Geological Identification Based on K-Means Cluster of Data Tree of Shield Tunneling Parameters

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Abstract—**The geological condition is complicated and changeable, and difficult to predict accurately, so the shield tunneling construction will face great risks, even lead to serious safety accidents. Real-time and accurate geological identification and prediction is an important guarantee for the safe construction of shield machine, which is also an important problem of shield technology. Based on the real-time tunneling control parameters of shield machine construction, an unsupervised data tree K-Means cluster method is proposed in this paper. Firstly, the correlation between shield tunneling parameters and geological types is analyzed to determine the main tunneling parameters which are greatly affected by geological changes. Secondly, the unsupervised data tree is used to optimize the K value of K-Means cluster algorithm, and then a geological recognition cluster algorithm based on main tunneling parameters is constructed. Finally, a simulation experiment is carried out based on the field construction data, and the accuracy of geological identification is 100%. The results show that the method can accurately identify geological categories and provide decision support for effective parameter regulation of shield machine.**

Index Terms—**Shield machine, tunneling parameter, geological identification, K-Means cluster, data tree**

I. Introduction

With the development of data analysis technology, it is possible to apply data mining technology to the analysis of shield tunneling process. Shield technology has become an important support for China's transportation infrastructure construction. For the shield tunneling method, it is necessary to survey the hydrogeological conditions of the construction site in advance, so as to regulate the shield machine in real-time and ensure construction safety and efficiency. Due to the complexity and changeability of geological conditions, the collection of geological information often has many limitations and inaccuracies. The real-time analysis of tunneling parameters can feed back the current geological information, which is of great help to the safety and quality of shield construction [1-3]. Therefore, how to use artificial intelligence and data mining technology to realize geology intelligent identification based on shield tunneling parameters is a hot and difficult problem in current shield technology research, which is also an important foundation to realize the intelligence of shield machine.

Some scholars have done some research on geological identification of shield tunneling construction. Zhu et al. [4] used BP neural network technology to identify the tunneling strata based on the data of working parameters, which collected from the shield experimental platform under different geological conditions. Based on the specific energy of shield tunneling, Liu et al. [5] established the recognition model of boulder stratum by using BP neural network. Shao [6] analyzed the variation laws of the tunneling parameters, such as jacking force, tunneling speed, cutter head torque, screw conveyor rotation speed in different strata conditions, and proposed a method of stratum identification based on learning vector quantization neural network. Li et al. [7] established the prediction model of shield tunneling parameters in composite strata by using BP artificial neural network method.

At present, most of the methods used to analyze geological strata with shield tunneling parameters are supervised BP neural network models, so the geological strata information accurately must be known when collecting data. Meanwhile, the neural network model can not effectively reflect the distribution characteristics of tunneling parameters under different geological conditions. Therefore, in this paper, an unsupervised K-Means cluster method of data tree is proposed, which can deeply mine the inherent relationship between shield tunneling parameters and geological types. Thus, the tunneling parameters under the same geological conditions are clustered into one category, so as to achieve the goal of geological identification. At the same time, it can effectively show the distribution of tunneling parameters under different geological conditions, and can provide reference for accurate adjustment and control of tunneling parameters of shield machine.

II. Analysis of The Relationship Between Geology and Shield Tunneling Parameters

A. Calculation of Main Tunneling Parameters

Shield machine is a comprehensive large-scale complex

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machinery equipment, the system includes many devices and components, such as cutter head, propulsion hydraulic cylinder, screw conveyor, segment erector, pressure sensor and so on, the structure of shield machine is shown in Fig. 1. In the process of shield construction, each subsystem will produce a mass of monitoring data. The tunneling parameters are different under different geological conditions, such as total thrust, tunneling speed, cutter head torque, earth pressure and so on. The calculation of the main tunneling parameters is deduced as follows.

