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Original Paper

An intelligent drilling guide algorithm design framework based on highly interactive learning mechanism

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ABSTRACT

Measurement-while-drilling (MWD) and guidance technologies have been extensively deployed in the exploitation of oil, natural gas, and other energy resources. Conventional control approaches are plagued by challenges, including limited anti-interference capabilities and the insufficient generalization of decision-making experience. To address the intricate problem of directional well trajectory control, an intelligent algorithm design framework grounded in the high-level interaction mechanism between geology and engineering is put forward. This framework aims to facilitate the rapid batch migration and update of drilling strategies. The proposed directional well trajectory control method comprehensively considers the multi-source heterogeneous attributes of drilling experience data, leverages the generative simulation of the geological drilling environment, and promptly constructs a directional well trajectory control model with self-adaptive capabilities to environmental variations. This construction is carried out based on three hierarchical levels: “offline pre-drilling learning, online during-drilling interaction, and post-drilling model transfer”. Simulation results indicate that the guidance model derived from this method demonstrates remarkable generalization performance and accuracy. It can significantly boost the adaptability of the control algorithm to diverse environments and enhance the penetration rate of the target reservoir during drilling operations.

1. Introduction

Currently, the development trend of oil and gas drilling in complex oil and gas reservoirs is characterized by ultra-deep water, ultra-deep strata, low permeability, and unconventionality. The 14th Five-Year Plan issued in 2021 and the outline document of the 2035 vision goal have made a comprehensive arrangement for the further development of the petroleum exploration industry. They proposed key core technologies to concentrate superior resources on oil and gas exploration and development, and promoted the intelligent upgrading of oil and gas field exploration (Zhao et al., 2021; Wang, 2020). As a pivotal technology in the field of drilling engineering, borehole trajectory control is confronted with the imperative of resolving a series of complex challenges. These challenges encompass nonlinear characteristics, severe interference, high-degree coupling, time-delay effects, and the timely degradation phenomenon that occur during the drilling process (Wang et al., 2021). The objective is to achieve the precise alignment between the actual drilling trajectory and the predesigned borehole trajectory through the regulation of drilling trajectory parameters.

Traditional borehole trajectory control predominantly centers around mechanism-based modeling and numerical solutions. The control command is usually based on open-loop or closed-loop proportional integral differential (PID) method (Hu and Ying, 2001; Wu and Shen, 2003), and various measures are taken to mitigate the accuracy loss caused by tracking error and viscous slip shock. In order to reduce the error of borehole drilling trajectory, Van de Wouw et al. (2016) proposed a three-dimensional borehole propagation model based on nonlinear delay differential equation. Liu and Samuel (2016) introduced the minimum curvature, balanced tangential and cubic spline, Bessel curve, etc., into the calibration process of borehole trajectory. Gulyayev et al.

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(2021) built a projected gradient optimal control model based on trajectory smoothness, drilling cost and track length. In order to solve the problem of stick-slip oscillation in drilling trajectory control, Kremers et al. (2015) used a robust control model to reduce the track oscillation in the transient closed-loop response. Auriol et al. (2020) proposed to incorporate the feedback law of stick-slip mitigation and the law of friction coefficient updating into the modeling process of the observer, which improved the robustness of drilling toolface control to a certain extent.

In recent years, the application of artificial intelligence in oil and gas production has received more and more attention (Fang et al., 2019; Li et al., 2023; Chen D. et al., 2024; Zhang et al., 2024; Hossein et al., 2023). Relying on intelligent algorithms to achieve accurate control and intelligent tracking of the drilling process can effectively improve the control efficiency in complex scenarios (Xu et al., 2024). In terms of real-time automatic control of borehole trajectory parameters, Sugiyama et al. (2014) realized dynamic regulation of drilling parameters based on continuous static measurement. Kamel et al. (2018) proposed a borehole trajectory control method of directional steering system based on real-time parameter optimization. Kullawan et al. (2017) realized the optimization of borehole trajectory sequence decision based on discrete stochastic dynamic programming. In terms of collaborative deployment of measurement-while-drilling (MWD) and trajectory optimization, Schlumberger's Power Drive X6 can realize integrated control of downhole drilling, and PetroChina's EISC system (Lei et al., 2022) can enable digital intelligence of drilling and production processes.

In summary, the current well trajectory control has a relatively solid numerical or empirical modeling foundation (Gao and Huang, 2024; Guo et al., 2024), but the relevant intelligent algorithms lack the ability to adapt quickly in complex and heterogeneous geological environments. In order to solve the problems of high complexity (Fang et al., 2023) and weak anti-interference ability of the modeling process of the mechanism model, this paper proposes a directional well trajectory control method based on high interactive learning mechanism. Through the process of “data acquisition-experience mining-interactive learning-generalization and transfer”, an empirical model oriented to multi-task formation under heterogeneous environments is constructed. This model enables intelligent perception and decision-making throughout the entire life cycle of borehole trajectory control, covering the stages of “before drilling, during drilling, and after drilling”.

2. Framework of borehole trajectory control algorithm for directional wells

The framework of the directional well borehole trajectory control method consists of the equipment sensing layer, data layer, algorithm layer, highly interactive borehole drilling visualization system, and equipment execution layer (see Fig. 1).

(1) The equipment sensing layer utilizes the sensors installed on the drill bit and power equipment to collect data during the drilling process.
(2) The data layer is tasked with the storage and generation of heterogeneous data, including MWD data, well logging data, rock structure data, and geophysical logging data.
(3) The algorithm layer depends on the hierarchical abstraction of geological-engineering drilling tasks and the learning of highly interactive timing strategies during the drilling operation. This enables the mining and migration of experiences throughout the entire life cycle, encompassing the pre-drilling, in-drilling, and post-drilling stages.
(4) The highly interactive experience-based drilling visualization system, by relying on sectional interpolation and trajectory interaction, organically integrates the data with intelligent control algorithms.
(5) The equipment execution layer is primarily responsible for the implementation of actions and the return of feedback within the actual operation scenarios.

3. Modeling of wellbore trajectory control tasks based on multivariate and heterogeneous data

In the actual oil and gas production scenarios, the wellbore trajectory control model is required to derive the control rules from a vast amount of heterogeneous historical drilling guidance data. It also needs to achieve the rapid transfer of existing experiences in complex environments, such as low and medium permeability blocks and diverse formation structures. The historical data acquired by the steering system is diverse in types and complex in composition, which comprehensively reflects the stratigraphic lithology, block structure, and dynamic properties during the geological steering process. Moreover, the size of the data samples is limited, and there may be some missing data at specific time points. Consequently, the task of wellbore trajectory control must be hierarchically decomposed, and an appropriate interactive decision-making model should be established based on the timing characteristics of control actions and MWD data.

