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Intelligent recognition of tunnel stratum based on advanced drilling tests

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Abstract: The reliable recognition of strata in front of tunnel face is significant for the stability and safety of the tunnel engineering project. Traditional advanced geological forecasting methods could not ensure high identification accuracy, low cost and short construction time simultaneously, and they can't satisfy the universality of stratum identification under different geological conditions. The advanced forecasting efficiency could be significantly enhanced if the drilling data of surrounding rocks in front of the tunnel face can be obtained while performing the conventional advanced borehole to attain the rock conditions at different drilling depths in real time, which would be convenient and efficient by not affecting the construction period. However, no objective and accurate stratum identification methods are found. In this paper, we proposed an intelligence analysis of drilling data and stratum recognition method based on neural network. It is used to analyze the advanced drilling test data of Jiudingshan Tunnel of Chuxiong−Dali highway and the analysis method was verified by the strata exposed after tunnel excavation. The results show that the error rate of stratum recognition using the single drilling parameter is about 35%. The combination of blow energy and blow number, water supply pressure and water supply rate cannot significantly improve the accuracy of stratum recognition. The combination of drilling speed, torque, rotation speed and propulsion can reduce the error rate to 22% for stratum recognition. The error rate can be sharply decreased by 9%−12% when the standard deviation of drilling parameters is introduced into the neural network model. The error rate of stratum recognition is less than 10% for random sampled data and it is less than 14% for a single borehole using the neural network model with the combination of multiple drilling test parameters.

Keywords: drilling test; neural networks; tunnel; stratum; intelligent recognition

1 Introduction

The proportion of newly-built highway tunnels in the southwestern mountainous areas in China usually exceeds 50%. The difficulty of construction under bad geological conditions is also increasing, which puts forward higher requirements for the safety control on tunnel construction. The reliable identification of the stratum in front of the tunnel is one of the important factors to ensure the stability and safety of the tunnel engineering. Traditional advanced geological forecasting methods mainly include geological survey methods, advanced pilot pit forecasting methods, various geophysical prospecting methods, and advanced drilling forecasting methods. The geological survey method is convenient in operation and does not delay the construction period. However, it is difficult to accurately predict the structure surface with a large inclination angle and the complex geological body, which puts forward a higher requirement on the geological knowledge and experience of the operator. The advanced pilot pit forecast method is relatively intuitive and has a high accuracy, but it has a long forecast distance and high cost. Geophysical prospecting methods mainly include electromagnetic wave reflection method and seismic wave reflection method. The electromagnetic wave reflection method, which belongs to a short-distance advanced forecasting method, is convenient in operation and has a high efficiency. However, it is difficult to distinguish between groundwater and broken rock mass because this method is easily disturbed by the surrounding electric and magnetic fields. The seismic wave reflection method has little interference on tunnel construction. It has a long prediction distance, which shows a good applicability to bad geological bodies. However, it has disadvantages such as inaccurate prediction position and insignificant response to small caves. The traditional advanced core drilling method is more reliable and accurate, but it requires the identification on drilling cores, which makes it difficult to obtain cores in weak interlayers. It has disadvantages such as high cost and prolonged tunnel construction time. If the drilling data of the surrounding rock in front of the tunnel face is acquired while the advance drilling is performed, the advance prediction efficiency can be greatly increased based on the real-time and accurate acquisition of the rock formations at different depths of the drilling and the stratigraphic division.

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Horner et al. (1977) evaluated the quality of formation and rock mass based on the drilling test technology. Many scholars including Smith[2], Pfister[3], Pazuki et al.[4], Gui et al.[5], Fortunati et al.[6], Colosimo[7], Garassino et al.[8], Suzuki et al.[9], Nishi et al.[10] and Sugawawa et al.[11] also used the drilling test methods in identification of formation boundary, foundation reinforcement, identification of weak layers, mud detection, rock engineering evaluation and cave detection.

Some geological survey equipment companies have also developed rapid drilling test systems, e.g., MWD of Japan Mining Research Corporation, DEFI of Jean Lutz of France, EXPLOFOR of Apageo of France. However, these systems can only achieve qualitative discrimination of rock formations.

Yue (2014) found that if the MWD information is collected according to the drilling time, the drilling depth-time curve of the drill bit shows a piecewise linear variation. Each segment of the drilling speed is a constant, which represents a uniform rock block[12]. Zeng et al. (2017) found that the drilling speed of the same type of rock is not constant under the same drilling tool conditions through MWD[13], and the concept of drilling specific energy was introduced to evaluate the rock mass quality. Gu[14] introduced the concept of drilling hardness in the identification of formation boundary. Tan et al. (2006, 2014) established a formation interface instrument identification system GIWD[15–16]. Based on the concept of drilling specific energy, the formation structure was identified during the diamond drilling in granite formations. A formation identification method based on drilling ability indicators. Tian et al. (2012) determined the nature of surrounding rock based on the drilling energy analysis[17]. The results were verified by drilling cores and TSP advance prediction etc. Qin et al. (2018) distinguished different rock masses by collecting the vibration spectrum and acoustic spectrum during the drilling process[18]. The experimental results proved that the accuracy of rock mass division by the acoustic spectrum was relatively high. LaBelle et al. (2000) proposed a neural network analysis method in the classification of rock formations based on indoor drilling tests[19] and the accuracy is up to 95.5%.

