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Analysis of Coordinated System Prediction System Based on Least Square Support Vector Machine

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Abstract: The accurate prediction of the dynamic performance of the coordinated system plays an important role in ensuring the safe, efficient and stable operation of the unit. Support vector machine (SVM) is a practical algorithm based on statistical learning theory, which has been widely used in pattern recognition, function fitting, time series prediction and so on. Least square support vector machine (LS-SVM) is a standard SVM rewriting method for solving the KKT problem of linear system. Based on LS-SVM, this paper realizes the prediction and analysis of coordinated system, and compares it with simulation experiments, which shows that this method has high accuracy.

1. Introduction

Suykens proposed the least squares support vector machine (LSSVM), which is an improvement of support vector machine (SVM). It uses equality constraints to refer to inequality ones, making the quadratic programming problem change to linear problem, and promoting the training speed of prediction model. It can be used in small samples. The prediction and identification of nonlinear complex system is better than that of back propagation neural network prediction model. The main problem of using LSSVM prediction model is to select the kernel function and corresponding parameters. The kernel function is different, and the parameters of the same and function are different accordingly, so the prediction effect is different either[1]. In this paper, the least square support vector machine is used to predict and analyze the coordination system.

2. Least Squares Support Vector Machine

Assuming $\{x_i, y_i\}_{i=1}^N$ samples, input $x_i \in R^n$ into n dimensions, and achieve the output $y_i \in R$ to create an estimation function:

$$r = w^T \varphi(x) + b$$

In the formula, $\varphi(x)$ refers to the mapping function of high-dimensional feature space, w refers to the deviation, and B is the weight vector. In this way, the nonlinear estimation function can be transformed into a linear function in a high-dimensional space. Based on the principle of minimizing structural risk, considering the sum of squared errors of regularized item feather, we can transform the estimation regression problem to the following constrained quadratic optimization problem, which has the unique optimal solution:

$$\min J(w,e) = \frac{1}{2} w^T w + \frac{1}{2} \gamma \sum_{i=1}^{N} e_i^2$$

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The constraints are as follows:

$$y_i = w^T \varphi(x_i) + b + e_i, i = 1,..., N$$

In the formula, e_i refers to the error and y is the adjustable super parameter, which is closely related to the model complexity and the minimum error. Unlike standard SVM, this is an equality constraint. Then, we use Lagrange function to transform the constrained optimization problem into unconstrained optimization problem

L(w,b,e,a)=J(w,e)-R(w,b,e,a)

$$R(w,b,e,a) = \sum_{i=1}^{N} a_i \left\{ w^T \varphi(xi) + b + e_i - y_i \right\}$$

In the formula, a_i refers to the multiplier. Set the above formula to 0 for the partial derivative under the optimized conditions, and eliminate the partial derivative to obtain the following equations:

$$\begin{bmatrix} 0 & 1_N^{\rightarrow} \\ 1_N^{\rightarrow} & \varphi(x_i)^T \varphi(x_j) + r^{-1} I_N \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix}$$

Where y = [y_1;...;yN] refers to a burst of n * n, which is obtained by Mercer condition:

$$\varphi(x_i)^T \varphi(x_j) = K(x_i, x_j), i, j = 1,..., N$$

$K(x_i, x_j)$ refers to the kernel function, which is obtained by the above formula:

If the kernel function is expressed as RBF, then:

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

In the formula, σ refers to the RBF kernel width parameter, and LSSVM model can have two parameters, which should be trained[2].

3. Optimal Kernel Function and Support Vector Machine

Through LS-SVM prediction model based on RBF, cross validation can be used to determine the best combination. The samples are divided into k parts, each time different data is used as the verification set and others as the training set. Through the test analysis of different verification sets, the least prediction error is used as LS-SVM parameters. When both γ and σ are finite parameter sets, the prediction error will appear and the actual demand will not be satisfied. In this way, the parameter combination of γ and σ is realized by adaptive optimization parameter method, and then the optimal combination is determined by cross validation.

Use RMS error as prediction error:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y(i) - u(i))^2}$$

In the formula, N refers to the number of samples, y(i) refers to the predicted value of samples, u(i) refers to the actual value of samples[3].