3.1. Hierarchical abstraction of complex multi-task drilling process

The main task of borehole trajectory control in oil and gas wells is to adjust the drilling parameters of the bit in real time to guide the borehole trajectory to the target oil reservoir (Wei and Liu, 2024). In the actual production field, there are usually numerous drilling and production tasks, which vary in formation characteristics, target depth, formation structure, and other aspects. Moreover, the measurement parameters and action decisions of borehole bits are frequently affected by errors resulting from nonlinear strong interference noise.

Based on the typical hierarchical architecture employed in algorithm design, the multi-task complex drilling control tasks can be categorized into the target drilling state search task layer and the target drilling state arrival path task layer. The high-level drilling guide task is divided into a series of subtasks for decision calculation (Kwon et al., 2024), so as to achieve the reuse and reconstruction of drilling experience. As is shown in Fig. 2, suppose U is the high-level drilling guide task set, S is the global drilling state of the drilling guide system, and each subtask $T_i, i \in U$ consists of a series of subdrilling state s_j and action sequence a_k. Based on a dataset that is analogous to the geological conditions of the block slated for drilling, the borehole guidance decision algorithm conducts learning from the environment. Through this process, it acquires a control strategy model that is well-suited to the specific drilling tasks at hand.

3.2. Deconstruction of borehole guidance process driven by multivariate heterogeneous data

Wellbore control tasks can be hierarchically organized into a sequential “state-action” sequence of drill-down targets, where each control cycle makes action decisions based on the observations of the current state. According to the mathematical model of

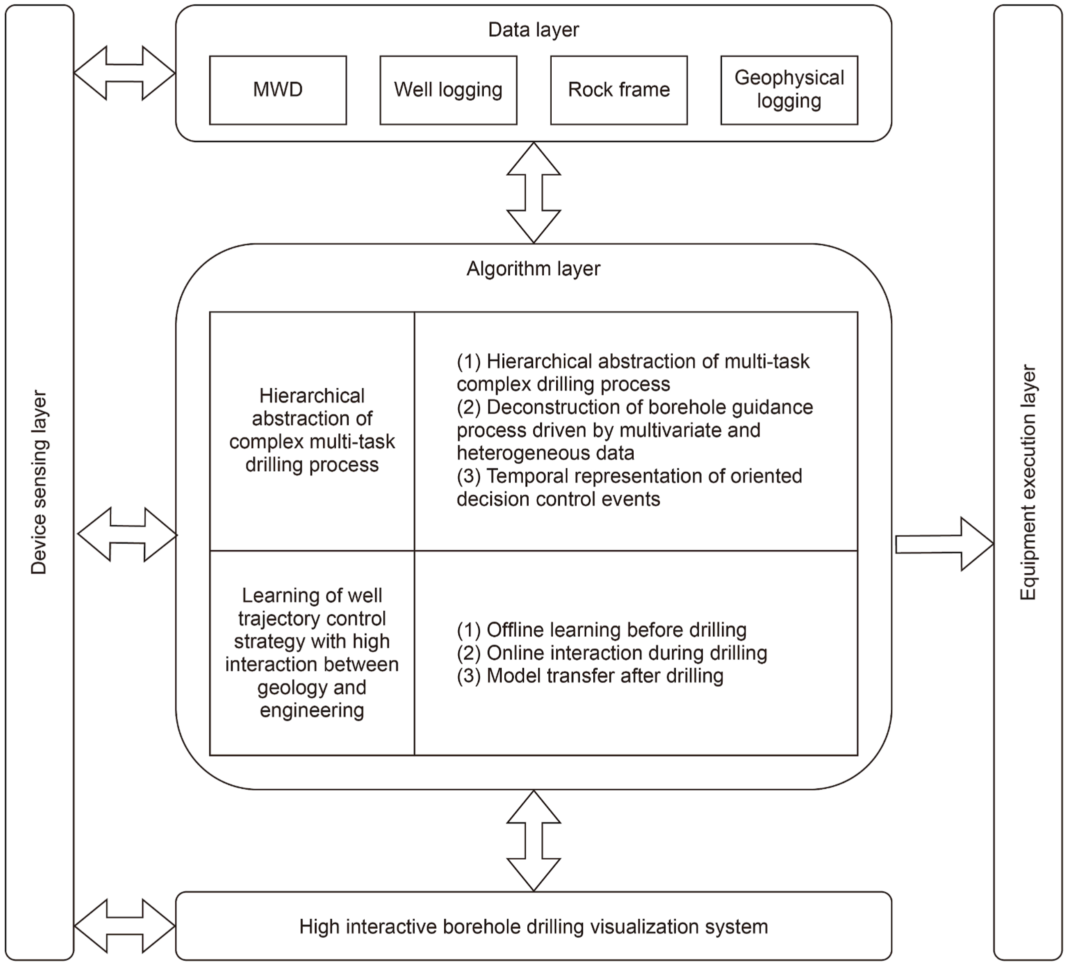

Fig. 1. Framework of borehole trajectory control algorithm for directional wells. The whole framework mainly consists of five layers: Data layer obtains measurement results from device sensing layer; device sensing layer generates real-time data for the drilling system; algorithms in algorithm layer process such data to perform decisions on well trajectory control; equipment execution layer accordingly take actions; high interactive borehole visualization system provides user interface to monitor the control process.

the actual drilling process, the bottomhole assembly (BHA) (Ji et al., 2024) serves as the core control object for the wellbore drilling trajectory, and MWD (Zhang, 2023; Hyungjoo and Hunjoo, 2023) is the key technology that enables the drilling system to complete signal feedback. The wellbore trajectory control process typically encompasses a variety of heterogeneous data, including formation characteristic parameters, logging depth, measurement curves during drilling, bit azimuth parameters, and the operational status of downhole drilling tools, among others.

Fig. 3 illustrates how we handled the multi-source heterogeneous data involved in the directional well drilling process. In the simulation environment, we utilize logging data to generate simulated data, such as natural gamma ray, acoustic time difference, array induction logging (ACS) curve, spontaneous potential (SP), upper limit of mud density, etc., for interactive experiments. The deconstruction of the borehole guidance process takes full account of the rich patterns embedded in the multi-source heterogeneous data. Through a workflow based on mechanism modeling and data-driven machine learning (Chen X.Y. et al., 2024) that includes “data acquisition-data cleaning-feature extraction-correlation analysis-visualization”, we maximize the extraction of experience from the borehole guidance process. This provides support for parameter screening and experience aggregation in high-interaction learning algorithms. To comprehensively integrate multi-source heterogeneous data samples and eliminate the application barriers among the original sampled data, a multi-dimensional total dataset can be acquired by integrating the features contained in each sub-dataset according to the sampling time. Meanwhile, by applying techniques such as outlier removal and data interpolation, the sampling intervals of the data sequences are standardized, and the sampling timestamps of different devices are synchronized. Methods like random forest and correlation coefficient are employed to screen important features for dimensionality reduction. The relationship between the changing trends of data sequences, drilling processes, and control instructions is analyzed to refine and extract data samples that reflect each typical drilling stage, thus forming a typical subset. The geological logging dataset obtained through feature fusion is vertically distributed according to the formation depth and horizontally distributed according to the formation attributes.