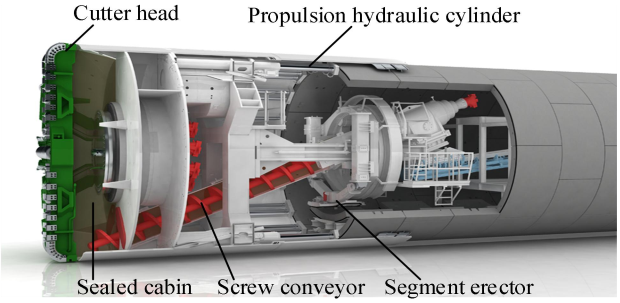

Fig. 1 The structure diagram of shield machine

(1) Total thrust

In the process of shield tunneling, the thrust is used to overcome the following force: the frictional resistance between the shield machine shell and the stratum, the forward propulsive resistance of the soil in front of the cutter head, the cohesive force of the soil, the frictional resistance of the shield tail sealing brush to the segment, the traction resistance of the supporting equipment. It is related to the buried depth of tunnel, geological parameters, control parameters, construction requirements [8]. The total thrust is:

$$\begin{aligned} F = {} & \mu_1 \gamma g D[\frac{\pi}{2}(1+k_0)H - \frac{1}{3}(2+k_0)D] + \mu_2 n_1 G_s \\ & + \mu_2 n_2 \pi D_S l p_T + \mu_3 G_C + \mu_1 G \\ & + \pi D^2 k_0 h \gamma (1-c)/4 + \pi D^2 p_0 c/4 \end{aligned} \quad (1)$$

where F is the total thrust, μ_1 is the friction coefficient between shield shell and the surrounding soil, γ is the soil density, g is the gravitational acceleration, D is the diameter of the shield body, k_0 is the lateral pressure coefficient of the soil, H is the depth of the shield, μ_2 is the friction coefficient between the shield tail sealing brush and the segment, n_1 is the number of rings of the inner segment in the shield tail, G_s is the weight of each segment, n_2 is the number of layers of the shield tail sealing brush, D_S is the outer diameter of the shield tail, l is the contact length of the sealing brush with the pipe ring, p_T is the pressure of the sealing brush, μ_3 is the friction coefficient between the rear mating vehicle and the track, G_C is the weight of the matching vehicle, G is the gravity of the shield machine, c is the cutter head opening rate, h is the distance between shield machine axis and the ground surface, p_0 is the earth pressure in the sealed cabin.

(2) Cutter head torque

In the process of cutting soil, the cutter head of shield machine will suffer the friction force between the cutter head and the soil, the resistance of stratum and the resistance of mixing soil, which are the main reasons for the formation of cutter head torque [9-10], the total torque of the cutter head can be obtained:

$$\begin{aligned} T = {} & \mu\gamma h\pi[(1+\lambda-\lambda c)D^3 k_0/12 + (1+k_0)D^2 L/4] \\ & + D^2 V_a q/8V_c + \mu\gamma H_0 D_l L_s R_s \end{aligned} \quad (2)$$

where μ is the friction coefficient between cutter head and the soil, λ is reduction factor, L is the width of the outer edge of cutter head, V_a is tunneling speed, V_c is cutter head rotation speed, q is uniaxial shear strength of the soil body, H_0 is the depth of mixing rod, D_l is the mixing surface diameter, L_s is the mixing rod length, R_s is the distance between mixing rod bottom and the shield machine center axis.

(3) Earth pressure in sealed cabin

The set value of the earth pressure in sealed cabin should be determined before shield tunneling. Earth pressure mainly includes water pressure, static earth pressure, and reserve pressure. The calculation formula is:

$$P = \gamma_w h + k_0[(\gamma - \gamma_w)]h + \gamma(H-h)] + P' \quad (3)$$

where γ_w is water density, h is the buried depth of the tunnel below the groundwater level, P' is a constant determined according to different geological.

From the calculation of the above-mentioned tunneling parameters, it can be concluded that the tunneling parameters, such as total thrust, tunneling speed, cutter head torque and earth pressure in sealed cabin are affected by the different geological parameters. But which tunneling parameters can directly reflect the geological category? It will be determined by the following correlation analysis between the tunneling parameters and the geological category.