The above research results of many scholars prove that the drilling test data can be used to identify the formation. The data usually collected during drilling in the drilling test includes the drilling rate, torque, propulsion force, number of revolutions, hydraulic pressure and acoustic frequency spectrum, vibration frequency spectrum, etc. The drilling speed, drilling energy, vibration and acoustic characteristics are often applied in the stratigraphic division. However, these methods lack objective stratigraphic division standards. For instance, the neural network analysis method is currently only used in laboratory drilling tests, and the validity of the drilling data obtained from actual engineering projects is worthy of further investigation.

In this paper, the intelligent analysis of drilling test data and stratum identification method was proposed based on the neural network, which is applied to analyze the advanced drilling test data obtained from the Jiudingshan tunnel of the Chuxiong–Dali highway. The feasibility and effectiveness of the neural network model based on drilling test data were validated by comparing the strata identification results with the actual rock formation.

2 Correlation between drilling test data and rock formation properties

During the drilling process of a drill bit, the amount of energy consumed by cutting a unit volume of rock reflects the difficulty of the drill bit to cut the rock. Tan et al. (2006) proposed a new calculation formula of rock drillability index related to the drilling rate, bit torque, drilling speed, propulsion force and torque[16], which can reflect the changes in formation lithology and is applied in the identification of the strata. Yu (2018) deduced that the work done by the drilling rig consists of work done by torque and work done by drilling pressure[20]. The energy consumed during drilling is comprised of the energy consumed by the friction between the drill bit and the bottom of the hole and the energy consumed by cutting and fragmentation of rocks. The energy consumption per unit volume of rock by a drill can be deduced as follows:

$$\eta_{\mathrm{c}} = \frac{2\pi NM - \pi\mu NF\left(2R\dfrac{L_2^1 + L_2^2 + L_2^3}{L_1 + L_2 L_3}\right) + FV_{\mathrm{d}}}{\pi R^2 V_{\mathrm{d}}} \tag{1}$$

where, N is the drill rotation speed; M is the torque of the drill; μ is the friction coefficient between the cutting edge of the drill and the rock at the bottom of the borehole; F is the drilling pressure of the drill; R is the radius of the drill; V_{d} is the drilling rate; and L_i is the length of the cutting edge in the i-th column.

Gao[21] thought that the drilling test data such as drilling rate, bit rotation speed, torque and propulsion force are related to the mechanical properties of rock mass. The SVR machine learning method was used to determine the uniaxial compressive strength of the rock, and the relationship between uniaxial compressive strength, cohesion, internal friction angle, rock mass strength, and the measured data while drilling was proposed.

The above study shows that the measured data including the drilling speed, torque, propulsion force and rotational speed during the drilling process can be used for formation identification. However, there are great uncertainties of the drilling parameters caused by different drilling rigs, drill bit wear conditions, and operators during the drilling process. Due to the large amount of data obtained, the test data usually exhibits strong randomness. The connection between different test parameters is not clear. It is difficult to obtain the quantitative relationships between drilling parameters and the rock properties without clearly understanding the rock breaking mechanism of the drilling tool. It is also challenging to quickly and accurately analyze the test data for the formation identification. Therefore, this paper tries to adopt the neural network method in machine learning to train the measured data and establish a reliable neural network model, which can quickly get the nonlinear mapping relationship between the complex drilling test data and different rock formations.

3 Data acquisition of drilling test

The Jiudingshan tunnel is a controlled project of Chuxiong–Dali highway. The tunnel is designed as a separate type with a maximum excavation width of 17.34 m. The starting and ending mileages on the left tunnel are fromK281+506 to K289+090, and the total length of the tunnel is 7560 m. The starting and ending mileages on the right side are from K281+506 to K289+090, and the total length of the tunnel is 7597 m. The Jiudingshan that the tunnel traverses is located at the watershed of the three major water systems, i.e., Jinsha River, Lancang River, and Red River. It is adjacent to the Binchuan fault and Erhai deep fault, respectively on the east and west, and is located at the composite part of different tectonic systems. The tunnel passes through poor geological zones such as contact zone of limestone and granite porphyry, karst zone, fault fracture zone and so on, with poor stability of surrounding rocks.

In order to ensure the safety of tunnel construction, many advanced drilling tests were carried out. The KOKEN RPD-180CBR multi-functional fast drilling rig produced by Japan Mining Research Company, which has strong applicability and can work under various geological conditions, was applied in the advanced drilling. The data acquisition system is shown in Table 1. The final drilling parameters include drilling speed, torque, rotation speed, propulsion, blow energy, number of blows, water supply rate, water supply pressure, EV energy (rock breaking energy per unit volume of rock). The information reflected by the propulsion, torque, blow pressure, and water delivery pressure when drilling the tunnel face is directly returned to the computer on the drilling rig through the sensor transfer box for reception and recorded in charts and numbers. All power sensing devices receive signals at the same time during data collection and the sampling interval is 2 cm drilled depth.

