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Adaptive Neural Network Tracking of a Class of Switched Nonlinear Systems with Time-varying Output Constraints

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Abstract: An approximation-based adaptive design problem for output-constrained tracking of a class of switched pure-feedback nonlinear systems is investigated under arbitrary switchings. All switched nonlinearities are assumed to be unknown. Contrary to the existing control results for uncertain switched pure-feedback nonlinear systems where the number of the used function approximators should be equal to the order of the systems, an adaptive control scheme based on only two neural networks is designed by using a system transformation and the common Lyapunov function method, regardless of the order of the system. In the proposed controller, the output constraints are used to establish designable time-varying bounds on the tracking performance. The stability and the constraint satisfaction of the resulting closed-loop system are shown in the sense of Lyapunov stability criterion. Finally, simulation examples are provided to illustrate the effectiveness of the proposed methodology.

Keywords: Switched nonlinear systems, neural networks, time-varying output constraints, arbitrary switching.

1. INTRODUCTION

In the last decades, several theoretical research efforts in the control design and stability analysis of switched nonlinear systems have appeared due to many practical hybrid applications such as chemical processes, automotive systems, and manufacturing processes, switching power systems, and so on (see [1–4] and references therein). In particular, the arbitrary switching effect on systems with nonlinearities unmatched in the control input has been regarded as an important and practical problem. To deal with this problem, some control methods [5–9] have been presented by combining the common Lyapunov function and the backstepping technique [10]. However, these results commonly assumed that the system model was perfectly known, that is, model uncertainties were not considered. Recently, adaptive control problems in the presence of uncertain switched nonlinearities in strict-feedback [11,12] or pure-feedback form [13,14] have been investigated by using online function approximators such as neural networks or fuzzy logic systems. Despite these efforts, the existing approaches [11–13] required the function approximators equal to the order of systems. Thus, as the order of systems increases, the number of the function approximators increases. It makes the structure of the control system complex.

The output-constrained control is a significant and challenging issue in the nonlinear control field because physical limitations of systems or control performance bounds can be described as output constraints. The control methods for nonlinear systems with static output constraints have been presented in [15–20] where the barrier Lyapunov function approach was used to design a stable controller with the constraint satisfaction. Furthermore, the time-varying output-constrained control problem was addressed for nonlinear affine or non-affine systems [21,22]. Recently, a transformation method was reported to treat non-affine nonlinear systems with time-varying output constraints [23].

It should be mentioned that the aforementioned results have three limitations: (L1) the existing work [23] deals with the time-varying output constrained problem using the transformation method, but non-switched systems are only considered; (L2) switched systems considered in [8, 9, 12] include only static constraints and affine nonlinearities; (L3) the existing approximation-based adaptive control approaches [11–13] for systems with switched nonlinearities unmatched in the control input depend on the function approximators equal to the order of systems which lead to the complexity of the controller. These limitations are strong motivations of this paper.

The purpose of this study is to present an adaptive

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approximation design approach for time-varying output-constrained tracking of a class of switched non-affine nonlinear systems under arbitrary switching. Switched non-affine nonlinearities are unmatched in the control input and unknown. An adaptive control scheme based on a system transformation is designed by using only two neural network approximators regardless of the order of the switched system. The main contribution of this paper is to relax the aforementioned limitations (L1)–(L3) of the existing results. From the common Lyapunov function method, it is proved that all the signals of the controlled closed-loop system are uniformly ultimately bounded and the output signal is regulated within preassigned time-varying constraints even at the moments that arbitrary switchings occur.

The rest of the paper is outlined as follows. The output-constrained tracking control problem is formulated in Section II. The approximation-based adaptive control design is presented in Section III. Simulation studies are given in Section IV. Finally, we conclude in Section V.

Notations: The symbol $\mathbb{R}^n$ denotes the n-dimensional Euclidean space. $\|\cdot\|$ stands for a Euclidian norm. $\binom{k}{n} = n!/(k!(n-k)!)$ means binomial coefficients.

2. PROBLEM FORMULATION AND PRELIMINARIES

Consider the following non-affine nonlinear switched systems

$$\begin{aligned} \dot{x}_i &= f_{i,\sigma(t)}(\bar{x}_i, x_{i+1}), \quad i = 1, \dots, n-1, \\ \dot{x}_n &= f_{n,\sigma(t)}(\bar{x}_n, u_{\sigma(t)}), \\ y &= x_1, \end{aligned} \tag{1}$$

where $\bar{x}_i = [x_1, x_2, \dots, x_i]^\top \in \mathbb{R}^i$, $i = 1, \dots, n$, are state variable vectors, y is the system output, and $\sigma(t) : [0, +\infty) \to M = \{1, 2, \dots, m\}$ is the switching signal. For any $j \in M$ and $i = 1, \dots, n$, $u_j \in \mathbb{R}$ is a control input of the jth subsystem and $f_{i,j}(\cdot) : \mathbb{R}^{i+1} \to \mathbb{R}$ are unknown continuous nonlinear functions of the jth subsystem.