B. Correlation Analysis Between Tunneling Parameters and Geology

The shield machine produces huge amount of data in the construction process, so the effective tunneling data selection is the premise to ensure the success of geological classification. When selecting the sample data, we should reduce the dimension of the sample data as possible under the premise of guaranteeing the classification effect. The correlation analysis method is used to analyze the correlation degree between the geological category and the tunneling parameters, as total thrust, advance speed, earth pressure, screw conveyor pressure, screw conveyor rotation speed, cutter head torque, so as to determine the main tunneling parameters for geological classification.

Pearson correlation coefficient method is introduced to calculate and judge in this paper. General, a correlation coefficient r greater than 0.7 indicates that the two variables are very closely related. r between 0.4 and 0.7 indicates that the two variables are closely related, and r less than 0.4 indicates that the relationship between the two variables is general. In addition, there is significant P value analysis in correlation analysis. In correlation analysis, two variables are assumed to have no correlation. But when the P value is less than 0.05, the assumption is invalid which indicates that there

TABLE I
CORRELATION ANALYSIS BETWEEN TUNNELING PARAMETERS AND GEOLOGICAL CATEGORY

		Total thrust	Tunneling speed	Earth pressure	Screw conveyor pressure	Screw rotation speed	Cutter head torque	Geological category
Total thrust	Pearson correlation	1						
	Significance (Two-tailed)							
Tunneling speed	Pearson correlation	.479**	1					
	Significance (Two-tailed)	.000						
Earth pressure	Pearson correlation	-.727**	-.126	1				
	Significance (Two-tailed)	.000	.128					
Screw machine pressure	Pearson correlation	.016	-.007	-.097	1			
	Significance (Two-tailed)	.848	.937	.247				
Screw rotation speed	Pearson correlation	.037	.118	.030	.093	1		
	Significance (Two-tailed)	.657	.161	.721	.269			
Cutter head torque	Pearson correlation	.164*	.307**	-.083	.442**	.113	1	
	Significance (Two-tailed)	.050	.000	.322	.000	.181		
Geological category	Pearson correlation	.959**	.555**	.734**	.001	.107	.169*	1
	Significance (Two-tailed)	.000	.000	.000	.990	.203	.044	

is correlation between the two variables.

The significance also means that the statistical analysis is universal. Usually, there are two levels of the significance namely $P < 0.05$ and $P < 0.01$, which are expressed by"*"and"**" respectively in the results. The smaller the significance P value, the more significant the correlation. TABLE I shows the results of correlation analysis between shield tunneling parameters and geology.

From TABLE I, it can be seen that the significant P values between total thrust, tunneling speed, earth pressure and the three geological categories of silty clay, gravel sand clay and gravel soil are 0.000, which indicates that there is significant correlation. The correlation coefficient r of total thrust, earth pressure and geological categories are 0.959 and 0.734 respectively, which shows that they are very closely related. r of tunneling speed and geological category is 0.555 greater than 0.4, which shows that they are closely related. Therefore, judging from the correlation coefficient, it also shows that there is strong correlation between the total thrust, tunneling speed, earth pressure and geological categories. But for the screw conveyor pressure, screw conveyor speed, cutter head torque, they are not significantly correlated with geological category. Moreover, the correlation coefficients r between the three parameters and geological category are all less than 0.4, which indicates that the correlation between them is not obvious.

In conclusion, according to the analysis of the correlation, the total thrust, tunneling speed and earth pressure which are most relevant to geological types are selected as the characteristic parameters for geological identification.

III. GEOLOGICAL IDENTIFICATION BASED ON K-MEANS CLUSTER OF DATA TREE

Each node of the data tree is composed of a number of cluster features (CF) . The data tree is built by looking down from the root node to find the leaf node closest to the new sample and the nearest CF node in the leaf node. When the new sample meets the threshold condition of the original node, the data tree retains the original structure. When the new node exceeds the threshold, the new node is established. In this way, the data tree structure is continuously established by absorbing or splitting.