10 sets of advanced drilling test data are collected from the right tunnel face of the Jiudingshan tunnel entrance, including the YK282+140 advance hole with a drilling depth of 72.20 m, YK282+214 advance hole with a drilling depth of 69.86 m, YK282+274 advance hole No.1 with a drilling depth of 70.20 m, YK282 advance hole No. 2 with a drilling depth of 70.18 m, YK282+340 advance hole No. 1 at the tunnel central line with a drilling depth of 38.84 m, YK282+340 advance hole No. 2 at the left position of the left wall arch with a drilling depth of 40.98 m, YK282+364 advance hole with a drilling depth of 31.10 m, YK282+403 advance hole with a drilling depth of 51.00 m, YK282+450 advanced hole with a drilling depth of 51.00 m, YK282+084.5 advanced hole with a drilling depth of 72.20 m. Among them, the first 9 sets of data are neural network model training data, and the last set of data is the verification data and does not participate in training.

Table 1 Data acquisition system

System unit	Detailed information
Data record unit	Save the data in the memory card while processing the signal of the sensor, recording and displaying in real time with the recorder
Sensor transfer box	Installed on the control unit or drilling rig, centralize the signals of all sensors
Depth sensor	Rotary encoder (1000 pulses/revolution), which converts the rotation angle of the sprocket of the drilling rig into pulses, and records the conveying volume of the power head
Torque sensor	The pressure sensor (35 MPa) is installed at the inlet and outlet of the hydraulic motor used for rotation to record the rotation hydraulic pressure and convert it into output torque
Rotation sensor	The flowmeter calculates the rotating working oil flow rate and converts it to the number of revolutions
Propulsion sensor	The pressure sensor (35 MPa) is installed on the forward and backward hydraulic circuit of the propulsion to record the propulsion hydraulic pressure and convert it into the propulsion force
Blow pressure sensor	The pressure sensor (35 MPa) is installed on the strike circuit to record the blow pressure. Calculate the blow ability and blow number based on the blow pressure
Water delivery flow rate sensor	The electromagnetic flow sensor (240 L) is set between the water pump and the drilling rig to record the water flow rate
Water delivery pressure sensor	The pressure sensor (10 MPa) is installed on the water pipe to record the tunneling water pressure
Drainage flow rate sensor	The electromagnetic flow sensor (240 L) is connected behind the water sealing device to record the drain flow rate
Drainage pressure sensor	The pressure sensor (10 MPa) is connected behind the water sealing device to record the drain water pressure
Fixture pressure sensor	The pressure sensor (35 MPa) records the hydraulic pressure on the closed side of the fixture. The recording is automatically interrupted when the pressure on the closed side of the fixture rises and the fixture is closed

Figure 1 shows the advance drilling record of the mileage YK282+214 and the actual strata observed after excavation. It can be seen that the correlation between the measured curves of drilling speed, propulsion, torque, etc., and the actual strata is not obvious and it is difficult to judge manually. Figure 2 is a scatter diagram of the combination of drilling speed, propulsion, torque, rotation speed, water supply rate, water supply pressure, blow energy and EV energy. The graphs on the diagonal are the kernel density estimates of these groups of data, which show no obvious rules. Taking the drilling speed as an example, it is generally considered that the drilling speed is fast when the rock formation is poor, and the drilling speed is slow when the rock formation is good. However, the drilling speeds of limestone, fractured limestone, and soft interlayers are all low, and the maximum frequency distribution of drilling speeds is also similar. The only difference is that the discreteness of the drilling speed of limestone and fractured limestone is small, while the discreteness of the drilling speed of soft interlayer is much larger. Therefore, both the drilling test data in formation identification and the statistical characteristics of different drilling test data are required to be considered in stratum identification.

