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Robust Adaptive Control of nonlinear switched Systems under external disturbances

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ABSTRACT: In this work, a robust adaptive neural network control is proposed for a class of nonlinear switched systems with external disturbances. The main idea is a design based on the approximation description of neural networks and the dwell-time approach. Under the separation of disturbances, we establish new linear matrix inequalities to give the control law. Stability analysis shows that all the closed-loop system signals are uniformly ultimately bounded, and the steady-state tracking error can be made arbitrarily small by appropriately choosing control parameters. The simulation results demonstrate the effectiveness of the proposed controllers.

KEYWORDS: Robust Adaptive Control; Nonlinear Switched Systems; Dwell-Time Lyapunov stability.

INTRODUCTION

A switched system is an essential class of hybrid dynamical systems to describe many industrial systems such as DC-DC converter, Z source, multilevel inverter, three-phase systems [1-6]. Hence, there have been a large number of publications about switched systems control. In practical systems, the influence of external disturbances and dynamic uncertainties are always appeared. Therefore, the requirement of robust adaptive control with Neural Networks should be considered. Although many different synthesis methods for switched systems have been available, e.g., optimal control, robust control, predictive control, and adaptive control, there are not many projects for switched system based on neural network [7-19]. The optimal control design has been presented in requires complicated computation and it is necessary to solve the unification of stability problem and optimality [7-9]. This challenge is also mentioned in predictive control [13,14]. The approaches of neural network, fuzzy technique as well as ANN, particle swarm optimization (PSO) was mentioned in several different systems such as photovoltaic inverter, transmission line, etc [20-24]. In an adaptive neural control is presented for a class of switched nonlinear systems with switching jumps and uncertainties in both system models and switching signals [25].

Although in this paper the author presented a method for a more complex system, this article did not mention the occurrence of interference and the implementation was difficult because of complex controllers. In the author has not analyzed the disturbance, so the results will lead to large attractive region [19]. In this work, we propose a new tracking control law for a class of switched nonlinear systems based on the error modelling. Our control objective is to design a switching law $\delta(t)$ and an equivalent robust adaptive neural network controller obtaining the stable closed-loop system. In order to fullfill this proposed control law, the consideration of Linear Matrix In equalities (LMIs) plays the role of intermediate step. Motivated from existing papers, this article presents the robust adaptive control scheme using LMIs and NNs to handle external disturbances and dynamic uncertainties in switched nonlinear systems. The rest of this article is organized as follows. The section 2 discusses the problem statement and proposed controller. Consequently, the section 3 describes the simulation results to validate the proposed robust adaptive control design. Finally, the summary and future direction are pointed out in section 4.

PROBLEM STATEMENT AND PROPOSED CONTROLLER

A class of switched nonlinear systems with external disturbances is considered as follows:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = x_3 \\ \dots \\ \dot{x}_n = f_\sigma(x) + g_\sigma(x)u + d_\sigma(x,t) \\ y = x_1 \end{cases} \tag{1}$$

Where $x = [x_1, \quad x_2, \quad \cdots \quad x_n]^T \in \mathbb{R}^n$ is the state vector, $u \in \mathbb{R}$ and $y = x_1 \in \mathbb{R}$ is the input, output of the system, respectively. The function $\sigma : [0, +\infty) \mapsto \Omega = \{1, 2, ..., N\}$ is a switching signal, which is a piecewise continuous function of time, and N is the number of subsystems. $f_\sigma(x); g_\sigma(x) \in \mathbb{R}$ are unknown smooth functions and $d_\sigma(x,t)$ is the external disturbances of the system.

The signal y_d and its time derivatives up to the $n-th$ order are continuous and bounded.

