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Heterogeneity identification method for surrounding rock of large-section rock tunnel faces based on support vector machine

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Abstract

Purpose – The purpose of the study is to quickly identify significant heterogeneity of surrounding rock of tunnel face that generally occurs during the construction of large-section rock tunnels of high-speed railways.

Design/methodology/approach – Relying on the support vector machine (SVM)-based classification model, the nominal classification of blastholes and nominal zoning and classification terms were used to demonstrate the heterogeneity identification method for the surrounding rock of tunnel face, and the identification calculation was carried out for the five test tunnels. Then, the suggestions for local optimization of the support structures of large-section rock tunnels were put forward.

Findings – The results show that compared with the two classification models based on neural networks, the SVM-based classification model has a higher classification accuracy when the sample size is small, and the average accuracy can reach 87.9%. After the samples are replaced, the SVM-based classification model can still reach the same accuracy, whose generalization ability is stronger.

Originality/value – By applying the identification method described in this paper, the significant heterogeneity characteristics of the surrounding rock in the process of two times of blasting were identified, and the identification results are basically consistent with the actual situation of the tunnel face at the end of blasting, and can provide a basis for local optimization of support parameters.

Keywords Rock tunnel, Surrounding rock, Heterogeneity, Support vector machine, High-speed railway

Paper type Research paper

1. Introduction

The excavation section area of single-tube double-track rock tunnel of a high-speed railway can reach 160 m^2. Affected by factors such as faults, dense joints, local weathering and stratigraphic boundaries, surrounding rocks of the tunnel face often reveal the heterogeneity characteristics during construction, which requires local optimization and adjustment to some design parameters in time. Currently, the heterogeneity is mainly identified by the on-site geological personnel, but this single means is of poor time efficiency and affected by the technical level of geological personnel. With continuous improvement of the development level of large construction equipment for rock tunnels in China, computer-controlled drill jumbos are being used more and more widely, and it is possible to judge the heterogeneity of surrounding rocks of the tunnel face according to their drilling parameters.

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Scholars at home and abroad have begun to use drilling parameters to identify the weathering degree and structural plane of stratum lithology a long time ago. In 1997, Honer and Sherrell (1977) started to use drilling technologies to evaluate stratum lithology. More recently, Qin, Wang, Pan, Sun, and Liu (2018) acquired the vibration spectrum and acoustic spectrum generated during the drilling process through tests, and then distinguished the stratum lithology. Tan, Yue, and Cai (2007), Tan, Cai, Yue, Tan, and Li (2006, 2007), Tan, Yue, Tan, and Li (2008), Tan *et al.* (2015), Yue (2014) carried out a series of studies on stratum information identification based on the hole drilling parameters during geological exploration and established a geo-formation identification while drilling (GIWD) system, to identify the stratum information including stratum lithology, weathering degree and geological interface. Niu, Zhang, Yu, Chen, Wu, and Liu (2019), by carrying out real-time comprehensive tests, analyzed the relationship between blasthole drilling parameters and surrounding rock types of coal mines, and identified the surrounding rock types of roadways. In order to make better use of drilling parameters, geological survey equipment companies in other nations have also developed rapid drilling and testing systems, such as DEFI of JEAN LUTZ, France, EXPLOFOR of Apageo, France, and MWD of KOKEN, Japan.

In recent years, with the deepening of machine learning research, machine learning theory is being applied to rock mass quality analysis gradually. Wedge, Hartley, Mcmickan, Green, and Holden (2019) used convolutional neural networks and the drilling parameters acquired during mineral prospecting to judge the stratum lithology, stratum boundary and other relevant information through algorithms and compared them with the manual judgment results. Zang (2006) normalized the petrofabric type, rock mass structure, joint development degree and other rock mass quality information by introducing the BP neural network principle to qualitatively forecast the rock mass quality. Nishitsuji and Exley (2019) compared the performance of support vector machine, deep learning and linear classifier, Bayesian classifier and other models in the classification of lithofacies types. They believed the deep learning method is more likely to become the dominant method for lithology classification in the future. Valentín *et al.* (2019) created a borehole image data classification model through the deep residual network by using the logging data obtained by ultrasonic and micro-resistivity imaging as the input; through this model, they identified four types of lithology, namely, calcareous rock, diabase, shale and siltstone. Cai (2002) selected seven types of parameters, including surrounding rock strength, gravity stress, rock mass integrity and mining influence, as the input into the neural network and, on this basis, identified the stability of surrounding rocks in roadway engineering. Research of the above scholars shows that it is feasible to use machine learning theory and drilling parameters to identify stratum lithology, stratum thickness, joint development degree and other geological structure information, but deep research is required in terms of further quantitatively identifying the conditions of surrounding rocks in different areas of the large-section rock tunnel face in practical engineering, evaluating the heterogeneity characteristics and guiding the adjustment of design parameters.

In this paper, based on the analysis of the rock breaking energy conversion relationship of the drill jumbo bit and the 299 samples recorded in the blasthole drilling process of Zhengzhou-Wanzhou high-speed railway tunnel, the author confirmed that four drilling parameters are strongly correlated with the surrounding rock class through the Pearson correlation coefficient and, on this basis, created a surrounding rock classification sample database for large-section rock tunnel faces. For the general geological conditions of Class III, IV and V surrounding rocks in large-section rock tunnels of high-speed railways, a surrounding rock classification model for large-section rock tunnel faces based on support vector machine (SVM) and 2 kinds of neural networks was built, and the same data were used to compare the performance of the three models. Relying on the SVM-based classification model, the nominal classification of blastholes and nominal zoning and classification terms were used to describe the heterogeneity identification method for the rock of tunnel faces, and the identification calculation was carried out for the 5 test tunnels of Zhengzhou-Wanzhou high-speed railway. Then, for the relatively poor rock parts of the arches and surrounding rocks of side walls of the large-section rock tunnels, suggestions for local optimization of support parameters were put forward.