Problem 1: Consider (1). Our problem is to design a common neural network controller $u_{\sigma(t)} \triangleq u$ for system (1) so that the output y satisfies $\underline{y}(t) < y(t) < \bar{y}(t)$ for all $t \geq 0$ under the desired signal y_d satisfying $\underline{y}(t) < y_d(t) < \bar{y}(t)$ where $\underline{y}(t)$ and $\bar{y}(t)$ denote the lower and upper bounding functions for the output constraint functions (i.e, the tracking error $y(t) - y_d(t)$ is bounded as $\underline{y}(t) - y_d(t) < y(t) - y_d(t) < \bar{y}(t) - y_d(t)$ even at the moment that arbitrary switching occurs).

Assumption 1 [23]**:** Let $g_{i,j}(\bar{x}_i, x_{i+1}) = \frac{\partial f_{i,j}(\bar{x}_i, x_{i+1})}{\partial x_{i+1}}$ for $i = 1, \dots, n$, $\forall j \in M$, and $x_{i+1} = u$. Then, $g_{i,j} \neq 0$ are unknown, but their signs are known. Furthermore, there exist constants $\underline{g}_{i,j} > 0$ and $\bar{g}_{i,j} > 0$ such that $\underline{g}_{i,j} < |g_{i,j}| < \bar{g}_{i,j}$ for $(\bar{x}_i, x_{i+1}) \in \Gamma_{i+1}$ and $\forall j \in M$ where $\Gamma_{i+1} \in \mathbb{R}^{i+1}$ is a compact set. Without loss of generality, the signs of $g_{i,j}$ are assumed to be positive.

Assumption 2: The desired signal y_d is continuous, differentiable up to the nth order, and $y_d^{(i)}$, $i = 0, \dots, n$, are available, and bounded as $|y_d^{(i)}| \leq \bar{y}_{i,d}$ with constants $\bar{y}_{i,d} > 0$.

Remark 1: The existing works [8, 9, 11–13] for switched nonlinear systems cannot provide any solution on Problem 1.

3. APPROXIMATION-BASED SIMPLE ADAPTIVE CONTROL SCHEME

3.1. Function approximation technique

The online function approximator is utilized to estimate unknown nonlinear functions derived from the design procedure of the proposed adaptive control scheme. In this paper, the linearly parameterized neural network is employed to approximate any continuous real-valued function $H(Z)$ over a compact set Γ_Z as follows [25]:

$$H(Z) = W^\top S(Z) + \varepsilon(Z), \tag{2}$$

where Z is the input vector, $W = [w_1, \dots, w_l]^\top \in \mathbb{R}^l$ with the node number $l > 1$ is the optimal weighting vector defined as $W = \arg\min_{\hat{W}}[\sup_{Z \in \Omega_Z} |H(Z) - \hat{W}^\top S(Z)|]$; $\hat{W}$ is an estimate of W, $S(Z) = [s_1(Z), \dots, s_l(Z)]^\top$; $s_i(Z)$, $i = 1, \dots, l$, are the basis functions chosen as the hyperbolic tangent function, and ε represents the reconstruction error. It is assumed that the optimal weight vector W and the approximation error ε are bounded as $\|W\| \leq \bar{W}$ and $|\varepsilon| \leq \bar{\varepsilon}$, respectively, where $\bar{W}$ and $\bar{\varepsilon}$ are unknown positive constants [25].

3.2. System transformation

For the simple control design, the input and output transformations reported in [23] for non-switched systems are applied to the switched system (1) as follows:

$$\dot{u} = -au + v, \tag{3}$$

$$\xi_1 = T^{-1}(y, \bar{y}, \underline{y}), \tag{4}$$

where $a > 0$ is a constant, u denotes a common control input, v is a transformed common control input, ξ_1 is a transformed output, and $T(\cdot)$ is a smooth invertible and strictly increasing function satisfying $\partial T(\cdot)/\partial \xi_1 > 0$, $\lim_{\xi_1 \to -\infty} T(\xi_1, \bar{y}, \underline{y}) = \underline{y}$, and $\lim_{\xi_1 \to \infty} T(\xi_1, \bar{y}, \underline{y}) = \bar{y}$. To represent the output constraint $\underline{y} < y < \bar{y}$ in the inequality form as the equation form, the function $T(\cdot)$ is defined as

$$T(\xi_1, \bar{y}, \underline{y}) = \frac{\bar{y} - \underline{y}}{2} \tanh(\xi_1) + \frac{\bar{y} + \underline{y}}{2}. \tag{5}$$

From (5), equation (4) becomes

$$\xi_1 = \tanh^{-1}\left(\frac{2y - \bar{y} - \underline{y}}{\bar{y} - \underline{y}}\right). \tag{6}$$