Define $e = y - y_d$ is the error of output. We have:

$$\begin{cases} \dot{e} = x_2 - \dot{y}_d \\ \ddot{e} = x_3 - \ddot{y}_d \\ \dots \\ e^{(i)} = x_{i+1} - y_d^{(i)}; (0,, i,, n-1) \\ e^{(n-1)} = x_n - y_d^{(n-1)} \\ e^{(n)} = f_\sigma(x) + g_\sigma(x)u + d_\sigma(x,t) - y_d^{(n)} \end{cases} \tag{2}$$

Because $f_i(x); g_i(x)$ are both unknown, so we use RBF NNs:

$$f_i = W_{fi}^T S_{fi} + \delta_{fi}; g_i = W_{gi}^T S_{gi} + \delta_{gi} \tag{3}$$

Where $i \in \Omega, W_{fi}; W_{gi}$ are vectors of adjustable weights

$S_{fik} = e^{\left[-\frac{(x-\omega_{fij})^T(x-\omega_{fij})}{\theta_{fij}^2}\right]}; S_{gik} = e^{\left[-\frac{(x-\omega_{gij})^T(x-\omega_{gij})}{\theta_{gij}^2}\right]}$ are Gaussian basis functions. $(w_{fij}; \theta_{fij}); (w_{gij}; \theta_{gij})$ are center vectors and width of the hidden element for RBF NNs to approximate the functions $f_i(x); g_i(x)$. The estimated value of RBF NNs is defined:

$$\hat{f}_i = W_{fi}^T S_{fi}; \hat{g}_i = \hat{W}_{gi}^T S_{gi} \tag{4}$$

The weights vector errors described by:

$$\tilde{W}_{fi} = W_{fi} - \hat{W}_{fi}; \tilde{W}_{gi} = W_{gi} - \hat{W}_{gi} \tag{5}$$

The optimal weights and RBF NNs reconstruction approximate error:

$$W_{fi}^{*} = \arg\min_{W_f \in \Omega_f} \left\{ \min_{i \in \Xi} \left\{ \sup_{x \in \mathbb{R}^n} \left| f_i(x) - \hat{f}_i(x) \right| \right\} \right\}$$

$$W_{gi}^{*} = \arg\min_{W_g \in \Omega_g} \left\{ \min_{i \in \Xi} \left\{ \sup_{x \in \mathbb{R}^n} \left| g_i(x) - \hat{g}_i(x) \right| \right\} \right\}$$

Assumption 1: There exists a number $g_{\min}$ such that nonlinear function $g_i(x)$ satisfied $|g_i(x)| \geq g_{\min} > 0; \forall x \in \mathbb{R}^n$. The signs of $g_i(x)$ is known, without loss of generality, we can assume that $g_i(x) > g_{\min} > 0; \forall x \in \mathbb{R}^n$. We consider a Hurwitz polynomial: $P(s) = s^n + r_{n-1}s^{n-1} + ... + r_1 s + r_0$

Define: $R = (r_{n-1};...;r_1;r_0)^T$; $E = \left(e^{(n-1)};...;\dot{e};e\right)^T$

We consider that the control:

$$u = \frac{1}{\hat{g}_\sigma}\left(-\hat{f}_\sigma + y_d^{(n)} - R^T E + u_{new}\right) \Rightarrow y_d^{(n)} = \hat{g}_\sigma u + \hat{f}_\sigma + R^T E - u_{new} \tag{6}$$

$$\Rightarrow e^{(n)} = \left(f_\sigma - \hat{f}_\sigma\right) + \left(g_\sigma - \hat{g}_\sigma\right)u + d_\sigma - R^T E + u_{new}$$

Define $w_\sigma = \delta_{f\sigma} + \delta_{g\sigma} u$.

