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Direct Adaptive H_∞ Control for a Class of Nonlinear Systems based on LS-SVM

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Abstract: A scheme of direct adaptive H_∞ control based on least squares support vector machines (LS-SVM) is proposed for a class of nonlinear uncertain systems. In this method, LS-SVM is employed to construct the adaptive controller, and an on-line learning rule for the weighting vector and bias is derived. A parameter selection method based on the genetic algorithm (GA) is given for LS-SVM regression with Gauss kernel. H_∞ control is used to attenuate the effect on the tracking error caused by LS-SVM approximation errors and external disturbances. Lyapunov theory is used to prove the uniformly ultimately bounded stability of the close-loop system. The simulation result shows the effectiveness and feasibility of the proposed method.

Keywords: Least Squares Support Vector Machines, Nonlinear Systems, Adaptive Control, H_∞ Control, Genetic Algorithm

1 Introduction

Least squares support vector machines (LS-SVM) has been proposed by Suykens et al. for modeling and control of nonlinear systems [1,2]. LS-SVM takes equality in instead of inequality constrains of SVM in the problem formulation such that LS-SVM is easy to train, which promotes the applications of LS-SVM and many function approximation and nonlinear control problems have been tackled with LS-SVM in the last decades [3,4,5,6]. However, those works lack the definite stability proof of the closed loop system using LS-SVM approaches.

A direct adaptive controller is developed incorporating LS-SVM, Lyapunov theory and H_∞ control theory under plant uncertainties and external disturbances in this paper. In this method, the LS-SVM is employed to approximate unknown nonlinear dynamics in the plant, and then the tracking error caused by LS-SVM approximation errors and external disturbance are tackled as the complex interference. To improve the resulting approximation precise, an innovative optimization algorithm known as the genetic algorithm (GA) [7,8] are adopted to automatically tune two parameters in LS-SVM design. It is shown that the designed controller ensures not only guarantee the asymptotic stability of the close-loop system, but also guarantees the tracking error to satisfy the set performance index by introducing H_∞ control. The numerical simulation is presented to show the effectiveness of the proposed method.

This paper is organized as follows. Section 2 presents the background about control problem in a class of nonlinear uncertain systems. LS-SVM and its parameters selection are briefly described in Section 3.The proposed direct adaptive H_∞ controller based on LS-SVM is designed in Section 4. Numerical examples are given to illustrate the effectiveness of the proposed method in section 5. Finally, conclusions are offered in Section 6.

2 Problem Formulation

Consider the nth-order nonlinear systems of the form

$$\begin{cases} x^{(n)} = f(x, \dot{x}, \cdots, x^{(n-1)}) + bu + d \\ y = x \end{cases} \tag{1}$$

where f is unknown but bounded continuous function, b is a positive unknown constant, d is a bounded disturbance signal of the system, $u \in R$ and $y \in R$ are the input and the output of the system, respectively. Let

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$\mathbf{x} = (x, \dot{x}, \cdots, x^{(n-1)})^T \in R^n$ is the state vector of the system which is assumed to be available.

Let y_m be a bounded reference signal, and $e = y_m - y$ the output tracking error.

The control objective is to force y follow the given reference signal y_m under the constraints that all signals involved must be bounded. Hence a feedback control $u(\mathbf{x}|\mathbf{W})$ base on LS-SVM and an adaptive law for adjusting the parameter vector $\mathbf{W}$ of LS-SVM are both determined to satisfy the following conditions.

(1) the closed-loop system is globally stable in the sense that all variables involved must be uniformly bounded.

(2) the following H_∞ tracking performance will be achieved with the given inhibitory level $\rho > 0$,

$$\int_0^{\bar{t}} \mathbf{e}^T \mathbf{Q} \mathbf{e} \le \mathbf{e}^T(0)\mathbf{P}\mathbf{e}(0) + \frac{1}{\eta}\tilde{\mathbf{W}}^T(0)\tilde{\mathbf{W}}(0) + \rho^2 \int_0^{\bar{t}} \omega^T \omega dt \tag{2}$$

Where $\bar{t} \in [0, \infty]$,$\mathbf{e} = [e, \dot{e}, \cdots, e^{(n-1)}]^T$,$\omega \in L_2[0,T]$, $\mathbf{Q} = \mathbf{Q}^T \ge 0$ and $\mathbf{P} = \mathbf{P}^T \ge 0$. ω is the compound interference caused by LS-SVM approximation errors and external disturbance, $\mathbf{W}$ is the parameter vector of LS-SVM, $\tilde{\mathbf{W}}$ is the estimate error vector of the LS-SVM, $\eta > 0$ is the learning rate of LS-SVM.

