A Deep Learning Based Geosteering Method Assembled with “Wide-angle Eye”

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ABSTRACT
The intelligent guided drilling system adopts the precise guided drilling geological system and a new rotary steering drilling tool to achieve deep drilling intelligent cruise. It can increase the amount of oil and gas exploration and ensure safety in production. However, the geosteering problem in deep wells and ultra-deep wells is still an outstanding issue due to the hostile environment for signal transmission. In this research, an autonomous geosteering method based on deep learning model is proposed, which is able to make the strategic decision of the drill bit direction in downhole operating mode. According to the characteristics of the Logging While Drilling (LWD) data, the “Wide-angle Eye” mechanism is embedded to feel the future change of stratum ahead and give preview information to the drill bit. Consequencely, the Drilling Decision Model is designed to be a Convolutional Neural Network (ConvNet). The performance of the proposed model was validated in simulation, and the experimental results indicate that the proposed method has high accuracy and robustness, appearing an enhanced capacity to predict stratigraphic changes.

CCS Concepts
• **Computing methodologies→ Machine Learning→ Machine Learning approaches→Neural networks**

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Keywords
Downhole Closed-loop Geosteering; “Wide-angle Eye” Mechanism; Deep Learning; Convolutional Neural Network.

1. INTRODUCTION
Drilling is the most expensive and technologically intensive process in oil field exploration and development[1]. Because of the complexity of the downhole geological conditions, the rock mechanics model is difficult to determine. Therefore, the development of intelligent drilling[2] technology has profound implications for the oil field industry renewal and the national energy security.

At present, the most advanced intelligent guided drilling method adopts the geosteering technology. It is a downhole semi-closed-loop method[3]. It mainly includes the ground and the downhole phases, that is, downhole data acquisition, storage, and pilot drill execution; ground analysis and decision-making. Based on the two-way transmission of real-time data, the ground and downhole operations work together to achieve control of the wellbore trajectory. However, this method highly relies on signal transmission speed and efficiency, and the downhole environment is complex, which is not conducive to real-time transmission of signals. Especially for deep wells and ultra-deep wells far from the ground[4], it is almost impossible to achieve effective data transmission while drilling. In addition, the analysis and decision-making in the ground involves complex human expert analysis and fine management, which has high labor costs.

To avoid signal transmission problems, as well as reducing labor costs, we propose a downhole closed-loop geosteering method based on the deep learning networks[5]. The overall drilling program is divided into two phases: one is the pre-drill analysis when the testing LWD (Logging While Drilling) information from the testing well is acquired and explored for drilling strategy development, and the other is the downhole self-directed drilling which is fully oriented by the LWD data. To obtain the predictive ability, the drilling guide system integrates the “wide-angle eye” for capturing the geological information from both the drill bit current position and nearby locations, and then to give the corresponding drilling decision direction.

The main contributions of this research are as follows:

1) propose a downhole closed-loop geosteering method which dispenses with manual intervention and signal bidirectional transmission in drilling process[6];
2) broaden the vision of the drilling guide system by the “Wide-angle Eye” mechanism;
3) design the Drilling Decision Model with the specific Neural Network architecture that applies to the “Wide-angle Eye” data.

The remainder of this paper is organized as follows: Section 2 describes the main problem to be solved and the framework of the proposed method; Section 3 analyzes the LWD data and expounds the procedure of the pre-drilling data processing; Section 4 gives the design details of the drilling decision networks; Section 5 illustrates the validation experiment and the result analysis; Section 6 is the conclusions and the future work.

2. PROBLEMS AND SOLUTION

To deal with the problems of high dependence on real-time signal transmission and complex work of human experts in geosteering[7], we developed a downhole closed-loop intelligent guidance method[8]. During the drilling process, the proposed system evaluates the current stratum environment by the LWD data and decides the drilling direction in real time, guiding the drill bit to the target stratum.

We develop the downhole closed-loop intelligent guidance system by two phases: data analysis and processing and drilling decision model construction. In the data analysis and processing, the LWD data from the testing well were utilized for stratum analysis and basic geosteering rule exploration[9]. To obtain better prediction ability, the “wide-angle eye” mechanism has been adopted; in the drilling decision model construction, a deep learning network model has been built to capture the complex nonlinearity of between the LWD information and the direction decision. Therefore, the proposed model can give the corresponding drilling direction according to real-time “wide-angle eye” data perceived by drill bit.