Here are three typical examples of the application of the data processing methods.

(1) In the face of the practical challenge where MWD parameters, including inclination angle, azimuth angle, tool face angle, formation resistivity, temperature, pressure, drilling speed, and the control parameters of the drilling rig (RIG) cannot be simultaneously acquired, along with inconsistent sampling periods, we take the following measures. First, we align the timestamps of the data. Then, based on methods

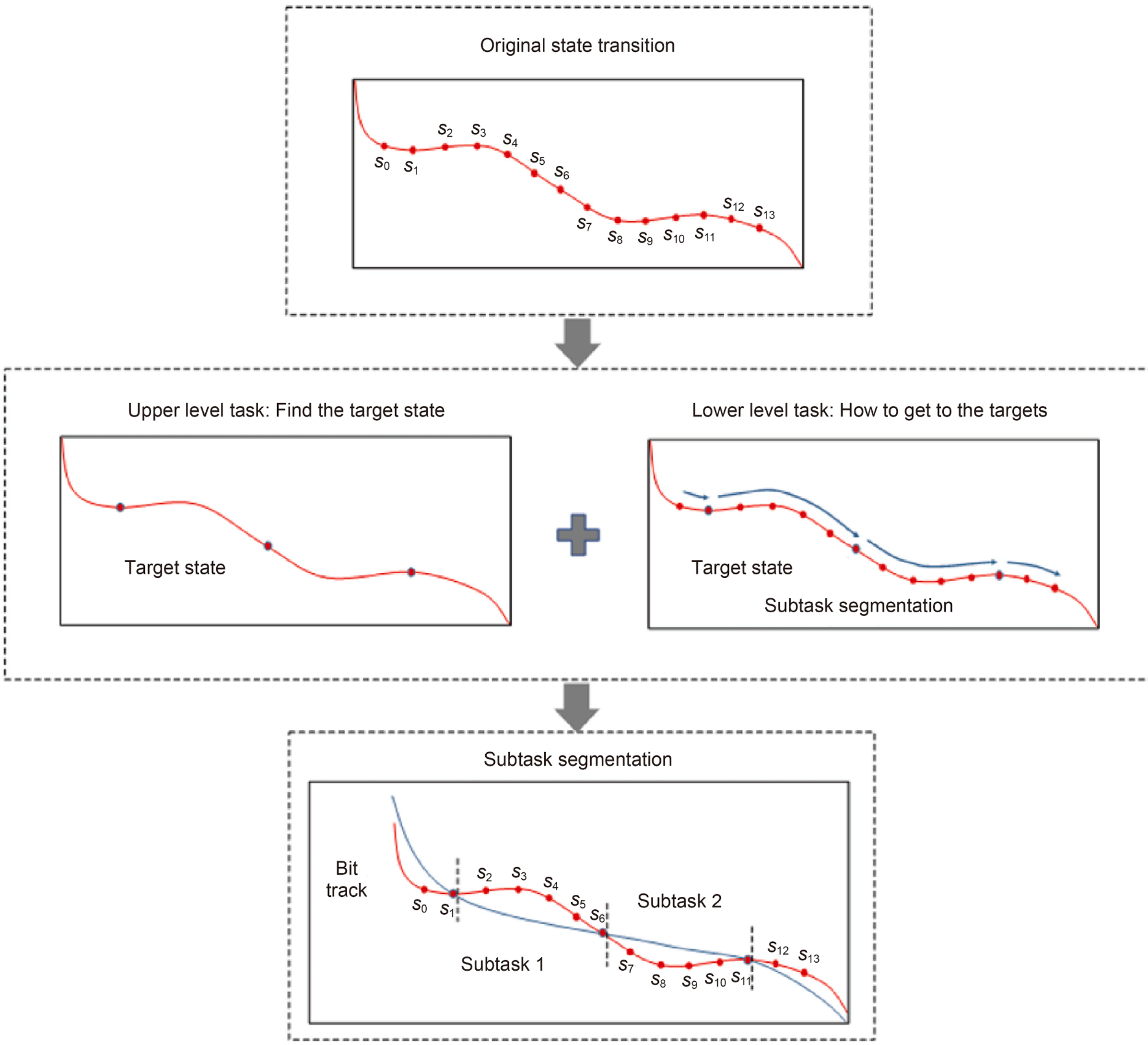

Fig. 2. Hierarchical division of wellbore trajectory control tasks. Considering the complexity of the wellbore trajectory control tasks, upper level task of target state search cooperate with lower level task of how to get to the target state. Subtasks direct the track process together.

such as linear and polynomial fitting, as well as machine learning models, we fill in the missing drilling data. We also normalize and enhance features at different scales. Additionally, by using techniques like boundary extraction and layer alignment, a data subset for the corresponding drilling subtask is constructed.

(2) To tackle the problem of making the data features from historical drilling data prior to drilling adaptable to the real-time features during the drilling process, we adopt the following approach. Historical drilling data is utilized for offline learning before drilling commences. Subsequently, the drilling experience gained from this offline learning is implemented during the drilling operation. When the drilling rig receives specific sensor feedback, this experience guides the rig to execute the corresponding actions.

(3) To enhance the richness of model data samples, we introduce a data generation mechanism that is based on generative adversarial networks, variational autoencoders, diffusion models, and large-scale models. This mechanism fully explores the patterns embedded in historical real drilling data. Furthermore, based on these discovered patterns, we further expand the size of the data samples. By integrating technologies such as feature alignment, we break down the data barriers between heterogeneous data sets.

3.3. Temporal representation of oriented decision control events

The borehole steering control subtask has obvious timing characteristics. Therefore, Markov decision process (MDP) model of borehole trajectory control (MDP) (Bolshakov and Alfimtsev, 2024) is established with subtasks as the basic unit. Markov decision process of borehole steering control decision consists of drilling state set S, steering action set A, discount factor γ, decision reward function $r(s, a)$ and state transition function $P(s', s|a)$. The steering agent and the environment constantly interact to obtain the maximum cumulative reward. The historical samples of borehole trajectory control are mainly long series data $D = (d_1, \ldots,$