2. Surrounding rock classification sample database for large-section rock tunnels based on machine learning

2.1 Energy conversion relationship of computer-controlled three-boom drill jumbo

The rock breaking process of the drill jumbo bit includes three motions overall: impact, rotation and propulsion. During specific working, the drill bit impacts the rock mass in front to break the rock through the impact motion, strips the inner wall of borehole while rotating to break the rock through the rotation motion and keeps in contact with the rock under the driving force through the propulsion motion. ZYS113 computer-controlled three-boom drill jumbo, independently developed by China, was used in the whole rock breaking process of Zhengzhou-Wanzhou high-speed railway, and the working process of its drill boom is shown in Figure 1.

If the moving drill bit in the drilling process is regarded as a particle, according to the principle of energy conservation, the energy conversion relationship of the work is made by the rig power system of the drill jumbo (Tan *et al.*, 2007) is

$$P = P_{\mathrm{k}} + P_{\mathrm{d}} + P_{\mathrm{f}} \tag{1}$$

where

$$P_{\mathrm{k}} = \frac{1}{2} m v^2$$

$$P_{\mathrm{d}} = F_{\mathrm{d}} S$$

where P is the total energy output by the rig power system, J; P_{k} is the kinetic energy generated by the bit during drilling, J; P_{d} is the shaft work done by the rig power system in the process of driving the impact motion of the bit, J; P_{f} is the friction work during the drilling process of the rig, J; m is the mass of the bit, kg; v is the feed speed recorded by the drill jumbo, m s^{-1}; F_{d} is the impact pressure recorded by the drill jumbo, bar; S is the absolute displacement of the bit during impact, m.

The surrounding rock class can well reflect the quality of surrounding rocks and the total energy required to be output by the rig power system. It is generally recognized that the higher the surrounding rock class, the poorer the quality of surrounding rocks, and the lower the energy required for rock breaking; and the lower the surrounding rock class, the better the quality of surrounding rocks, and the higher the total energy required to be output by the rig power system.

The friction work P_{f} during the drilling process of the rig consists of two parts: one part of the energy is used for the friction of the rig and finally is dissipated in the form of sound and

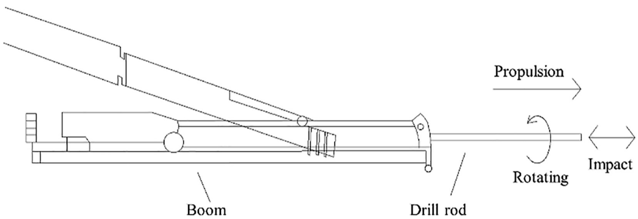

Figure 1.
Working process of ZYS113 computer-controlled three-boom drill jumbo

heat; and the other part of the energy is used for the borehole bottom friction and lateral friction in the drilling process of the bit, that is, the effective work (friction work) for rock breaking. Since the friction loss of the rig is negligible, it is not taken into account in this paper. Then, the friction work during the drilling process of the rig in unit time is

$$P_{\mathrm{f}} = P_{\mathrm{fb}} + P_{\mathrm{fs}} \tag{2}$$

where

$$P_{\mathrm{fb}} = \pi D F_{\mathrm{h}} n$$

$$P_{\mathrm{fs}} = F_{\mathrm{t}} \Delta S$$

where P_{fb} is the energy consumed by the friction between drill rod and borehole wall in unit time, J; P_{fs} is the energy for rock breaking by lateral friction during the rotation of the bit in unit time, J; D is the diameter of the bit, m; F_{h} is the rotational pressure recorded by the drill jumbo, bar; n is the rotary speed of the bit, $\mathrm{r \cdot s^{-1}}$; F_{t} is the propulsion pressure recorded by the drill jumbo, bar; ΔS is the absolute displacement of the bit during the propulsion motion, m.

According to the energy conversion relationship, in the process of tunnel face blasthole drilling, the effective work input by the computer-controlled three-boom drill jumbo is related to four drilling parameters: feed speed, impact pressure, propulsion pressure and rotary pressure. Therefore, when studying the machine learning model, we can establish the requirements for data type according to the derivation results of the energy conversion relationship and the specific form of the machine learning model. In the training process of the machine learning model, the input layer data and output layer data can be manually assigned. Therefore, the four drilling parameters can be considered as the input layer data of the surrounding rock classification model for large-section rock tunnels, and the surrounding rock class data can be considered as the output layer data.

2.2 On-site acquisition of drilling parameters and surrounding rock class data

Considering the creation of the surrounding rock classification sample database later and the generalization of the samples in the database, according to the actual construction schedule, five large-section rock tunnels of Zhengzhou-Wanzhou high-speed railway, including Xiangjiawan, Xinhua, Chufeng, Gaojiaping and Xiangluping tunnels, were selected as the test tunnels for the on-site acquisition of drilling parameters and surrounding rock class data. Class III, IV and V surrounding rocks can be found in the strata where the five test tunnels pass through. There is no special geological environment along these tunnels, and the main lithology is limestone, dolomite and shale.

According to the *Code for Design of Railway Tunnel* (National Railway Administration of the People's Republic of China, 2017), surrounding rock class is comprehensively determined by two methods: qualitative classification and quantitative index. The rock classification steps are as follows: obtaining the qualitative description of the rock hardness and rock mass integrity through geological sketch of the tunnel face on site; preliminarily obtaining the value of the quantitative rock classification index I_{BQ} by carrying out the rebound test, compressive strength test and wave velocity test of rock and the wave velocity test of rock mass, and then obtaining the value of the corrected $I_{[\mathrm{BQ}]}$ by introducing the indices of groundwater, geostress and main structural plane occurrence.

The calculation methods of the BQ value I_{BQ} and corrected BQ value $I_{[\mathrm{BQ}]}$ of the quantitative indexes of surrounding rocks are as follows:

$$I_{\mathrm{BQ}} = 100 + 3R_{\mathrm{c}} + 250K_{\mathrm{v}} \tag{3}$$

where R_c is the saturated uniaxial compressive strength of rock, reflecting the hardness of rock, MPa; K_v is the rock mass integrity.

$$I_{[BQ]} = I_{BQ} - 100(K_1 + K_2 + K_3) \tag{4}$$

where K_1 is the correction coefficient for influence of groundwater; K_2 is the correction coefficient for the occurrence of major weak structural plane; and K_3 is the correction coefficient for influence of initial geostress.

