Research on displacement prediction of shield tunneling through existing tunnel based on LSSVM

Xianguo Wu[1,*], Tiemei Zeng[2], Yanyan Tao[3], and Hongyu Chen[4]

[1] School of Civil Engineering & Mechanics, Huazhong University of Science and Technology, Wuhan, Hubei, 430074, China
[2] Wuhan Metro Group Co Ltd, Wuhan, Hubei, 430030, China
[3] School of Urban Construction, Wuchang Shouyi University, Wuhan, Hubei, 430074, China
[4] School of Civil and Environmental Engineering, Nangyang Technological University, Singapore, 6397898, Singapore

Abstract. The construction scale of the shield tunnel underpass is expanding day by day. In order to study the safety influence and deformation control of the shield tunnel underpass on the existing tunnel, the LSSVM model is established. Based on the collected soil storage pressure, foam volume, simultaneous grouting volume and other six shield construction parameters and corresponding sample data of the tunnel bottom displacement, the horizontal displacement and settlement displacement of the existing tunnel bottom caused by the approach construction are predicted. Taking a subway project as an example, the research results show that the prediction model of shield tunneling under the existing tunnel bottom level and settlement displacement has strong generalization ability and rapid and accurate prediction effect. This method can provide reference for similar projects.

1 Introduction

With the widespread rise of my country's underground rail transit system, there are more and more shield tunnel construction projects. The greatest risk that may occur during the shield construction of the tunnel is excessive ground level and settlement displacement. Therefore, in order to ensure the safety of subway tunnel construction and operation, it is of great significance to adopt reliable measures to predict horizontal displacement and settlement displacement[1].

At present, a large number of domestic and foreign documents study the influence of tunnel construction from the perspective of surface settlement. There are three main research methods: theoretical formula[2], numerical simulation[3], and model test[4]. Theoretical formula method such as Wang et al.[5]derived the differential equation of adjacent pipeline deformation caused by tunnel excavation based on the Winkler foundation model to analyze the uplift or settlement deformation. Numerical simulations such as Li et al.[6] used FLAC3D to establish a three-dimensional numerical simulation model, and analyzed the impact of the staged construction of the foundation pit on the station and the existing subway tunnel. Model tests such as Ma et al.[7] conducted a series of three-dimensional centrifuge model tests to study the effect of parallel double tunnels of different depths on existing buried pipelines in dry sand. The above methods all have a certain value for the study of the settlement of the adjacent shield tunnel construction. However, the theoretical formula method is usually only suitable for specific situations and has poor accuracy. The numerical simulation accuracy is general but time-consuming and labor-intensive, and the model test accuracy is high but the instruments are expensive and time-consuming.

Chen et al.[8] predicted the maximum surface settlement based on artificial neural network method. However, the generalization performance of ANN in prediction is poor[9]. Therefore, in view of the shortcomings of the above methods, in order to control the impact of the shield construction on the existing tunnels, this paper proposes an intelligent algorithm framework based on the LSSVM algorithm. A shield construction parameter index system is established to make high-precision nonlinear predictions of the horizontal displacement and settlement displacement of the existing tunnel bottom.

2 LSSVM

The least squares support vector machine (LSSVM) improves the traditional SVM, and uses the least squares linear system as the loss function to transform the inequality constraints of the optimization problem in the SVM into equation constraints[10]. Suppose the training sample set (x_i, y_i) , $x_i \in R^n$, $y_i \in \{-1, +1\}$, $i = 1,2,\cdots,N$ Where N represents the total number of training samples, n is the dimension of the sample space, and y is the class label of the sample. According to the principle of structural risk minimization, the optimal classification surface of the classification problem of LSSVM is obtained by the following optimization problem[11]:

* Corresponding author: wxg0220@126.com

$$\begin{cases} \min R(\omega,\xi) = \frac{1}{2}\omega^T\omega + \frac{1}{2}c\sum_{i=1}^{N}\xi_i \\ y_i\left[\omega^T\varphi(x)+b\right] = 1-\xi_i \text{ ,i} = 1,2,\cdots,\text{N} \end{cases} \quad (1)$$

Among them, $\varphi(\cdot)$ is the nonlinear mapping, ω is the weight, ξ_i is the error variable, and $c > 0$ is the penalty coefficient. Therefore, the Lagrange function corresponding to the optimization problem of LSSVM is:

$$\begin{aligned} L(\omega,b,\xi,a) &= \frac{1}{2}\omega^T\omega + \frac{1}{2}c\sum_{k=1}^{N}\xi_i^2 \\ &-\sum_{k=1}^{N}a_i\left\{y_i\left[\omega^T\varphi(x_i)+b\right]-1+\xi_i\right\} \end{aligned} \quad (2)$$

Among them, the *Lagrange* multiplier $a_i > 0(i = 1,2,\cdots,N)$. Optimize the above formula to make the partial derivatives of ω, b, a_i, and ξ_i equal to 0, and then use the Mercer condition to get: $\varphi(x_j) = y_i y_j K(x_i, x_j)$, where $K(x_i, x_j)$ is the core function. The optimal regression function can be obtained by the least square method as[12]:

$$f(x) = \sum_{i=1}^{l} a_i y_i K(x_i, x_j) + b \quad (3)$$

3 Prediction of bottom displacement of existing tunnel based on LSSVM

3.1 Data acquisition and preprocessing

By consulting a large number of related documents and according to the actual engineering situation, the factors that are more sensitive to the deformation of the existing tunnel are selected as the input parameters of the tunnel bottom displacement prediction. The horizontal displacement of the arch bottom and the settlement displacement of the arch bottom are used as prediction output parameters.

In order to prevent the sample from being overwhelmed or not converging because the data is too large or too small, the sample data needs to be preprocessed. In this paper, the input variables and output are normalized to the interval [-1,1], so that each parameter can be effective in the prediction process.

3.2 Kernel function parameter optimization

The kernel function has a great influence on the prediction accuracy of GA-LSSVM. The research should select the appropriate kernel function according to the characteristics of the experimental object. The Gaussian kernel function has the advantages of the radial basis kernel function while maintaining good anti-interference ability. Therefore, this paper will use the Gaussian kernel function as the kernel function of the prediction model for research, and the expression is as in formula (4).

$$K(x_i, x) = \exp(-\frac{\|x_i - x\|^2}{2\sigma^2}) \quad (4)$$

Among them, x_i is the input variable, and x is the output variable.

After determining the kernel function, in order to ensure the generalization level of LSSVM, this paper will use K-fold cross-validation, which can avoid the under-learning or over-learning state of the LSSVM model.

3.3 Evaluation of prediction results

In order to verify the prediction accuracy of the LSSVM model, the goodness of fit R^2 is introduced to test. The goodness of fit R^2 represents the fitting effect between the predicted value and the true value. The closer the goodness of fit is to 1, the higher the prediction effect.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}_i\right)^2} \quad (5)$$

Where n is the number of samples in the test set; $y_i\,(i = 1,2,...n)$ is the true value of the i-th sample; $\hat{y}_i\,(i = 1,2,...n)$ is the predicted value of the i-th sample.

4 Case study

4.1 Background

This research is based on a subway line 4 under the subway line 2. Line 2 and Line 4 are upper and lower crossing tunnels, and the angle of the plane projection is approximately 90°. The diameter of the shield machine is D=6.2m, the length is 7.5m, and the outer diameter of the existing tunnel is also 6.2m. The soil layer of the existing tunnel is soft clay, and the Poisson's ratio is 0.28. The elastic modulus of the soil is 24.5Mpa, the thickness of the lining structure is 0.3m, the buried depth of the tunnel is 18m, and the concrete of the lining structure is C50.