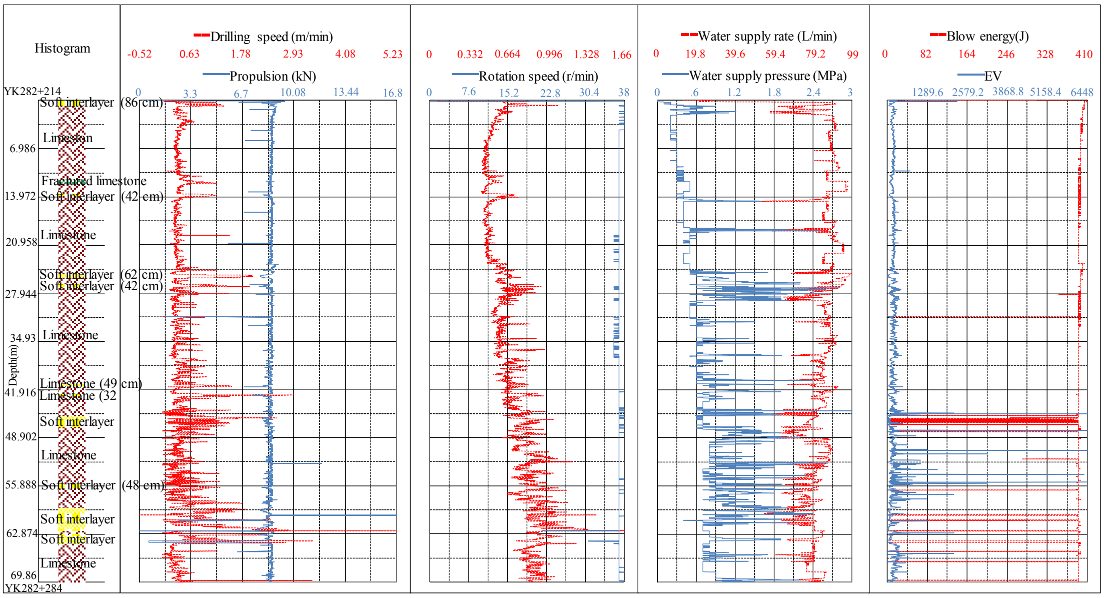
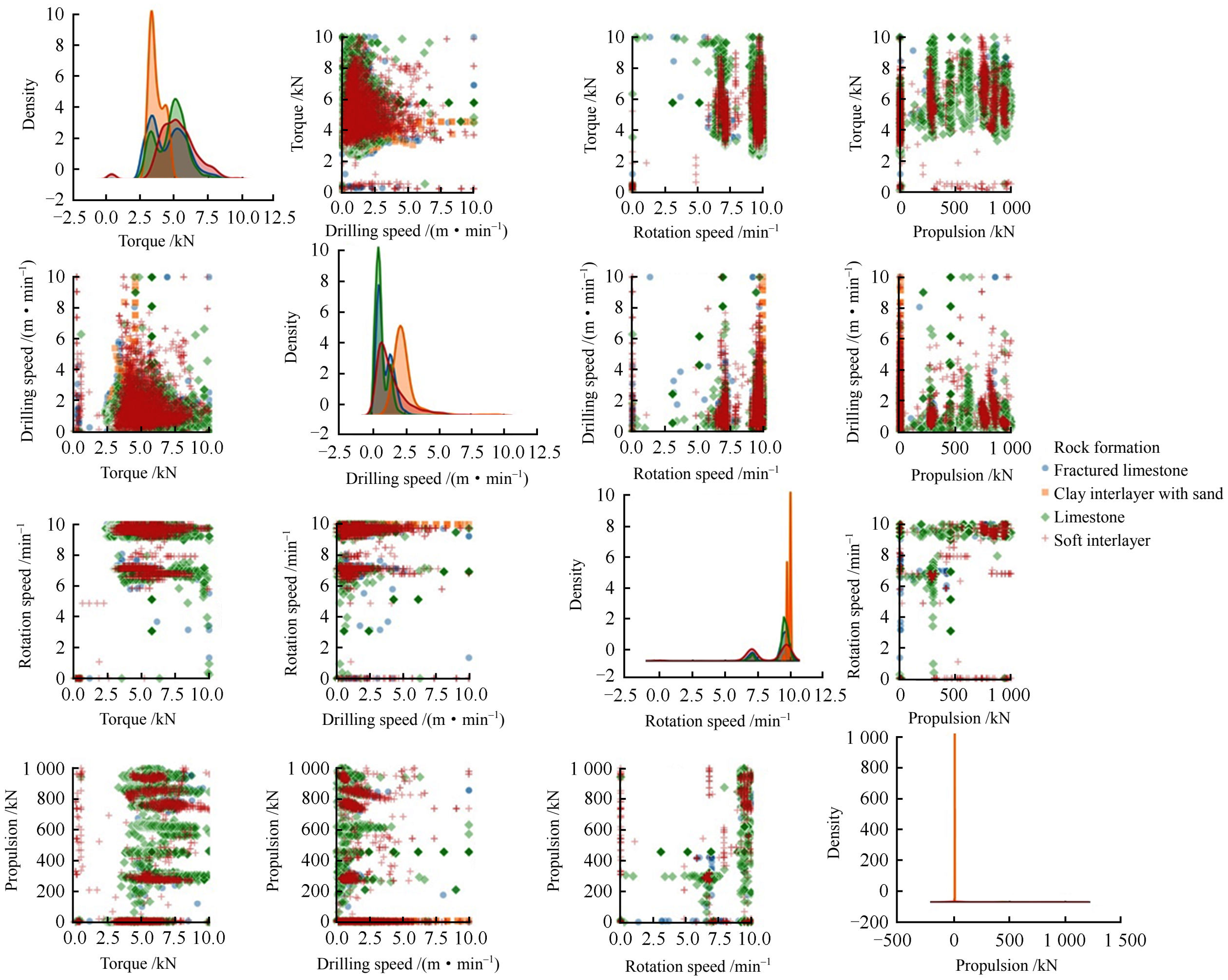
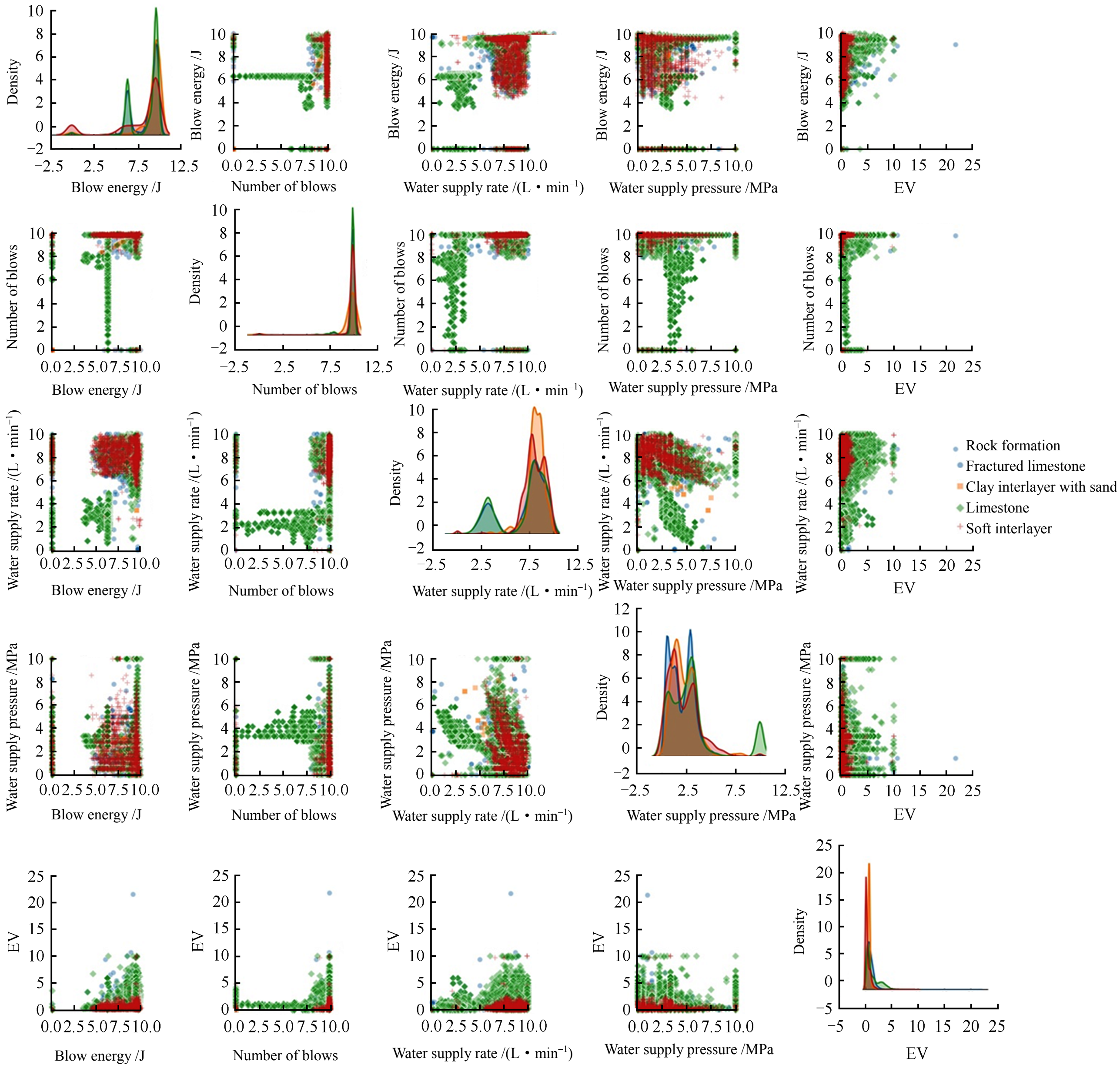


