Research of The Extreme Learning Machine Model of Rapid Classification of Surrounding Rock of Highway Tunnel

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Abstract

Aiming at the problem of the existing intelligent optimization algorithm, such as slow learning speed, and sensitivity to parameter selection, extreme learning machine (ELM) is used for classification of surrounding rock. In terms of classification index, combined with speed and accuracy, the rapid classification standard parameters are formulated, and based on the BQ method in highway tunnel design specification, the corresponding sample are collected from the tunnel in past and under construction, thus established the rapid classification of surrounding rock Extreme Learning Machine model of highway tunnel in construction period. In the end, the rapid classification parameters of working face of the under construction tunnel is measured, and provided to the model to achieve fast and accurate classification. By Quilling tunnel practical validation, the judgment results of the model are tally with the actual construction situation, it is proved that the model can be used to guide the tunnel surrounding rock rapid classification of the construction phase.

Keywords

Surrounding rock, springback intensity, training sample, hidden layer.

1. Introduction

The tunnel surrounding rock classification is a comprehensive quantitative indicator of evaluating the geological conditions of tunnel engineering, and is the basis of tunnel construction. In the reconnaissance and design stage of highway tunnel, geological survey gives priority to geological mapping, drilling and geophysical exploration are beneficial supplements. The Drilling control range is not big due to lacking of boreholes, The level of surrounding rock has a bigger difference between this stage and actual construction stage.

In literature [1], the SVM and neural network was used in the surrounding rock classification and a good result was got. But due to the slow learning speed of BP network, constantly iterations were needed in the training process, and parameter selection sensitivity, the training step or improper selection of learning rate all can directly impact the overall effect of feedforward neural network. In the application process of SVM, the Difficulty in determining parameters was existed and a lot of time was needed to adjust parameters and training.

Before the training of Extreme Learning Machine (ELM), only the nodes number of hidden network are needed to be set , the input weight and the offset value of the hidden layer element of the network are not needed to be adjust in the execution process, and the unique optimal solution can be obtained, Easy parameter selection, Fast learning and good generalization are advantages of ELM. Combined with the practice of surrounding rock classification in the construction period of Qiling tunnel in liaoning province, the rapid classification index of surrounding rock was given, The ELM model of surrounding rock classification was established, it made the surrounding rock classification more reliable and faster, It provided important basis for design change and site construction.

2. Extreme Learning Machine Model of Surrounding Rock Classification

2.1 Principle of Extreme Learning Machine

The network training model of ELM uses forward single hidden layer structure. m,M,n respectively represent network input layer, hidden layer and node number of the output layer, we have N different samples (x_i,t_i) , among them, $x_i=[x_{i1},x_{i2},...,x_{im}]^T\in R^m$, $t_i=[t_{i1},t_{i2},...,t_{im}]^T\in R^n$, then the network training Model can be expressed as:

$$\sum_{i=1}^{M}\beta_i g(w_i\cdot x_i+b_i)=o_j,\quad j=1,2,...,N \tag{1}$$

in the formula: $w_i=[w_{i1},w_{i2},...,w_{im}]^T$ is the input weight vector which connects network input layer node and the ith hidden layer node, $\beta_i=[\beta_{i1},\beta_{i2},...,\beta_{in}]^T$ is the input weight vector which connects the ith hidden layer node and network output layer node, $o_i=[o_{i1},o_{i2},...,o_{in}]^T$ is network output value, b_i is offset value, g(x) is excitation function, it may be"sigmoid"or"Hardlim".