3 LS-SVM and Its Parameter Selection

3.1 LS-SVM Regression

In the section, we briefly discuss LS-SVM regression. For further details on LS-SVM we refer to Ref. [1].

Given the following training sample set(D): $D = \{(\mathbf{x}_k, y_k)\,|k = 1, 2, \cdots, N\}$, where is the total number of training data pairs, $\mathbf{x}_k \in R^n$ is the regression vector and $y_k \in R$ is the output. The following model is taken

$$f(\mathbf{x}) = w^{\mathrm{T}}\varphi(\mathbf{x}) + b \tag{3}$$

where the nonlinear mapping $\varphi : R^n \to R^{n_h}$ maps the input data into a so-called high dimensional feature space (which can be infinite dimension). The regularized cost function of the LS-SVM is given as:

$$\begin{gathered} \min J(\mathbf{w}, \varepsilon) = \tfrac{1}{2}\mathbf{w}^T\mathbf{w} + \tfrac{1}{2}\gamma \sum_{k=1}^{N} \varepsilon_k^2 \\ s.t. y_k = \mathbf{w}^T\varphi(\mathbf{x}_k) + b + \varepsilon_k, k = 1, 2, \cdots, N \end{gathered} \tag{4}$$

where $\mathbf{w} \in R^{n_h}$ is the weight vector, $\varepsilon_k \in R$ is slack variable, $b \in R$ is a bias term and $\gamma \in R$ is regularization item. The Lagrangian corresponding to Eq. (4) can be defined as follows:

$$L(\mathbf{w}, b, \varepsilon; \alpha) = J(\mathbf{w}, \varepsilon) - \sum_{k=1}^{N} \alpha_k \left\{\mathbf{w}^T\phi(\mathbf{x}_k) + b + \varepsilon_k - y_k\right\} \tag{5}$$

where $\alpha_k \in R(k = 1, 2, \cdots, N)$ are the Lagrange multipliers. Using the Karush-Kuhn-Tucker (KKT) conditions, we get the linear equations

$$\begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 & \vec{1}^T \\ \vec{1} & \Delta + \gamma^{-1}\mathbf{I} \end{bmatrix}^{-1} \begin{bmatrix} 0 \\ \mathbf{y} \end{bmatrix} \tag{6}$$

with $\mathbf{y} = [y_1, \cdots, y_N]^T \in R^N$, $\bar{\mathbf{1}} = [1, \cdots, 1]^T \in R^N, \alpha = [\alpha_1, \cdots, \alpha_N]^T, \Delta_{kl} = \varphi(\mathbf{x}_k)^T\varphi(\mathbf{x}_l) = K(\mathbf{x}_k, \mathbf{x}_l), \forall k, l = 1, 2, \cdots, N$ is the kernel function satisfying Mercer′s condition. In this paper, the Gaussian RBF kernel $K(\mathbf{x}_k, \mathbf{x}_l) = exp(-\|\mathbf{x}_k - \mathbf{x}_l\|^2/2\sigma^2)$ is chosen as the kernel function, where σ is the kernel parameter. And the resulting LS-SVM regression model becomes

$$f(\mathbf{x}) = \sum_{k=1}^{N} \alpha_k K(\mathbf{x}, \mathbf{x}_k) + b \tag{7}$$

where α_k,b are the solution to Eq. (6).

It is well known that LS-SVM generalization performance depends on a good setting of regularization parameter γ and the kernel parameter σ. In order to achieve the better generalization performance, the parameters of LS-SVM can be selected by GA.

3.2 Hyper-Parameters based on GA Algorithm

For the problem of parameters selection by GA, each set of γ and σ is taken as an individual in a population, and the estimated generalization error as the fitness. As the k-fold cross-validation is a very reliable method to estimate the generalization error [1,2], it is employed in this paper. In k-fold cross-validation, the training data is randomly split into k roughly equal subsets. An LS-SVM decision rule is trained using $(k-1)$ of these subsets and validated on the subset left out. This procedure is repeated k times with each of the k subsets used as the validation subset in turn. Averaging the validation errors over the k trials gives an estimate of the generalization error. The flowchart of the GA-based parameters selection algorithm for the LS-SVM is shown in Fig. 1.