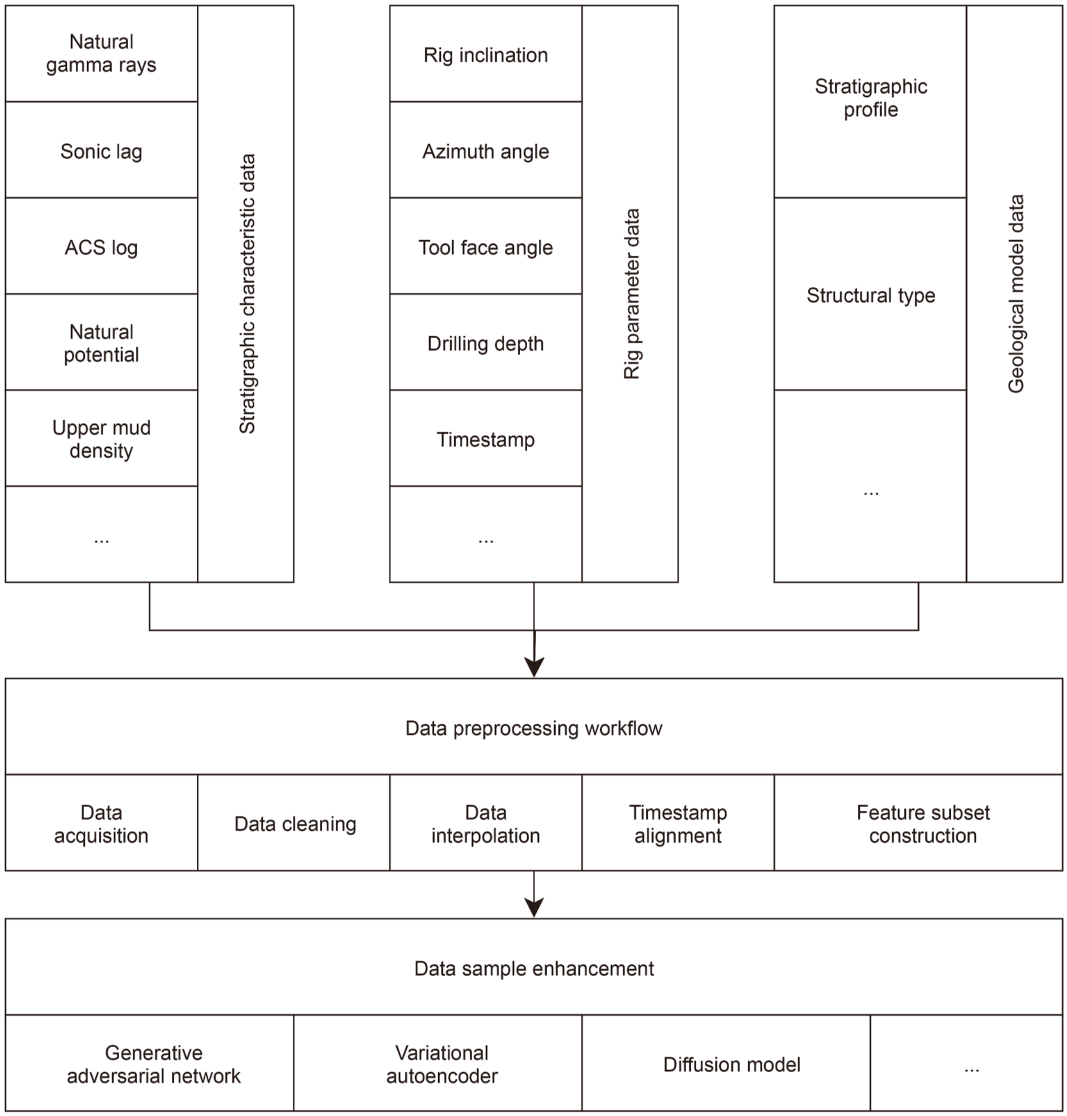

Fig. 3. Drilling guidance data processing flow.

$d_n)^T$, $d_i = (s_0, \ldots, s_t, a_0, \ldots, a_t)$. Each long sequence of data corresponds to a wellbore trajectory in a particular geological environment, and the decision control events taken by the steering agent guide the direction and path of the drill bit. Considering the Markov property of the actual drilling process state, the state transition distribution function of the guiding model satisfies the following equation $P(s_{t+1}|s_t) = P(s_{t+1}|s_t, s_{t-1}, \ldots, s_1)$. It is evident that the intelligent decision-making algorithm will depend on the perception of the current environmental conditions to determine the control action.

4. Learning of well trajectory control strategy with high interaction between geology and engineering

The borehole trajectory agent is required to dynamically adjust the drilling trajectory decision-making strategy in accordance with real-time field parameters, and it should possess the capability to adapt to novel scenarios. Fig. 4 illustrates the process by which the wellbore guidance intelligent agent proposed in this article acquires control experience through interaction with the environment. The control strategy model serves as the core of the highly interactive geological guidance control method in geological engineering. An approach based on the framework of “offline learning before drilling, online interaction during drilling, and model transfer after drilling” is adopted to establish a highly interactive learning model for wellbore trajectory control. The wellbore trajectory drilling control method throughout the entire process, which is based on the highly interactive learning mechanism, can address the issue where the limited scale of sequential data restricts the learning effectiveness of the control algorithm. Moreover, it can enhance the robustness of the control decision-making for complex multi-task borehole steering.

4.1. Pre-drilling offline learning based on historical MWD data

To enhance the convergence speed of the control strategy, the directional well empirical trajectory control agent is required to extract patterns from historical drilling data. By doing so, it can reduce the search space when formulating the control strategy, thereby enabling it to reach the target state more swiftly. The high interaction mechanism between geology and engineering closely integrates the geological model, engineering model, and