From (6), notice that if ξ_1 is bounded, it holds that $\underline{y}(t) < y(t) < \bar{y}(t)$ for all $t \geq 0$. Thus, our control problem is restated as follows: *Design the common controller v using only two neural network approximators such that ξ_1 is uniformly bounded in the presence of output constraints and unknown switched pure-feedback nonlinearities.*

For the controller design, we will introduce the two state transformations. Firstly, consider the following transformation

$$\begin{aligned} s_1 &= y = x_1 \triangleq b_{1,j}(x_1), \\ s_2 &= \dot{s}_1 = f_{1,j}(x_1,x_2) \triangleq b_{2,j}(\bar{x}_2), \\ s_{i+1} &= \dot{s}_i = \textstyle\sum_{k=1}^{i} \frac{\partial b_{i,j}(\bar{x}_i)}{\partial x_k} f_{k,j}(\bar{x}_k, x_{k+1}) \\ &\triangleq b_{i+1,j}(\bar{x}_{i+1}), \end{aligned} \tag{7}$$

where $i = 2,\dots,n$ and $j \in M$. Using (7), the switched system (1) with (3) can be converted into the following form

$$\begin{aligned} \dot{s}_i &= s_{i+1}, \quad i = 1,\dots,n, \\ \dot{s}_{n+1} &= f_j(\bar{x}_n,u) + g_j(\bar{x}_n,u)v, \\ y &= s_1, \end{aligned} \tag{8}$$

where

$$\begin{aligned} f_j(\bar{x}_n,u) &= \sum_{k=1}^{n-1} \frac{\partial b_{n+1,j}(\bar{x}_n,u)}{\partial x_k} f_{k,j}(\bar{x}_k,x_{k+1}) \\ &\quad + \frac{\partial b_{n+1,j}(\bar{x}_n,u)}{\partial x_n} f_{n,j}(\bar{x}_n,u) \\ &\quad - \frac{\partial b_{n+1,j}(\bar{x}_n,u)}{\partial u} au, \\ g_j(\bar{x}_n,u) &= \frac{\partial b_{n+1,j}(\bar{x}_n,u)}{\partial u}. \end{aligned} \tag{9}$$

From Assumption 1, owing to

$$\begin{aligned} \frac{\partial b_{2,j}(\bar{x}_2)}{\partial x_2} &= g_{1,j}(x_1,x_2), \\ \frac{\partial b_{i+1,j}(\bar{x}_{i+1})}{\partial x_{i+1}} &= \frac{\partial b_{i,j}(\bar{x}_i)}{\partial x_i} \frac{\partial f_{i,j}(\bar{x}_i,x_{i+1})}{\partial x_{i+1}} \\ &= \prod_{k=1}^{i} g_{k,j}(\bar{x}_k,x_{k+1}), \end{aligned}$$

there exist unknown constants $\underline{g}_j = \prod_{k=1}^{n} \underline{g}_{k,j}$ and $\bar{g}_j = \prod_{k=1}^{n} \bar{g}_{k,j}$ such that $\underline{g}_j < g_j(\bar{x}_n,u) \leq \bar{g}_j$ for $\forall j \in M$.

Secondly, consider the transformed state variables $\xi_1 = T^{-1}$, $\xi_2 = \dot{\xi}_1, \dots, \xi_{n+1} = \xi_1^{(n)}$. Then, their time derivatives using (1), (3), (4), and (8) are given by

$$\begin{aligned} \dot{\xi} &= A\xi + B[\alpha f_j(\bar{x}_n,u) + \alpha g_j(\bar{x}_n,u)v + \psi(Z_\psi)], \\ \xi_1 &= C^\top \xi, \end{aligned} \tag{10}$$

where $j = 1,\dots,m$, $\alpha = \partial T^{-1}/\partial y = 2/[(1 - \tanh^2(\xi_1))(\bar{y} - \underline{y})]$, $A = \begin{bmatrix} 0 & I_{n\times n} \\ 0 & 0 \end{bmatrix} \in \mathbb{R}^{(n+1)\times(n+1)}$, $B = [0,\dots,0,1]^\top \in \mathbb{R}^{n+1}$, $C = [1,0,\dots,0]^\top \in \mathbb{R}^{n+1}$, and

$$\begin{aligned} \psi(Z_\psi) &= \sum_{l=1}^{n} \binom{n}{l} \left[\frac{\partial T^{-1}}{\partial y}\right]^{(l)} y^{(n-l+1)} \\ &\quad + \sum_{l=0}^{n} \binom{n}{l} \left[\frac{\partial T^{-1}}{\partial \bar{y}}\right]^{(l)} \bar{y}^{(n-l+1)} \\ &\quad + \sum_{l=0}^{n} \binom{n}{l} \left[\frac{\partial T^{-1}}{\partial \underline{y}}\right]^{(l)} \underline{y}^{(n-l+1)} \end{aligned} \tag{11}$$

with $Z_\psi = [\bar{x}_n^\top, \bar{y}, \dots, \bar{y}^{(n+1)}, \underline{y}, \dots, \underline{y}^{(n+1)}]^\top$. Notice that the transformation between $\xi \triangleq [\xi_1,\dots,\xi_{n+1}]$ and $\bar{x}_{n+1}$ is a smooth map and a diffeomorphism [23] and thus (10) is a reasonable transformation. In addition, it is guaranteed that $\alpha \neq 0$ from the property $|\tanh(\xi_1)| < 1$.