K-Means cluster algorithm has the advantages of simplicity and high speed of calculation [11], but the determination of K value needs to be judged by experience, which is often faced with new conditions and has certain risks in the process of shield tunneling. Therefore, the data tree is used to judge the sample characteristics of shield tunneling parameters, and to improve the reliability and intelligence degree of identifying geology by using tunneling data. The specific geological identification algorithm based on data tree K-Means cluster is as follows:

(1) Each data sample includes three characteristics: total thrust, tunneling speed and earth pressure. Look down from the root node to the nearest leaf node and the nearest CF node in the leaf node. Judge whether the new sample is less than the threshold. If it is less than the threshold, the new sample is absorbed, otherwise the new node is split. Judge whether the number of nodes reached the maximum. If the number of nodes reached the maximum, a new leaf node is split, and finally a data tree is established.

(2) According to the data tree, the K value is determined by selecting the appropriate sample distance and the number of branches of the corresponding data tree. For the sample of shield tunneling parameters, the experiment proves that when the sample distance is 3000, the appropriate K value can be determined by the corresponding branch node.

(3) Determination of the initial centroid

Step1. Take the first sample as the first center of mass.

Step2. For each sample, calculate its Euclidean distance to the center of mass.

Step3. Select the sample with the largest Euclidean distance as the other center of mass.

Step4. Repeat Step2 and Step3 until the center of mass has been determined.

Given the centroid vector $C(c_1, c_2, \cdots, c_Q)$ and another sample vector $X(x_1, x_2, \cdots, x_Q)$, $Q = 3$, which means that the sample includes three attributes: total thrust, tunneling speed and earth pressure. C_q is the value of the qth attribute of the centroid, and X_q is the value of the qth attribute of the sample, $q = 1, 2, \cdots, Q$. So the Euclidean distance between the sample and the centroid is calculated as follows:

$$d = \sqrt{\sum_{q=1}^{Q} (X_q - C_q)^2} \tag{4}$$

After the initial k centroids are generated, the algorithm begins the iterative assignment process.

(4) In each iteration of the algorithm, each sample is assigned to the cluster represented by its nearest centroid. Distance is represented by Euclidean distance, so the distance from the sample i to the centroid j is:

$$d_{ij} = \left\| X_i - C_j \right\|^2 = \sum_{q=1}^{Q} (X_{qi} - C_{qj})^2 \tag{5}$$

where X_i is a vector composed of the attribute value of the sample i, C_j is the centroid vector of cluster j, Q is the number of attributes, X_{qi} is the value of the qth attribute of the ith sample, C_{qj} is the qth attribute value of the cluster j centroid.

For each sample, calculate its distance from each centroid. The record is assigned to the cluster whose centroid is closest to this record. In this process, a sample will be moved from one cluster to another. After all records have been assigned, update the centroid of each cluster.

(5) Update the centroid and set the assigned sample. The number of samples in the jth cluster is m_j, and the vector is obtained by recalculating the centroid of this cluster:

$$\overline{X_j} = (X_{1j}, X_{2j}, \cdots, X_{Qj}) \tag{6}$$

where the qth $(q = 1,2,\cdots,Q)$ component of vector X_{qi} is:

$$X_{qi} = \frac{\sum_{i=1}^{m_j} X_{qi}(j)}{m_j} \tag{7}$$

where $X_{qi}(j)$ is the value of the qth attribute of the sample i in the cluster j.

(6) The stop rule. After each iteration, calculate the distance between the old and new centroids before and after each cluster iteration. For example, after the tth iteration, the distance between the new and old centroid of the jth cluster is: $\|C_j(t) - C_j(t-1)\|$, where $C_j(t)$ is the centroid vector of the jth cluster at the tth iteration, $C_j(t-1)$ is the centroid vector at the previous iteration. Thus, k clusters produce k results. Select the maximum value $\max_j \|C_j(t) - C_j(t-1)\|$, and the algorithm terminates if the maximum value is less than the predefined tolerance for differences. Otherwise, keep iterating.

