Study of Intelligent Identification Method for Drilling Condition and Lithology in Underground Coal Mine Based on Deep Learning

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Abstract: It is important to accurately master the downhole drilling parameter information and drilling formation lithology for the sake of efficient and reasonable gas extraction, hole arrangement and construction safety. According to different detection information, an identification & interpretation model for drilling engineering parameters and a lithology identification & interpretation model in while-drilling azimuthal Gamma logging were established. Next, the drilling conditions were judged and the lithology was discriminated. However, this method relied heavily upon the professional quality and working experience of workers. By numerically simulating the influence laws of azimuthal Gamma logging on the amplitude values of detection data under different borehole sizes, a more suitable method was chosen and applied to the automatic lithology explanation and identification during the logging. An object identification method combining deep convolutional neural network (CNN) and multi-weight multi-task learning mechanism was established, followed by the residual network design, in an effort to elevate the network training rate.

1. Introduction

Various complicated and uncertain factors exist in the coal mining field, and different geological conditions will be encountered whenever possible in the drilling process, such as lithological changes, change of formation pressure, borehole collapse, etc., all of which bring about complicated and varying factors to the drilling process, influence the drilling work and perplex the field engineers. Over the years, the researchers dedicated to the drilling work have made efforts to establish the mathematical models describing the lithology identification and changes of drilling engineering parameters in well drilling. However, the solution multiplicity and low prediction precision existing in the real-time analysis and identification of data collected while drilling have been troubling researchers owing to the variability of geological conditions and complexity of established models, so it is crucial to build the mathematical nonlinear prediction models with high identification accuracy.

According to research findings, the neural network modeling ability can be considerably improved by increasing the numbers of layers and parameters in the neural network, but in early-stage researches, the deep neural network could be easily trapped into the local optimum, so it was difficult to exert the learning ability of deep complex models. Subsequently, Hioton put forward a layered learning proposal based on restricted Boltzmann machine (RBM), and this proposal was applied to the deep neural network (DNN) training so that the DNN could jump out of the local optimum. After the network training problem was solved, the deep learning based on deep neural network (Areletal et al., 2020) was widely
applied to image (Ciregan et al., 2012) and speech (Collobert et al., 2008; Hioton et al., 2012) recognition, etc. Diversified new network structures have been developed from DNN.

As deep learning has outstanding advantages in artificial intelligence (AI) and is capable of avoiding the disturbance of human factors and reducing the labor intensity with high prediction accuracy, it is necessary to introduce it into the geological engineering field for the intelligent identification of lithology and drilling conditions, which can facilitate the relevant research work.

2. Establishment of Intelligent While-Drilling Identification Network Based on Deep Learning

By combining the theoretical research of deep learning, data network algorithm design and test data verification, the research work was carried out following the three coordinated principal lines—“basic theoretical research”, “network model design” and “comparative validation research”, expecting to ensure the novelty of theoretical research on the intelligent identification of working conditions and formations as well as its applicability to coal mining engineering.

2.1. Establishment of identification & interpretation model for drilling engineering parameters and lithology identification & interpretation model in while-drilling azimuthal Gamma logging

This paper aims to establish a mathematical working condition identification model that describes the changes of drilling parameters and a lithology identification & interpretation model in while-drilling Gamma logging (horizontal well). The data quality is the key to the interpretation accuracy of established models. A simulation analysis of drilling engineering parameters such as drilling pressure, torque, drilling rate, temperature and annular pressure will be implemented by combining mathematical simulation and drilling experimental data. Next, unreasonable abnormal data will be excluded, and the principal component analysis method will be used to seek for the corresponding relationships between drilling states and parameters.

Different denoising methods were compared and the optimized method was given, in order to solve the low signal to noise ratio (SNR) problem of azimuthal Gamma logging data. A 3D numerical calculation model was established, the drilling process along coal seam was monitored by combining while-drilling azimuthal Gamma logging with inclinometry, and the drilling distance from drill to bed interface was quantitatively calculated. A fast coal-rock interface forward and inversion model was built through the azimuthal Gamma logging data. The numerical simulation method was used to explore the response laws of while-drilling azimuthal Gamma logging under different borehole sizes. The corresponding correction charts were established to correct the borehole influence factors in the while-drilling azimuthal Gamma logging, improve the data quality, and provide a reliable data quality guarantee for the fast forward and inversive calculation of azimuthal Gamma data and intelligent identification of drilling formation lithology and formation interface.

