Deformation prediction of foundation pit with PCA-SVM

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Abstract. Using the principal component (PCA) strong ability of extracting effective features of foundation pit horizontal displacement monitoring data (monitoring, monitoring temperature, relative humidity, excavation depth) characteristics analysis .extracting the effective principal component, constructing the PCA SVM regression prediction model, and the analysis result through comparing with the measured values show that: the displacement data of prediction model based on PCA and SVM was more higher accuracy than a model using SVM, higher reliability, which means has certain applicability in engineering application.

Introduction

Support vector machine (SVM) method is learning methods based on statistical learning theory and structural risk minimization principle, and it good at extrapolating ability in terms of regression prediction, and it is suitable for small samples statistical learning problems. Existed in the work of foundation pit deformation forecast of foundation pit engineering geological conditions and the parameters of the rock mass and the uncertainty on the mechanics, Combined with principal component analysis and support vector machine (SVM) model, constructing a prediction model based on PCA - the SVM prediction model to analysis and predict the deflection of the foundation pit engineering.

This experiment choose the foundation pit engineering in Jilin province people's hospital as the research object, using 0.5 second grade total station leica TS30 regular observation of the slopes, and recording and monitoring the observation time, monitoring temperature, relative humidity, excavation depth and other factors that affect the displacement of foundation pit at the same time. PCA-SVM model is established according to the sample data, the forecast of foundation pit horizontal displacement estimates, compared with the measured data, the analysis model of prediction accuracy, PCA-SVM model for the feasibility of the foundation pit displacement prediction.

Method

Support Vector Machines

Support Vector machine SVM (Support Vector those) is a kind of machine learning algorithms based on statistical learning theory. The input vector from the original space is mapped to high-dimensional feature space by selecting the corresponding nonlinear mapping function and using structural risk minimization criterion to improve the generalization ability of the models. The learning algorithms minimum sampling error and reduce the model to the upper bound of the generalization error at the same time. the method has the characteristics of high precision, fast operation speed compared with traditional machine learning algorithms. For nonlinear indivisible samples, the dual form of SVM is[1-4]:

$$\max \sum_{i=1}^{n} a_i - \frac{1}{2} \sum_{i,j=1}^{n} a_i a_j y_i y_j K(x_i, x_j) \tag{1}$$

In the type: $K(x_i, x_j)$ is a kernel function used for nonlinear mapping, Choose a different form of kernel function that means adopt different nonlinear mapping, the sample from the original space is mapped to high-dimensional feature space.

Principal component analysis

The deformation index of the monitoring reflect change of foundation pit horizontal displacement information in different degree and range, but there will be a certain correlation between various indicators, so the deformation of the information provided have a certain redundancy. On the premise of information amount of conservation ,principal component analysis through orthogonal linear transformation to remove all indexes of relevant information which based on the relationship between the variables to reduce the correlation between indicators to extract the influence of the deformation information. The information between principal component was unrelated and has no duplicate or redundant through principal component analysis. Principal component analysis steps are as follows:

(1)The original data standardization: To eliminate the original variable dimension which was different, the effects of numerical difference which was too large, a standardized processing to the original variable was needed.

(2)To establish correlation matrix R, and calculating the eigenvalue and eigenvector,namely:

$$\rho_{ij} = \frac{\sum_{k=1}^{m} x_{ik} \cdot x_{jk}}{\sqrt{\sum_{k=1}^{m} x_{ik}^2 \sum_{k=1}^{m} x_{jk}^2}} \qquad i, j = 1, 2, \ldots, n \tag{2}$$

(3)Determine the number of principal components. Variance contribution rate and cumulative variance contribution rate :

$$p_i = \frac{\lambda_i}{\sum_{i}^{m} \lambda_i} \times 100\% \tag{3}$$

Results

To construct multiple independent variable factors for feature extraction based on principal component analysis. The observed total number of excavation depth, temperature, relative humidity, the four deformation factors as sample data , As shown in Table 1:

Table1.No1 observation point displacement form

Observation days (d)	Temperature (˚C)	Relative humidity	Excavation depth(m)	Cumulative displacement (mm)
0	14	0.73	0	0
2	15	0.63	0.8	0.6
4	13	0.62	2.2	0.9
5	12	0.67	2.6	1.00
7	16	0.54	2.8	1.3
8	15	0.64	4.2	1.8
9	17	0.71	5.4	2.9
10	15	0.45	5.8	3.5
11	16	0.54	5.8	3.6
12	18	0.56	6.0	5.3
13	21	0.56	6.5	6.6
14	17	0.75	6.5	6.7
15	19	0.56	6.5	6.7

Choose 1 of the monitoring data as the research object, By extracting the first 10 period of multifactor sample "active ingredients", and using the SVM model to predict 11 to 15 issue of the displacement, Comparing and analyzing the results respectively with single support vector machine (SVM) model to predict the results and foundation pit horizontal displacement measured data. Predicted results as shown in table 2 and figure 1:

Table2. No1 model predicted results contrast

observation sequence	Measured value(mm)	SVM(mm)	Relative error(%)	PCA-SVM(mm)	Relative error(%)
11	3.4	3.481	2.3823	3.452	1.529
12	4.4	3.972	9.7272	4.059	7.750
13	4.5	4.885	8.5556	4.298	4.489
14	5.2	4.994	3.9615	5.071	2.481
15	5.2	5.176	4.6154	5.135	1.25

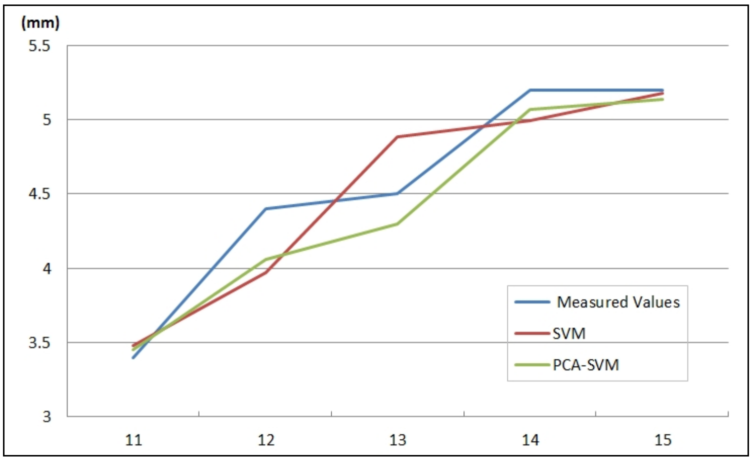

Fig.1 Relationship of predictive value and real value

From the prediction results and the comparison and analysis of the real values can be seen , the model prediction accuracy is higher which combined with principal component analysis and support vector machine (SVM), the minimum relative error is only 1.25% . There is obvious improvement in overall accuracy compared with the conventional support vector machine (SVM) model to predict the result.

Conclusions

(1)In the forecast of foundation pit horizontal displacement，it can improve the generalization ability of the model when joined the factors related to the deformation such as the temperature, relative humidity, excavation depth and others to enhance reliability.

(2)The performance of the forecast model is more excellent which established by combining with PCA and SVM method, compared with the observed precision, maximum relative error is 7.75%, the minimum error is only 1.25%.

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