IV. Simulation Experiment of Geological Identification

A. Data Sample Overview

The data in this paper come from some sections of subway construction project in China. The shield tunneling parameters are collected under gravel sand clay, silty clay and gravel soil, including total thrust, tunneling speed and earth pressure in sealed cabin. There are 147 groups of data in this experiment, and each group of data includes three characteristic attributes: total thrust, tunneling speed and earth pressure. There are 39 groups sample data of silty clay, 67 groups sample data of gravel soil and 41 groups sample data of gravel sand soil . In order to analyze conveniently, the dynamic change process of the three parameters under different geological conditions is presented in a graphic form, as shown in Fig. 2-Fig. 4.

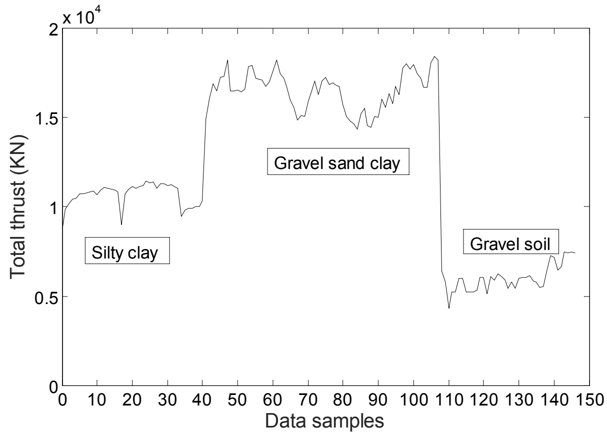

Fig. 2 The data sample of total thrust in different geology

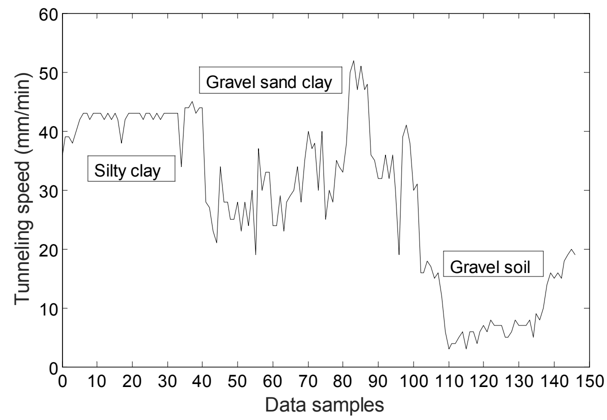

Fig. 3 The data sample of tunneling speed in different geology

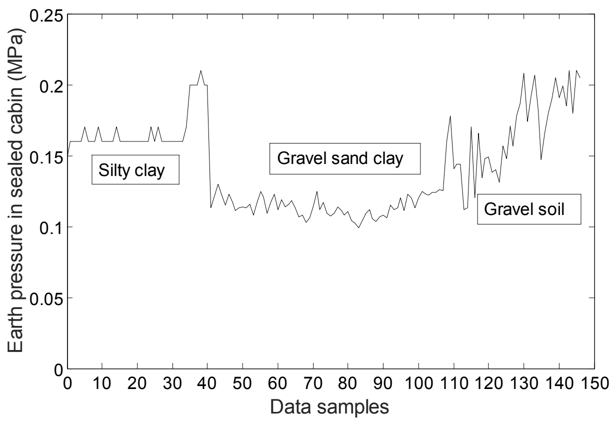

Fig. 4 The data sample of earth pressure in different geology

As can be seen from Fig. 2-Fig. 4, the change trends of total thrust, tunneling speed and earth pressure in different geological conditions are obvious and different. Among them, the change of total thrust is the most obvious in the three geological types. The fluctuation of tunneling speed is relatively large in gravel soil, and the fluctuation of earth pressure is relatively large in gravel sand clay.