3.3. Adaptive neural network estimator

The transformed state variables $\xi_2, \dots, \xi_{n+1}$ in (10) are unavailable owing to the unknown function terms $f_{i,j}$ and $g_{i,j}$. Thus, to estimate these transformed state variables, a common adaptive estimator using one neural network approximator is presented as

$$\begin{aligned} \dot{\hat{\xi}} &= A\hat{\xi} + K\hat{W}_o^\top S_o(Z_o) + L\tilde{\xi}_1, \\ \hat{\xi}_1 &= C^\top \hat{\xi}, \end{aligned} \tag{12}$$

$$\dot{\hat{W}}_o = \lambda_o(S_o(Z_o)\tilde{\xi}_1 - \sigma_o \hat{W}_o), \tag{13}$$

where $\hat{\xi} = [\hat{\xi}_1,\dots,\hat{\xi}_{n+1}]$ is the estimate vector of ξ, $L = [l_1,\dots,l_{n+1}]^\top$ is the design vector to make the matrix $\bar{A} = A - LC^\top$ strictly Hurwitz, $\tilde{\xi}_1 = \xi_1 - \hat{\xi}_1$, $\lambda_o > 0$ and $\sigma_o > 0$ are the design constants, $Z_o = [u, v, Z_\psi^\top]^\top$ is the input vector of the neural network approximator $\hat{W}_o^\top S_o(Z_o)$; $\hat{W}_o$ is an estimate of the optimal weighting vector W_o and S_o denotes the basis function of the neural network approximator, and K is selected as $K = P^{-1}C$ with the positive definite matrix $P = P^\top$ satisfying $\bar{A}^\top P + P\bar{A} + \kappa PP \leq -Q$ with a design constant $\kappa > 0$ and a positive definite matrix Q. Notice that the solution P satisfying $\bar{A}^\top P + P\bar{A} + \kappa PP \leq -Q$ always exists for a stable $\bar{A}$ [24].

Remark 2: The proposed adaptive observer (12) is commonly used for all subsystems regardless of arbitrary switchings and the adaptive law (13) only requires an output information of state variables.

3.4. Adaptive neural network controller

For the control design, we define the error surface θ as

$$\begin{aligned} \theta &= \xi_1^{(n)} + \chi_{n-1}\xi_1^{(n-1)} + \cdots + \chi_1\dot{\xi}_1 + \chi_0\xi_1 \\ &= \chi^\top \xi, \end{aligned} \tag{14}$$

where $\chi = [\chi_0,\dots,\chi_{n-1},1]^\top$ is chosen so that the polynomial $s^n + \chi_{n-1}s^{n-1} + \cdots + \chi_1 s + \chi_0$ is Hurwitz. Then, the time derivative of θ is given by

$$\dot{\theta} = \alpha f_j(\bar{x}_n, u) + \alpha g_j(\bar{x}_n, u)v + \psi(Z_\psi) + \sum_{k=1}^{n} \chi_{k-1}\xi_1^{(k)}. \tag{15}$$

A common adaptive neural network controller for switched system (10) is proposed as

$$v = \frac{1}{\alpha}(-k_c\hat{\theta} - \hat{W}_c^\top S_c(Z_c)), \tag{16}$$

$$\dot{\hat{W}}_c = \lambda_c(S_c(Z_c)\hat{\theta} - \sigma_c|\hat{\theta}|\hat{W}_c), \tag{17}$$

where $\hat{\theta} = \chi^\top\hat{\xi}$, $k_c > 0$, $\lambda_c > 0$, and $\sigma_c > 0$ are design constants, $Z_c = [u, Z_\psi^\top]^\top$ is the input vector of the neural network approximator $\hat{W}_c^\top S_c(Z_c)$; $\hat{W}_c$ is an estimate of the optimal weighting vector W_c and S_c denotes the basis function of the neural network approximator.

Lemma 1: For the adaptive law (17), there exists a compact set $\Omega_w = \{\hat{W}_c | \|\hat{W}_c\| \le \bar{S}_c/\sigma_c\}$, where $\|S_c(Z_c)\| \le \bar{S}_c$ with $\bar{S}_c > 0$, such that $\hat{W}_c(t) \in \Omega_w$ for all $t \ge 0$ provided that $\hat{W}_c(0) \in \Omega_w$.