Fig. 1 Drilling test data of YK282+214



(a) Pairwise combination scatter plot and kernel density estimation of the drilling speed, propulsion, torque, rotation speed



(b) Pairwise combination scatter plot and kernel density estimation of the blow number, blow pressure, water supply rate, water supply pressure, EV

Fig. 2 Scatter plot and frequency distribution chart of drilling test data

4 Neural network analysis method of drilling test data

In order to establish the non-linear relationship between the complex advanced drilling test data and the formation, the neural network method in machine learning is introduced to train the measured data, including drilling speed, torque, rotation speed, propulsion, blow energy, number of blow, water supply rate, water supply pressure and EV energy. A nonlinear mapping model is established to identify the formation in front of the tunnel face, which can provide basis for the support design and optimized construction of tunnel.

The neural network, which is one of the machine learning methods, is a mathematical model that simulates the thought pattern of the human brain. Neural network method is proposed on the basis of modern biological research on the processing and storage of received information by human brain tissues, and is used to simulate the structure and behavior of the human brain neural network. A neural network is a complex network system (see Fig. 3) formed by connections between multiple simple processing units. It is composed of input layer, a hidden layer, and an output layer. Units of neural networks in different layers are connected by different weights. The numbers of hidden layers and processing units determine the complexity of the network. Each processing unit processes the information passed from the previous layer. It is assumed that the information transmitted by all processing units in the previous layer is a n-dimensional vector. When the processing unit receives the information, it firstly calculates the weighted sum of each component $\sum w_i X_i$ (w_i is the weight of each component), and a threshold b acts as the input of the activation function of the processing unit. The activation function performs a linear or non-linear operation on the input value and then outputs it. The output information of the processing unit to the next layer of processing unit is then obtained as $y = \varphi(b + \sum w_i X_i)$.

The raw data (torque, drilling speed, rotation speed, propulsion, blow energy, number of blows, water supply rate, water supply pressure, EV energy) received by the sensor during the drilling process and their respective standard deviations are used as the input variables of the input layer data in the neural network model. The formation identification is the final results of the output layer in the neural network model. The ultimate goal of the neural network is to identify rock formations by analyzing the drilling test data with a minimum error, and obtain the recall rate and accuracy of a specific formation classification, which are considered as auxiliary evaluation indexes for formation classification. The recall rate represents the ratio of the number of searching a certain layer to the total number of the layer. Accuracy represents the ratio of the number of stratum found to the total number of layers. When the recall rate and accuracy are close to 1, demonstrating a high accuracy of stratigraphic classi-fication.

