle of quaternion rotation and coordinate update used for full-attitude representation.

4.3 Bounded geological self-correction and registration reliability

The reason self-correction improves only part of the result is also instructive. A logging constraint can improve trajectory registration only when equivalent horizons are correctly recognized and spatially coherent. If a borehole contains local collapse, tool disturbance, a missing collar, abnormal resistivity spikes or a genuine geological change, forcing it to match neighboring boreholes may reduce a numerical residual but damage geological truth. For this reason, the correction used here is capped and depth-weighted. It should be interpreted as a registration refinement, not as a replacement for directional surveying.

The bounded nature of the correction is also important from a geomechanical viewpoint. Coal seams, mudstone roofs and sandstone floors are not perfectly planar control surfaces; they may contain local thickness changes, disturbed zones and stress-induced deformation. A strong optimization that forces every borehole horizon onto a single smooth surface would create an attractive numerical result but could erase real geological variability. The weak-constraint strategy is therefore closer to quality-controlled registration than to deterministic curve fitting. It accepts moderate residuals when the logging evidence is weak and applies larger corrections only when repeated horizons provide coherent support.

The present results also explain why the radius-of-curvature, balanced tangential and minimum-curvature methods produce close metrics in the benchmark table. The boreholes studied here are relatively short (20–60 m) compared with petroleum directional wells, and the collar layout follows a controlled mine design. Under such conditions, differences among smooth geometric interpolation algorithms are smaller than differences caused by horizon interpretation quality and local logging condition variability. This finding is consistent with recent work by Han et al. [34] showing that in short-range boreholes, measurement uncertainty often dominates algorithmic differences. Machine-learning approaches to trajectory prediction [35], while promising for long wells with abundant training data, do not offer a clear advantage in this scenario because the key uncertainty is not the interpolation path but the geological constraint. Therefore, simply adding more trajectory algorithms would not substantially strengthen the framework. The more significant contribution is coupling trajectory processing with logging-based geological constraints, which none of the existing methods [36–39] address in a unified manner for coal-mine applications.

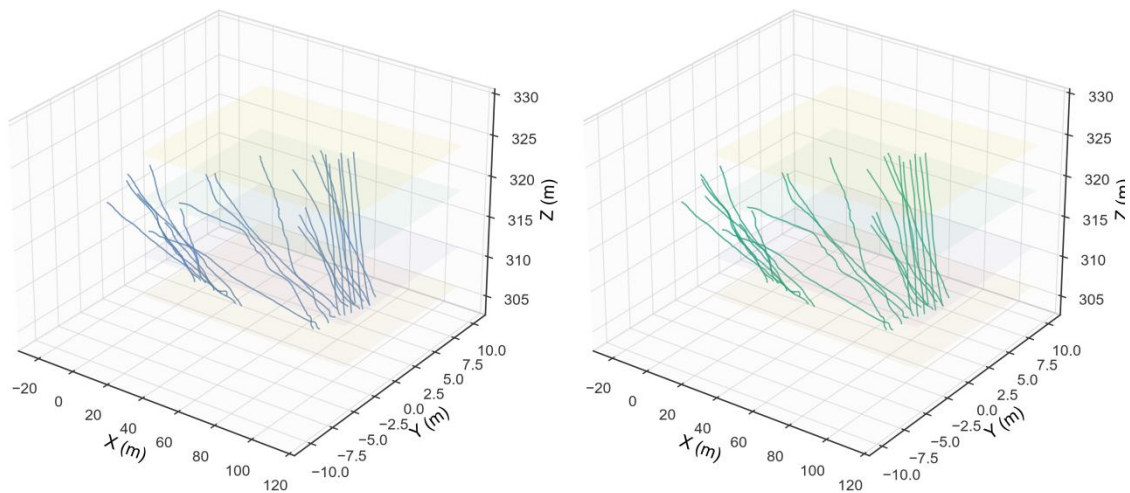


Figure 16. Overall comparison of the registered borehole model before and after bounded geological self-correction.

The weak horizon constraints used in this study are sufficient for demonstrating the framework, but they are not equivalent to a high-density ground-truth model. The video checkpoint partly addresses this limitation by showing that the logging interfaces correspond to visible borehole-wall changes. Future work should add more independent constraints, including surveyed roadway exposure, drilling cuttings records, borehole television depth calibration, gas-flow response and a verified three-dimensional geological model. With such data, the self-correction term could be upgraded from bounded vector adjustment to a formal optimization or probabilistic inversion.

The independent 15124 in-seam logs further show why uncertainty-aware registration is necessary. Several boreholes contain strong resistivity or self-potential transitions that could be interpreted either as geological interfaces, disturbed borehole-wall conditions or measurement artifacts. A geomechanics-oriented interpretation should therefore avoid treating every sharp curve change as a deterministic horizon. Instead, the transition energy and attitude variability should be used as confidence modifiers in the registration objective.