According to (3), (4), (5), we have:

$$\dot{E} = AE + B\left(u_{new} + \tilde{W}_{f\sigma} S_{f\sigma} + \tilde{W}_{g\sigma} S_{g\sigma} u + w_\sigma + d_\sigma\right) \tag{7}$$

Assumption 2: For each $\delta \in \Omega$, there exists numbers $\alpha, \rho_\sigma > 0$ and matrix $H_\sigma > 0$ such that:

$$d_\sigma^T d_\sigma \leq \alpha^2 E^T H_\sigma^T H_\sigma E + \rho_\sigma^2$$

Lemma 1: If there exists matrices $Q_m > 0$ and positive number $\gamma_1, \gamma_2, k_X, k_Y$ such that the following linear matrix inequalities (9-12) are feasible, there exists matrices $P_m = P_m^T > 0$ and $\|K\| \leq k_X k_Y$ to assurance that (8) holds.

$$\left(A + BK\right)^T P_m + P_m\left(A + BK\right) + \left(\gamma_1^{-2} + \gamma_2^{-2}\right) P_m B B^T P_m + \gamma_2^2 \alpha^2 H_m^T H_m \leq -Q_m \tag{8}$$

$$\begin{bmatrix} AY + YA^T + BX + X^T B^T & B & Y & \gamma_2 Y H_m^T \\ B^T & -\left(\gamma_1^{-2} + \gamma_2^{-2}\right)^{-1} I & 0 & 0 \\ Y & 0 & -Q_m^{-1} & 0 \\ \gamma_2 H_m Y & 0 & 0 & -\frac{1}{\alpha^2} I \end{bmatrix} \leq 0 \tag{9}$$

$$Y = Y^T > 0 \tag{10}$$

$$\begin{bmatrix} -k_X^2 I & X^T \\ X & -I \end{bmatrix} < 0 \tag{11}$$

$$\begin{bmatrix} Y & I \\ I & k_Y I \end{bmatrix} > 0 \tag{12}$$

Lemma 2: Let $x \in \mathbb{R}^p, y \in \mathbb{R}^q$ and M, N are appropriately dimensioned matrices, then for any positive number and every appropriately dimensioned matrix $X(t)$ satisfying $X^T(t)X(t) \leq I$, we have:
$2x^T MXNy \leq \theta x^T MM^T x + \theta^{-1} y^T N^T Ny$

Theorem 1: Assume that for each $m \in \Omega$, the LMIs (9-12) has a solution. By using the adaptive laws:

$$\begin{cases} \dfrac{d}{dt}\hat{W}_{gi} = \mathrm{T}_{gi}^{-1} B^T P_i E S_{gi} u - \mu_g \mathrm{T}_{gi}^{-1} \hat{W}_{gi} \quad \text{when } \delta(t) = i \\ \dfrac{d}{dt}\hat{W}_{gi} = \mu_g \mathrm{T}_{gi}^{-1} \hat{W}_{gi} u \text{ when } \delta(t) \neq i \end{cases} \tag{13}$$

$$\begin{cases} \dfrac{d}{dt}\hat{W}_{gi} = \mathrm{T}_{gi}^{-1} B^T P_i E S_{gi} u - \mu_g \mathrm{T}_{gi}^{-1} \hat{W}_{gi} \quad \text{when } \delta(t) = i \\ \dfrac{d}{dt}\hat{W}_{gi} = \mu_g \mathrm{T}_{gi}^{-1} \hat{W}_{gi} u \text{ when } \delta(t) \neq i \end{cases} \tag{14}$$

and the state feedback control law $u_{new} = KE$ with (K, P_m) is the solution of the (8) and the average dwell-time satisfies $T > \dfrac{\mu_2 \ln\left(\dfrac{\mu_2}{\mu_1}\right)}{\mu_0}$ with:

$$\mu_1 = \min\left(\lambda_{min}(P_1), \lambda_{min}(P_2), \ldots, \lambda_{min}(P_N), \lambda_{min}\left(\mathrm{T}_f^{-1}\right), \lambda_{min}\left(\mathrm{T}_g^{-1}\right)\right)$$

$$\mu_2 = \max\left(\lambda_{max}(P_1), \lambda_{max}(P_2), \ldots, \lambda_{max}(P_N), \lambda_{\max}\left(\mathrm{T}_f^{-1}\right), \lambda_{\max}\left(\mathrm{T}_g^{-1}\right)\right)$$

$$\mu_0 = \min\left(\lambda_{min}(Q_1), \lambda_{min}(Q_2), \ldots, \lambda_{min}(Q_N), \mu_f, \mu_g\right)$$

we can appropriately choose design parameters such that the state tracking error satisfies $\lim_{t\to\infty} \|E(t)\|^2 \leq \kappa$ for any given constant $\kappa > 0$.