Proof: Define $V_W = (1/(2\lambda_c))\hat{W}_c^2$. Its time derivative is

$$\dot{V}_W = \hat{W}_c\left(S_c(Z_c)\hat{\theta} - \sigma_c|\hat{\theta}|\hat{W}_c\right) \le -|\hat{\theta}|\|\hat{W}_c\|\left(-\bar{S}_c + \sigma_c\|\hat{W}_c\|\right).$$

Here, $\dot{V}_W < 0$ when $\|\hat{W}_c\| > \bar{S}_c/\sigma_c$. Thus $\hat{W}_c(t) \in \Omega_w$ for all $t \ge 0$ if $\hat{W}_c(0) \in \Omega_w$. □

Remark 3: We would like to emphasize that

(i) The common adaptive control approaches using function approximators were presented for switched nonlinear systems without constraints [11, 13] or with static output constraints [12]. The function approximators equal to the order of the systems should be employed to implement the controller reported in [11–13]. However, the proposed common adaptive control scheme (i.e., (12) and (16)) requires only two neural network approximators. Besides, the time-varying output constraint problem is treated in this paper.

(ii) In [23], the system transformation method was employed to design the adaptive control scheme for non-switched nonlinear systems. However, this paper considers an adaptive tracking problem in the presence of arbitrarily switched non-affine nonlinearities and time-varying output constraints

4. STABILITY ANALYSIS

The stability analysis of the proposed control scheme using only two neural networks is shown in the following procedure. Firstly, we consider the Lyapunov function candidate V_o as

$$V_o = \tilde{\xi}^\top P\tilde{\xi} + \frac{1}{\lambda_o}\tilde{W}_o^\top\tilde{W}_o, \tag{18}$$

where $\tilde{\xi} = \xi - \hat{\xi}$ and $\tilde{W}_o = W_o - \hat{W}_o$.
Taking its time derivative and using $K = P^{-1}C$ and $\tilde{\xi}_1 = \tilde{\xi}^\top C$, we have

$$\begin{aligned}\dot{V}_o =& \tilde{\xi}^\top(\bar{A}^\top P + P\bar{A})\tilde{\xi} - \frac{2}{\lambda_o}\tilde{W}_o^\top\dot{\hat{W}}_o \\ &+ 2\tilde{\xi}^\top P(Bh_o^j - K\hat{W}_o^\top S_o) \\ =& \tilde{\xi}^\top(\bar{A}^\top P + P\bar{A})\tilde{\xi} - \frac{2}{\lambda_o}\tilde{W}_o^\top\dot{\hat{W}}_o \\ &+ 2\tilde{\xi}^\top P(Bh_o^j - Kh_o^j + Kh_o^j) - 2\tilde{\xi}^\top PK\hat{W}_o^\top S_o \\ =& \tilde{\xi}^\top(\bar{A}^\top P + P\bar{A})\tilde{\xi} - \frac{2}{\lambda_o}\tilde{W}_o^\top\dot{\hat{W}}_o \\ &+ 2[\tilde{\xi}_1 + \tilde{\xi}^\top P(B-K)]h_o^j - 2\tilde{\xi}_1\hat{W}_o^\top S_o \end{aligned} \tag{19}$$

for any $j \in M$ where $h_o^j = \alpha f_j(\bar{x}_n, u) + \alpha g_j(\bar{x}_n, u)v + \psi(Z_\psi)$. Similar to [13], there exists a continuous function $H_o(Z_o)$ satisfying the following condition

$$\begin{aligned}&[\tilde{\xi}_1 + \tilde{\xi}^\top P(B-K)]h_o^j \\ &\le [\tilde{\xi}_1 + \tilde{\xi}^\top P(B-K)]H_o(Z_o), \quad \forall j \in M.\end{aligned} \tag{20}$$

From the function approximation property of neural networks, the unknown nonlinear function $H_o(Z_o)$ can be approximated over the compact set Γ_{Z_o} as follows:

$$H_o(Z_o) = W_o^\top S_o(Z_o) + \varepsilon_o(Z_o), \tag{21}$$

where W_o is the optimal weighting vector satisfying $\|W_o\| \le \bar{W}_o$ with a constant $\bar{W}_o$ and ε_o denotes the reconstruction error satisfying $|\varepsilon_o| \le \bar{\varepsilon}_o$ with a constant $\bar{\varepsilon}_o > 0$. Using (13), (19), (20), and (21) and the following inequality

$$\begin{aligned}&[\tilde{\xi}_1 + \tilde{\xi}^\top P(B-K)](W_o^\top S_o + \varepsilon_o) \\ &\le \tilde{\xi}_1(W_o^\top S_o + \varepsilon_o) \\ &\quad + \frac{1}{2}\tilde{\xi}^\top PP\tilde{\xi} + \frac{1}{2}\|B-K\|^2|W_o^\top S_o + \varepsilon_o|^2\end{aligned}$$