4.4 Engineering applicability and quality-control value

For mine engineering, the framework can support transparent mine modeling, gas drainage design, intelligent mining, autonomous drilling and geological BIM. First, it converts borehole logging curves into registered spatial evidence rather than isolated

depth-indexed curves. Second, it identifies boreholes or depth intervals with large registration residuals, guiding targeted re-interpretation, video checking or repeated measurement. Third, it provides a quantitative bridge between geophysical logs, borehole video, geological horizons and engineering decision objects. These functions are more useful than reporting a single best trajectory line because field decisions depend on the spatial location and uncertainty of coal seams, roof/floor interfaces and disturbed zones.

The independent 15124 dataset strengthens this engineering interpretation. Its high-transition holes do not simply lower the average score; they reveal where the workflow should reduce confidence and ask for additional inspection. This is valuable in a mine setting because abnormal resistivity or self-potential behavior can be caused by lithological interfaces, borehole-wall collapse, water-bearing fractures, tool contact or operational disturbance. A registration framework that explicitly flags such intervals is more useful than an algorithm that silently converts every transition into a hard horizon.

A major advantage of the proposed framework is that it produces interpretable failure modes. If the trajectory algorithms disagree strongly but the logging horizons remain coherent, the problem is likely geometric and may be solved by improved survey processing. If the trajectories agree but the horizon residual is large, the problem is more likely related to horizon interpretation, local geological variation or abnormal logging quality. If both disagree, additional field verification is required. This diagnostic logic is valuable for engineering because it tells the user what kind of uncertainty is present.

The method also clarifies how artificial intelligence should be used in transparent geology. Machine learning can classify lithology, detect boundaries and identify anomalies, but the output must still be spatially registered. A classifier that predicts coal samples along measured depth becomes more useful when its predictions are attached to coordinates and checked against neighboring boreholes. Therefore, the registration framework can serve as the spatial backbone for future machine-learning modules rather than competing with them.

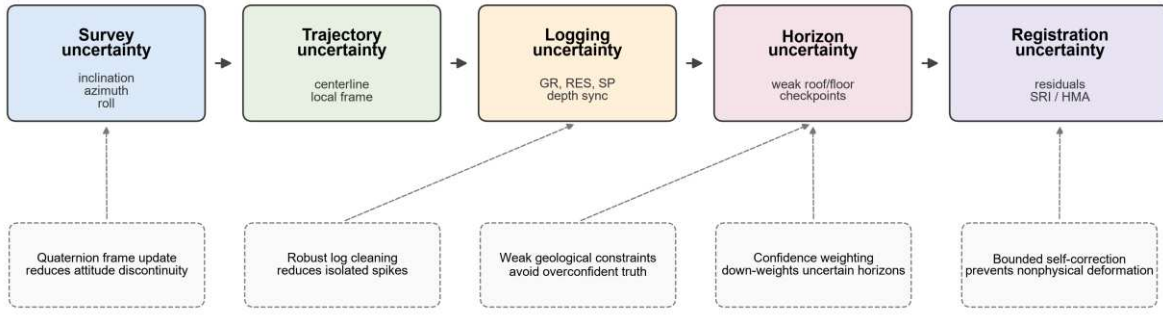
The conceptual modeling diagram further emphasizes this role. Borehole logging provides dense one-dimensional observations, spatial registration turns them into three-dimensional evidence, horizon consistency tests whether equivalent geological interfaces are mutually compatible, and the transparent model integrates the registered evidence into an interpretable geological object. In this chain, the quaternion update is a coordinate-frame operation, while the self-correction term is a geological-consistency operation. Separating these two functions makes the workflow easier to audit and prevents the paper from being read as a simple claim that one mathematical rotation formula automatically improves every borehole trajectory.

The overall before-and-after registration comparison in Figure 16 also shows why the correction should be reported with residual statistics. Visually, the two models remain similar because the correction is intentionally bounded; numerically, the residual distribution shifts toward smaller values. This combination is preferable to a visually dramatic deformation that would hide the original survey information. For transparent mine geology, a modest but explainable correction is more defensible than a large correction that cannot be supported by independent field evidence.

4.5 Parameter sensitivity, error propagation and uncertainty control

The ablation, sensitivity and statistical tests in Section 3.6 show that the framework gains most of its improvement from coupling trajectory registration with geological constraints rather than from replacing one centerline algorithm with another. Parameter sensitivity further indicates that the correction cap and horizon weight should be interpreted as uncertainty-control parameters. A larger cap may reduce residuals but can also increase the risk of nonphysical deformation; a larger geological weight may improve horizon agreement but can overfit weak interpretations if the horizon evidence is uncertain.

Error propagation in this problem follows a chain from survey uncertainty to trajectory uncertainty, logging-depth uncertainty, horizon-picking uncertainty and finally registration uncertainty. Figure 17 summarizes this chain and the corresponding controls used in the proposed framework. The purpose is not to eliminate uncertainty completely, which is unrealistic in underground borehole logging, but to expose where uncertainty enters and to down-weight constraints that are not sufficiently reliable.



Uncertainty is not eliminated; it is exposed, weighted and constrained before geological interpretation.