4 Direct Adaptive H_∞ Controller Design and Stability Analysis Based on LS-SVM

First, let $\mathbf{k} = (k_n, k_{n-1}, \cdots, k_1)^T \in R^n$ be such that all roots of the polynomial $h(s) = s^n + k_1 s + \cdots + k_n$ are in the open left-hand plane. If the function f and the constant b are known, and $d = 0$, then the control law

$$u^* = \frac{1}{b}[-f(\mathbf{x}) + y_m^{(n)} + \mathbf{k}^T\mathbf{e}] \tag{8}$$

applied to system (1) can result in $e^{(n)} + k_1 e^{(n-1)} + \cdots + k_n e = 0$, which implies that

$\lim_{t\to\infty} e(t) = 0$ (the main objective of control). Since f and b are unknown, and $d \neq 0$, then the optimal control u^* can not be implemented. Hence, the adaptive controller based on LS-SVM will be designed to approximate this optimal control.

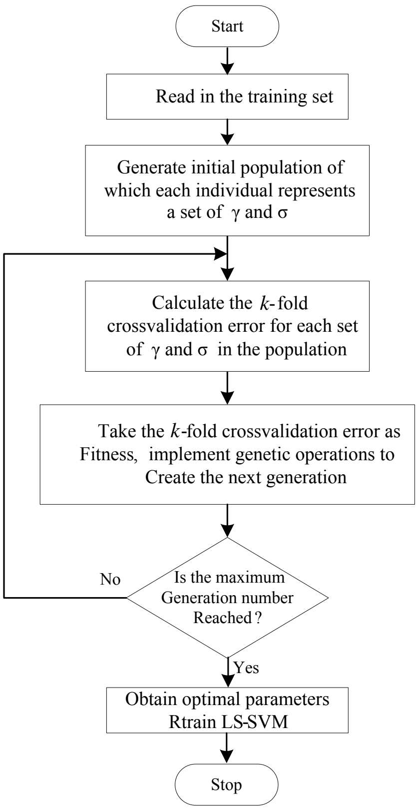


Fig. 1 Structure of least support vector machines

The control u is supposed to consist of an adaptive control $\hat{u}(\mathbf{x}|\mathbf{W})$ based on LS-SVM and a H_∞ robust control v, i.e.,

$$u = \hat{u}(\mathbf{x}|\mathbf{W}) - v \tag{9}$$

where

$$v = -\frac{1}{r}\mathbf{B}^T\mathbf{Pe} \tag{10}$$

$r > 0$ is a design parameter, $\mathbf{P}$ is a symmetric positive definite matrix satisfying the Riccati equation

$$\mathbf{PA} + \mathbf{A}^T\mathbf{P} + \mathbf{Q} - \frac{2}{r}\mathbf{PBB}^T\mathbf{P} + \frac{2}{\rho^2}\mathbf{PBB}^T\mathbf{P} = 0 \tag{11}$$

where $r \leq 2\rho^2$. Substituting (9) into (1), we will have

$$x^{(n)} = f(\mathbf{x}) + b[\hat{u}(\mathbf{x}|\mathbf{W}) - v] + d \tag{12}$$

After some straightforward manipulation, we can obtain the error of the closed-loop system

$$\dot{\mathbf{e}} = \mathbf{Ae} + \mathbf{B}[u^*(\mathbf{x}) - \hat{u}(\mathbf{x}|\mathbf{W})] + \mathbf{B}v - \mathbf{B}d/b \tag{13}$$

where

$$\mathbf{A} = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 1 & \cdots & 0 & 0 \\ & \cdots & & \cdots & & \\ 0 & 0 & 0 & \cdots & 0 & 1 \\ -k_n & -k_{n-1} & -k_{n-2} & \cdots & -k_2 & -k_1 \end{bmatrix}, \mathbf{B} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ b \end{bmatrix}$$

LS-SVM is used to approximate the optimal control. The output of LS-SVM is

$$\hat{u}(\mathbf{x}|\mathbf{W}) = \mathbf{W}^T\beta \tag{14}$$

where

$$\mathbf{W} = [\, w_1 \; w_2 \; \cdots \; w_{N+1}]^T,$$
$$\beta(\mathbf{x}) = [1, K(\mathbf{x}_1,\mathbf{x}), \cdots, K(\mathbf{x}_N,\mathbf{x})]^T.$$