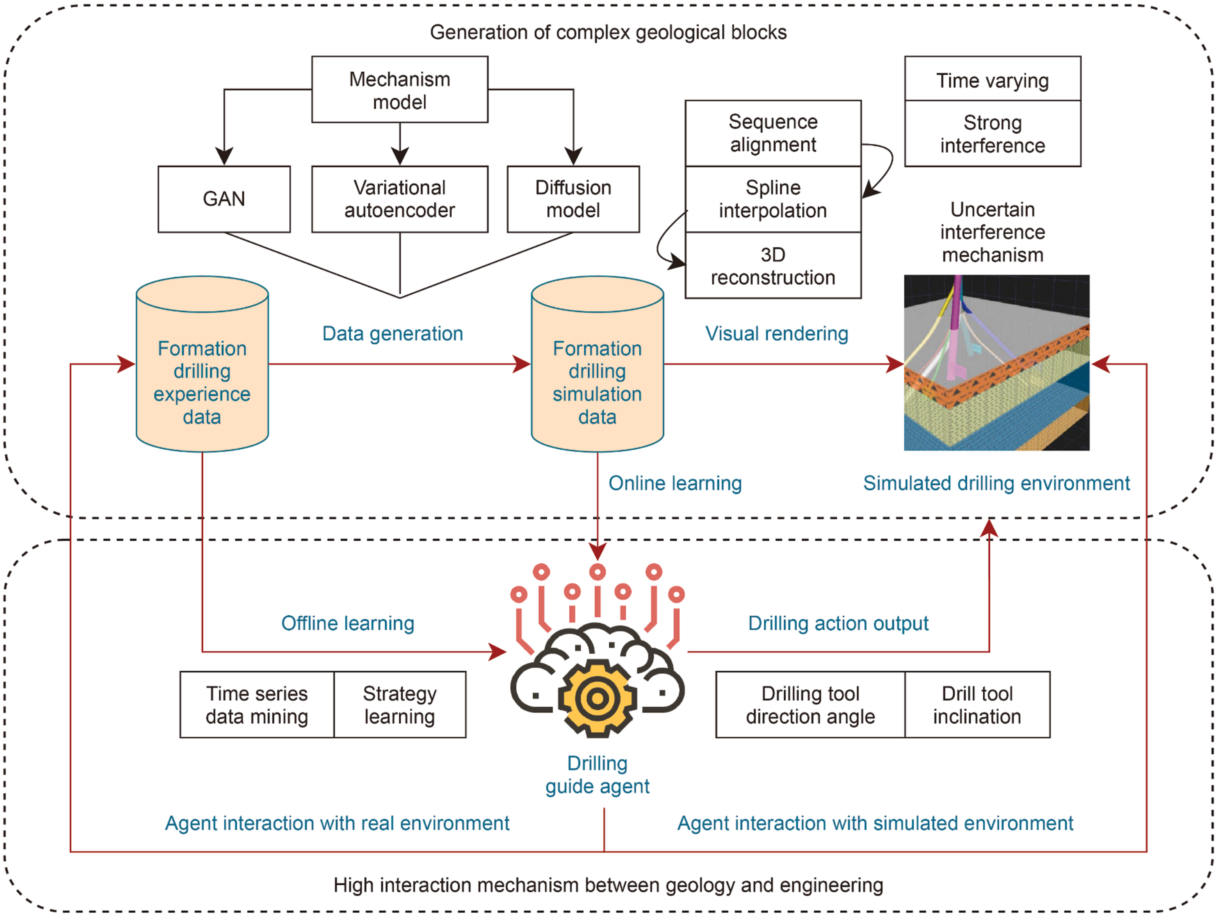

Fig. 4. Borehole oriented agent interactive learning process.

geophysical model. Through formation section interpolation and model prediction techniques, it uncovers the control factors and decision-making experiences within the interactive drilling process. This learning process is accomplished prior to actual drilling and solely relies on static information, such as MWD data, the sequence of control actions, and state observations generated during previous drilling operations. Statistical analysis and machine learning techniques, including model mapping, action prediction, and offline reinforcement learning, are employed to expedite the optimization rate of the control model. Pre-drilling learning allows the wellbore trajectory control model to assimilate historical while-drilling data, which facilitates the movement of the wellbore trajectory towards the target formation.

4.2. The steering agent interacts online with the drilling environment

The simulation environment plays a pivotal role in the learning process of the agent. To accurately depict the parameter flow in actual borehole drilling, the construction of the simulation environment necessitates an understanding of the characteristics of expert experience data. This, in turn, enables it to more effectively guide the agent in completing the learning of the drilling strategy. Generative models, such as generative adversarial networks, variational autoencoders, and diffusion models (Yan et al., 2024), have the capability to generate new extended data based on the distribution patterns embedded within data samples. Among these, the diffusion model introduces noise to the original data through a forward process and recovers the original data via a reverse process. It demonstrates superior FID (Frechet Inception Distance) performance in image generation tasks (Seung and Yong-Goo, 2022). By applying denoising diffusion models, fractional-based models, and stochastic differential equation models to the data amplification task, the learning capacity of large models can be fully exploited, providing substantial data support for the construction of the simulated geological environment. The borehole steering agent receives real-time state inputs from the simulated environment and analyzes the MWD observation data to incrementally perceive the current drilling state and the environment surrounding the drill bit. Simultaneously, the agent assesses the control actions to be implemented, taking into account the prior domain experience of the mechanism model. In contrast to the traditional approach of pre-modeling all position data, this method significantly reduces computational costs and supports the real-time incremental construction of geological models. Moreover, it can generate a multitude of diverse drilling environments, preventing the model from being trapped in a specific drilling scenario locally. This effectively enhances the robustness of the algorithm during the training process.

4.3. Wellbore trajectory control strategy model transfer after drilling

The control models generated through offline learning prior to drilling and online interactive generation during the drilling process typically rely on the specific drilling environment. To enhance the adaptability of the control model, the learning strategy of the drilling guidance agent in a new environment can be formulated based on the concept of transfer learning. By leveraging machine learning techniques, the knowledge acquired from the source domain can be mapped onto the new target task. The wellbore trajectory migration model can boost the adaptability of the drilling guidance agent when data samples are limited. This is achieved through empirical mapping and reuse, enabling the rapid and batch production or verification of the drilling guidance algorithm.

5. Application of drilling guide in typical complex oil and gas fields

The experimental oil and gas block represents an oil and gas reservoir with a complex geological structure. Initially, technicians create a three-dimensional (3D) simulated drilling environment based on the formation distribution data. They then train a general decision-oriented model by relying on the process of "data acquisition-experience mining-interactive learning-generalization and transfer learning". The steering performance of the control model is evaluated in three distinct stages: before drilling, during drilling, and after drilling. Subsequently, the model is deployed on the production equipment to enable efficient drilling operations (as illustrated in Fig. 5). In this section, a simulated drilling environment is constructed based on three logging datasets. The details of these three datasets are as follows.

(1) A logging dataset from a basin in western China, which comprises 25 geological logging characteristic parameters and contains a total of over 6800 data samples.