The spatial position relationship between the shield and the existing tunnel is: the buried depth of the upper tunnel vault is 8.2m, and the buried depth of the lower tunnel vault is 14.4m. The clear distance between the upper and lower tunnels is 3.1m, and the length of the two tunnels is 6.2m in diameter. The problem to be solved is to study the influence of the optimization of shield construction parameters on the deformation of the adjacent existing tunnel for the construction of the shield tunnel at a close distance.

4.2 Data acquisition and preprocessing

A large number of documents have shown that the factors that are more sensitive to the deformation of existing tunnels include cutter head torque, jacking force, foam volume, grouting volume, driving speed and earth pressure of chamber[13].

Increasing the torque of the cutter head will increase the disturbance range of the surrounding soil.

As the jacking force increases, the force of the shield machine on the soil will increase.

Foam is usually used to improve the properties of the soil in order to reduce the torque of the cutter head of the shield machine and reduce the disturbance to the ground.

With the continuous increase of the grouting volume, the maximum ground settlement will continue to decrease.

The change of the soil stress field is related to the change of the driving speed. The large change of the driving speed can easily cause the change of the soil stress field.

After the earth pressure of chamber changes, the deformation of the soil around the shield tunnel will change due to the interaction, which will cause the ground settlement.

Therefore, this paper will take the above six parameters as input parameters, and use the horizontal displacement of the existing tunnel bottom and the settlement displacement of the arch bottom as the predicted output parameters. The selected LSSVM training sample data is shown in Table 1, and the value range of each input parameter in the training sample is shown in Table 1.

Table 1. Monitored sample data.

Variables	Data		
	Min	Max	Ave
Cutter head torque (kPa)	1927	3264	2291
Jacking force (kN)	15049	26667	21711
Foam volume (m^3)	10.1	14.2	12.1
Grouting volume (m^3)	14.0	18.9	17.1
Driving speed (mm/min)	17	34	24
Earth pressure of chamber (kPa)	243	332	291
Horizontal displacement of arch bottom(mm)	0.4	1.1	0.78
Settlement displacement of arch bottom(mm)	1.8	2.9	2.26

4.3 Kernel function parameter optimization

StandardScale is used to standardize the training samples, and GA algorithm is used to optimize the model parameters c, g, and p of LSSVM. The search range of the penalty coefficient c in the LSSVM model parameters is set to [0,100], the search range of the kernel function width parameter g is [0,1000], and the search range of p is [0.01,1]. The 5-fold cross-validation method was selected to model the kernel function width parameter g and the penalty coefficient c obtained by GA optimization, and the optimal parameters of the LSSVM prediction model of the arch bottom horizontal displacement and settlement displacement were obtained. The optimization results of the prediction parameters of the arch bottom horizontal displacement and the arch bottom settlement displacement are shown in Fig. 1 and Fig. 2 respectively.

It can be seen from Fig. 1 that the penalty coefficient best c=17.4949, the kernel function parameter best g=915.08, p=0.43452, and the minimum root mean square error is mse=0.083303.

Similarly, it can be seen from Fig. 2 that the penalty coefficient best c=31.1065, the kernel function parameters best g=0.13542, p=0.4438, and the minimum mean square error value is mse=0.07707.