Proof:

We define: $\hat{A} = A + BK$. From (7), we have: $\dot{E} = \hat{A}E + B\left(\tilde{W}_f S_{f\sigma} + \tilde{W}_g S_{g\sigma} u + w_\sigma + d_\sigma\right)$

We consider the Lyapunov candidate function: $V_m = E^T P_m E + \mathrm{T}_f^{-1} \tilde{W}_f^T \tilde{W}_f + \mathrm{T}_g^{-1} \tilde{W}_g^T \tilde{W}_g$

The time derivative of V_m:

$$\dot{V}_m = E^T\left(\hat{A}^T P_m + P_m \hat{A}\right)E + 2\left(w_m + d_m\right)^T B^T P_m E$$
$$+2\tilde{W}_f^T\left[B^T P_m E S_{fm} + \mathrm{T}_f^{-1}\dot{\tilde{W}}_f\right] + 2\tilde{W}_g^T\left[B^T P_m E S_{gm} u + \mathrm{T}_g^{-1}\dot{\tilde{W}}_g\right]$$

By using the adaptive laws (13), (14), we obtain that:

$$\dot{V}_m = E^T\left(\hat{A}^T P_m + P_m \hat{A}\right)E - \mu_f \tilde{W}_f^T \hat{\mathrm{W}}_f - \mu_g \tilde{W}_g^T \hat{\mathrm{W}}_g + 2\left(w_m + d_m\right)^T B^T P_m E$$

Applying lemma 2, we have:

$$2w_m^T B^T P_m E \le \gamma_1^{-2} E^T P_m B B^T P_m E + \gamma_1^2 w_m^T w_m$$
$$2d_m^T B^T P_m E \le \gamma_2^{-2} E^T P_m B B^T P_m E + \gamma_2^2 d_m^T d_m$$

We have:

$$\dot{V}_m \le E^T\left(\hat{A}^T P_m + P_m \hat{A} + \left(\gamma_1^{-2} + \gamma_2^{-2}\right) P_m B B^T P_m\right)E + \gamma_1^2 w_m^T w_m + \gamma_2^2 d_m^T d_m + 2\mu_f \tilde{W}_f^T \mathrm{W}_f + 2\mu_g \tilde{W}_g^T \mathrm{W}_g$$

Using assumption 2 we have:

$$\dot{V}_m \le E^T\left(\hat{A}^T P_m + P_m \hat{A} + \left(\gamma_1^{-2} + \gamma_2^{-2}\right) P_m B B^T P_m + \gamma_2^2 \alpha^2 H_m^T H_m\right)E$$
$$+\gamma_1^2 w_m^T w_m + \gamma_2^2 \rho_m^2 + 2\mu_f \tilde{W}_f^T \mathrm{W}_f + 2\mu_g \tilde{W}_g^T \mathrm{W}_g$$

Because $\left(K, P_m\right)$ is the solution of the (8), we have:

$$\dot{V}_m \le -E^T Q_m E + 2\mu_f \tilde{W}_f^T \mathrm{W}_f + 2\mu_g \tilde{W}_g^T \mathrm{W}_g + \gamma_1^2 w_m^T w_m + \gamma_2^2 \rho_m^2$$

We have the following inequalities:

$$2\tilde{W}_f^T \mathrm{W}_f = \left\|\tilde{W}_f\right\|^2 + \left\|\mathrm{W}_f\right\|^2 - \left\|\mathrm{W}_f - \tilde{W}_f\right\|^2 \ge \left\|\tilde{W}_f\right\|^2 - \left\|\mathrm{W}_f - \tilde{W}_f\right\|^2$$
$$2\tilde{W}_g^T \mathrm{W}_g = \left\|\tilde{W}_g\right\|^2 + \left\|\mathrm{W}_g\right\|^2 - \left\|\mathrm{W}_g - \tilde{W}_g\right\|^2 \ge \left\|\tilde{W}_g\right\|^2 - \left\|\mathrm{W}_g - \tilde{W}_g\right\|^2$$