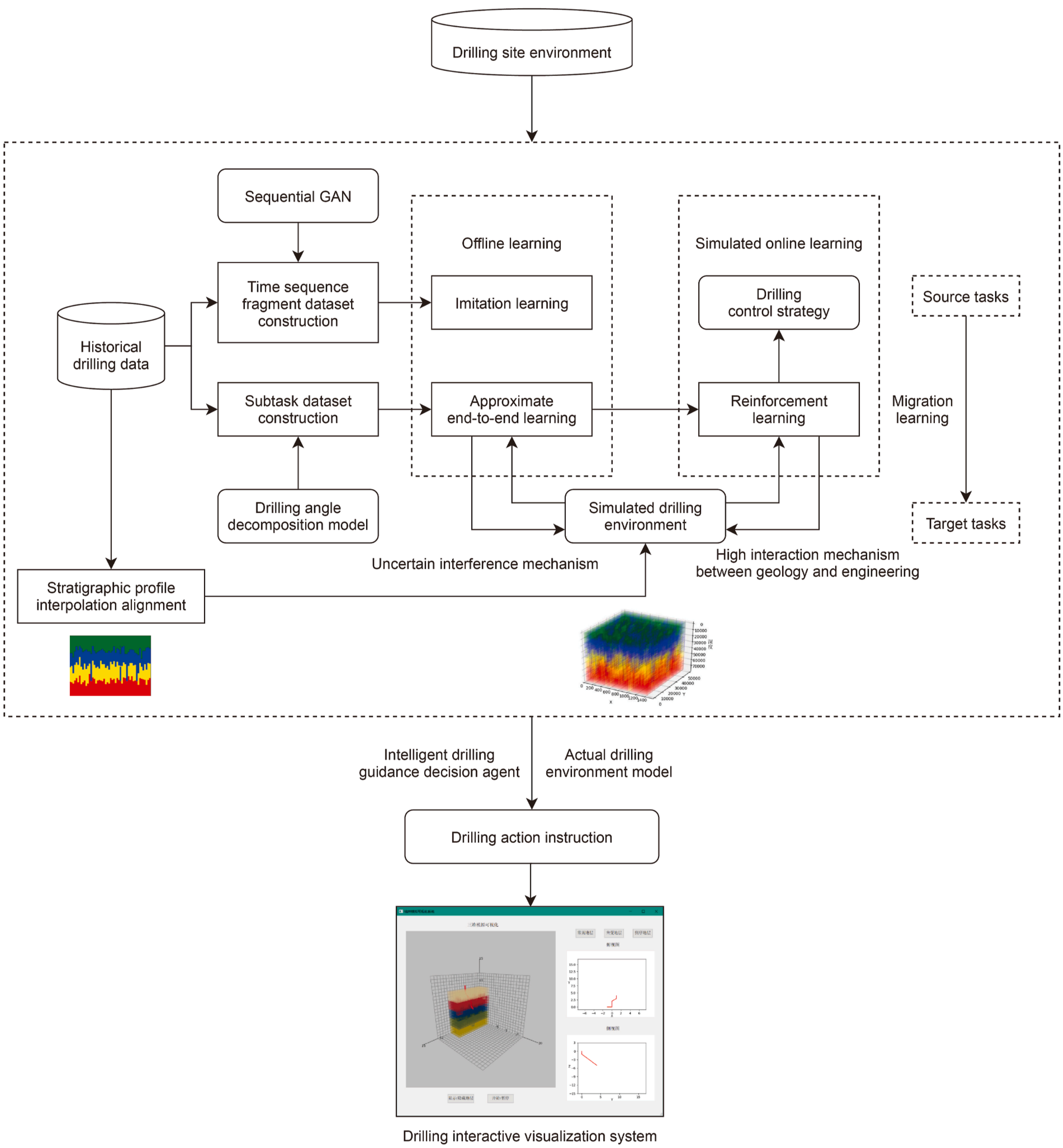

Fig. 5. A typical interactive borehole trajectory control framework.

Table 1
Generation of sequence 0 geological feature data.

Sample No.	Natural gamma	Sonic lag	ACS log	Spontaneous potential	Upper mud density
1	112.173913	66.388894	23.766100	71.990747	1.9529520
2	110.869680	67.211742	25.009145	72.222222	1.921165
3	115.652177	66.858000	27.006172	72.359115	1.9351472

(2) The Kansas oil and gas logging dataset in the United States, consisting of 11 geological logging characteristic parameters with a cumulative total of more than 3500 data samples.
(3) The logging dataset provided by the Kansas Geological Survey in the United States, which includes 14 geological logging characteristic parameters and has a total of over 8700 data samples.

Due to the disparities in feature types and sampling periods among the three logging datasets, the techniques of temporal alignment, data interpolation, and feature selection introduced in the previous framework were employed for preprocessing. Random forest and cross-validation recursive feature elimination algorithms were utilized to select five significant geological features, namely DCAL (Differential Caliper), SP (Self Potential), MI (Resilience Intermediate Array), MCAL (Normal Caliper), and MN (Resilience Wide Array). The preprocessed historical drilling data will be utilized to simulate the generation of the drilling environment and the process of drilling interactive learning.

5.1. Data-driven simulation drilling environment modeling

A generative adversarial network is incorporated into the model of complex geological blocks and the generation process of formation characteristic parameters. The visualization data of the formation distribution, along with the original characteristic data such as natural gamma ray, acoustic time difference, array induction logging (ACS) curve, spontaneous potential (SP), and the upper limit of mud density, are respectively used as the inputs to the network (as shown in Table 1). A least square generating adversarial network (Mao et al., 2017) used in this example is composed of generator G and discriminator D, and the least square is used as the discriminator loss function to solve the gradient disappearance problem (see Fig. 6). In this example, the employed adversarial generative network integrates bidirectional Long Short-Term Memory (LSTM) to extract contextual information from time series data. The model is then trained and optimized using the Adam optimizer. The hyperparameter configurations for the adversarial generative network are presented in Table 2. The intricate three-dimensional (3D) simulated geological block is created through multi-step accumulation, achieved by aligning and interpolating the block profiles within the sample set. This approach effectively enhances the data richness of geological survey samples, thereby providing the necessary environmental setup for the drilling decision-making algorithms (as depicted in Figs. 7 and 8).

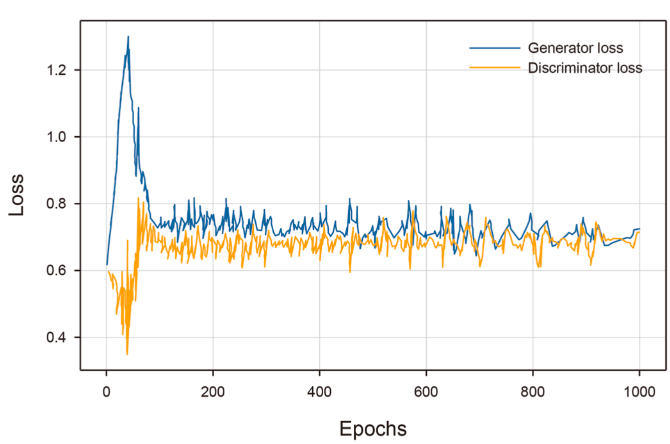

Fig. 6. Loss function diagram of stratigraphic data generation model. After approximately 200 iterations, the losses of the discriminator and generator networks tend to converge, indicating that the parameters meet the requirements for expanding geological data.

5.2. Experience learning of directional well steering decision making

Based on the behavior cloning method, the state-action mapping is extracted from the time series MWD dataset, and supervised learning is conducted to generate the basic control strategy model for the drilling agent. Taking into account the cumulative error of the direct fitting model, approximate end-to-end learning is further introduced to optimize the sequential decision-making process. For each subtask within the task set, the parameters of the basic control strategy model are updated via the back-propagation mechanism of state error. Through continuous learning, a more refined control strategy is obtained. The intelligent-oriented offline model accepts the multi-dimensional data samples of the enhanced model. According to the movement direction of the drill bit, nine azimuth-oriented labels for the screw drill tool are constructed, namely: upper left, lower left, upper right, lower right, forward, leftward deviation, rightward deviation, upward, and downward. The intelligent-oriented dataset is then learned from and mined through the supervised learning model of deep learning.