In practical engineering, the determination of surrounding rock class is mainly qualitative, supplemented by quantitative determination. The geological sketch of the tunnel face in test tunnels was acquired as the qualitative determination result. The values of I_{BQ} and corrected $I_{[BQ]}$ of surrounding rocks were calculated as the quantitative determination result through a few rebound tests, compressive strength tests and wave velocity tests of rock and the wave velocity tests of rock mass. The four drilling parameters of the target tunnel face were acquired to determine the surrounding rock class of the tunnel face by means of mutual verification of quantitative and qualitative determination results.

2.3 Analysis of correlation between drilling parameters and surrounding rock class

At the beginning of blasthole drilling, ZYS113 computer-controlled three-boom drill jumbo can automatically record the blasthole position information. During blasthole drilling, the drill jumbo will automatically record and save the four blasthole drilling parameters – feed speed, impact pressure, propulsion pressure and rotation pressure – when drilling each 20 mm. This function of the drill jumbo – automatically recording the blasthole position information and collecting four drilling parameters of each blasthole on each tunnel face in real time – lays a technical foundation for the creation of the surrounding rock classification database.

For each test tunnel, if each blasthole on the tunnel face and the drilling data recorded for each blasthole have the same weight, the surrounding rock class of the tunnel face corresponding to the geological sketch of the tunnel face and the average value of each drilling parameter recorded for all blastholes can be obtained by calculating the average value of each drilling parameter of each blasthole and the average value of each drilling parameter of all blastholes on the tunnel face. The scatter diagrams of the average values of four drilling parameters of Class III, IV and V surrounding rocks in five test tunnels are drawn, as shown in Figure 2. Figure 2 shows that there is obvious stratification among the feed speed, impact pressure, propulsion pressure and rotation pressure under different surrounding rock classes.

The introduction of an irrelevant variable will reduce the accuracy of the classification model; thus, for a classification model based on machine learning, it is required to judge whether variables are strongly correlated – the positive or negative correlation between variables does not affect the model. Therefore, the Pearson correlation coefficient is used to quantitatively evaluate the correlation between each drilling parameter and the surrounding rock class, and the absolute value of Pearson correlation coefficient is used to measure the correlation degree between each drilling parameter and the surrounding rock class.

The Pearson correlation coefficient $\Upsilon = -1$ indicates the absolute negative correlation between the two variables. $\Upsilon = 1$ indicates the absolute positive correlation, and $\Upsilon = 0$ indicates no correlation. Its calculation formula is

$$\Upsilon = \frac{\sum_{i=1}^{N}\left(x_i - \overline{x}\right)\left(y_i - \overline{y}\right)}{\sqrt{\sum_{i=1}^{N}\left(x_i - \overline{x}\right)^2}\sqrt{\sum_{i=1}^{N}\left(y_i - \overline{y}\right)^2}}$$

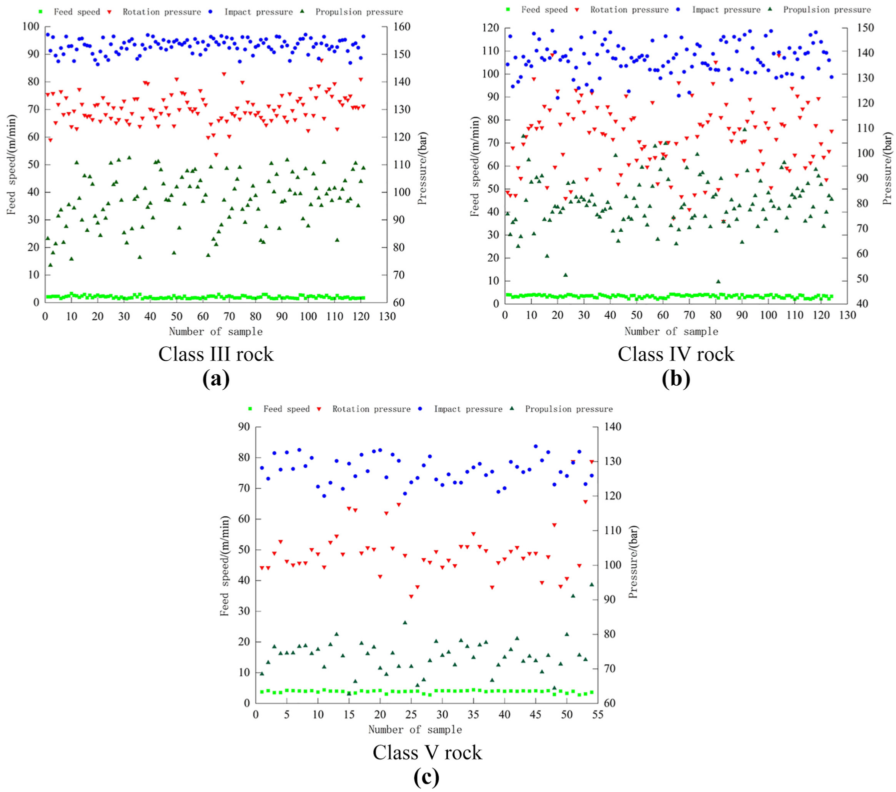

Figure 2. Distribution of rock drilling parameters under different surrounding rock classes

$$\Upsilon \in [-1, 1] \tag{5}$$

where x_i is the average value of each drilling parameter of a single tunnel face in the samples; $\overline{x}$ is the average value of each drilling parameter of all sample tunnel faces; y_i is the surrounding rock class of a single tunnel face; $y_i \in \{III, \mathrm{IV}, \mathrm{V}\}$, i is the number of each sample tunnel face; $\overline{y}$ is the average value of the surrounding rock classes of all sample tunnel faces; and N is the maximum number of the sample tunnel face.

