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Horizontal Displacement Prediction Research of Deep Foundation Pit Based on the Least Square Support Vector Machine

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***Abstract*-Using of the least square support vector machine to predict the horizontal displacement of deep foundation pit. According to the measured time series data of horizontal displacement of foundation pit, using the least square support vector machine (SVM) to set up the relation model of foundation pit horizontal displacement and time, taking the actual excavation monitoring data as learning and training samples and testing samples, the calculated results and the actual monitoring results were compared and analyzed. The results show that using the least squares support vector machine (SVM) to predict the horizontal displacement of foundation pit, which was with higher prediction accuracy, the method with prediction error is small, fast calculation, less data, etc., precision can satisfy the need of engineering. The method Confirmed that is an effective method to solve the problem of the foundation pit deformation prediction.**

Keywords-Least square support vector machine; Deep foundation pit; Horizontal displacement; prediction.

I. INTRODUCTION

The rapid construction of urban high-rise buildings and the underground traffic network promote deep foundation pit engineering increasing in number and size, deep foundation pit in excavation process in the soil stress release will lead to pit deformation, the safety of foundation pit and surrounding buildings will have a serious impact, so it is particularly important to monitor and predict deformation of the deep foundation pit. Accurate prediction of deformation of deep foundation pit has been a hot research topic in recent years. Many scholars have conducted in-depth research and achieved fruitful results, Support vector machine technology are widely used in the results of its small sample training, support high dimensional feature space, fast convergence and other characteristics[1-3]. Due to the traditional prediction method has certain limitation, this paper apply the least square support vector machine model to predict the deep foundation pit horizontal displacement deformation based on the support vector machine principle, the model can effectively solve problems contain small sample, nonlinear, high dimension and local minima, etc.

II. STUDY AREA (ENGINEERING SURVEY)

Jilin Province People's hospital medical comprehensive building is located in the intersection of Hongqi Street and Xinyi Road in Changchun. It is in Jilin Province People's Hospital. The project is medical comprehensive building foundation pit; excavation depth is about 1.74 meters, excavation perimeter of 363.7 meters. In order to grasp the foundation deformation, to find adverse sinking phenomenon of construction timely, and to take measures to ensure the construction carried out smoothly. As the same time, the safety use of surrounding buildings and providing information for the future rational design are the reasons to monitor the construction of this project.

There are many inflection points in foundation pit, and the edge of each is unequal, we arrange 22 horizontal displacement observation points according to a certain distance, which distributed each corner and straight line segments of foundation pit. Each point masonry 300*300*300mm (long * wide * high) concrete pier in the top of crown beam, and install spherical horizontal observation point mark in concrete pier, Schematic diagram of point plane as shown in Figure 1.

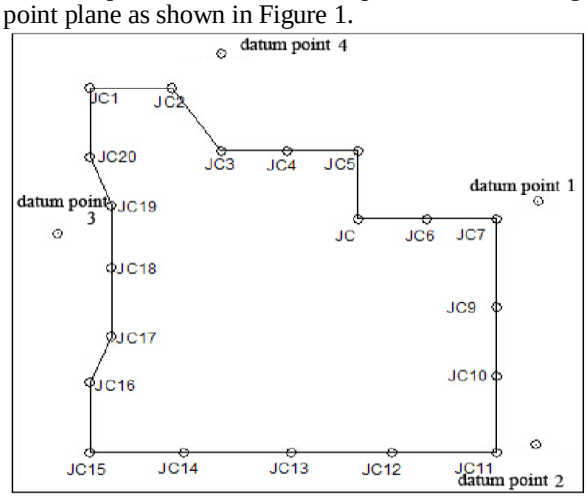

Figure 1. Layout plan of reference point and monitoring point

III. METHOD

Support vector machine SVM is a machine learning algorithm 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, using the rule of structure risk minimization, reducing upper bound of the generalization error of a model while minimizing the sample error, so as to enhance the generalization ability of the model. Compared with traditional machine learning algorithm, SVM has the advantages of high precision, fast computing speed characteristics.

For nonlinear separable samples, the dual form of SVM is [4-6]

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

In the formula, $K(x_i, x_j)$ is a kernel function to use for carrying out nonlinear mapping, and the different forms of kernel function are chosen to represent the different nonlinear mapping, which lead the samples to map from the original space to the high dimensional feature space.