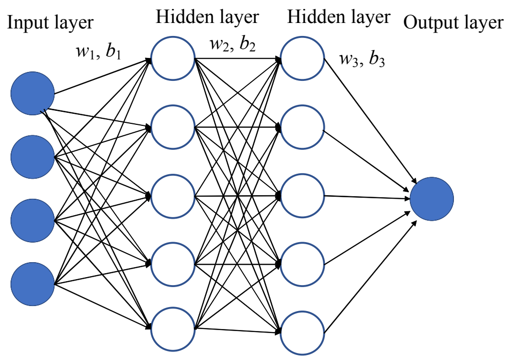


Fig. 3 Schematic diagram of neural network

Four formations have been numbered based on the observed lithology after excavation of tunnel, and they are regarded as the target data for neural network training (see Table 2).

Table 2 Stratum number

Lithology	Number
Fractured limestone	1
Limestone	2
Clay interlayer with sand	3
Soft interlayer	4

The back propagation algorithm has been applied in the neural network for the dataset training and two hidden layers have been used. The neural network model with different hidden layers is designed to understand their impacts on the stratum identification. It is shown in Fig.4 that the error rate of stratum identification gradually decreases with the increase of hidden layers. When the number of hidden layers is 17–19, the error rate tends to be stable. Therefore, the number of hidden layers is selected to be 18 in the neural network.

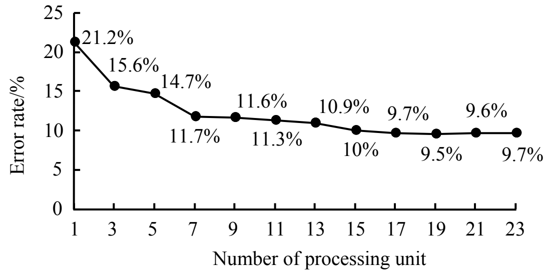


Fig. 4 Error rate curve of neural network

Many assemblages of input drilling variables are used to investigate their impacts on the training. It is shown in Fig.2 that the accurate estimation on geological formation is not only related to the drilling parameters, but also presents the correlation with the statistic results of drilling parameters. The standard deviation of drilling parameters can be regarded as the input variables for training in the neural network model, which can increase the accuracy of stratum identification[19]. Therefore, the standard deviation of drilling parameters, whose scope is based on a group of single parameter during a single drilling process, has been introduced in the training of neural network model.

The 9 groups of advanced drilling test data, with a total of 33113 lines, have been selected in the neural network training. The final one group of data acts as the validation data. The 70% of the data is randomly selected from these 9 groups of data as a training dataset, 15% as a cross-validation dataset, and 15% as a test dataset. The classification of stratum and error rate are as the final training results. There are 21 kinds of training schemes (see Table 3), considering the single drilling parameter (scenario 1–9) and their combinations (scenario 10); the assemblage of drilling speed, torque, rotation speed and propulsion (scenario 11), and their combinations with the respective standard deviations (scenario 14); the assemblage of blow energy and the number of blows (scenario 12) and their combinations with the respective standard deviations of these parameters (scenario 15); the assemblage of water supply rate and water supply pressure (scenario 13) and their combinations with the respective standard deviations of these parameters (scenario 16); the combination of EV energy and its standard deviation (scenario 17); the assemblages of drilling speed, torque, number of revolutions and propulsion and their corresponding standard deviations with other parameters (scenario 18–20); the assemblage of drilling speed, torque, rotation speed, propulsion, blow energy, the number of blows, water supply rate, water supply pressure and EV energy with their respective standard deviations (scenario 21).

The learning curve of neural network model can be seen in Fig.5. It shows that the errors of training dataset, validation dataset and test dataset decrease with the increase of training number. The minimum error of validation dataset occurs after the 48th iteration. The error of validation dataset and training dataset are low and their difference is small. It implies that there exists no over-fitting or under-fitting in the neural network stratum identification models, that is, the model performs too well in the training samples, resulting in poor performance in the validation set and test set, or the model has a low degree of fit, leading to poor performance in the training dataset, validation dataset and test dataset.

Table 3 Training scheme of neural network

Drilling parameters	Scenario number																				
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Drilling rate/(m • min^{-1})	■									■	■			■				■	■	■	■
Torque/kN		■								■	■			■				■	■	■	■
Rotation speed /min^{-1}			■							■	■			■				■	■	■	■
Propulsion/kN				■						■	■			■				■	■	■	■
Blow energy/J					■					■		■			■				■		■
Number of blows						■				■		■			■				■		■
Water supply flow rate /(L • min^{-1})							■			■			■			■				■	■
Water supply pressure /MPa								■		■			■			■				■	■
EV energy									■	■							■	■	■		■
Drilling rate std.														■				■	■	■	■
Torque std.														■				■	■	■	■
Rotation speed std.														■				■	■	■	■
Propulsion std.														■				■	■	■	■
Blow energy std.															■				■		■
Number of blows std.															■				■		■
Water supply rate std.																■				■	■
Water supply pressure std.																■				■	■
EV std.																	■	■			■

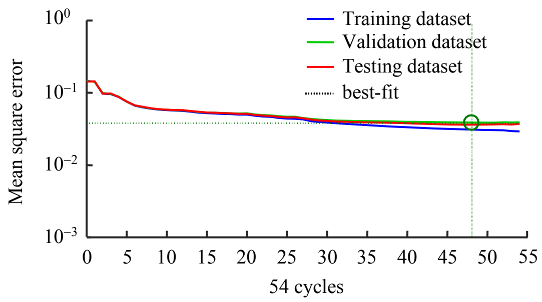


Fig. 5 Learning curve of the experiment No.21

5 Stratum identification by neural network model

The stratum identification results based on 21 groups of neural network model are shown in Table 4, which includes the error rates of stratum identification based on each training scheme and the recall rate and accuracy of single layer identification.