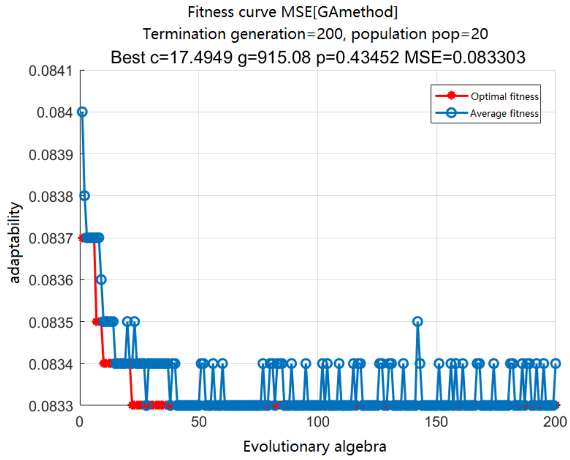

Fig. 1. Horizontal displacement of arch bottom model parameters

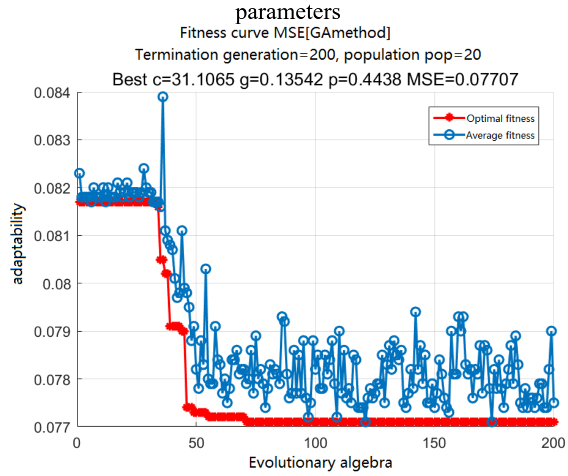

Fig. 2. Settlement displacement of arch bottom model parameters

4.4 Forecast result analysis

Based on the optimization results of the LSSVM kernel function parameters, the training set is used for learning simulation. The LSSVM arch bottom horizontal displacement and arch bottom settlement displacement prediction models are established respectively. According to the above steps, the prediction result of the arch bottom horizontal displacement is shown in Fig. 3, and the prediction result of the arch bottom settlement displacement is shown in Fig. 4.

It can be found from Fig. 3 that the LSSVM model can predict the changes in the horizontal displacement of the arch base well. Based on the LSSVM model, the predicted goodness of fit for the arch bottom horizontal displacement is 0.9987. It can be seen that the model fits well, and the error between the predicted value and the actual value is very small.

It can be found from Fig. 4 that the LSSVM model can make a good prediction of the change of the arch bottom settlement displacement. Based on the LSSVM model, the predicted goodness of fit for the arch bottom settlement displacement is 0.9964. It can also be seen that the model fits well, and the predicted value of the sample is very close to the experimental value..