Least squares support vector machine (SVM) is an extension of a support vector machine (SVM), the least squares linear system replace the traditional support vector machine to solve the problem of pattern recognition, quadratic programming method is adopted to reduce the computation complexity and improve the solving speed, mainly reflected in: The empirical risk is changed from Once Party to the Two party, equality constraints instead of inequality constraints, in the ω [7-9] space it can be described as:

$$\min \Phi(\boldsymbol{\omega}, e) = \frac{1}{2} \boldsymbol{\omega}^{\mathrm{T}} \boldsymbol{\omega} + \frac{\gamma}{2} \sum_{i=1}^{n} e_i^2 \tag{2}$$

In the formula, ω is the weight vector, b is parameters to be determined, γ is tolerant of penalty coefficient, e_i is the relaxation factor, the values are larger than 0.Constraint conditions are:

$$y_i = \boldsymbol{\omega}^{\mathrm{T}} \phi(x_i) + b + e_i \tag{3}$$

To solve the above problems, the LSSVM regression function model is obtained:

$$f(x) = \sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b \tag{4}$$

IV. RESULT

A. Forecast Model Establishment

According to the measured data of the horizontal displacement of deep foundation pit, a prediction model is established to predict the deformation of foundation pit support structure based on least square support vector machine. The edit program steps of subroutine in LS-SVMlab toolbox as shown below: 1) Read data and standard samples; 2) LS-SVM parameter optimization: LS-SVM requires only two parameters to call. GAM and sig2 is the least squares support vector machine parameters, the GAM is the regularization parameter, determines the minimized and the degree of smoothing of Minimize and smooth of adaptive error, sig2 is the kernel function parameters, B is the threshold. Take NO19 point as the example, it is parameters result is c=0.0008, g=0.9859.As shown in Figure 2 and 3 ; 3) Training the prediction model which has been determined to optimize the parameters: using trainlssvm function to build model, according to the input and output samples and preset training function parameters, the model train the network and get the support vector and response threshold of least squares support vector machine, the trainlssvm function is one of the important function of LS-SVM toolbox[10,11], is also the least squares support vector machine training function; 4) Model accuracy test: Call simlssvm function to predict the accuracy of the test, the function is similar to the SIM function in neural network toolbox, which was used to verify the accuracy of the model.

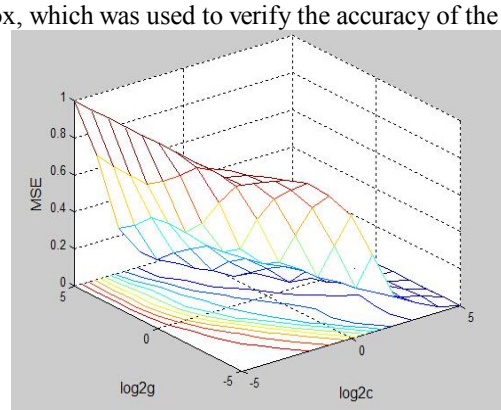

Figure 2. 3D View Plot of Parameter selections

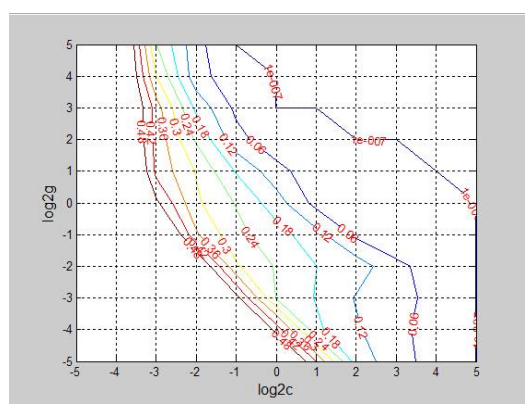

Figure 3. Contour map of Parameter selection

B. Prediction Accuracy Analysis

The foundation pit horizontal displacement observation data has a total of 38, so take the 28 observational data as the training samples of the least squares support vector machine (SVM) model , then predict the other 10 observation point displacement and be compared with the measured value to predict the accuracy. Due to the poor prediction result of some pretreated data. We selected NO3 and NO13 which the prediction result is better as the research object, and the prediction results and measured value were comparative analyzed, as shown in Figure 4, Figure 5.

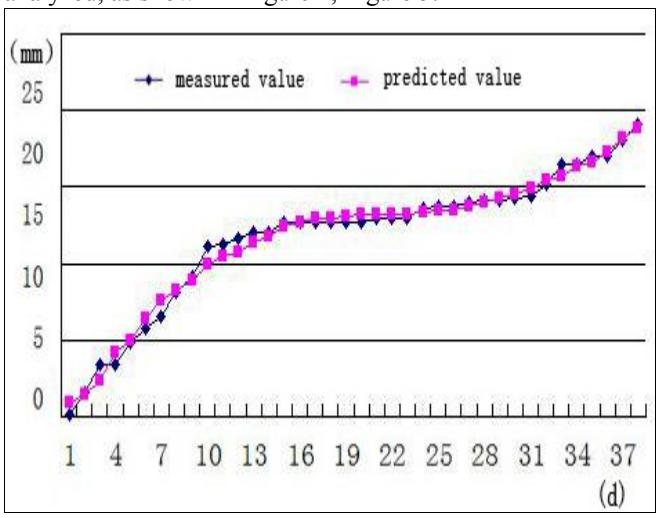

Figure 4. Contrast diagram between predicted value and measured value of NO3 observation point