The error rate is up to 29.8%–36.7% when using the single drilling parameter in the stratum identification (scenario 1–9). It implies that the single drilling parameter can’t be used in the stratum identification by neural network.

Scenario 10 uses all the drilling parameters in the input data, and the error rate of formation identification drops to 19.0%. Compared with the training results of schemes 1–9, the recognition error rate of all drilling parameter combinations is up to 18.4% lower than that of a single drilling parameter, which shows that the combination of all drilling parameters can greatly reduce the formation recognition error rate.

The comparison of the results of scenarios 11, 12, 13 and scenarios 1–9 shows that the combination of 2–4 parameters can reduce the error rate of formation recognition, but the effect is not significant. Among them, the combination of drilling speed, torque, rotation speed, and propulsion can greatly reduce the error rate of formation recognition. Compared with the combination of blow energy and number of blows, the error rate is reduced by 11.9%, while the error rates are reduced by 6% and 11.5% compared to the combination of water supply pressure and water supply rate, and EV energy, respectively. This is consistent with the results based on the drilling energy analysis proposed by Yu (2018) [20] and Tan et al. (2006) [16]. It shows that the drilling speed, torque, propulsion force, rotational speed and other parameters can be used to divide the formation with good results.

The comparison of the results of scenarios 11 and 14, scenarios 12 and 15, scenarios 13 and 16, and scenarios 9 and 17 shows that the input data is combined with the respective standard deviation can significantly reduce the error rate in the range of 9% and 14.0%. Among them, the combination of drilling speed, torque, number of revolutions, propulsion force and their respective standard deviations has the lowest error rate (i.e., 13.7%).

Table 4 Results of stratum identification

Test number	Formation 1		Formation 2		Formation 3		Formation 4		Error rate of stratum identification /%
	Recall rate /%	Accuracy /%	Recall rate /%	Accuracy /%	Recall rate /%	Accuracy /%	Recall rate /%	Accuracy /%	
1	9.3	42.2	96.1	67.3	1.8	100	20.2	51.3	34.7
2	4.4	62.6	98.2	63.5	0.0	0.0	6.9	54.4	37.1
3	13.1	48.4	94.9	63.6	0.0	0.0	3.3	63.3	37.4
4	35.5	59.9	91.1	73.5	0.0	0.0	38.3	56.5	29.8
5	5.8	35.4	93.8	66.3	0.0	0.0	30.1	53.4	35.8
6	0.0	0.0	99.4	63.3	0.0	0.0	4.1	41.4	36.7
7	86.1	56.2	97.5	65.5	0.0	0.0	5.1	60.0	35.0
8	24.3	63.5	95.5	70.0	0.0	0.0	26.1	56.3	31.4
9	0.0	0.0	96.7	66.3	0.0	0.0	45.7	61.4	34.2
10	51.9	74.8	93.9	83.2	50.7	69.8	74.9	77.4	19.0
11	45.1	68.7	92.5	80.6	38.7	60.0	68.9	70.5	22.7
12	4.6	32.1	95.4	67.3	1.8	14.3	31.5	58.3	34.6
13	43.5	59.8	90.4	75.4	16.7	58.8	35.5	58.2	28.7
14	76.4	80.2	93.2	90.3	55.8	70.5	74.0	77.7	13.7
15	73.4	69.7	90.5	82.2	9.0	70.0	34.0	68.8	21.9
16	72.2	84.3	94.2	85.1	36.9	82.8	49.2	63.1	17.2
17	64.0	71.3	90.7	84.7	32.4	40.0	60.5	70.1	20.2
18	78.6	80.2	92.5	90.6	43.8	69.6	74.0	76.7	13.8
19	77.2	77.7	91.9	91.3	51.2	82.7	75.7	74.7	14
20	83.9	85.6	94.5	93.4	63.6	73.1	79.9	80.4	10.3
21	85.4	85.3	94.5	94.0	68.7	75.0	81.0	82.7	9.6

The comparison of the results between scenario 18, 19, 20 and the combination of scenario 15, 16 and 17 demonstrates that the error rate (10.3%) drops the most after adding the water supply rate, the water supply pressure and their respective standard deviations, which is 3.4% less than that of the combination of drilling speed, torque, rotation speed, propulsion and their standard deviations alone. Compared with the scenario 21, the difference is only 0.7%. It shows that the combination of drilling speed, torque, rotation speed, propulsion force, water flow, water pressure and their respective standard deviations can be used as the main parameters in the neural network to identify the formation.

The error rate is reduced by 9.4% in the scenario 21 after adding the standard deviation of drilling parameters based on the scenario 10, and the final error rate is only 9.6%.