The calculation results of the Pearson correlation coefficients between drilling parameters and surrounding rock classes are shown in Table 1. It can be seen from Table 1 that each of the four drilling parameters has a strong correlation with the surrounding rock class. To be specific, the feed speed is positively correlated with the surrounding rock class, which indicates that the greater the feed speed, the higher the surrounding rock class; the propulsion pressure, impact pressure and rotation pressure are negatively correlated with the surrounding rock class, which demonstrates that the larger the values of the three parameters, the lower the surrounding rock class (see Table 2).

2.4 Creation of surrounding rock classification sample database for large-section rock tunnel faces

The steps are as follows: carrying out the geological sketch, wave velocity test and saturated uniaxial compressive strength test of the tunnel faces by using the five test tunnels;

identifying the surrounding rock classes of the 299 sample tunnel faces; and mutually verifying the obtained results of the geological sketch, wave velocity test and saturated uniaxial compressive strength test. Therefore, the ZYS113 computer-controlled three-boom drill jumbo was used to obtain the drilling parameters of the sample tunnel faces, creating a surrounding rock classification sample database for large-section rock tunnel faces. In this database, the tunnel name, four drilling parameters, surrounding rock class, main lithology and geological sketch of the tunnel face constitute the main body, and the results of the rebound test, the compressive strength test and the wave velocity test of rock and the wave velocity test of rock mass constitute the secondary geological information.

3. Surrounding rock classification model for large-section rock tunnel faces based on machine learning

According to the surrounding rock classification sample database for large-section rock tunnel faces created in this paper, a surrounding rock classification model for large-section rock tunnel faces based on support vector machine and two kinds of neural networks was built, respectively, and the accuracy of the three models was compared in two cases: prediction set and sample replacement.

3.1 Surrounding rock classification model for large-section rock tunnel faces based on support vector machine

Essentially, it is problematic determining the surrounding rock class of large-section rock tunnel face. Due to the unfavorable on-site construction environment and construction

Table 1.
Pearson correlation coefficients between drilling parameters and surrounding rock class

Drilling parameter	Average value of the drilling parameter $\bar{x}$	Average value of the surrounding rock class $\bar{y}$	Pearson correlation coefficient Υ
Feed speed /$(\mathrm{m \cdot min^{-1}})$	2.914 7	3.775 9	0.806 8
Impact pressure /bar	118.185 1	3.775 9	−0.898 4
Propulsion pressure /bar	67.267 9	3.775 9	−0.441 0
Rotation pressure /bar	85.787 2	3.775 9	−0.684 8

Table 2.
Surrounding rock classification sample database for large-section rock tunnel faces

Surrounding rock class	Tunnel name	Main lithology	Sample size: Geological sketch	Sample size: Drilling parameter
III	Xinhua	Dolomite, slate, shale	24	24
	Xiangjiawan	Shale, limestone	97	97
IV	Gaojiaping	Shale, limestone	21	21
	Chufeng	Dolomite, etc.	18	18
	Xinhua	Dolomite, slate, shale	44	44
	Xiangjiawan	Shale, limestone	6	6
	Xiangluping	Mudstone	35	35
V	Gaojiaping	Shale, limestone	46	46
	Xinhua	Dolomite, slate, shale	8	8
Total			299	299

schedule, collectable sample size is small. Therefore, the support vector machine (SVM) method was adopted in the study since it can solve the classification problem well, prevent the "curse of dimensionality" and ensure good "robustness." As a typical machine learning method, SVM (Burges, 1998; Cortes & Vapnik, 1995; Dietrich, Opper, & Sompolinsky, 1999; Zhao, 2005) theoretically provides a way to avoid high-dimensional space complexity and directly solve the corresponding high-dimensional space classification decision-making problem through the inner product function (kernel function). The kernel function form in the model is given manually, thus avoiding the "curse of dimensionality" and guaranteeing the accuracy of the model even if the sample size is small.

The surrounding rock classification model for large-section rock tunnel faces based on SVM ("SVM-based classification model") consists of the input layer, the hidden layer and the output layer. The input layer contains four nodes which are the four drilling parameters mentioned above: feed speed, impact pressure, propulsion pressure and rotation pressure. The hidden layer contains 62 nodes; and the output layer contains one node, the surrounding rock class. The input and output layer data need to be assigned manually. Based on the surrounding rock classification sample database for large-section rock tunnel faces, a machine learning database of the surrounding rock classification model for large-section rock tunnel faces was created. The database consists of a training set and a prediction set. A total of 150 samples were randomly selected from the sample library as the training set for model building, and the other 149 samples were used as the prediction set to verify the model accuracy. Table 3 illustrates the number of samples in training set and prediction set of the database under different surrounding rock classes.

The traditional function fitting method is to establish the low-dimensional mapping relationship between the four drilling parameters and the surrounding rock classes. This method can reduce the calculation workload, but its accuracy is greatly affected by the mapping function. In order to solve this problem, in this paper, the four nodes of the input layer are nonlinearly transformed to map the data in the input layer to a high-dimensional feature space. In the SVM-based classification model structure obtained, the input layer contains four nodes, the hidden layer 62 nodes and the output layer one node. The radial basis function (RBF) is selected as the kernel function type. The penalty factor C is the weight of the interval size and classification accuracy preference in the adjustment and optimization direction, that is, the tolerance to error. A larger value of C means less tolerable to error, and the over-fitting is more likely to occur. A smaller value of C means the under-fitting is more likely to occur. No matter the value of C is too large or too small, the generalization ability of the model will be deteriorated. In this paper, $C = 1.4$. γ is a parameter of the RBF function. It decides the distribution plane of the four drilling parameters after they are mapped onto the new feature space. The larger the value of γ, the less the support vectors. The smaller the value of γ, the more the support vectors. In this paper, $\gamma = 51.2$. The number of support vectors determines the number of iterations, so the more the number of support vectors, the larger the number of iterations. The larger the number of iterations, the more likely over-fitting will occur. On the contrary, the smaller the number of iterations, the lower accuracy the rock classification mode will tend to have. In this paper, the number of support vectors is 62.