Liang pointed out that the raining goal of ELM is to find the most optimal S,β , which makes the error of network output value and corresponding actual value namely cost function become a minimum.

$$\min(E(S,\beta))=\sum_{j=1}^{N}\left\|o_j-t_j\right\| \tag{2}$$

in the in the formula: $S=(w_i,b_i,i=1,2,...,M)$, which contains network input weight value and hidden node offset value. $\min(E(S,\beta))$ can be write further as:

$$\begin{aligned}&\min(E(S,\beta))=\\&\min_{w_i,b_i,\beta}\left\|H(w_1,...,w_m,b_1,...,b_m,x_1,...,x_m)\beta-T\right\|\end{aligned} \tag{3}$$

in the in the formula: H represents the hidden layer output matrix of the network about the sample, β represents output weight matrix, T represents the target value matrix of the sample set. They can be respectively defined as:

$$\begin{aligned}&H(w_1,...,w_m,b_1,...,b_m,x_1,...,x_m)=\\&\begin{pmatrix}g(w_1x_1+b_1)&\cdots&g(w_Mx_1+b_M)\\\vdots&\ddots&\vdots\\g(w_1x_N+b_1)&\cdots&g(w_Mx_N+b_M)\end{pmatrix}_{N\times M}\end{aligned}\quad \beta=\begin{bmatrix}\beta_1^T\\\vdots\\\beta_M^T\end{bmatrix}_{M\times n},\quad T=\begin{bmatrix}t_1^T\\\vdots\\t_M^T\end{bmatrix}_{N\times n} \tag{4}$$

The network training process of ELM is a nonlinear optimization problem which takes equation (2) as the objective function. When the activation function g(x) of the network hidden layer node is infinitely differentiable, network parameters do not need to be fully adjusted, the input connection weighted value w and hidden node offset value b can be randomly selected at the beginning of training and fixed during training. Learning process of Extreme Learning Machine can be equivalent to find the least squares solution $\hat{\beta}$ of linear system $H\beta=T$ normal form, the formula is:

$$\hat{\beta}=H^{+}T \tag{5}$$

in the in the formula: H^{+} is the Moore-Penrose generalized inverse of hidden layer output matrix H .

The optimal solution has the following important properties: (1) the minimum training error can be obtained through the optimal solution; (2) The smallest norm of weight and the optimal generalization performance can be gained; (3) the least squares solution of the norm is unique, therefore, the algorithm does not produce local optimal solution.

It is observed that the values of w and b don't need to be adjust in training, they can be adjusted only according to the corresponding algorithm, then we can get the global optimal solution, the process of parameter selection is relatively easy, training speed is improved significantly and can not be cauhgt in locally optimal solution.

2.2 Selection of Classification Indicators and Field Measurement Methods

2.2.1 Resilient Strength of Surrounding Rock

According to the BQ sorting technique of"JTGD70-2004 highway tunnel design code", the paper uses five-stage classification. Combined with qiling tunnel construction, the uniaxial saturation compressive strength is replaced by the resilient strength of surrounding rock and the joint ductility is increased, the corresponding standards of qualitative and quantitative are established for other indexes.

In literature [2], A large number of comparative tests were conducted on the resilient strength of surrounding rock and uniaxial saturation compressive strength of the same section, the results of regression analysis showed that there was a corresponding relation between the above two indexes, so the resilience strength can be directly used as the input index of the ELM model.

2.2.2 Volumetric Joint Number And Joint Ductility

For different engineering geological formations or lithologic sections of the testing bracing surface, Representative outcrop or excavation wall surface are selected to perform joint statistics.When counting the joints, first, the groups number of the joints of bracing surface is determined, Then the spacing of each set of joints is measured separately. Separate statistics need to be done when Semi-through or through joints exist on the bracing surface, then we determine the joint ductility index.