$$\Rightarrow \dot{V}_m \le -E^T Q_m E - 2\mu_f \left\|\tilde{W}_f\right\|^2 - 2\mu_g \left\|\tilde{W}_g\right\|^2 + 2\mu_f \tilde{W}_f W_f + 2\mu_g \tilde{W}_g W_g + \gamma_1^2 w_m^T w_m + \gamma_2^2 \rho_m^2$$

From assumption 2 we imply that there exists a constant c such that:

$$2\mu_f \tilde{W}_f W_f + 2\mu_g \tilde{W}_g W_g + \gamma_1^2 w_m^T w_m + \gamma_2^2 \rho_m^2 \le c$$

From the definition of $\mu_0; \mu_1; \mu_2$ we have:

$$\mu_1\left(\left\|E\right\|^2 + \left\|\tilde{W}_f\right\|^2 + \left\|\tilde{W}_g\right\|^2\right) \le V_m \le \mu_2\left(\left\|E\right\|^2 + \left\|\tilde{W}_f\right\|^2 + \left\|\tilde{W}_g\right\|^2\right)$$

Then: $V_i \le aV_j; \forall i, j \in \Omega, \dot{V}_i \le -bV_i + c; \forall i \in \Omega$ with $a = \frac{\mu_2}{\mu_1}; b = \frac{\mu_0}{\mu_2}$

We define:

$$W_{\sigma(t)}(t)=e^{bt}\left(V_{\sigma(t)}(t)-\frac{c}{b}\right);\ \dot{W}_{\sigma(t)}(t)=e^{bt}\left(\dot{V}_{\sigma(t)}(t)+bV_{\sigma(t)}(t)-c\right)\le 0$$

Let ϑ such that $t_M \le \vartheta < t_{M+1}$ then $\vartheta = t_M + \Delta$ with $0 \le \Delta < T$,we have:

$$W_{\sigma(t_M)}(t_M+\Delta)\le W_{\sigma(t_M)}(t_M)\Rightarrow e^{b(t_M+\Delta)}\left(V_{\sigma(t_M)}(t_M+\Delta)-\frac{c}{b}\right)\le e^{bt_M}\left(V_{\sigma(t_M)}(t_M)-\frac{c}{b}\right)$$

$$\Rightarrow V_{\sigma(t_M)}(\vartheta)\le e^{-b\Delta}V_{\sigma(t_M)}(t_M)+\frac{c}{b}\left(1-e^{-b\Delta}\right)$$

Similar way, we have:

$$V_{\sigma(t_j)}\left(t_{j+1}^{-}\right)\le e^{-bT}V_{\sigma(t_j)}\left(t_j\right)+\frac{c}{b}\left(1-e^{-bT}\right)$$

$$V_{\sigma(t_M)}(t_M)\le aV_{\sigma(t_{M-1})}(t_M)\le a\left[e^{-bT}V_{\sigma(t_{M-1})}(t_{M-1})+\frac{c}{b}\left(1-e^{-bT}\right)\right]$$

$$V_{\sigma(t_{M-1})}(t_{M-1})\le aV_{\sigma(t_{M-2})}(t_{M-1})\le a\left[e^{-bT}V_{\sigma(t_{M-2})}(t_{M-2})+\frac{c}{b}\left(1-e^{-bT}\right)\right]$$

$$V_{\sigma(t_2)}(t_2)\le aV_{\sigma(t_1)}(t_2)\le a\left[e^{-bT}V_{\sigma(t_1)}(t_1)+\frac{c}{b}\left(1-e^{-bT}\right)\right]$$

$$V_{\sigma(t_1)}(t_1)\le aV_{\sigma(t_0)}(t_1)\le a\left[e^{-bT}V_{\sigma(t_0)}(t_0)+\frac{c}{b}\left(1-e^{-bT}\right)\right]$$