6 Error analysis of neural network model

Figure 6 is the error matrix of test data in the training scenario 21. The first 4 columns of the fifth row are the recall rates of each stratum, with the minimum and maximum values of 68.7% and 94.5%, respectively. The first 4 lines in the 5th column show the accuracy of each stratum, which is in the range of 75.0% and 94.0%. The 5th line and 5th column are the final test results, where the red numbers represent the error rate and the green numbers represent the accuracy.

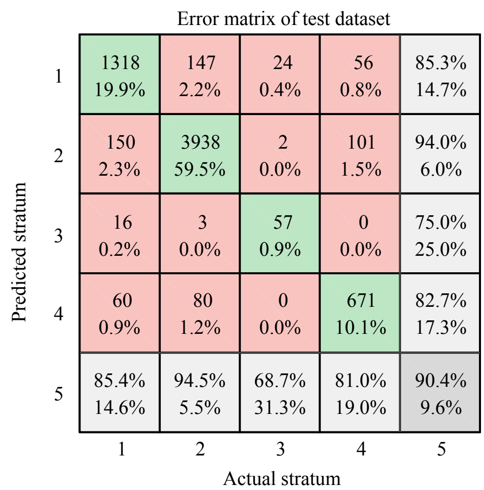


Fig. 6 Error matrix of the training experiment No.21

The standard deviation of one specific drilling parameter is a constant during one drilling process, implying that the standard deviation has no practical significance for the formation identification during a single drilling process. However, after adding many sets of drilling data, the standard deviation of drilling parameters can greatly improve the accuracy of formation recognition. This indicates that the standard deviation can be used to correct the drilling parameters of the rig under different drilling conditions and different operators. Since the drilling test data often shows certain statistical characteristics, the correction of drilling parameters by standard deviation is useful in studying the quantitative relationship model between drilling parameters and rock and soil mechanical properties.

The YK282+084.5 advance hole drilling data that is not used for neural network training, is applied in the rock formation identification by the trained model. Figure 7 shows the comparison between the results of formation recognition and the actual stratum. The red dot or line represents the actual stratum, and the blue dot or line shows the result of stratum recognition. The recognition error rate is 13.82%. It can be seen that the deviation between the formation recognition result and the actual formation mainly occurs at the formation boundary and weak interlayer. This is because there is a transition phenomenon in the lithology at the stratum boundary. The drilling test data may be judged to be a certain formation or another, which leads to errors in the recognition by the neural network model. On the other hand, the actual stratum division is also revealed in the tunnel excavation process, and there is uncertainty in stratum division caused by human judgment.

The neural network model can achieve accurate and intelligent recognition of most kinds of stratum, and the wrong recognition result at the stratum boundary is acceptable in engineering, which has a weak impact on the safety control of tunnel.

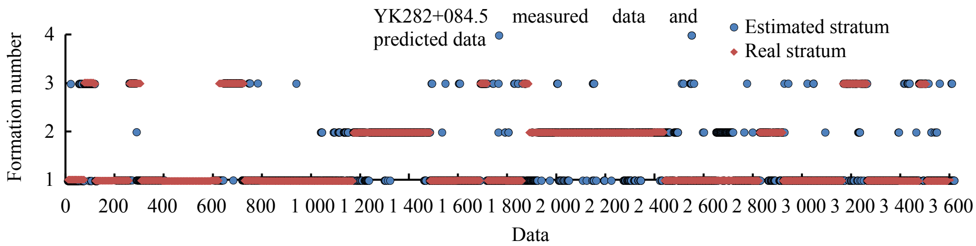


Fig. 7 Comparison of recognized stratum based on neural network method and the true stratum

7 Conclusions

It is difficult to predict the variation law of drilling test data such as drilling speed, propulsion force, torque and actual formation. Both the drilling test data and the statistical characteristics should be considered in the formation identification.

Considering the discreteness of drilling test data, a neural network analysis method for drilling test data is proposed, and a nonlinear mapping model for drilling test data and formation recognition is established. The analysis results of the drilling test data of Jiudingshan tunnel show that the accuracy of random sampling of formation recognition is more than 90%, and the accuracy of stratum recognition for a single borehole is more than 86%.

Some drilling parameters such as the drilling speed, torque, rotation speed, propulsion force and their respective standard deviations are relatively sensitive to the formation recognition, and the combination of water supply rate, water supply pressure and their respective standard deviations can be used as the main input parameters of the neural network model for the formation identification.

The amount of drilling test data has a certain impact on formation recognition. More test data is helpful to further improve the accuracy of formation recognition. The geological conditions encountered in this test are limited, so the training on more rapid drilling data from different geological conditions in engineering can improve the applicability of the model.

The neural network model has difficulties in identifying stratum boundaries and soft interlayers, and the drilling parameters fluctuate greatly in these areas. The intelligent identification of weak interlayer is worthy of further study. All input and output data in each group of BP neural network are independent, leading to the variation law at the stratum boundary cannot be considered. The accuracy of stratigraphic division can be improved by acquiring more rapid drilling data of different engineering and using the recurrent neural network model to train the data. Recurrent neural networks have some advantages in learning sequence data, and they are widely applied in language recognition and machine translation. The recurrent neural network can recognize the formation of a certain depth considering the conditions around the formation and make predictions. However, a greater amount of data is required than that of the BP neural network if a relatively high accuracy rate is to be obtained.

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