2.2.3 Undergroud Water

For convenience, the score is based on the size and flow of groundwater that can be observed by the naked eye, the higher the score, the less developed the groundwater, the scoring criteria is shown in Table 1:

Table 1. Groundwater score table

State	Score	State	Score
dry	0.9~1.0	linear	0.4~0.6
wet	0.8~0.9	strands	0.2~0.4
drip	0.6~0.8	water inrush	<0.2

2.2.4 Occurrence of Main Structural Plane Occurrence

According to the favorable degree of relationship between structure surface occurrence and tunnel, we grade from high to low, score distributes between 0~1. In view of the relationships between structural plane and tunnel orientation in RMR rating system, we consider 3 cases, see Table 2:

Table 2. Relation between structural plane and tunnel strike

angle of structural plane strike and tunnel axial	dip angle of structure plane	score
90°	>45°	0.8~1.0
	20°~45°	0.6~0.8
0°	20°~45°	0.4~0.6
	>45°	0.2~0.4
-	0~20°	0~0.2

2.3 Classification Model of Surrounding Rock Based on Extreme Learning

The rapid classification process of surrounding rock based on ELM is: the surrounding rock classification index is collected according to the site test method introduced previously, then, according to BQ classification method of surrounding rock of the design specification of highway tunnel , the grades of tunnel surrounding rock are determined. The samples are then divided into two parts, part is training samples, part is testing samples, and use these samples to train extreme learning machine. The training process is as follows: we randomly assign the network input weights w_i and hidden layer bias values b_i, then compute the hidden layer output matrix H and hidden layer output weight matrix β, the actual output value of the network is calculated from H and β and compared with the expected value to obtain the training precision, in this way, a rapid classification model of surrounding rock is obtained.

3. Extreme Learning Machine Model for Rock Classification

3.1 Project Introduction

The qiling tunnel is located in the ganjingzi district of Dalian in southern liaoning province, the engineering area belongs to Changbai middle low mountain area. Ground elevation 600m to 830m, the ratio is 100m to 200m. Exposed stratum in the work area are mainly Jurassic fluvial lacustrine rocks, andesite and Quaternary basalt. The basalt mainly consists of primary joints, and a few of them are directional fractures, and the engineering geological condition is poor. The buried conditions of underground water level in the tunnel area are mainly pore diving and bedrock fissure water in the loose accumulation layer, which is supplied by atmospheric precipitation and excreted to gullies and valleys. The tunnel is a separate two-hole tunnel. The distance between the design lines of the two holes is about 13 ~ 35m, and they are displayed in a straight line. The initial range mileage of the left line is ZK274+160, the finish mileage is ZK275+784, and the total length is 1624m. The initial mileage of the right line is RK274+170, the finish mileage is RK275+770, and the total length is 1600m. The maximum excavation width of the tunnel is about 11.00m and the height is 6.60m. The surrounding rock of tunnel is mainly class III, IV and V.

3.2 Acquisition of Training Samples

The work of surrounding rock classification runs through the whole construction period of qiling tunnel. Here, several typical sections are selected from qiling tunnel, and 34 groups are selected in combination with the accumulated projects in the past. Among them, 29 groups are taken as training samples, and the remaining 5 groups are taken as test samples. The results are shown in Table 3.