yields

$$\begin{aligned}\dot{V}_o \le& \tilde{\xi}^\top(\bar{A}^\top P + P\bar{A})\tilde{\xi} - 2\tilde{W}_o^\top(S_o\tilde{\xi}_1 - \sigma_o\hat{W}_o) \\ &+ 2\tilde{\xi}_1(W_o^\top S_o + \varepsilon_o) + \tilde{\xi}^\top PP\tilde{\xi} \\ &+ \|B-K\|^2|W_o^\top S_o + \varepsilon_o|^2 - 2\tilde{\xi}_1\hat{W}_o^\top S_o \\ \le& \tilde{\xi}^\top(\bar{A}^\top P + P\bar{A})\tilde{\xi} - \sigma_o\|\tilde{W}_o\|^2 + \sigma_o\|W_o\|^2 \\ &+ \tilde{\xi}^\top PP\tilde{\xi} + \|B-K\|^2|W_o^\top S_o + \varepsilon_o|^2 \\ &+ 2\tilde{\xi}_1\varepsilon_o.\end{aligned} \tag{22}$$

Secondly, we consider the Lyapunov function candidate V_c as $V_c = (1/(2\underline{g}))\theta^2$ with $\underline{g} = \min_{j=1,\ldots,m}\{\underline{g}_j\}$, and its time derivative along (15) is

$$\dot{V}_c = \theta \frac{g_j(\bar{x}_n,u)}{\underline{g}}(h_c^j + \alpha v), \tag{23}$$

where $h_c^j = [\alpha f_j(\bar{x}_n,u) + \psi(Z_\psi) + \sum_{k=1}^n \chi_{k-1}\xi_1^{(k)}]/g_j(\bar{x}_n,u)$. Similar to [13], there exists a continuous function $H_c(Z_c)$ satisfying the following condition

$$\begin{aligned}&\theta g_j(\bar{x}_n,u)h_c^j/\underline{g}\\ &\quad \le \theta g_j(\bar{x}_n,u)H_c(Z_c)/\underline{g}, \quad \forall j \in M.\end{aligned} \tag{24}$$

Applying the function approximation property of neural networks, we get

$$H_c(Z_c) = W_c^\top S_c(Z_c) + \varepsilon_c(Z_c), \tag{25}$$

where W_c is the optimal weighting vector satisfying $\|W_c\| \le \bar{W}_c$ with a constant $\bar{W}_c$ and ε_c denotes the reconstruction error satisfying $|\varepsilon_c| \le \bar{\varepsilon}_c$ with a constant $\bar{\varepsilon}_c > 0$. Using (16), (23), (24), and (25), it is obtained that

$$\begin{aligned}\dot{V}_c &\le \theta \frac{g_j(\bar{x}_n,u)}{\underline{g}}(-k_c\hat{\theta} + \tilde{W}_c^\top S_c + \varepsilon_c)\\ &= \theta \frac{g_j(\bar{x}_n,u)}{\underline{g}}[-k_c\theta + k_c(\theta - \hat{\theta}) + \tilde{W}_c^\top S_c + \varepsilon_c]\\ &\le -k_c\theta^2 + k_c\frac{g_j(\bar{x}_n,u)}{\underline{g}}\theta\chi^\top\tilde{\xi} + \theta\frac{g_j(\bar{x}_n,u)}{\underline{g}}\iota,\end{aligned} \tag{26}$$

where $\iota = \tilde{W}_c^\top S_c + \varepsilon_c$.

Finally, we consider the total Lyapunov function candidate as $V = V_o + V_c$. Substituting (19) and (26) into $\dot{V} = \dot{V}_o + \dot{V}_c$, we have

$$\begin{aligned}\dot{V} \le\ & \tilde{\xi}^\top(\bar{A}^\top P + P\bar{A})\tilde{\xi} - \sigma_o\|\tilde{W}_o\|^2 + \tilde{\xi}^\top PP\tilde{\xi}\\ &+ \|B-K\|^2|W_o^\top S_o + \varepsilon_o|^2 - k_c\theta^2 + \sigma_o\|W_o\|^2\\ &+ k_c\frac{g_j(\bar{x}_n,u)}{\underline{g}}\theta\chi^\top\tilde{\xi} + \theta\frac{g_j(\bar{x}_n,u)}{\underline{g}}\iota + 2\tilde{\xi}_1\varepsilon_o.\end{aligned} \tag{27}$$