Surrounding rock class	Number of samples: Training set	Number of samples: Prediction set
III	61	60
IV	62	62
V	27	27
Total	150	149

Table 3. Number of samples in machine learning database of surrounding rock classification model for large-section rock tunnel faces

In the process of model building, a classification hyperplane needs to be built first. The classification hyperplane Y can be expressed as

$$\begin{cases} Y = \mathrm{sign}[(\boldsymbol{w} \cdot \boldsymbol{x}) + b] \\ Y \geq 1 \end{cases} \tag{6}$$

where sign(.) is the sign function; $\boldsymbol{w}$ is the weight vector; $\boldsymbol{x}$ is the input vector, that is drilling parameters; and b is the threshold.

In the high-dimensional feature space, the following decision function for classification is used to output the surrounding rock class:

$$y = \mathrm{sign}\left[\sum_{j=1}^{62} \lambda K(\boldsymbol{x}, \boldsymbol{x_j}) + b\right] \tag{7}$$

where

$$K(\boldsymbol{x}, \boldsymbol{x}_j) = \exp\left(-\gamma \|\boldsymbol{x} - \boldsymbol{x}_j\|^2\right) \gamma > 0$$

where λ is the multiplying factor; $K(\boldsymbol{x}, \boldsymbol{x}_j)$ is the kernel function of the support vector machine, representing the normalization result of the surrounding rock class values, where $\boldsymbol{x}_j$ is the output value corresponding to each input vector after high-dimensional mapping.

Samples in prediction set are input to the SVM-based training model for large-section rock tunnels for calculation, and the surrounding rock classification accuracy of the samples in the prediction set is used to represent the applicability of the classification model under the general geological conditions of large-section rock tunnels. The accuracy calculation method is:

$$A_c = \frac{a_y}{A_y} \tag{8}$$

where A_c is the accuracy of a surrounding rock class; a_y is the number of a surrounding rock class accurately identified by the SVM-based classification model; and A_y is the total number of that surrounding rock class identified.

The SVM-based classification model was used for the calculation of the samples in the prediction set, and the classification accuracy obtained is shown in Table 4. Table 4 shows that the classification accuracy of SVM-based classification model is 93.7% for Class III surrounding rock, 89.3% for Class IV surrounding rock and 73.3% for Class V surrounding rock. The average accuracy of the prediction set is defined as the ratio of the number of the samples correctly identified by the SVM-based classification model for large-section rock tunnels to the total number (149) of samples in the prediction set, and the accuracy of the calculated result is 87.9%.

Table 4.
Identification results of samples in prediction set obtained by SVM-based classification model

Surrounding rock class	Actual number	Number of samples correctly identified by SVM-based classification model	Accuracy/%
III	63	59	93.7
IV	56	50	89.3
V	30	22	73.3

3.2 Surrounding rock classification model for large-section rock tunnel faces based on neural networks

The surrounding rock classification model for large-section rock tunnels based on two common neural networks – radial basis function (RBF) and back propagation (BP) – was built, respectively. Considering the types of actual input and output data, model calculation time and other relevant factors in this paper, the parameters of the surrounding rock classification model for large-section rock tunnels based on two neural networks are shown in Table 5. By using the samples in the training set and prediction set of the SVM-based model, the identification results of the samples in the prediction set were calculated by the surrounding rock classification model for large-section rock tunnels based on the two neural networks, as shown in Table 6. Table 6 shows that with the same training set and prediction set, the surrounding rock classification model for large-section rock tunnels based on RBF neural network ("RBF-based classification model") has a prediction set classification accuracy of 76.5%. The surrounding rock classification model for large-section rock tunnels based on BP neural network ("BP-based classification model") has a prediction set classification accuracy of 85.9%. Both of them are lower than the accuracy of the SVM-based classification model, which is 87.9%.

3.3 Comparison among surrounding rock classification models for large-section rock tunnel faces based on different machine learning

In order to further verify the generalization of the surrounding rock classification models for large-section rock tunnel faces, field tests were carried out in the test tunnels. A total of 14 new samples were collected from Xinhua Tunnel and Gaojiaping Tunnel with diverse lithological distribution and complex distribution of surrounding rock classes, and these new samples were identified one by one by the classification models based on SVM and two neural networks, respectively. The comparison between the identification results and actual results are shown in Table 7. According to the identification results, the accuracies of new samples

Model	Number of input layer nodes	Number of hidden layers	Number of hidden layer nodes	Number of output layer nodes	Objective function	Number of iterations
RBF-based classification model	4	1	150	1	Mean square error	150
BP-based classification model	4	3	9	1	Mean square error	9

Table 5. Parameters of classification models based on two neural networks

Surrounding rock class	Prediction set identification results RBF-based classification model			Prediction set identification results BP-based classification model		
	Actual number of samples	Number of samples correctly identified by the model	Accuracy/%	Actual number of samples	Number of samples correctly identified by the model	Accuracy/%
III	63	54	85.7	63	60	95.2
IV	56	41	73.2	56	48	85.7
V	30	18	63.3	30	20	66.7

Table 6. Prediction set identification results of classification models based on two neural networks

Table 7.
Comparison between identification results of surrounding rock classification model for large-section rock tunnel face and actual surrounding rock classes

Sample no	Tunnel name	Chainage	Actual surrounding rock class	Identification results of different surrounding rock classification models SVM	RBF	BP
1	Gaojiaping	DK451 + 300	III	III	III	III
2	Gaojiaping	DK451 + 304	III	III	III	III
3	Gaojiaping	DK451 + 308	III	III	III	III
4	Gaojiaping	DK451 + 312	III	III	III	III
5	Gaojiaping	DK451 + 316	III	III	III	III
6	Xinhua	DK552 + 884	III	III	III	III
7	Xinhua	DK552 + 888	III	III	IV	III
8	Xinhua	DK552 + 892	III	III	IV	III
9	Gaojiaping	DK451 + 337	III	IV	IV	IV
10	Gaojiaping	DK451 + 500	IV	IV	IV	IV
11	Gaojiaping	DK451 + 000	IV	IV	IV	V
12	Gaojiaping	DK452 + 003	IV	IV	IV	IV
13	Xinhua	DK545 + 394	V	V	IV	IV
14	Xinhua	DK454 + 396	V	V	V	V

under the classification models based on three different types of machine learning were further obtained, as shown in Table 8. It can be seen from Table 7 and Table 8 that in the case of sample replacement, the SVM-based classification model has a higher accuracy and better generalization than the two neural network-based classification models.