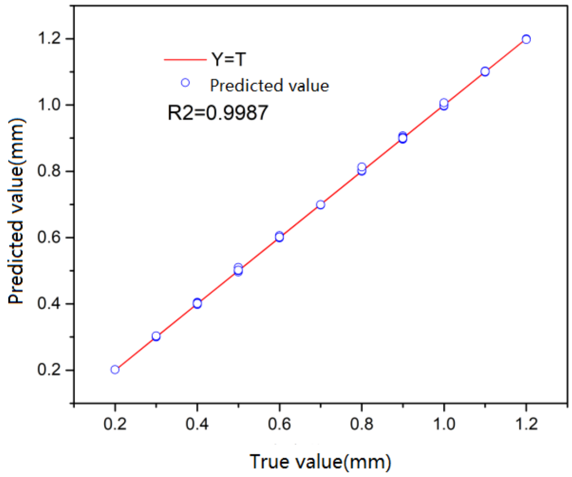

Fig. 3. Horizontal displacement of arch bottom prediction result

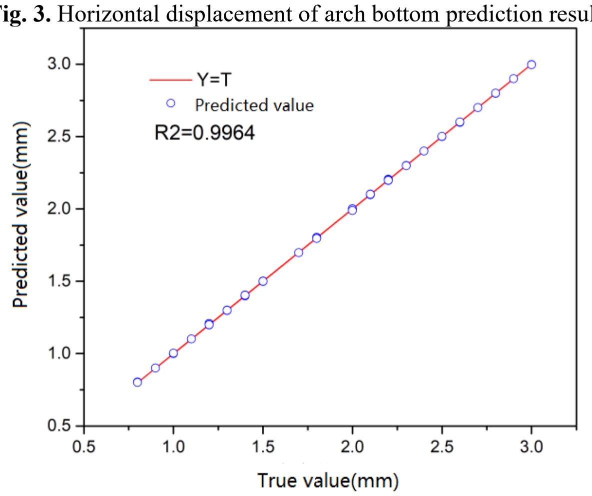

Fig. 4. Settlement displacement of arch bottom prediction result

5 Conclusion

In this paper, an intelligent prediction model of LSSVM is developed, which realizes the high-precision prediction of the horizontal displacement and settlement displacement of the shield under the existing tunnel bottom, which has important engineering value.

Taking the Wuhan subway project as an example, in view of the shortcomings of the traditional grid search method for parameter optimization, the soil tank pressure, foam volume, simultaneous grouting volume, tunneling speed, cutter head torque and jacking force are selected as input parameters. A prediction model based on LSSVM for the displacement of the existing tunnel bottom is proposed. The goodness of fit for the prediction of the horizontal displacement at the bottom of the tunnel is 0.9987. The goodness of fit for the prediction of the horizontal displacement at the bottom of the tunnel is 0.9964. The high accuracy of the model and good prediction effect reflect the feasibility of this method..

References

1. Zhang, D.M., et al., *Predicting the grouting effect on leakage-induced tunnels and ground response in saturated soils.* Tunnelling and Underground Space Technology, **65**: p. 76-90(2017)
2. Liang, R., et al., *Simplified method for evaluating shield tunnel deformation due to adjacent excavation.* Tunnelling and Underground Space Technology, **71**: p. 94-105(2018)
3. Jin, Y.-F., et al., *Three-dimensional numerical analysis of the interaction of two crossing tunnels in soft clay.* Underground Space, **4**(4): p. 310-327(2019)
4. Huang, H., X. Huang, and D. Zhang, *Centrifuge modelling of deep excavation over existing tunnels.* Proceedings of the ICE - Geotechnical Engineering, **167**: p. 3-18(2014)
5. Wang, Y., Q. Wang, and K. Zhang, *An Analytical Model for Pipe-Soil-Tunneling Interaction.* Procedia Engineering, **14**: p. 3127-3135(2011)
6. Li, M., et al., *Numerical study on responses of an existing metro line to staged deep excavations.* Tunnelling and Underground Space Technology, **85**: p. 268-281(2019)
7. Shaokun, M., et al., *Responses of pipeline to side-by-side twin tunnelling at different depths: 3D centrifuge tests and numerical modelling.* Tunnelling and Underground Space Technology, **66**: p. 157-173 (2017)
8. Chen, R.-P., et al., *Prediction of maximum surface settlement caused by earth pressure balance (EPB) shield tunneling with ANN methods.* Soils and Foundations, **59**(2): p. 284-295(2019)
9. Zhou, J., et al., *Feasibility of Random-Forest Approach for Prediction of Ground Settlements Induced by the Construction of a Shield-Driven Tunnel.* International Journal of Geomechanics, **17**: p. 04016129(2016)
10. Zhai, Y., et al., *Adaptive LSSVM based iterative prediction method for NOx concentration prediction in coal-fired power plant considering system delay.* Applied Soft Computing, **89**: p. 106070(2020)
11. Shao, M., et al., *Prediction of energy consumption in hotel buildings via support vector machines.* Sustainable Cities and Society, **57**: p. 102128(2020)
12. Prayogo, D., et al., *Combining machine learning models via adaptive ensemble weighting for prediction of shear capacity of reinforced-concrete deep beams.* Engineering with Computers(2019)
13. Zhou, C., et al., *Visibility graph analysis on time series of shield tunneling parameters based on complex network theory.* Tunnelling and Underground Space Technology, **89**: p. 10-24(2019)