The following objective is to design the control u and the adaptive law of the weight vector $\mathbf{W}$ to realize the control task. First, the optimal weight vector $\mathbf{W}^*$ is defined as

$$\mathbf{W}^* = \arg\min_{\mathbf{W}\in\Omega}\left[\sup_{\mathbf{x}\in D}|\hat{u}(\mathbf{x}|\mathbf{W}) - u^*(\mathbf{x})|\right] \tag{15}$$

where $\Omega = \{\mathbf{W}|\|\mathbf{W}\| \leq M\}$ and $D = \{\mathbf{x}|\|\mathbf{x}\| \leq M_1\}$ are the feasible region of the weight vector and the state vector, respectively, M and M_1 are specified by the designer. We assume that $\mathbf{W}$ and $\mathbf{x}$ never reach the boundary Ω and D. The minimum approximation error is defined as

$$\omega_n = u^*(\mathbf{x}) - \hat{u}(\mathbf{x}|\mathbf{W}^*) \tag{16}$$

Substituting (14) and (16) into (13), we get the error equation of the closed-loop system

$$\begin{aligned}\dot{\mathbf{e}} = \mathbf{Ae} + \mathbf{B}\{[u^*(\mathbf{x}) - \hat{u}(\mathbf{x}|\mathbf{W}^*)] \\ +[\hat{u}(\mathbf{x}|\mathbf{W}^*) - \hat{u}(\mathbf{x}|\mathbf{W})]\} + \mathbf{B}v - \mathbf{B}d/b\end{aligned} \tag{17}$$

or equivalently

$$\dot{\mathbf{e}} = \mathbf{Ae} - \mathbf{B}\tilde{\mathbf{W}}^T\beta + \mathbf{B}v + \mathbf{B}\omega \tag{18}$$

where $\omega = \omega_n - d/b$, and $\tilde{\mathbf{W}} = \mathbf{W} - \mathbf{W}^*$ is the estimate error of the parameter vector $\mathbf{W}$.

$$\dot{\mathbf{W}} = \eta\mathbf{e}^T\mathbf{PB}\beta \tag{19}$$

Theorem. For the nonlinear system (1) if the adaptive control scheme based on LS-SVM is chosen as (9), and the adaptive law of the parameter is chosen as (19), then the whole adaptive control scheme guarantees the following properties:

i) $\mathbf{x}, u \in L_\infty$.

ii) the following H_∞ tracking performance (2) will be achieved with the given inhibitory level ρ.

Proof. We choose the Lyapunov function as

$$V = \frac{1}{2}\mathbf{e}^T\mathbf{Pe} + \frac{1}{2\eta}\tilde{\mathbf{W}}^T\tilde{\mathbf{W}} \tag{20}$$

Differentiated with respect to t, we get

$$\dot{V} = \frac{1}{2}(\dot{\mathbf{e}}^T\mathbf{Pe} + \mathbf{e}^T\mathbf{P}\dot{\mathbf{e}}) + \frac{1}{2\eta}(\dot{\tilde{\mathbf{W}}}^T\tilde{\mathbf{W}} + \tilde{\mathbf{W}}^T\dot{\tilde{\mathbf{W}}}) \quad (21)$$

Since $\dot{\tilde{\mathbf{W}}} = \dot{\mathbf{W}}$, and according to (18), (21) becomes

$$\begin{aligned}\dot{V} &= \tfrac{1}{2}[\mathbf{e}^T\mathbf{A}^T\mathbf{Pe} + v\mathbf{B}^T\mathbf{Pe} - \tilde{\mathbf{W}}^T\beta\mathbf{B}^T\mathbf{Pe} + \\ &\omega\mathbf{B}^T\mathbf{Pe} + \tfrac{1}{\eta}\dot{\mathbf{W}}^T\tilde{\mathbf{W}} + \mathbf{e}^T\mathbf{PAe} + \mathbf{e}^T\mathbf{PB}v - \\ &\mathbf{e}^T\mathbf{PB}\tilde{\mathbf{W}}^T\beta + \mathbf{e}^T\mathbf{PB}\omega + \tfrac{1}{\eta}\tilde{\mathbf{W}}^T\dot{\mathbf{W}}]\end{aligned} \quad (22)$$