5.3. Multi-task driven drilling agent interactive learning

Wellbore trajectory offline learning network receives 5-dimensional inputs, namely, well depth L, current azimuthϕ_o, current inclinationα_o, target azimuthϕ_t, and target inclinationα_t, and passes the output BHA azimuth and inclination angle into the network to predict the$Q$ value of the action selected by the agent in the current state. Taking into account the continuity characteristics of the borehole trajectory, this example employs the actor-critic algorithm, Deep Deterministic Policy Gradient (DDPG), which is based on the deterministic strategy gradient, to implement the offline learning method framework. Strategies based on the random experience replay mechanism and the priority

Table 2
Hyperparameters for stratigraphic GAN model.

Parameter name	Value
Learning rate of D	0.0001
Learning rate of G	0.00035
Number of iterations	1000
Optimizer	Adam

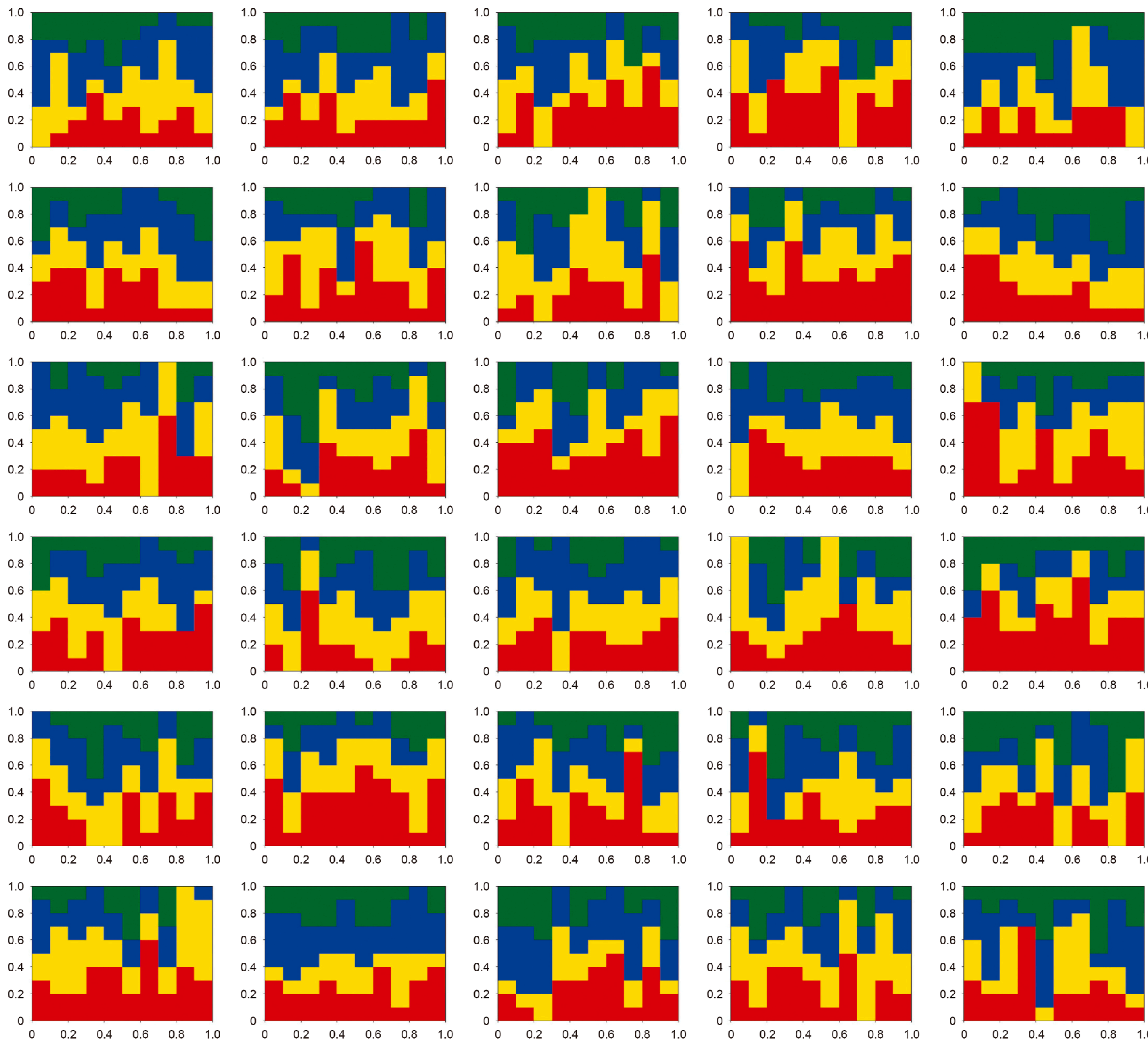

Fig. 7. Formation profile generation. A generative algorithm is used to iteratively generate formation profiles, where red, yellow, blue and green represent one formation type respectively, providing data support for the training of intelligent drilling guidance model.

experience replay mechanism are respectively adopted to enhance the learning performance of the drilling guidance agent. The discrete points measured by the MWD system are associated with the borehole trajectory authority by means of the cylindrical helix method (Ma and Yuan, 2017). The coupling between the borehole drilling control actions and the while-drilling parameters is achieved through iterative updates in an incremental fashion. A preset experience track is utilized as the target path, and the actual borehole drilling decision-making process is required to match the preset track to the highest extent possible. When the drilling decision action provided by the agent deviates from the preset trajectory path, the algorithm will assign a low reward value to the current decision. This enables the agent to continuously learn the drilling guidance strategy that meets the target expectations.