$$V_{\sigma(t_M)}(t_M)\le \left(ae^{-bT}\right)^M V_{\sigma(0)}(0)+\frac{1-\left(ae^{-bT}\right)^M}{1-ae^{-bT}}.\frac{ac}{b}.\left(1-e^{-bT}\right)$$

$$V_{\sigma(t_M)}(\vartheta)\le e^{-b\Delta}.\left(ae^{-bT}\right)^M V_{\sigma(0)}(0)+\frac{c}{b}.\left(1-e^{-bT}\right).\left[e^{-b\Delta}.a.\frac{1-\left(ae^{-bT}\right)^M}{1-ae^{-bT}}+\frac{1-e^{-b\Delta}}{1-e^{-bT}}\right]$$

If $T>\dfrac{\mu_2\ln\left(\dfrac{\mu_2}{\mu_1}\right)}{\mu_0}=\dfrac{\ln a}{b}$ then $0<ae^{-bT}<1$ so, when $\vartheta\to+\infty$ or $M\to+\infty$ then:

$$\lim_{\vartheta\to\infty}\left\|E(\vartheta)\right\|^2\le\frac{c}{\mu_1}.\frac{1-e^{-bT}}{b}.\left[a.\frac{1}{1-ae^{-bT}}+\frac{1}{1-e^{-bT}}\right]=\Theta$$

We can find the value b such that $\Theta\le\kappa$ with any given number $\kappa>0$.

Remark 1: The adaptive law is established from LMI solver leads the stability of closed system. Moreover, it should be noted that the existence of solution in LMI solver is satisfied. Moreover, the ammount of computation is remarkable reduced in compare with the exsting optimal and MPC control law [7,8,9].

SIMULATION RESULTS

The proposed control law is applied for the switched system as follows: Let $N = 2$ and the subsystems of the switched system are :

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = f_1(x) + g_1(x)u + d_1(x,t) \end{cases}; \qquad \begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = f_2(x) + g_2(x)u + d_2(x,t) \end{cases}$$

with:

$$f_1(x) = 10x_1 + \sin(x_2); g_1(x) = \sin(x_1) + 2$$
$$f_2(x) = x_1x_2; g_2(x) = 3\cos(x_2) + 5$$

The initial values of state vectors is $x(0) = [3 \quad -2]^T$ and the desired output signal is $y_d = \sin(t)$. Choosing that the parameter matrices:

$$Q_1 = \begin{bmatrix} 1 & 0 \\ 0 & 6 \end{bmatrix}; Q_2 = \begin{bmatrix} 4 & 0 \\ 0 & 3 \end{bmatrix}; R = \begin{bmatrix} 3 \\ 1 \end{bmatrix}; H_1 = H_2 = \begin{bmatrix} 1 & 0 \\ 0 & 3 \end{bmatrix}$$

$$k_X = 10; k_Y = 12; \alpha = 0.01; \gamma_1 = 2; \gamma_2 = 1$$

According to the results from (9) to (12), we have:

$$P_1 = \begin{bmatrix} 11.9505 & 0.6987 \\ 0.6987 & 2.1110 \end{bmatrix}; K_1 = [-2.3613 \quad -6.6521]$$
$$P_2 = \begin{bmatrix} 11.9386 & 0.7953 \\ 0.7953 & 1.6324 \end{bmatrix}; K_2 = [-3.3333 \quad -5.1965]$$

From (13) and (14) with $\mu_f = 0.7; \mu_g = 0.3$ and $\Gamma_{f_1} = 0.2; \Gamma_{f_2} = 0.1; \Gamma_{g_1} = 0.3; \Gamma_{g_2} = 0.2$ we obtain the high performance of simulation results shown in Figure. 1, 2, 3.