B. Results and Analysis of Geological Identification

According to the 147 groups of data under silty clay, gravel sand clay and gravel soil, the data tree of the sample data is constructed, and the K value is determined according to the structure of the data tree. Then, the K-Means cluster analysis of the sample data is carried out. For the construction of the data tree, the Euclidean distance method is used to calculate the distance between samples, and the average distance method is used to construct the system data tree. The data tree constructed by data sample is shown in Fig. 5.

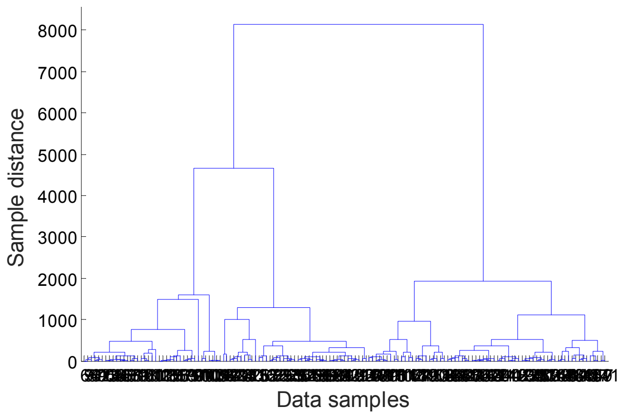

Fig. 5 The data tree constructed based on data samples

Analyze the data samples through the data tree construction. In Fig. 5, the vertical coordinate is the sample data distance, and the horizontal coordinate is the sample data number. When the sample distance is 3000, the clustering result of the sample data can reach the best effect, which accords with the actual geological category number of the sample data. Therefore, the number of branch nodes of the data tree is determined to be $K=3$ corresponding to the sample distance of 3000. After getting the K value from the data tree, the geological classification is identified by cluster analysis. The data samples of the three kinds of geology are marked with different graphic symbols, so as to check the accuracy of the cluster result of geological identification. The marked result is shown in Fig. 6.

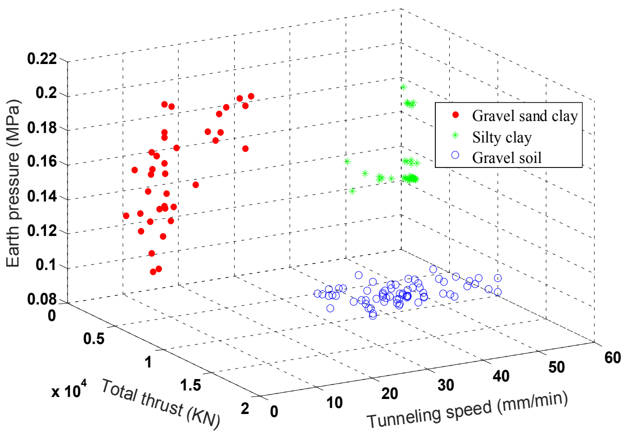

Fig. 6 The data samples marked by geological type

Fig. 6 shows the distribution of sample points in space. The geological classification result is marked as follow: gravel sand clay is marked dot, silty clay is marked star, gravel soil is marked hollow circle. The sample data are analyzed by cluster analysis, and the cluster classification is matched with the geological classification which achieves the aim of geological identification. Check the accuracy of geological identification comparing with the marked results of geological classification in Fig. 6. In cluster analysis, cross symbol is used to mark gravel sand clay geology, x symbol is used to mark silty clay geology, and pentagram symbol is used to mark gravel geology. The analysis results of data tree K-Means cluster algorithm are shown in Fig. 7.