Fig. 9 illustrates the comparison results between the actual drilling trajectory generated by the algorithm proposed in this article and the preset trajectory. The example experiments demonstrate that the target model, which is based on transfer learning and the DDPG algorithm, exhibits a favorable convergence effect in terms of the target rate. The maximum deviation of the borehole trajectory under interference constraints diminishes as the number of training sessions increases, ultimately converging to zero. This outcome indicates that the intelligent drilling guidance framework presented in this paper is capable of fulfilling the task of borehole guidance. Furthermore, in comparison with the random experience replay strategy, the model based on the priority experience replay mechanism converges more rapidly and demonstrates superior performance. The drilling rate of the borehole trajectory adaptive control, which is based on formation profile interpolation and the migrated DDPG algorithm, is approximately 10% higher than that of the preset borehole trajectory. After convergence, the maximum deviation distance is

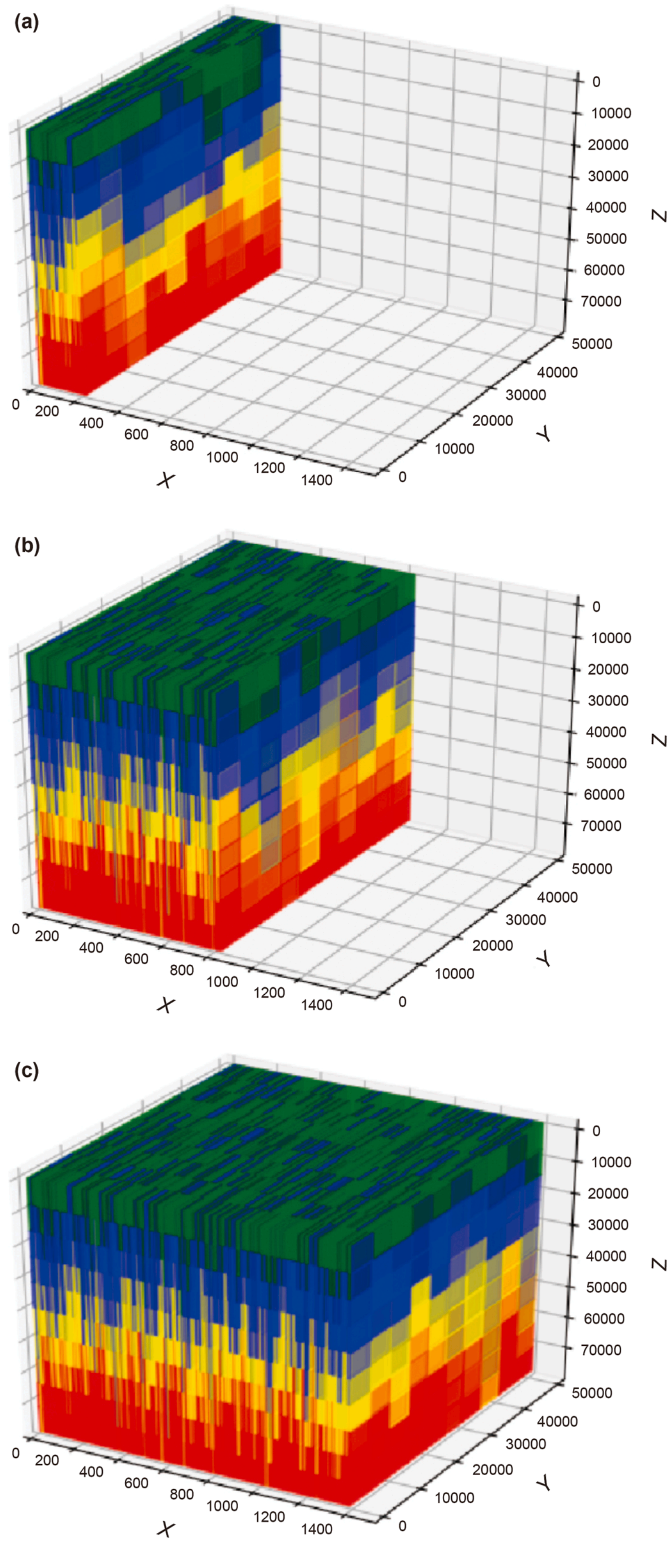

Fig. 8. Complex geological profile data generation. (**a**) Geological blocks generated at the beginning of the interaction, (**b**) block generated during the interaction, (**c**) complete geological block.

roughly 81.6% lower than that achieved by the traditional Proportional-Integral-Derivative (PID) method, and the target hit rate is approximately 65% higher than that of the PID method. The learning method for the drilling guidance agent, which is founded on the highly interactive learning mechanism, possesses excellent anti-interference capabilities. It can successfully guide the drilling equipment to reach the formation target area and effectively enhance the drilling rate of the target reservoir.

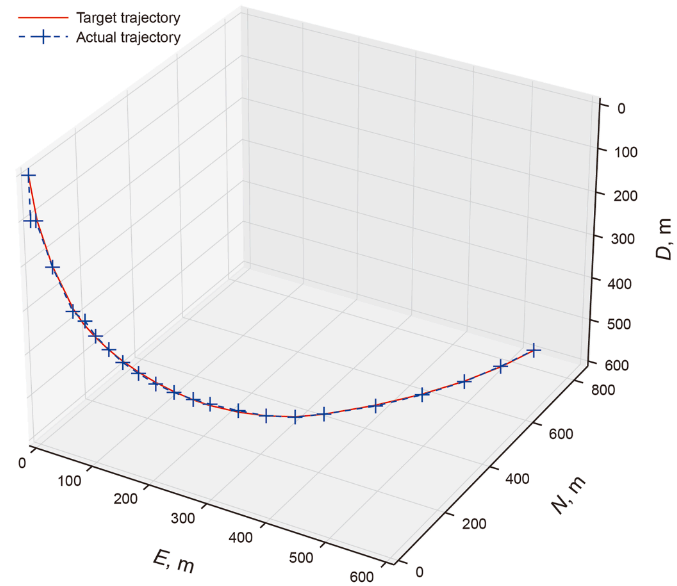

Fig. 9. Adaptive well trajectory versus preset trajectory. The drilling trajectory generated by the algorithm accords with the preset trajectory height.

However, there are still several limitations of the algorithm, including computing cost, data dependence, generalization, etc.

(1) The wellbore trajectory control algorithm framework put forward in this article relies on preset trajectories and is unable to dynamically track target trajectories that might be adjusted during the construction process.
(2) When the complexity of the preset wellbore trajectories is increased, the existing algorithms demand a longer training time.
(3) The cost of data governance is relatively high. It is necessary to simulate numerous different scenarios to ensure that the algorithm can adapt to various formation conditions.

Further work can be carried out around these limitations to continuously improve the algorithm's capabilities. Specifically, we will build an integrated method of systematic data processing and try to build a training platform for intelligent drilling guide algorithms.

6. Conclusion

In this paper, a framework of an adaptive interactive learning control method is proposed, which focuses on the key technical issues of wellbore trajectory. By leveraging an interactive simulated drilling environment, the processes of data acquisition, experience mining, interactive learning, and generalization transfer are achieved during the borehole guidance operation. The method put forward in this study can be effectively applied to the drilling tasks in actual oil and gas fields. It is capable of enhancing the deployment efficiency of the algorithm and significantly increasing the drilling rate of the target oil and gas reservoirs.

CRediT authorship contribution statement

Yi Zhao: Writing – original draft, Methodology, Formal analysis. **Dan-Dan Zhu:** Writing – review & editing, Project administration, Conceptualization. **Fei Wang:** Methodology, Formal analysis, Data curation. **Xin-Ping Dai:** Software, Methodology, Data curation. **Hui-Shen Jiao:** Validation, Formal analysis, Data curation. **Zi-Jie Zhou:** Visualization, Software, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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