From (10), we can obtain

$$\begin{aligned}\dot{V} &= \tfrac{1}{2}\mathbf{e}^T(\mathbf{PA} + \mathbf{A}^T\mathbf{P} - \tfrac{2}{r}\mathbf{e}^T\mathbf{PBB}^T\mathbf{P})\mathbf{e} - \\ &\tilde{\mathbf{W}}^T(\beta\mathbf{B}^T\mathbf{Pe} - \tfrac{1}{\eta}\dot{\mathbf{W}}) + \tfrac{1}{2}\omega\mathbf{B}^T\mathbf{Pe} + \tfrac{1}{2}\mathbf{e}^T\mathbf{PB}\omega]\end{aligned} \quad (23)$$

Based on the adaptive law (19) and the Riccati equation (11), we can obtain

$$\begin{aligned}\dot{V} &= -\tfrac{1}{2}\mathbf{e}^T\mathbf{Qe} - \tfrac{1}{2\rho^2}\mathbf{e}^T\mathbf{PBB}^T\mathbf{Pe} + \tfrac{1}{2}\omega\mathbf{B}^T\mathbf{Pe} \\ &= -\tfrac{1}{2}\mathbf{e}^T\mathbf{Qe} - \tfrac{1}{2}\left(\tfrac{1}{\rho}\mathbf{B}^T\mathbf{Pe} - \rho\omega\right)^T\left(\tfrac{1}{\rho}\mathbf{B}^T\mathbf{Pe} - \rho\omega\right) + \tfrac{1}{2}\rho^2\omega^2 \\ &\le -\tfrac{1}{2}\mathbf{e}^T\mathbf{Qe} + \tfrac{1}{2}\rho^2\omega^2 \le -\tfrac{1}{2}\lambda_{\min}(\mathbf{Q})\|\mathbf{e}\|^2 + \tfrac{1}{2}\rho^2|\bar{\omega}|^2\end{aligned} \quad (24)$$

where $\bar{\omega}$ is the upper bound of ω, $\lambda_{\min}(\mathbf{Q})$ is the minimum eigenvalue of the matrix $\mathbf{Q}$. From the above equation, we can know when $\|\mathbf{e}\| \ge \rho|\bar{\omega}|/\lambda_{\min}(\mathbf{Q})$, then $\dot{V} < 0$. Hence, we can establish that $\mathbf{x}, u \in L_\infty$.

Integrating the above equation from 0 to $\bar{t}$ yields

$$V(T) - V(0) \le -\frac{1}{2}\int_0^{\bar{t}} \mathbf{e}^T\mathbf{Qe}dt + \frac{1}{2}\rho^2\int_0^{\bar{t}} \omega^T\omega dt \quad (25)$$

Since $V(T) \ge 0$, from (25) we can obtain

$$\begin{aligned}&\tfrac{1}{2}\int_0^{\bar{t}} \mathbf{e}^T\mathbf{Qe}dt \le V(0) + \tfrac{1}{2}\rho^2\int_0^{\bar{t}}\omega^2 dt = \tfrac{1}{2}\mathbf{e}^T(0)\mathbf{Pe}(0) + \\ &\tfrac{1}{2\eta}\tilde{\mathbf{W}}^T(0)\tilde{\mathbf{W}}(0) + \tfrac{1}{2}\rho^2\int_0^t \omega^T\omega dt\end{aligned} \quad (26)$$

Therefore, the theorem holds. □

5 Simulation Result

Consider the following nonlinear system

$$\begin{cases}\dot{x}_1 = x_2 \\ \dot{x}_2 = -0.1x_2 - x_1^3 + 12\cos t + u + d \\ y = x_1\end{cases} \quad (27)$$

where $f = -0.1x_2 - x_1^3 + 12\cos t$, $b = 1$, d is the square wave disturbance whose vibration amplitude is ± 1, and period is 2π.

In this example, in order to research the control effect for nonlinear systems, we will adopt the LS-SVM and neural networks to construct the adaptive controller, respectively. The reference signal is assumed to be $y_m = \sin t$. Let $\mathbf{k} = [k_2, k_1]^T = [1, 2]^T$, and the control is chosen as

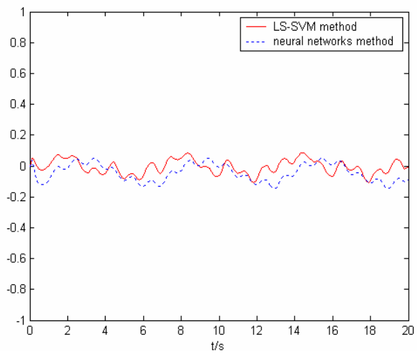
$$u^* = [-0.1x_2 - x_1^3 + 12\cos t - \sin t + 2\dot{e} + e]$$