3. DATA ANALYSIS AND PROCESSING

The original LWD data from the testing well include both the directional-drilling measurements and geological information. Because the proposed drilling method is oriented by the stratums, we only focus on the geological part. Generally, the available measurement in LWD technology contains natural gamma ray, neutron porosity, resistivity, sonic, etc. And the testing LWD data is supposed to reveal the fundamental stratigraphic distribution in oilfield by formation identification methods.

Since the proposed method is able to directly give directional strategy according to the real-time drilling stratums, the LWD data should be tagged by the corresponding directional strategy label for model learning. In addition, we adopt the “Wide-angle Eye” Mechanism for predictive ability and use them as experimental data.

3.1 “Wide-angle Eye” Mechanism

In the drilling process, the geosteering system is supposed to accomplish apperceive stratum environment around the drill bit through various sensors and then make directional decision[10]. We can treat such instantaneous data acquisition as an “eye” capturing the visual information.

Imagine if the viewing angle of this “eye” is narrow, and the system only acquires the geological data from exact location of the drill bit but ignores the near stratums. Then, the directional decision made by the geological data could be a local optimum which easily lead to two problems in drilling process:

1) The drill bit may frequently change its direction around the stratum junction if different stratums are subject to opposite directional strategies;
2) The drill bit may not notice the formation change until it drills out of the target stratum.

Therefore, the predictive ability to evaluate the change trend of encountered stratum is essential to reduce the drilling cost.

In this research, we adopt a “Wide-angle Eye” mechanism to equipped the proposed geosteering system with such predictive ability. It is actually a sliding window method which captures multiple LWD data spreading along the depth and shifts by certain rows for each data creation. By utilizing such “wide-angle data” for training, the proposed system can perceive the nearby stratum profile, not only the stratum information of the drill bit location. A LWD dataset sampled from a testing well in some basin in West China is presented in Fig.1, where each row is a five-dimension vector data for certain depth, with ACS(us/ft), σbc (Mpa), SH(Mpa), Pp(Mpa) and g(cc) as the features[11]. Under the “Wide-angle Eye” mechanism, a 5×5 sliding window extracts the matrix data along the depth.

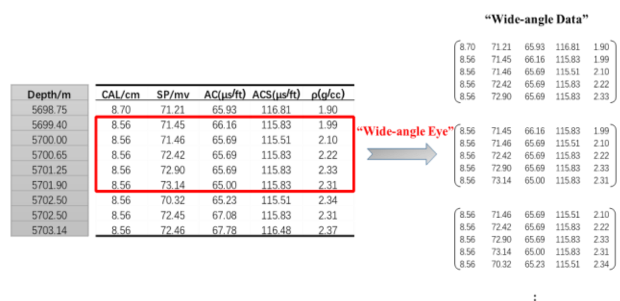

Figure 1. “Wide-angle Eye” mechanism: multiple consecutive LWD data in depth domain constitute the matrix form data.

3.2 Direction Strategy Labeling

To enable the geosteering system to directional decision-making ability, the training data (“wide-angle data”) should be tagged with corresponding direction strategy label. In this research, we restrict the drill bit movement in a two-dimension space for simplify the labeling process, and the direction strategy d is discretized as follows:

$$d = \begin{cases} +1, & upward\ movement \\ 0, & forworad\ movement \\ -1, & downward\ movement \end{cases} \quad (1)$$

Which indicates the movement of the drill bit?

It is notable that the equation (1) does not restrict the step adjustment of the directional movement. In the actual drilling process, the whips tock system is limited by its mechanical structure and the instantaneous adjustment is small. And considering the proposed geosteering system makes decisions in real time, it can compensate the deficiency under the small step adjustment and high sampling rate of LWD data, which also gives a smooth direction curve. In addition, the absence of the backward movement is also due to the mechanical structure.

Because the ideal direction strategy mechanism is supposed to guide the drill bit into the oil reservoir, the stratigraphic sequence information is essential to determine the decision rules. Depending on the domain expert knowledge, we can manually label the direction strategy tags.