Then, from Lemma 1, we have

$$\begin{aligned}\theta\frac{g_j(\bar{x}_n,u)}{\underline{g}}\iota &\le \frac{1}{2}\theta^2 + \frac{1}{2}\bar{g}^2(\|W_c - \hat{W}_c\|\bar{S}_c + \bar{\varepsilon}_c)^2/\underline{g}^2\\ &\le \frac{1}{2}\theta^2 + \frac{1}{2}\bar{\iota}^2,\end{aligned} \tag{28}$$

$$\begin{aligned}&k_c\frac{g_j(\bar{x}_n,u)}{\underline{g}}\theta\chi^\top\tilde{\xi} + 2\tilde{\xi}_1\varepsilon_o\\ &\qquad \le \frac{1}{2}\theta^2 + (\kappa-1)\tilde{\xi}^\top PP\tilde{\xi} + \bar{\varepsilon}_o^2,\end{aligned} \tag{29}$$

$$\begin{aligned}&\|B-K\|^2|W_o^\top S_o + \varepsilon_o|^2\\ &\qquad \le \|B-K\|^2(\bar{W}_o\bar{S}_o + \bar{\varepsilon}_o)^2,\end{aligned} \tag{30}$$

where $\bar{\iota} = \bar{g}((\bar{S}_c/\sigma_c + \bar{W}_c)\bar{S}_c + \bar{\varepsilon}_c)/\underline{g}$; $\bar{g} = \max_{j=1,\dots,m}\{\bar{g}_j\}$ and these exists a design constant $\kappa > 0$ such that $(1/2)k_c^2(\bar{g}/\underline{g})^2\tilde{\xi}^\top\chi\chi^\top\tilde{\xi} + \tilde{\xi}^\top\tilde{\xi} \le (\kappa-1)\tilde{\xi}^\top PP\tilde{\xi}$. Utilizing (28), (29), and (30) and choosing $k_c = k_c^* + 1$, (27) becomes

$$\begin{aligned}\dot{V} &\le \tilde{\xi}^\top(\bar{A}^\top P + P\bar{A})\tilde{\xi} - \sigma_o\|\tilde{W}_o\|^2 + \tilde{\xi}^\top PP\tilde{\xi}\\ &\quad + \|B-K\|^2(\bar{W}_o\bar{S}_o + \bar{\varepsilon}_o)^2 - k_c^*\theta^2\\ &\quad + (\kappa-1)\tilde{\xi}^\top PP\tilde{\xi} + \bar{\varepsilon}_o^2 + \frac{1}{2}\bar{\iota}^2 + \sigma_o\|W_o\|^2\\ &\le -\tilde{\xi}^\top Q\tilde{\xi} - \sigma_o\|\tilde{W}_o\|^2 - k_c^*\theta^2\\ &\quad + \|B-K\|^2(\bar{W}_o\bar{S}_o + \bar{\varepsilon}_o)^2 + \bar{\varepsilon}_o^2 + \frac{1}{2}\bar{\iota}^2 + \sigma_o\|W_o\|^2\\ &\le -\gamma V + \Delta,\end{aligned} \tag{31}$$

where $\gamma = \min\{\lambda_{\min}(Q)/\lambda_{\max}(P), 2\underline{g}k_c^*, \sigma_o\lambda_o\}$; $\lambda_{\min}(Q)$ denotes the minimum eigenvalue of Q and $\lambda_{\max}(P)$ denotes the maximum eigenvalue of P, and $\Delta = \sigma_o\bar{W}_o^2 + (1/2)\bar{\iota}^2 + \|B-K\|^2(\bar{W}_o\bar{S}_o + \bar{\varepsilon}_o)^2 + \bar{\varepsilon}_o^2$. Then, we get $V(t) \le e^{-\gamma t}V(0) + \frac{\Delta}{\gamma}(1 - e^{-\gamma t})$. Using $(1/2)\theta^2 \le V(t)$, we have

$$\theta^2(t) \le 2e^{-\gamma t}V(0) + \frac{2\Delta}{\gamma}(1 - e^{-\gamma t}). \tag{32}$$

As time increases, the error surface θ exponentially converges to the compact set $\mathcal{G} = \{\theta \,|\, |\theta| \le \sqrt{2\Delta/\gamma}\}$. Thus, ξ_1 is bounded. In addition, from (6), the boundedness of ξ_1 ensures $\underline{y}(t) < y(t) < \bar{y}(t)$ for all $t \ge 0$, which leads to $\underline{y}(t) - y_d(t) < y(t) - y_d(t) < \bar{y}(t) - y_d(t)$.

Based on the stability analysis for the proposed adaptive control scheme, the main result of this paper is presented in the following theorem.

Theorem 1: Consider the uncertain switched non-affine nonlinear systems (1) with time-varying output constraints and arbitrary switchings. Under Assumptions 1–2, the proposed output-constrained tracking scheme using only two neural networks guarantees that

(i) all the signals of the closed-loop system are bounded and the output constraints are not violated,

(ii) the tracking error $y(t) - y_d(t)$ satisfies $\underline{y}(t) - y_d(t) < y(t) - y_d(t) < \bar{y}(t) - y_d(t)$ for $\forall t \ge 0$,

regardless of unknown non-affine nonlinearities unmatched in the control input.