The comprehensive analysis of Table 4 - Table 8 shows that, in the case of a small sample size, the SVM-based classification model has better "robustness" than the RBF-based and BP-based classification neural networks models. This verifies the research results of Zhu, Pan, Zhang, Wang, Gu, and Xu (2007). With the same sample size, different classification methods produce different classification results, but with the increase of sample size, the classification accuracy of SVM-based classification model continuously rises.

Due to the limitation of site conditions, the samples collected were limited. Due to the complicated and random distribution of geological conditions of the surrounding rock, the classification accuracy of each surrounding rock classification model for large-section rock tunnels is affected by the sample size to a large extent. Therefore, the SVM-based classification model still has identification errors in the prediction set and 14 new samples. The next step is to further acquire the drilling parameters and surrounding rock classes of the tunnel face on site to enlarge the sample size and improve the identification accuracy of surrounding rock classification of the tunnel face.

4. Rock heterogeneity identification of large-section rock tunnel faces

In tunnel engineering, the quality of rock mass directly affects the design of tunnel support structures. Rock mass quality scoring methods that characterize the quality of rock mass, such as the rock mass rating (RMR) analysis method and Q analysis method, function to quantitatively identify the quality of surrounding rock. However, in practical application in China, due to the limitation of on-site construction conditions, tunnel support structures are generally designed according to the index of surrounding rock class (National Railway Administration of the People's Republic of China, 2017), and the heterogeneity characteristics of different rock mass quality of tunnel face will directly affect the safety and economy of tunnel construction. In order to distinguish from the traditional surrounding rock classification of tunnel faces, this paper describes the heterogeneity identification method for the surrounding rock of tunnel faces by using the nominal classification of blastholes and

Surrounding rock class	Identification results of SVM-based classification model			Identification results of RBF-based classification model			Prediction set identification results BP-based classification model		
	Actual number of samples	Number of samples correctly identified by the model	Accuracy/%	Actual number of samples	Number of samples correctly identified by the model	Accuracy/%	Actual number of samples	Number of samples correctly identified by the model	Accuracy/%
III	9	8	88.9	9	6	66.7	9	8	88.9
IV	3	3	100.0	3	2	66.7	3	2	66.7
V	2	2	100.0	2	1	50.0	2	1	50.1

Table 8.
Comparison among accuracy of the classification models based on three different types of machine learning

nominal zoning and classification terms, and puts forward local optimization suggestions for the support structures of large-section rock tunnels.

In the process of a single blasting cycle, the heterogeneity identification process of the surrounding rock of tunnel face in SVM-based classification model is shown in Figure 3. During identification, the four drilling parameters of each blasthole on the tunnel face are used as input data for the nominal classification of each blasthole, and at the same time, the tunnel face zoning is conducted according to the information of blasthole position on the tunnel face. Then, in combination with the nominal classification of each blasthole and the details of the tunnel face zoning, the nominal zoning and classification of the tunnel face is carried out. Finally, the heterogeneity characteristics of the surrounding rock of large-section rock tunnel face are obtained through analysis according to the classification results.

4.1 Tunnel face zoning

For the five test tunnels of Zhengzhou-Wanzhou high-speed railway, the distribution of blastholes was drawn according to the tunnel blasting contour line and blasthole position information, as shown in Figure 4. Considering the actual tunneling conditions and the size effect of the rock mass itself, the tunnel face was divided into six layers and six columns (34 blocks in total) in a unit of 2 m, with the central axis of the tunnel as the datum line and the tunnel vault as the datum point. The zoning results of the tunnel face and the number of each zones are shown in Figures 5 and 6, respectively.

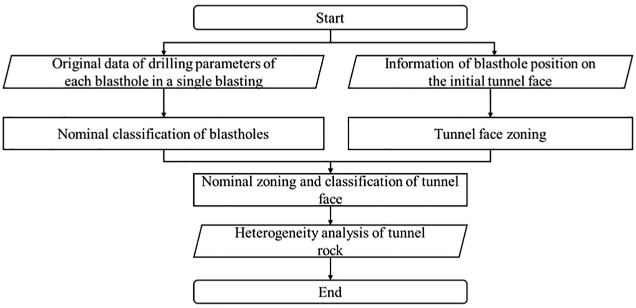

Figure 3.
Heterogeneity identification process of the surrounding rock of tunnel face