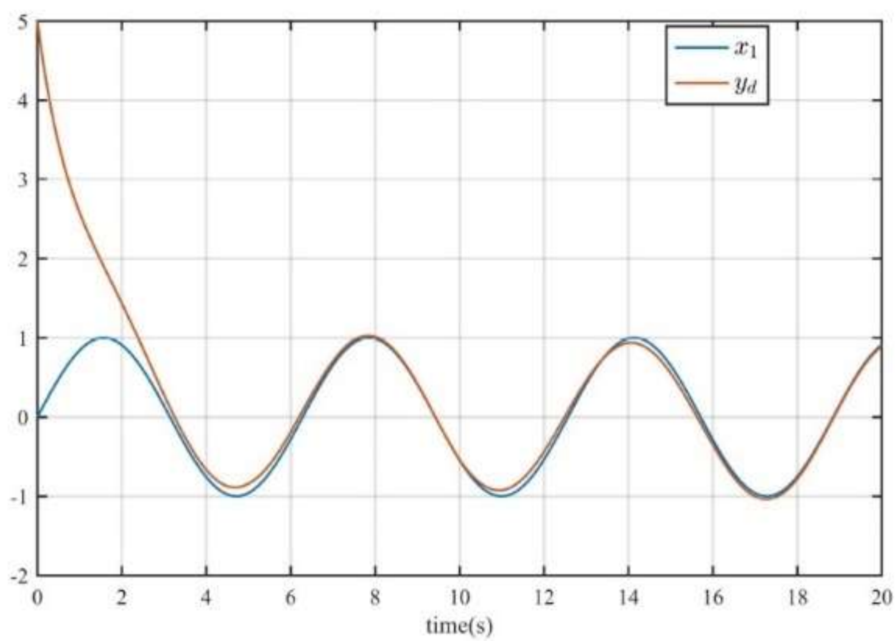


Figure 1. The response of x1

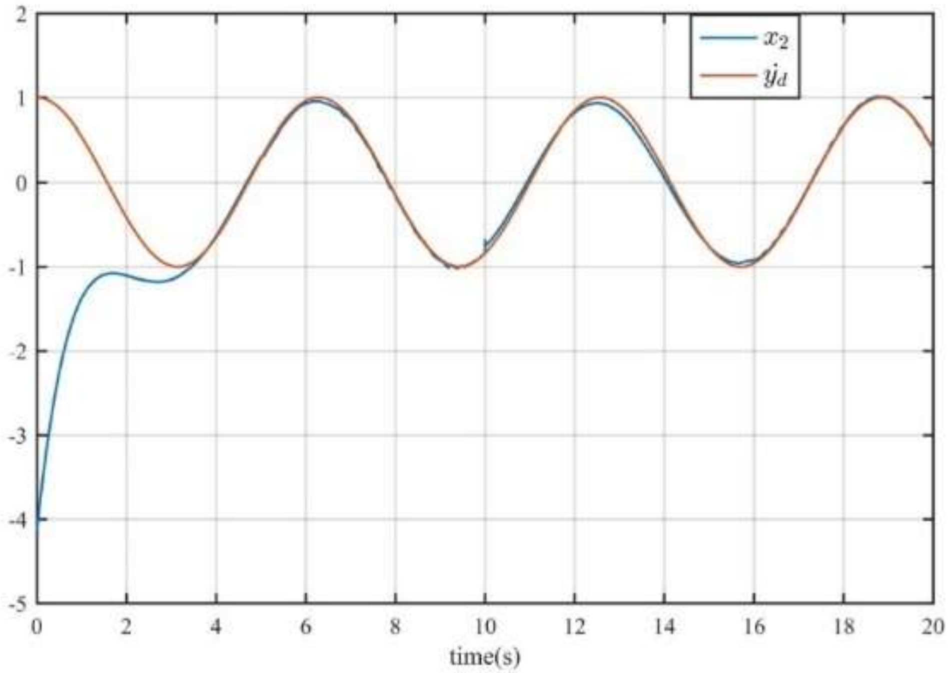
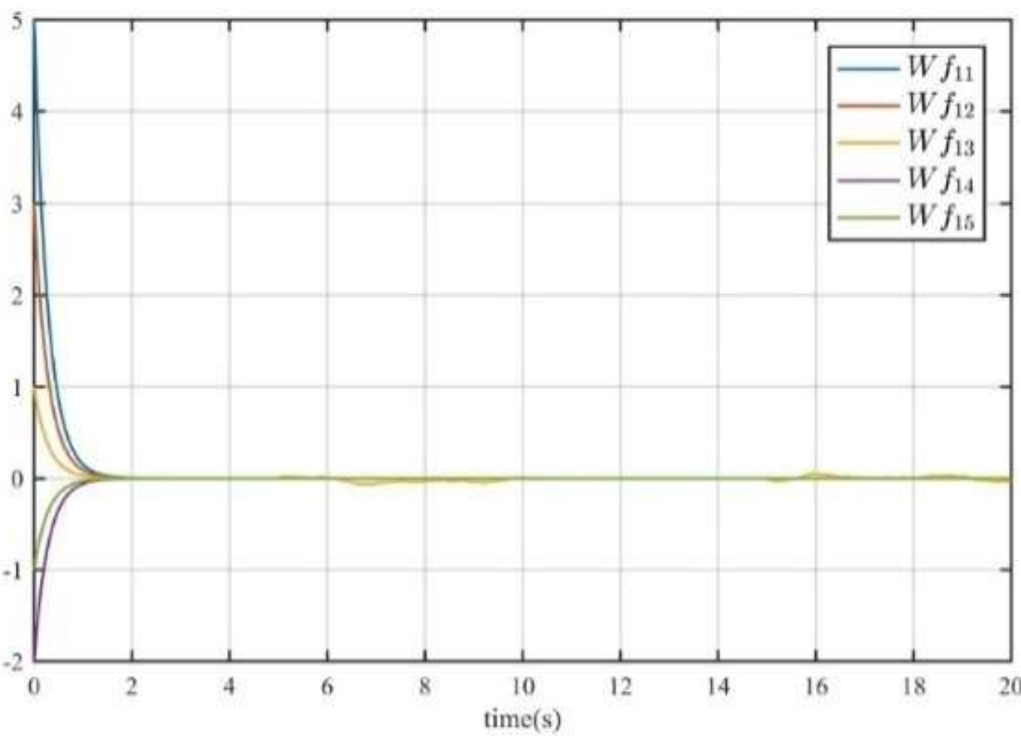
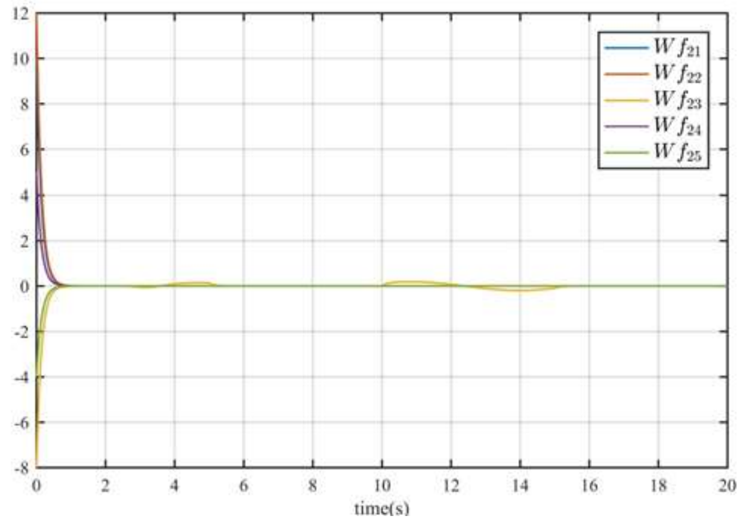


Figure 2. The response of x2



(a) The first Neural Network



(b) The second Neural Network

Figure 3. The training of Neural Networks

CONCLUSION

This paper has investigated the problem of robust adaptive tracking control of switched nonlinear systems. The neural network controllers have been designed for subsystems of the switched nonlinear system. Finally, the convergence of the state tracking errors and signal bound of the closed-loop system are guaranteed under this method.

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