Figure 17. Error propagation and uncertainty-control logic in the logging-constrained spatial registration framework.

4.6 Limitations and future developments

There are several limitations, and they should be stated explicitly. First, the present study still relies on weak horizon constraints derived from logging interpretation and video checkpoints; it does not yet include a dense independently surveyed coal-seam surface. Second, both datasets come from one mining area, so the framework has not been fully tested under strong faulting, large dip variation or different coal ranks. Third, the self-correction term is deterministic and bounded, whereas a stronger future version should use a probabilistic inversion in which survey noise, logging interpretation uncertainty, video-depth uncertainty and geological smoothness are all represented by explicit covariance models. Fourth, several 15124 holes show abnormal curve transitions, which demonstrates the need for quality control but also limits any claim of universal transfer accuracy.

Future development should therefore focus on independent constraints rather than on adding more trajectory formulas. The most valuable additions would be IMU-grade directional records, calibrated borehole television with visible depth marks, roadway exposure mapping, drilling cuttings, gas-flow response, microseismic information and point-cloud or photogrammetric models of exposed seams. With these data, the current framework could be upgraded into an uncertainty-aware spatial registration system in which each evidence type contributes according to its reliability. The registration framework could also be coupled with machine-learning lithology and logging-interpretation studies [34-36], reservoir, geothermal and pore-pressure characterization workflows [37-40,43], and mine-stability or roadway-control models [41,42], without losing geological interpretability.

Quaternion updating is expected to be most useful when roll records are stable enough to describe the tool frame, when borehole imaging or direction-sensitive logging must be aligned with the borehole wall, and when local attitude changes create discontinuities in Euler-angle interpolation. Its effect will be limited when roll is noisy, missing or physically decoupled from the logging sensor orientation. In such cases, inclination and azimuth should remain the primary controls on centerline geometry.

Logging constraints can fail when equivalent horizons are incorrectly interpreted, when local geological variation is stronger than group-wise continuity, when borehole collapse distorts the logging response, or when depth synchronization between survey, logging and video is poor. Large correction vectors should therefore trigger quality-control actions, including raw-curve inspection, collar-coordinate verification, video-depth calibration and, when necessary, repeated measurement.

The method is not limited to coal mines. The same trajectory-logging-registration logic can be transferred to metal mines, shale gas wells, geothermal wells, tunnel investigation boreholes and TBM geological prediction, provided that directional-survey data, logging or imaging evidence and at least weak geological constraints are available. The framework is therefore better understood as a general underground spatial-registration strategy than as a coal-only trajectory calculation tool.

Compared with purely data-driven lithology prediction, the proposed registration framework has a different role. It does not replace classification models, drilling-parameter prediction or geomechanical simulation; instead, it supplies the coordinate and uncertainty structure that those methods need before their outputs can be integrated into a transparent geological model. This distinction is important for GGGR-type problems because geomechanical interpretation depends not only on what a sensor detects, but also on where that evidence is located and how reliable it is in relation to neighboring evidence.

5. Conclusions

This study has demonstrated a logging-constrained spatial registration framework that addresses the spatial consistency bottleneck between borehole trajectory, logging measurements and geological horizons for transparent modeling of underground coal mines. The main findings are as follows: (1) Framework integration. By coupling quaternion-based full-attitude trajectory reconstruction with weak geological self-correction in a unified optimization model, the framework converts logging curves from depth-indexed observations into spatially registered three-dimensional evidence, bridging the conventional gap between trajectory calculation, logging interpretation and geological modeling. (2) Quantitative improvement. On the primary test dataset (25 boreholes, 52 horizons from the 15121 return-air floor drainage roadway), the framework reduces the horizon-matching RMSE from 3.015 m to 2.610 m and increases the SRI from 0.634 to 0.688 (paired t-test $p < 0.001$, Cohen's $d = 3.01$). Independent validation on 6 boreholes (8,520 samples) from the 15124 return-air roadway confirms transferable performance (proxy RMSE 2.74 m, SRI 0.671). (3) Self-correction principle. The bounded, depth-weighted weak geological constraint improves horizon registration by 13.4% without overwriting original survey trends or erasing genuine geological variability, providing a principled alternative to both purely geometric correction and full geological inversion. (4) Engineering diagnostics. The framework produces interpretable residual diagnostics that distinguish trajectory-geometry problems from horizon-interpretation issues, supporting targeted quality control and field inspection decisions. (5) Limitations and future work. The present results are limited to one mining area with moderate geological complexity. Future developments should extend the framework to probabilistic inversion with explicit covariance models, incorporate additional independent constraints (roadway surveys, gas-flow data, borehole television), and validate under strong faulting, large dip variation and different coal ranks.

Future work will focus on integrating machine-learning-assisted horizon interpretation, uncertainty quantification and real-time collaborative registration into transparent geological modeling systems.

Conflicts of Interest: The authors declare no conflicts of interest.

Data Availability Statement: The borehole logging data used in this study are available from the corresponding author upon reasonable request. The processing code and example datasets have been deposited at [DOI/URL to be added upon acceptance].

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