Consequently, a mapping between the “wide-angle data” and direction strategy based on the above stratum-oriented rules can be established.

4. DRILLING DECISION MODEL CONSTRUCTION

Because a “wide-angle data” is composed of 2D arrays containing LWD information in continues depth, Convolutional Neural Network (ConvNet)[12] is supposed to be suitable to process such multiple array data.

The typical architecture of ConvNets is structured as alternating convolutional layers, non-linearity and pooling layers, followed by more convolutional and fully-connected layers, while the backpropagating gradients allows all the weights in filter banks to be trained. It has been widely used in the field of image processing.

As the matrix format with several dimensions, the “Wide-angle Eye” data has its own unique properties due to the geological characteristics and engineering practice. Therefore, it is necessary to modify the conventional ConvNet to adapt to the “Wide-angle Eye” data learning.

As Fig.2 illustrates, the Drilling Decision Model is proposed with the architecture of 7 main layers[13].

The input is the “Wide-angle Eye” data with a typical ConvNet[14] input format, which is a 5×5 matrix of 5 features and 5 rows of LWD data. The first two layers are the convolution layers, which are composed of 32 and 128 feature filters, respectively. The feature filters in the first layer are designated with the 3×3 receptive fields to extract the global LWD features of stratums. In the ConvNet, the role of the pooling layer is to merge semantically similar features into one. Nevertheless, the “Wide-angle Eye” data itselves have quite low dimension. Because of the high measurement cost, the sampling interval of discrete depth locations in the testing well cannot be very small, greatly restricting the volume of the available LWD data for training. Therefore, the semantic similarity merging operation of the pooling layers on the feature position is not necessary. Without the pooling manipulation, the representation feature maps of the second convolution layers directly stream into the fully convolution layers, preparing features for drilling decision classification. The SoftMax layer in the last maps the outputs to the probability of drilling decision making.

To handle the issue of overfitting, a dropout layer has been inserted between the first and the second full convolution layers. In addition, the rectified linear units (ReLU) has been assembled following the first two full convolution layers, respectively, to accelerate the convergence. Therefore, the ReLU and dropout modules build up a powerful sparse-based regularization for the deep network and address the overfitting problem for drill bit steering decision[15].

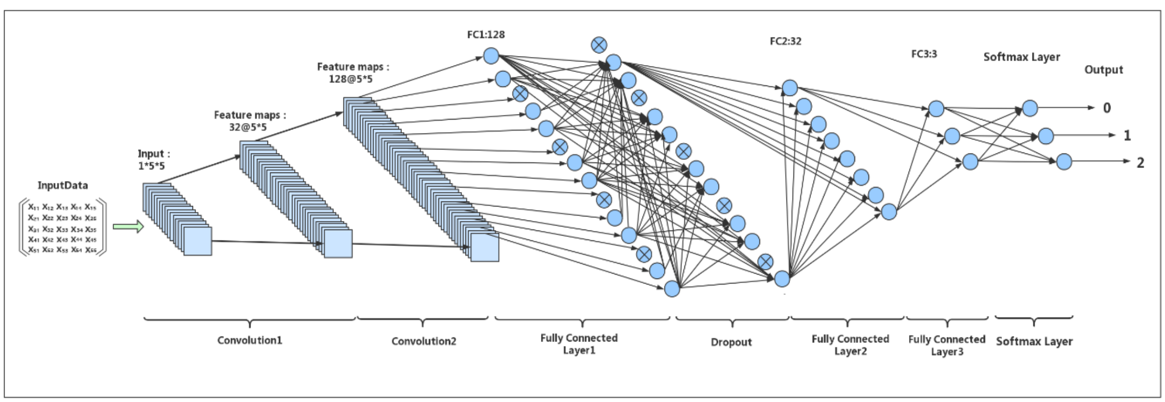

Figure 2. Architectural hierarchy of Drilling Decision Model.