Table 3. Learning samples of the surrounding rock data of ailing tunnel

Tunnel name	Pile number	Grade	Rut	Kev	W	S	Tunnel name	Pile number	Grade	Rut	Kev	W	S
Da lian Qi ling Tunnel	YK276+633	III	59.34	0.61	0.85	0.55	Ge Zhen Tunnel	K11+100	III	56.89	0.61	0.85	0.55
	YK276+695	III	58.64	0.57	0.85	0.55		K11+123	III	59.09	0.57	0.85	0.55
	YK276+763	V	48.38	0.44	0.65	0.45		K11+136.8	III	55.41	0.58	0.75	0.50
	YK276+776	V	47.94	0.34	0.62	0.45		K11+147.3	III	54.75	0.54	0.85	0.55
	ZK275+194.7	V	47.11	0.35	0.75	0.50		K10+755	V	43.23	0.31	0.66	0.55
	ZK275+248.2	V	47.07	0.45	0.65	0.50		K10+783	V	47.30	0.34	0.82	0.55
	ZK275+298	IV	52.54	0.40	0.74	0.55		K10+798	V	46.66	0.33	0.73	0.55
	ZK275+389	IV	51.82	0.43	0.76	0.60		K10+834	V	47.33	0.30	0.67	0.50
	ZK276+526	III	57.76	0.58	0.75	0.52		K10+852	V	49.88	0.33	0.84	0.55
	ZK276+659	III	59.79	0.54	0.85	0.55		K10+864.3	V	48.40	0.36	0.84	0.55
	ZK276+720	IV	51.57	0.47	0.68	0.52		K10+892	IV	54.25	0.46	0.68	0.50
	ZK276+792.2	V	48.85	0.41	0.80	0.45		K10+912	IV	53.60	0.44	0.69	0.55
	ZK276+771	V	48.81	0.43	0.80	0.50		K10+943	IV	53.35	0.43	0.77	0.50
	ZK275+468	IV	52.87	0.62	0.68	0.60		K10+962	IV	55.59	0.41	0.70	0.50
	ZK276+693	III	58.64	0.65	0.88	0.60		K10+991	IV	52.79	0.44	0.75	0.55
	YK276+653	III	58.38	0.68	0.82	0.50		K11+032	IV	51.34	0.40	0.80	0.55
	ZK275+281	IV	52.57	0.42	0.72	0.58							
	YK276+763	V	48.51	0.40	0.60	0.45							

I, II, Excellent surrounding rock is rare in tunnel construction, therefore, these two types of surrounding rocks have not been included in the training set. Select the last 5 groups in the above table as test samples, the predicted results of the test limit learning machine are identical with the actual classification results.

3.3 Surrounding Rock Classification in the Construction Period of Qiling Tunnel

After the network training meets the requirements, the rapid grading parameters of the excavated working face are measured and provided to the trained extreme learning machine for identification, so that the surrounding rock can be quickly classified according to the information disclosed on the bracing surface in the construction stage. For some sections, The level of surrounding rock identified by extreme learning machine and that of the original designed surrounding rock are compared, the results are shown in Table 4.

Table 4. Comparison between the level of surrounding rock identified by ELM and original design level of surrounding rock

Pile Number	Forecast Grade	Design Grade	Integrity	Groundwater	Structural Plane
YK276+521	IV	IV	0.55	0.85	0.52
ZK276+521	IV	III	0.62	0.85	0.58
YK275+458	III	IV	0.72	0.87	0.53
ZK275+478	IV	IV	0.58	0.75	0.51

4. Conclusion

Based on the factors influencing the classification of surrounding rocks, convenience of acquisition and Combined with monitor displacement and classification indicators of BQ method, we have established the extreme learning machine model for surrounding rock classification.The surrounding rock of qiling tunnel is classified by the extreme learning machine and compared with the investigation results, It is proved that the model built by ELM has a practicability and can meet the needs of engineering application.

When the excitation function is determined, ELM only needs to set the number of hidden nodes and the parameter is easy to select. The algorithm does not need to adjust the input weight of the network and the bias of hidden units, so the speed of algorithm training is greatly improved.

References

[1] Li Fang, Baguio Liu: Support Vector Classification Model of Tunnel Surrounding Rock Classification, Journal of Railway, vol.35 (2013), 108-114.

[2] Zhengguo Zhu, Chancing Qian: Evaluation method of geological conditions for surrounding rock of highway tunnel and Application Research on Fuxin Tunnel, Journal of Engineering Geology, vol.15(6)(2007), 789-795.

[3] Cupping Zhou, Liang Zhang: Classification of Tunnel Surrounding Rock Based on Improved BP Network Algorithm, Journal of China University of geosciences, vol.30 (2005), and 480-486.

[4] Penguin Li, Annan Jiang: Research on Rapid Classification of Surrounding Rock of Highway Tunnel in Construction Period, Survey of City, vol.1 (2016), 149-153.