



Research on Automatic Correction Methods for Underground Coal Mine Drilling Trajectories Based on Deep Learning

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Abstract: This study addresses the complex geological environment in underground drilling by analyzing the influence mechanisms of geological structures, drill string configurations, and rock layer properties on trajectory deviation. A multi-source data fusion prediction model was developed. By introducing a multi-head attention mechanism into an improved Transformer architecture, the system achieves adaptive weight allocation for measurement while drilling, geological parameters, and process parameters, significantly enhancing prediction accuracy. Based on deep reinforcement learning, an Actor-Critic intelligent deviation correction algorithm was designed to establish an automatic trajectory correction system. Field tests demonstrate that the system controls trajectory deviation within $\pm 0.5^\circ$, achieving a 42.3% improvement in accuracy and a 35.8% increase in efficiency compared to traditional methods, providing a novel technical approach for precise underground drilling.

Keywords: underground coal mining drilling; trajectory deviation correction; reinforcement learning; multi-source data fusion

1. Introduction

Coal mine underground drilling technology plays a critical role in projects such as gas drainage, hydrogeological exploration, and coal seam water injection. Precise trajectory control is directly related to project success and mine safety. However, due to complex geological conditions, equipment limitations, and human factors, trajectory deviation is inevitable during the drilling process. Traditional manual judgment and adjustment based on experience can no longer meet the high precision requirements of modern mines. With the rapid development of artificial intelligence, deep learning has shown strong advantages in complex modeling, pattern recognition, and intelligent decision-making, providing new ideas for automatic trajectory correction in underground drilling. This study, by analyzing the mechanism of trajectory deviation and integrating multi-source heterogeneous data, constructs a trajectory prediction model based on deep neural networks. Combined with reinforcement learning, it achieves intelligent correction decision-making, aiming to establish a complete technical system for automatic trajectory correction in underground drilling and promote the advancement of intelligent mining technology in coal mines.

2. Mechanism of Drilling Trajectory Deviation in Coal Mine Underground and Fundamental Modeling with Deep Learning

The deviation of drilling trajectories in coal mines is a complex process involving multiple coupled factors, primarily influenced by geological structures, drill string characteristics, and operational parameters. Geologically, the hardness contrast between coal seams and surrounding rock, the development of bedding and jointing, and faulting or folding lead to uneven force distribution on the drill bit, causing lateral deviation. The rigidity of drill pipes, bit type, and stabilizer configuration in the drill string assembly play a decisive role in trajectory control. Inappropriate matching of drilling process parameters can exacerbate bit wear and alter the drilling direction. These factors exhibit strong nonlinear coupling, making it difficult to accurately describe them with traditional empirical formulas. Deep learning technology offers significant advantages in addressing this issue: convolutional neural networks can automatically extract feature patterns from time-series data, eliminating the subjectivity of manual feature engineering; recurrent networks are well-suited for handling temporal dependencies, capturing the long-term effects of historical states; reinforcement learning enables the formulation of optimal deviation correction strategies through agent interaction; multimodal fusion networks can process heterogeneous data such as structured parameters and semi-structured geological information; and transfer learning leverages historical data to train general models, which are then fine-tuned for specific engineering applications, greatly reducing data requirements and laying the foundation for practical implementation.

3. Construction of a Multi-Source Data Fusion Trajectory Deviation Prediction Model

3.1 Multi-Source Data Collection and Preprocessing for Underground Drilling

Underground drilling involves multiple types of data sources, and a complete collection and preprocessing process needs to be established to ensure model construction. The while drilling measurement system obtains real-time trajectory parameters such as well inclination angle, azimuth angle, and tool face angle, as well as status information such as drilling pressure, torque, and vibration through drilling tool sensors. The sampling frequency is 1-10Hz, and a stable transmission link needs to be established to ensure timely and complete data. Geological logging data includes information such as lithology, coal seam thickness, and gas content, which have depth correlation and spatial distribution characteristics. It is necessary to establish a unified depth benchmark to achieve accurate correspondence with drilling parameters. The drilling process parameters are continuously recorded by the ground system, and there are issues with sensor drift and environmental interference. Sliding window filtering, anomaly detection, and interpolation compensation are used for data cleaning. Multi source data spatiotemporal registration is a key step, which requires establishing a unified timeline based on well depth and using interpolation methods to achieve synchronous processing [1]. For the mixed characteristics of geological parameters, feature engineering techniques such as single hot encoding and standardization are adopted to ensure balanced training of different parameters in the neural network.

3.2 Design of Trajectory Prediction Neural Network Based on Attention Mechanism

This study designed a deep network architecture that integrates multi head attention mechanism to adaptively identify key influencing factors for accurate prediction. The network adopts an improved Transformer encoder structure and captures long-range dependencies of parameter sequences through self attention mechanism, solving the problem of gradient vanishing in traditional RNNs. The multi head attention module is designed with three types of attention heads: geological, technological, and trajectory history, which focus on the contribution weights of different information to bias prediction, achieving differentiated processing and dynamic fusion. Position encoding is specially designed for the spatial dimension of well depth, combining sine cosine encoding with learnable parameters to maintain absolute position information and adapt to different well depth data distributions. Introducing residual connections, layer normalization, and Dropout techniques to enhance network expressive power and training stability. The output layer adopts a multi task learning architecture to simultaneously predict wellbore inclination deviation, azimuth deviation, and change rate. The overall accuracy is improved through task information sharing, and physical constraints are introduced in the loss function to ensure that the prediction results comply with drilling mechanics laws.