5. EXPERIMENT AND ANALYSIS

5.1 Experimental Settings

The LWD data sampled from the well logging curves of a certain oilfield in western China were adopted as the testing well data to verify the proposed geosteering solution. The original LWD data is composed of 25 attributions, including depth, natural gamma, natural potential and time difference of sound waves, etc. The size of the dataset is 6000 samples with the corresponding stratum labels. And the label set includes 4 different types of sandstone stratums[16].

In the real drilling process, the actual geophysical phenomena are not able to be known in advance, though the testing well can provide basic knowledge. To simulate such uncertainty, we build the drilling simulation environment based on the deep convolutional generative adversarial networks (DCGAN)[17], which generates the real-time LWD data according to the location of drill bit.

To validate the performance of the proposed method, we set up a baseline model as control group, which used AdaBoost Classifier without “Wide-angle Eye” mechanism.

5.2 Result Analysis

Fig. 3 illustrate the training performances of the proposed drilling decision model[18]. It demonstrates that the proposed model has fast convergence rate and low loss in geosteering ability learning. In the first 200 epochs, the proposed model acquired continued growth of the accuracy rate and fall of the loss rate. After 300 epochs of training, the model has achieved 84.37% training accuracy and 0.037 training loss.

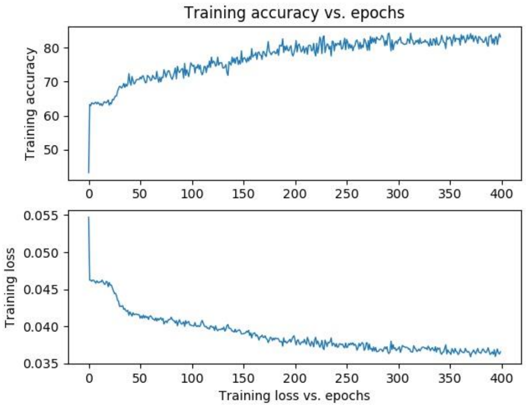

Figure 3. Training result of the proposed model

The testing experiments have been conducted by the DCGAN-generated data[19], and the well trajectories are visualized[20] in Fig.4. The drill bit explored the nearby field by capturing the real-time LWD data to form "wide-angle" data, but ignoring the distant space. The explored field are represented by the blue, green or yellow blocks, respectively, while the ignored fields are indicated by the dark purple ones. And the well trajectory of the proposed model is represented by the black line. The well trajectory of the baseline model is indicated by brown line.

The simulation results illustrate that the proposed method is capable of guiding the drill bit to the object stratum according to the real-time LWD data, regardless of the initial position. The proposed model scented the future change of the stratum and gave preview control to the driller, while the baseline model often felt the change only when the driller was already out of the previous stratum[21]. Therefore, the adoption of the "Wide-angle Eye" mechanism can avoid frequent adjustment of drill bit along stratum boundary.

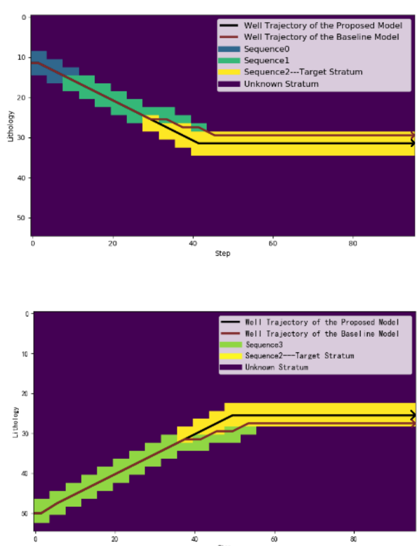

Figure 4. Simulated Drilling Process of the Proposed Model and Baseline Model

6. CONCLUSIONS AND FUTURE WORK

In this research, a downhole closed-loop geosteering method has been proposed for autonomous directional decision-making. It introduces the "Wide-angle Eye" mechanism for previewing the stratum changes and providing expedite decisions to lower drilling cost. The main part is a deep learning based geosteering model, which can quickly acquire the stratum features and produce accurate directional decision.

Currently, the drilling experiments were conducted in a brief simulation environment considering some uncertainty, however, it is very difficult to simulate the complexity and invisibility of stratum. In future, we are going to focus on the construction of the simulation environment and the improvement of the geosteering model to handle the various stratum situations.

7. ACKNOWLEDGMENTS

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