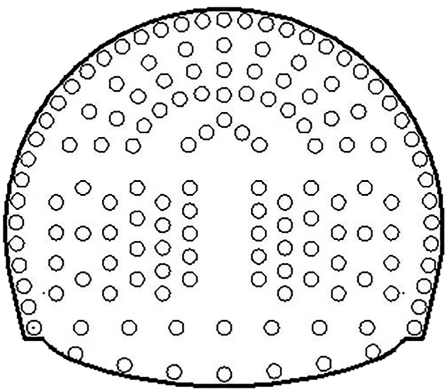

Figure 4.
Distribution of blastholes

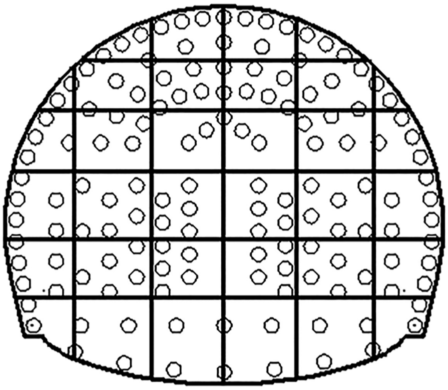

Figure 5.
Tunnel face zoning

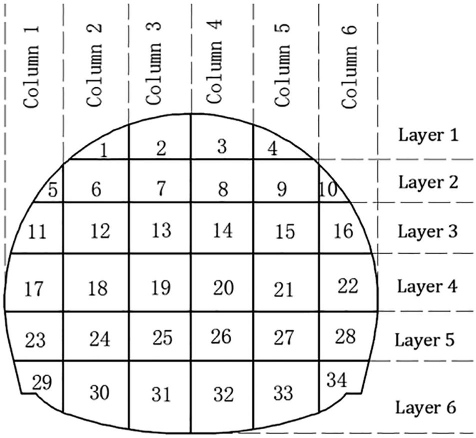

Figure 6.
Tunnel face numbering

4.2 Identification method and results

In the process of one blasting construction, the average value of each drilling parameter of each blasthole was acquired as the input data. Through the calculation of the classification model, the nominal classification diagram of blastholes on the tunnel face was obtained. The nominal classification diagram of blastholes was colored according to the nominal classification calculation results of blastholes, as shown in Figure 7. Dark blue indicates the nominal class of the blasthole is Class I, light blue Class II, green Class III, yellow Class IV, light red Class V and dark red Class VI. The higher the nominal class of the blasthole, the worse the rock mass quality in the blasthole area. The lower the nominal class of the blasthole, the better the rock mass quality in the blasthole area.

On the basis of nominal classification and zoning of blastholes on the tunnel face, the weighted average and rounding-off of the nominal classes of blastholes in each zone of the tunnel face were calculated to realize the nominal zoning and classification of the tunnel face, and then the heterogeneity of the surrounding rock of the tunnel face was analyzed in the manner of nominal zoning and classification. The formula to calculate the surrounding rock class of zone *s* of the tunnel face is

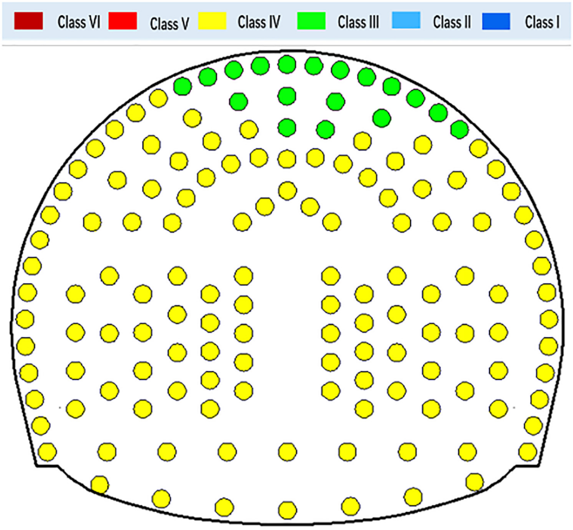

Figure 7.
Schematic diagram of color filling effect of nominal classification of blastholes

$$y_s = \mathrm{round}\left(\frac{\sum_{u=1}^{i_b} r_u}{i_b}\right) \tag{9}$$

where y_s is the surrounding rock class of zone s of the tunnel face; round (.) is a rounding function; r_n is the class of a single blasthole; u is the blasthole number; i_b is the number of blastholes in zone s of the tunnel face; and s is the zone number after tunnel face zoning.

Drilling parameters of all tunnel faces in the acquisition area were calculated by the above method, and the classification result of each zone of the tunnel face serves as the output according to the calculation results and zone numbers. Then, each zone of the tunnel face was colored regarding the numerical calculation results of zoning and classification.

Based on the proposed heterogeneity identification method for the surrounding rock of large-section rock tunnel faces, the heterogeneity identification algorithm for the surrounding rock of large-section rock tunnel faces was written with the MATLAB software and computer language. Through machine calculation, during the blasting processes of Xiangjiawan Tunnel (D2K584 + 320-D2K584 + 325) and Chufeng Tunnel (DK532 + 553-DK532 + 558), the surrounding rock of the tunnel face shows obvious heterogeneity characteristics, and the surrounding rock class in some areas is poor. The analysis results of the typical section are shown in Figure 8. As shown in Figure 8, for D2K584 + 320 Section of Xiangjiawan Tunnel, the vault is yellow, indicating the rock is Class IV surrounding rock, and the rest of the areas are green, indicating the rock is Class III surrounding rock; for DK532 + 553 Section of Chufeng Tunnel, the left arch foot is yellow, indicating the rock is Class IV surrounding rock, and the rest of the areas are green, indicating the rock is Class III surrounding rock. After a blasting cycle was completed, according to the geological sketch, rebound test and saturated uniaxial compressive strength test of the rock of the new tunnel face revealed, the heterogeneity characteristics of the surrounding rock of typical sections within the blasting