2.2. Establishment of object identification method combining deep convolutional neural network (CNN) and multi-weight multi-task learning mechanism

The deep CNN was integrated with the multi-weight multi-task learning mechanism to explore an object identification scheme with more complete performance. In general, the neural network will conduct overall training and parameter optimization of all tasks, but the effect will certainly be far from ideal under a great difference among the tasks in the complexity. Therefore, the tasks were divided into main tasks and auxiliary tasks, where the former, on which the particular emphasis was laid, were pertinently optimized, the training intensity among multiple tasks was balanced and coordinated by assigning different weight values, thus facilitating the processing of tasks concerned. A deep CNN model was acquired by improving the traditional CNN model. With the deep learning and CNN combined, the operating rate was accelerated, and the object identification efficiency was improved. The calculation flow combining deep CNN and multi-weight multi-task learning mechanism is as shown in Figure 1.
Figure 1 Calculation Flow Combining Deep CNN and Multi-Weight Multi-Task Learning Mechanism

2.3. Mechanism research on intelligent identification of while-drilling detection data, lithology and working conditions

The deep CNN was introduced into the real-time analysis of while-drilling detection data in underground coal mine. The network parameters and object identification & extraction features were determined through the real-time analysis of while-drilling azimuthal Gamma logging data and practical drilling engineering parameters. The local features of this network were extracted using convolution kernel, the features at different positions were calculated through the pooling layer, and the low-resolution statistics of convolution layer was made through the sampling method, so as to improve the accuracy.

The trained deep learning network was compared with three classification and identification methods—SVM, PNN and GRNN—from three aspects, namely network training time, network back-discrimination accuracy and network forecast accuracy. The intelligent identification and validation were implemented by combining the geological data, lithology data and field working conditions. If the effect of established network model was poor, the network parameters would be timely adjusted until the network structure was optimized.

In consideration of complex field construction environment in the underground coal mine, the research goal and contents will be combined, so will the simulation analysis method and test data verification, in order to improve the identification accuracy by virtue of the optimized deep neural network and solve the intelligent identification problems of drilling states and formation lithology. By analysis and decision-making with the help of the established deep CNN, the formation lithology and coal-rock interface information at the present position of drill could be timely identified thanks to the effective utilization of while-drilling logging data and drilling parameter information, so as to obtain the formation information in coal mine roadway. This method, which is an effective extension of traditional drilling technology, can avoid the disturbance of human factors, reduce the job intensity and improve the analysis and forecast accuracy of drilling data. Moreover, it can provide a reliable and intuitive basis for the coal-rock interface detection and ensuring the safety of construction state, and contribute essential geological parameters to the safety mining of similar mines. The network establishment method is as shown in Figure 2.
3. Conclusion

1) A large quantity of drilling experimental data and test data of drilling rig is needed to establish an interpretation model for engineering parameters. In this study, the intelligent identification pattern for while-drilling engineering parameters was established under complex underground drilling conditions, such as jamming and breaking of drilling rig, bit bouncing and blind hole. A 3D numerical simulation model of azimuthal Gamma logging was built to analyze the partially low SNR problem in the while-drilling azimuthal Gamma logging data. Different denoising methods were compared, the optimized method was given, and a fast coal-rock interface forward and inversion model was established.

2) Nearly ten parameters were fed back by the azimuthal Gamma logging unit and engineering parameter gauges. However, the direct correlations of these parameters with the drilling state and lithology were unclear, yet. In order that they can be used to effectively and accurately reflect the complex drilling state and lithology, the convolution layer and pooling layer should be combined to form multiple convolution groups and extract the features layer by layer. In the end, the classification was completed through several fully-connected layers.

3) Both deep CNN and multi-weight multi-task learning mechanism are object identification methods with their respective strengths. In this study, the tasks were divided into main tasks and auxiliary tasks, where the former were optimized as an emphasis by assigning different weight values, the training intensity among multiple tasks was balanced and coordinated, thus avoiding a series of network problems such as “conflict”, endless loop “trap” and “degradation or variation” after parameter adjustment and reaching the 1+1>2 effect. Next, the residual network was designed, and the residual blocks were connected by means of leap, so as to mitigate the vanishing gradient problem brought by the increasing depth in the deep neural network and elevate the network training rate.
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