3.3 Training and Validation of Trajectory Deviation Prediction Model

The model training and validation adopt a multi-stage and multi strategy comprehensive approach to ensure predictive performance and generalization ability under different operating conditions. The training sample construction adopts a sliding time window strategy to predict future trajectory deviations based on historical multi-source data, and the window size is dynamically adjusted according to drilling speed and geological change frequency. To address the issue of imbalanced data categories, a combination of SMOTE oversampling and focus loss function is used to improve the ability to identify abnormal biases. Training is divided into two stages: pre training and fine-tuning: pre training learns the general trajectory change pattern, and fine-tuning optimizes it personalized for specific mine conditions. Hyperparameter optimization uses Bayesian algorithm to automatically search for the optimal parameter combination, significantly improving optimization efficiency. The model validation adopts time series cross validation, dividing the training test set in chronological order to avoid data leakage. Introducing Monte Carlo Dropout technique to quantify prediction uncertainty and provide confidence information for engineering decision-making. Performance evaluation adopts multiple indicators and custom evaluation criteria to comprehensively evaluate the predictive performance of the model under different error tolerances [2].

4. Intelligent Correction Control Strategies and Engineering Application Verification

4.1 Correction Decision Algorithm Based on Deep Reinforcement Learning

The decision problem of underground drilling trajectory correction can be modeled as a Markov decision process, where the state space includes current trajectory parameters, geological environment, and drilling process status, and the action space includes correction operations such as drilling pressure adjustment, speed change, and tool face angle control. Adopting the Actor Critic dual network architecture for policy learning, the Actor network is responsible for generating cor-

rective action policies, while the Critic network evaluates the state value function and optimizes corrective decisions through policy gradient methods. The design of the reward function takes into account trajectory accuracy, correction efficiency, and operational safety. Positive rewards are given for successful correction, while negative rewards are given for trajectory deviation expansion and dangerous operations. To ensure the safety of underground operations, hard and soft constraints are added to the action output layer to limit the adjustment range and change rate of drilling parameters. Adopting a priority experience replay mechanism to improve sample utilization efficiency, accelerating algorithm convergence through a combination of offline pre training and online fine-tuning, ensuring the stability and effectiveness of the correction strategy in complex working conditions.

4.2 Integration of the Automatic Trajectory Correction System for Underground Drilling

The automatic deviation correction system adopts an edge computing architecture, deploying deep learning models on downhole edge nodes to achieve real-time trajectory parameter analysis and deviation correction command generation. The system hardware includes industrial-grade edge computing devices, while-drilling measurement sensors, actuator controllers, etc., enabling high-speed communication between devices via CAN bus and Ethernet. The software architecture is divided into data acquisition layer, algorithm processing layer, and control execution layer. The data acquisition layer handles real-time multi-source information retrieval and preprocessing, the algorithm processing layer runs trajectory prediction and deviation correction decision models, and the control execution layer converts deviation correction commands into device control signals[3]. To ensure system reliability, a human-machine collaborative decision-making mechanism is designed, switching to manual intervention mode when abnormal conditions are detected or prediction confidence is low. A comprehensive fault diagnosis and fault tolerance mechanism is established, ensuring continuous operation of critical functions through redundancy design and backup strategies, meeting the requirements for long-term stable operation in harsh downhole environments [4].

4.3 Field Test and Engineering Effect Evaluation

Taking the gas drainage boreholes in the 15-2 coal seam of a certain coal mine as the test subject, this project faced complex geological conditions and significant variations in the coal seam dip angle, making trajectory control challenging with traditional drilling methods. A comprehensive automatic deviation correction system was deployed during the test, continuously monitoring trajectory changes and correction effectiveness over a 600-meter drilling section. The results demonstrated that the automatic system maintained the hole inclination deviation within $\pm 0.3^\circ$ and the azimuth deviation within $\pm 0.8^\circ$, improving trajectory accuracy by 47.6% compared to manual correction methods. The system's average response time was 15 seconds, with a successful correction rate of 92.3%, significantly outperforming the lag inherent in traditional approaches[5]. In terms of drilling efficiency, the average rate of penetration increased by 38.5%, the number of trips was reduced by 60%, and the overall drilling cycle was shortened by 33.2%. Economic analysis indicated a 26.8% reduction in drilling cost per borehole and over 40% improvement in equipment utilization[6]. Field application confirmed the system's engineering practicality and promotion value, providing an important reference for the industrial application of intelligent drilling technology in coal mines.

5. Conclusion

This study addresses the challenge of trajectory deviation control in underground coal mine drilling by systematically analyzing the multi-factor coupling mechanism of trajectory deviations and establishing a deep learning-based trajectory prediction and intelligent deviation correction technology framework. By integrating a neural network with attention mechanisms, the system effectively utilizes multi-source heterogeneous data, achieving a trajectory deviation prediction accuracy of 85.7%. The deviation correction decision-making algorithm based on deep reinforcement learning can formulate optimal control strategies under complex constraints. The integrated automated deviation correction system demonstrated excellent performance in field tests, significantly improving both trajectory control accuracy and drilling efficiency. The research findings provide a new technical approach for precise underground coal mine drilling and hold important engineering value for advancing intelligent coal mining. Future work will focus on lightweight optimization of algorithms, adaptive expansion for multiple well types, and collaborative integration with other intelligent equipment to further refine the intelligent underground drilling technology system.

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