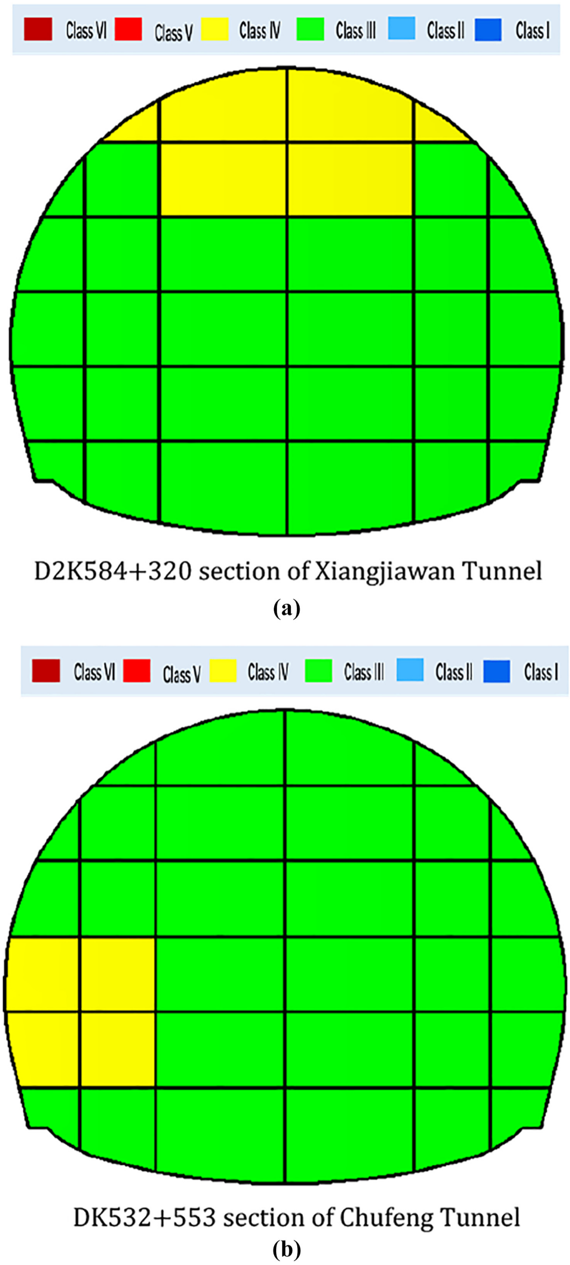

Figure 8. Heterogeneity characteristics of the surrounding rock of tunnel face of typical sections of test tunnels identified by the method described in the paper

chainage range of the two tunnels were identified, as shown in Figure 9. Through comparison, the machine calculation results shown in Figure 8 and the photos of the tunnel face at the blasting end point shown in Figure 9 are basically consistent.

4.3 Suggestions on local optimization of tunnel initial support and tunnel face reinforcement

According to the judgment results, the design parameters such as the layout position, spacing and shotcrete position of the initial support anchor bolt in the area with poor rock mass quality of the target tunnel face are locally optimized, as shown in Table 9. It can be seen from Table 9 that the spacing between anchor bolts of the optimized initial support is reduced from 1.5 m to 1.2 m, and shotcrete is adopted as the tunnel face reinforcement for areas with poor rock quality of the tunnel face, which improves the safety and economy of tunnel construction.

5. Conclusions

(1) For the five test tunnels of Zhengzhou-Wanzhou high-speed railway, the geological data of 299 tunnel faces were acquired, including geological sketch and drilling parameters, to build a surrounding rock classification sample database for large-section rock tunnel faces, which includes chainage of tunnel faces, drilling parameters, surrounding rock classes, results of rebound test, compressive strength test and wave velocity test of rock and rock mass. Based on the chainage, drilling parameters and surrounding rock class of each tunnel face in the sample database, the function conversion relationship during drilling of ZYS113 computer-controlled three-boom drill jumbo was analyzed from the perspective of energy, and a surrounding rock classification database for large-section rock tunnel based on machine learning was constructed.

(2) Based on the SVM principle and drilling parameters, a surrounding rock classification model for large-section rock tunnel face based on SVM was constructed and compared with the classification model based on RBF and BP neural network models. In the prediction set of SVM classification model, the classification accuracy is 93.7% for Class III surrounding rock, 89.3% for Class IV surrounding rock, 73.3% for Class V surrounding rock and the average classification accuracy is 87.9%. With a small number of samples, the SVM classification model shows better "robustness." In case of sample replacement, the classification accuracy of SVM classification model is still the same with better generalization.

(3) According to the method in this paper, the heterogeneity of the surrounding rock of the tunnel face in the 5 test tunnels of Zhengzhou-Wanzhou high-speed railway was judged by tunnel face zoning, nominal classification of blastholes and nominal zoning and classification of tunnel face, and it was found that the surrounding rock of the tunnel face shows significant heterogeneity characteristics in case of one blasting cycle in Xiangjiawan Tunnel and Chufeng Tunnel, respectively. The heterogeneity characteristics of surrounding rocks calculated with the model are basically consistent with the photos of the tunnel face exposed after blasting, which verifies

D2K584+325 section of Xiangjiawan Tunnel
(a)

DK532+558 section of Chufeng Tunnel
(b)

Figure 9. Identification results of heterogeneity characteristics of the surrounding rock of tunnel face of typical sections at blasting end points of test tunnels

Table 9. Local optimization suggestions based on heterogeneity identification of the surrounding rock of tunnel face

Tunnel name	Chainage range	Surrounding rock class	Original design: Anchor bolts for initial support: Position	Original design: Anchor bolts for initial support: Spacing in longitudinal direction /m	Original design: Anchor bolts for initial support: Spacing in circumferential direction /m	Original design: Tunnel face reinforcement: Position of shotcrete	Local optimization suggestions: Anchor bolts for initial support: Position	Local optimization suggestions: Anchor bolts for initial support: Spacing in longitudinal direction /m	Local optimization suggestions: Anchor bolts for initial support: Spacing in circumferential direction /m	Local optimization suggestions: Tunnel face reinforcement: Position of shotcrete
Xiangjiawan	D2K584 + 320~D2K584 + 325	III	Arch wall	1.5	1.5		Arch wall	1.2	1.2	Arch
Chufeng	DK528 + 532~DK532 + 558	III	Arch wall	1.5	1.5		Arch wall	1.2	1.2	Left sidewall

the feasibility of this method to analyze the heterogeneity of surrounding rocks of tunnel face.

(4) According to the judgment results of the heterogeneity of surrounding rocks of the tunnel face, for the areas with relatively poor surrounding rock on the arch and the side wall, it is proposed to reduce the spacing of the anchor bolts from 1.5 m to 1.2 m and to make local optimization suggestions for the support parameters of shotcrete for the areas with poor surrounding rock quality on the tunnel face, so as to improve the safety and economy of tunnel construction.

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