Support vector machine (SVM) is a practical algorithm based on statistical learning theory, which is based on the principle of structural risk minimization and has been approved by rigorous theory. Through the analysis of two pattern recognition problems, the basic idea of SVM is to select the optimal classification surface, separate the two samples, and ensure that the two samples have a large distance. Based on the actual situation, we will encounter nonlinear and indivisible mode. In this case, SVM uses nonlinear transformation to make it map in linear separable high-dimensional space, and uses the concept of kernel function to transform the inner product calculation of high-dimensional space to low-dimensional input space, and calculates kernel function. By using Lagrange multiplier method, the maximum interval problem can be transformed into a dual problem, and the corresponding parameters can be obtained.

Generally speaking, support vector machine is a learning method to solve the kernel function problems such as nonlinear classification, density estimation and function fitting. At first, it was introduced by the theory of statistical learning and the principle of structural risk minimization. Quadratic programming is generally used in the process of solving optimization problems. This value function is the regular least square equation with equality constraints for linear KKT system, which can be solved by iteration. LS-SVM is closely related to Gaussian process and regularized network, but it pays attention to the most primitive dual relationship. The kernel function relationship of classical pattern recognition algorithms, such as unsupervised learning and kernel discriminant analysis extension, can use repetitive control and network. LS-SVM toolbox has regression, classification, prediction and other algorithms, which are implemented by MATLAB[4].

4. Prediction and Analysis of Coordinated System Based on Ls-Svm

Using LS-SVM toolbox function to achieve the training and learning of the dynamic characteristics of the coordinated system, the system prediction model can be obtained, using part of the test data to achieve the prediction of the prediction model and MATLAB for simulation, so as to get the error between the comparison curve and prediction.

Suppose the unstable nonlinear system:

$$\dot{x} = \frac{1-e^{-x(t)}}{1+e^{-x(t)}} + u(t)$$

X (T) = 0 is the initial value, and the control target refers to the step signal 1(t) of x(t) tracking unit.

Set the controller parameters as γ=2.5,Q=12,ko=3. According to the above analysis, A=-ko=-3,P=2. Set LS-SV, input to x = [x]. Using offline training to get the initial parameter setting of LS-SVM weight, and then realize online adaptive simulation control[5]. Figure 1 is the state X and expected response, and figure 3 is the curve of controlling quantity.

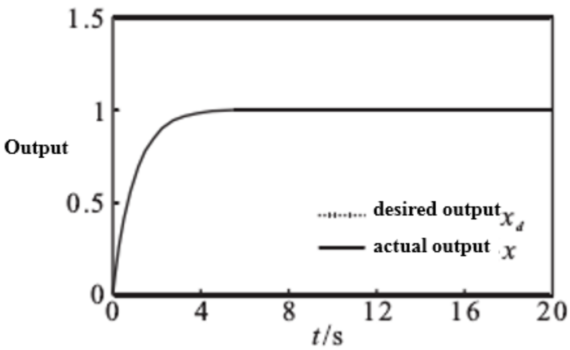

Fig.1 The State X and Expected Response

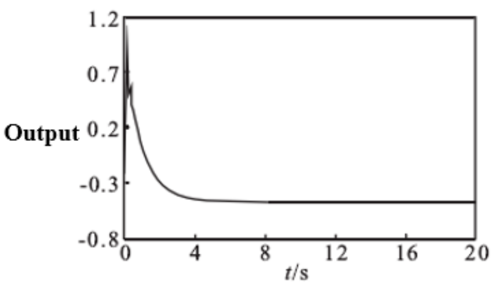

Fig.2 The Curve of Control Quantity

The following simulation results show that the system training and testing errors are as follows:

Output power set to NE:

RMSEtrain=0.0038

RMSEtest=0.0134

The main steam pressure is set to TP:

Rmsetrain = 4.0570e-004

RMSEtest=0.0039

Table 1 Shows the Error Comparison between Ls-Svm and Other Algorithms. It Can Be Seen ThatLs-Svm Algorithm is Effective and the Prediction Error is Smaller Than Other Algorithms[6].

Table 1 Ls-Svm and Other Algorithms Error Comparison

algorithm	predicted error	
	Ne	Pt
BP netural network	0.9425	0.0652
I-SMO algorithm	0.7215	0.0251
LS-SVM algorithm	0.0134	0.0034

5. Conclusion

The paper proposes a coordinated system prediction method based on LS-SVM. The adaptive controller is created based on LS-SVM, and the regulation of online parameters of the adaptive controller is realized by stability theory. In this paper, the algorithm is proved and the system can meet the actual needs by adjusting the design parameters. The simulation results show that the adaptive controller and method based on LS-SVM are effective.

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