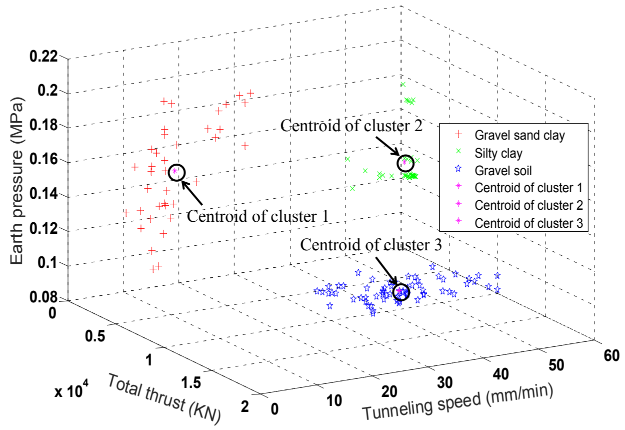

Fig. 7 Results of geological identification

As can be seen from Fig. 7, the sample data of each symbol are grouped together, and the asterisk is the centroid of the cluster, which proves the cluster result is correct. Through the comparison of Fig. 7 and Fig. 6, it can be seen that the cross symbol corresponds to the dot, and the x symbol corresponds to the star symbol, which indicates that the silty clay geology is correctly recognized. The pentagram symbol corresponds to the hollow circle symbol, which indicates that the gravel soil geology is correctly recognized.

In order to further analyze the accuracy of geological identification, the confusion matrix is introduced to verify the identification results. Confusion matrix, also known as error matrix, is a standard form of precision evaluation, which is expressed by the matrix of rows and columns. In unsupervised learning, the confusion matrix is a visualization tool, where each row of the matrix represents the predicted value and each column represents the actual value. The experimental data include: 39 groups of sample data in silty clay, 41 groups of sample data in gravel sand clay, 67 groups of sample data in gravel soil. The confusion matrix of the evaluation of geological classification results is shown in Eq. (8).

$$confMat=\begin{pmatrix}39&0&0\\0&41&0\\0&0&67\end{pmatrix} \tag{8}$$

The confusion matrix of classification results is shown as diagonal matrix, and the values on diagonal represent the values of the correct results for the predicted category. The diagonal values of the confusion matrix are 39, 41 and 67, and the number of sample groups corresponding to the three geological classes are 39, 41 and 67 respectively. The results are the same, which shows that the predicted results of the geological identification are the same as the actual situation.

So, the precision rate of geological identification is 100%. This also proves the effectiveness of the proposed method.

C. Effectiveness Comparison of The Methods

In order to verify the effectiveness of the proposed method, it is compared with BP neural network which is the common geological identification algorithm. 122 groups of samples are used as training set and 25 groups are used as test set in the sample data. The three characteristic attributes of the data sample are total thrust, tunneling speed and earth pressure of the sealed cabin, which are taken as the input of BP neural network, and the number of the geological categories is taken as the output of BP neural network. The BP neural network is trained with 122 groups of training samples, so the BP neural network model is obtained. Then the model is used to classify for the 25 groups of test samples. At the same time, the data tree K-Means cluster algorithm is used to identify the 25 groups of test samples. The comparison results of the two methods are shown in Fig. 8.

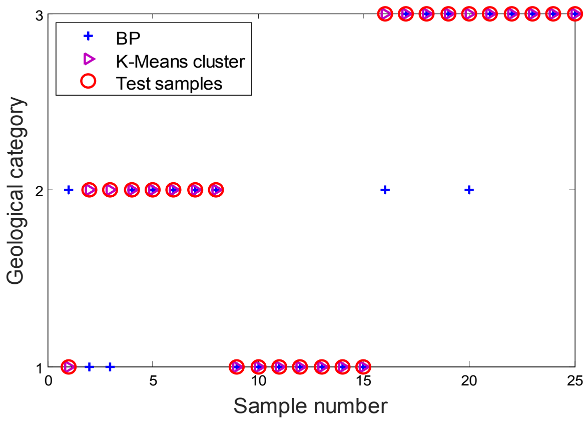

Fig. 8 Comparison of geological identification results between K-Means cluster and BP neural network

As shown in Fig. 8, the plus marks the results of geological identification by BP neural network, and the triangle marks the results of geological identification by K-Means cluster algorithm, and the hollow circle marks the actual geological category of the test samples. The samples number of the test set is 25. It can be seen from Fig. 8 that there are 5 groups of identification errors for the result of BP neural network, so the precision rate of geological identification is 80%. But the geological identification results of the K-Means cluster algorithm perfectly match with the real geology of the test set, so the precision rate is 100%.