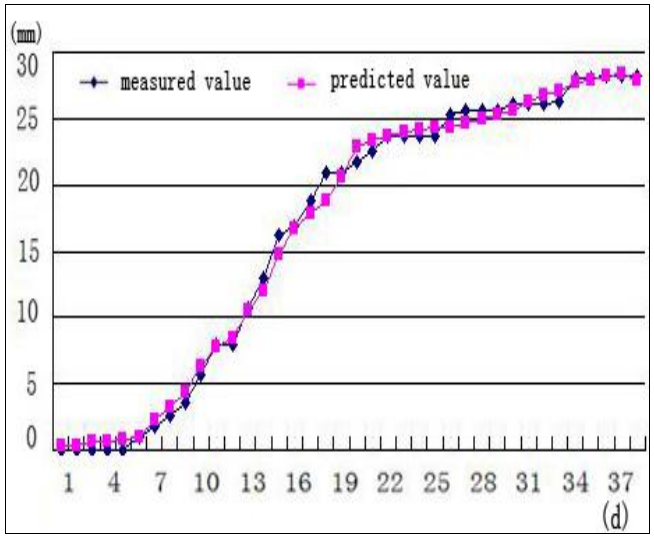

Figure 5. Contrast diagram between predicted value and measured value of NO13 observation point

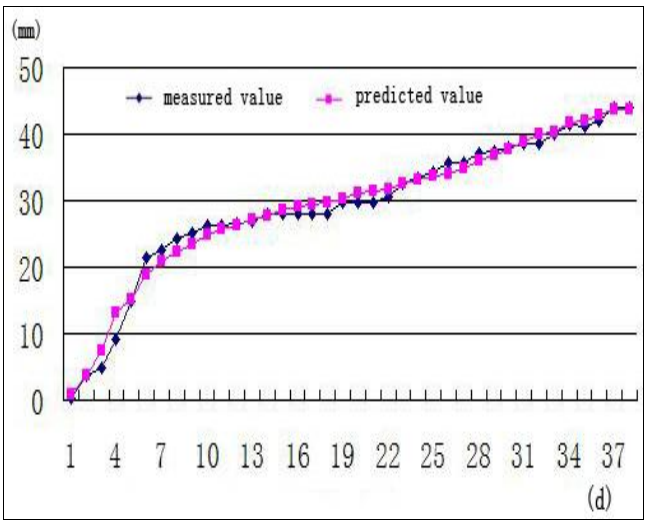

Figure 6. Contrast diagram between predicted value and measured value of NO20 observation point

The calculation result of relative mean error of each point as shown in table 1, table 2, and table 3:

TABLE I. COMPARATIVE ANALYSIS TABLE BETWEEN PREDICTED VALUE AND MEASURED VALUE OF NO3 OBSERVATION POINT

Observation time series of NO3	Measured Value (mm)	SVM predicted value (mm)	relative error (%)
29	14.2	14.221	0.148
30	14.3	14.506	1.441
31	14.4	14.931	3.687
32	15.2	15.400	1.316
33	16.5	15.650	5.152
34	16.5	16.305	1.182
35	17.0	16.575	2.500
36	17.0	17.253	1.488
37	18.0	18.141	0.783
38	19.1	18.911	0.989
average relative error(%)		1.865	

TABLE II. COMPARATIVE ANALYSIS TABLE BETWEEN PREDICTED VALUE AND MEASURED VALUE OF NO13 OBSERVATION POINT

observation time series of NO13	measured value(mm)	SVM predicted value(mm)	relative error(%)
29	25.6	25.307	1.144
30	26.1	25.691	1.567
31	26.1	26.251	0.578
32	26.1	26.824	2.773
33	26.3	27.099	3.038
34	28.0	27.711	1.032
35	28.0	27.909	0.325
36	28.2	28.262	0.219
37	28.2	28.358	0.560
38	28.2	27.911	1.025
average relative error(%)		1.226	

TABLE III. COMPARATIVE ANALYSIS TABLE BETWEEN PREDICTED VALUE AND MEASURED VALUE OF NO20 OBSERVATION POINT

observation time series of NO20	measured value(mm)	SVM predicted value(mm)	relative error(%)
29	37.3	36.778	1.399
30	38.1	37.636	1.218
31	38.5	38.784	0.738
32	38.6	39.897	3.360
33	40.1	40.428	0.818
34	41.1	41.641	1.306
35	41.1	42.068	2.355
36	42.1	42.954	2.028
37	44.1	43.679	0.955
38	44.1	43.672	0.971
Average relative error(%)		1.515	

V. CONCLUSIONS

The predicted and measured values are compared analysis and the result characteristic summarized as shown below:

- The predicted values predicted by the LS-SVM model are in agreement with the measured values, which are related to the input values of the training samples;
- The relative errors of the predicted values of the 3, 13 and 20 monitoring points were randomly changed, not according to a certain rule, which was caused by the instability of the deformation rate of the first 28 phase of the training samples;
- From the comparison chart of the predicted values and measured values of the selected two monitoring points can find that: the result of using LS-SVM prediction model for predicting the horizontal displacement of deep foundation pit can basically meet the requirement of deformation monitoring. It is feasible to apply the least squares support vector machine prediction model to predict deep foundation pit horizontal displacement, and the prediction results has certain practical significance to ensure the safety of foundation pit construction and early warning of danger.

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