The initial condition is assumed to be $x_1(0) = x_2(0) = 0$. To collect the training data, the Gaussian noise with zero mean and standard deviation 1 is selected as the input. By solving the physical model (27) using the fourth-order Runge-Kutta method, the input and output data of (27) are collected. The two-dimensional search space of γ and σ^2 is $[1, 10^4]$ and $[0.1, 10^3]$. The population size and the maximum generation number are set to 30 and 100, respectively. By the proposed GA-based tuning method with the 5-fold cross-validation error as fitness, the optimal set of (γ, σ^2) is found at $(5188.8, 9.7)$.

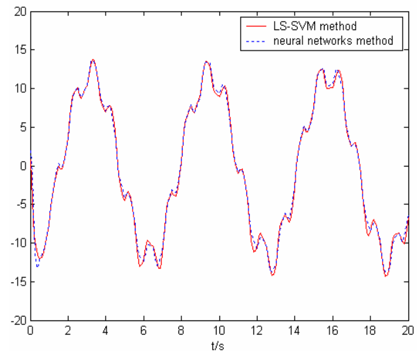
Select the positive definite matrix $\mathbf{Q} = diag(10, 10)$, and the given inhibitory level $\rho = 0.1, 0.05$, and $r = 0.02, 0.005$. Then after solving the Riccati equation (11), we obtain the positive definite matrix

$$\mathbf{A} = \begin{bmatrix} 0 & 1 \\ -1 & -2 \end{bmatrix}, \mathbf{P} = \begin{bmatrix} 15 & 5 \\ 5 & 5 \end{bmatrix}$$

The simulation results are shown in Fig.2 ($\rho = 0.1$) and Fig.3 ($\rho = 0.05$).

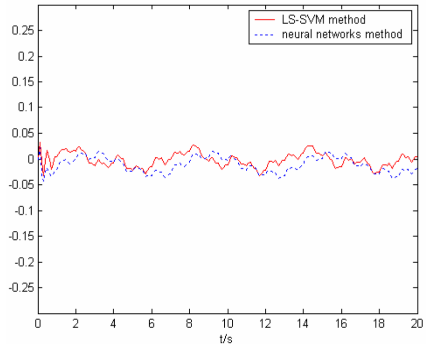


(a) Tracking error

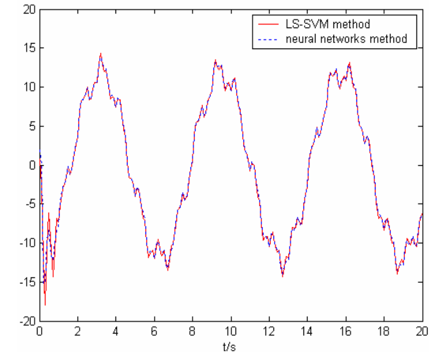


(b) Control input

Fig. 2 Simulation results with $\rho = 0.1$



(a) Tracking error



(b) Control input

Fig. 3 Simulation results with $\rho = 0.05$

According to the simulation results, we can conclude when the value of ρ is smaller, the tracking effect is better, but the control gain is bigger accordingly (the control input ranges from -14.3508 to 13.707 in $\rho = 0.1$, and the control input ranges from -17.8989 to 14.2823 in $\rho = 0.05$). Hence, the reasonable selection for the inhibitory level ρ is very necessary in practical applications.

At the same time, the control precision based on LS-SVM (the average error is 0.0057 with $\rho = 0.1$ and 0.0021 with $\rho = 0.05$) is higher than that based on neural networks (the average error is with $\rho = 0.1$ and 0.0113 with $\rho = 0.05$).

6 Conclusions

A direct adaptive H_∞ control scheme based on LS-SVM is developed for a class of nonlinear uncertain systems. LS-SVM is employed to approximate the optimal control, and an on-line learning rule for the weighting vector and bias is derived. The GA is adopted to optimize the parameters of LS-SVM. H_∞ control is used to attenuate the effect on the tracking error caused by LS-SVM approximation errors and external disturbance. Based on Lyapunov stability theory, it is rigorously proved that the stability of the whole closed-loop system is assured and the tracking performance is achieved.

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