V. Conclusion

In order to accurately identify the geology of underground construction, a data tree K-Means cluster method is proposed based on shield tunneling parameters. The correlation analysis method is introduced to determine the shield tunneling parameters which are most closely related to the geological conditions. Through the analysis, total thrust, tunneling speed and earth pressure are determined as the three attributes of the samples data set for geological recognition. The k value of K-Means cluster algorithm is optimized by data tree, and the geological recognition cluster algorithm is established based on shield tunneling parameters. The simulation results show the effectiveness of the proposed method and the conclusions are as follows:

(1) The k value is optimized effectively by K-Means cluster algorithm of data tree, and it is more scientific and reliable than the traditional method by experience. The data tree can also directly reflect the degree of affinity between the sample points.

(2) Compared with other methods, the method in this paper can identify the geological categories efficiently, and has higher accuracy. It shows that the data-driven method can effectively mine the stratum information and geological characteristics, and can accurately predict the geology. This provides a decision-making basis for the safe tunneling control. In the future, more shield tunneling parameters can be collected to construct a large number of data samples, so that a better geological classification model can be established. This will also provide theoretical reference for shield machine to realize intelligent geological identification.

References

[1] F. Ebrahim and R. Jamal, "Correlation of tunnel convergence with TBM operational parameters and chip size in the Ghomroud tunnel, Iran," Tunnelling and Underground Space Technology, vol. 23, no. 6, pp. 700-710, 2008.

[2] L. Stefan, G. Rüdiger, O. Peter, et al, "Seismic investigations of the Piora Basin using S-wave conversions at the tunnel face of the Piora adit (Gotthard Base Tunnel)," International Journal of Rock Mechanics & Mining Sciences, vol. 45, no. 1, pp. 86-93, 2008.

[3] A. H. Zettler, R. Poisel, D. Lakovits, et al, "Control system for tunnel boring machines (TBM): a first investigation towards a hybrid control system," International Journal of Rock Mechanics & Mining Sciences, vol. 35, no. (4-5), pp. 674, 1998.

[4] B. D. Zhu, G. F. Gong, R. L. Zhou, and G. B. Liu, "Identification of strata with BP neural network based on parameters of shield driving," Journal of Zhejiang University (Engineering Science), vol. 45, no. 5, pp. 851-857, 2011.

[5] J. D. Liu, J. B. Guo, and X. D. Wang, "Recognition methods for boulder geology based on shield tunneling parameters," Tunnel Construction, vol. 39, no. 7, pp. 1132-1140, 2019.

[6] C. M. Shao, "Identification of strata with LVQ neural network based on shield tunneling parameters," Journal of Shijiazhuang Tiedao University (Natural Science), vol. 29, no. 1, pp. 93-96, 2016.

[7] C. Li, T. Li, Z. Li, and J. W. Zhan, "Prediction and analysis of shield boring parameters in a mixed ground based on BP neural network," China Civil Engineering Journal, vol. 50, no. S1, pp. 145-150, 2017.

[8] G. H. Cui, G. Q. Wang, E. G. He, and X. W. Gao, "Calculation and analysis to the main technical parameters of the tunnel boring machine," Mining & Processing Equipment, no. 12, pp. 11-14, 2006.

[9] X. H. Yang, "Study on boring parameters of composite EPB shield in sandy cobble strata and study on ground deformation rule," Tunnel Construction, vol. 34, no. 8, pp. 721-730, 2014.

[10] Q. Lv and D. M. Fu, "Research on torque of cutterhead for earth pressure balance shield with simulation experimental,"Chinese Journal of Rock Mechanics and Engineering, vol. 25, no. (supp.1), pp. 3138-3143, 2006.

[11] A. W. Rosyadi and N. Suciati, "Image segmentation using transition region and K-Means clustering," IAENG International Journal of Computer Science, vol. 47, no. 1, pp. 47-55, 2020.