5. SIMULATION STUDIES

5.1. Example 1

Consider the uncertain switched pure-feedback nonlinear system (1) with $n = 3$, $\sigma(t) : [0,\infty) \to M = \{1,2,3\}$, $f_{1,1} = 0.05\cos x_1 + x_2$, $f_{1,2} = 0.2x_1 + x_2$, $f_{1,3} = 0.1\sin x_1 + x_2$, $f_{2,1} = (1 - 2^{x_1x_2})/(1 + 2^{x_1^2}) + x_3 + 0.1\tanh x_3$, $f_{2,2} = (1 - \exp(x_1x_2))/(1 + \exp(x_1x_2)) + x_3 + 0.05\sin x_3$, $f_{2,3} = (1 - 3^{x_1^2})/(1 + 3^{x_1^2}) + x_3 + 0.07\cos x_3$, $f_{3,1} = 0.2 \times 3^{-x_2^2x_3^4} + (0.9 + 0.05\exp(-x_1^2))u + 0.2\cos u$, $f_{3,2} = 0.2\exp(-x_2^4x_3^6) + (0.9 + 0.05\exp(-x_1^2))u + 0.1\sin u$ and $f_{3,3} = 0.3 \times 2^{-x_2^4x_3^4} + (1.1 + 0.05\exp(-x_1^2))u + 0.3\tanh u$.

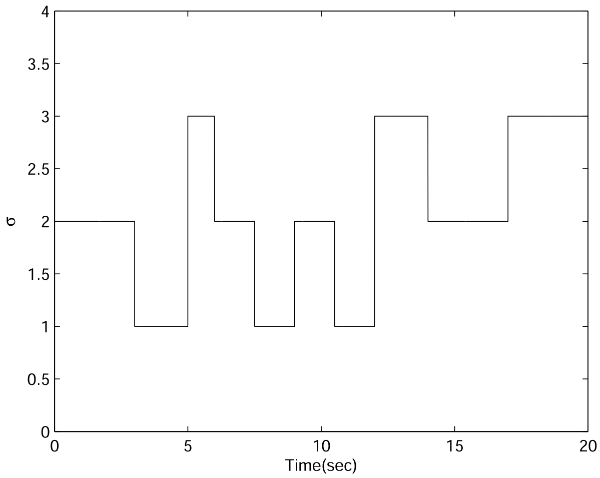
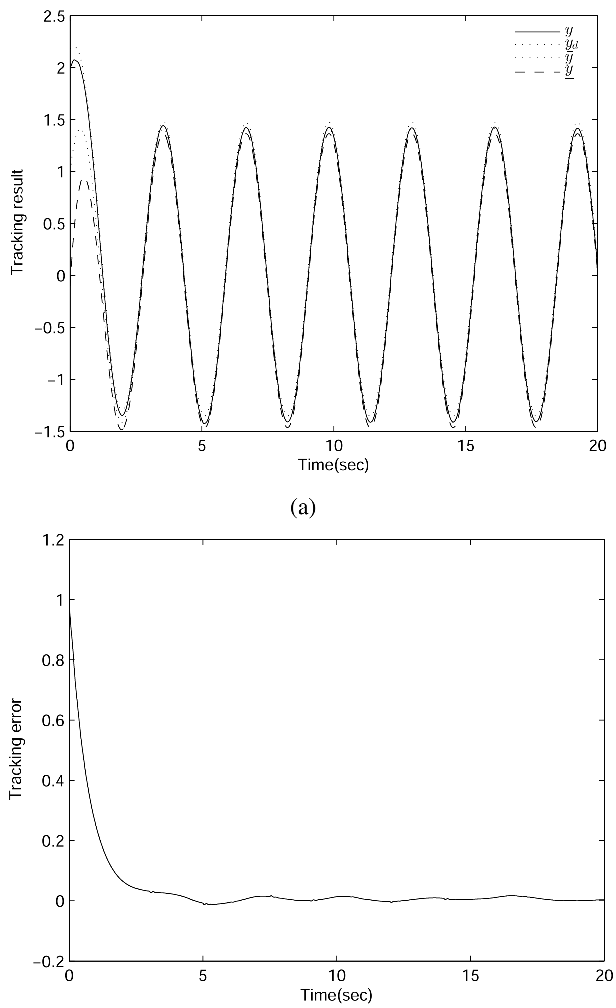


Fig. 1. Switching signal σ for example 1.



(a)

(b)

Fig. 2. Tracking result and error for example 1 (a) Tracking result (b) Tracking error $y - y_d$.

The desired signal y_d is defined as $y_d = \cos(2t) + \sin(2t)$. The initial conditions of the state variables are set to $x_1(0) = 2$ and $x_2(0) = x_3(0) = 0$. The lower and upper bounds of constraints are given by $\underline{y} = -1.05\exp(-2t) - 0.05 + y_d$ and $\bar{y} = 1.12\exp(-1.5t) + 0.06 + y_d$, respectively. Two neural network approximators with 30 hidden nodes and their basis functions chosen as the hyperbolic tangent function are employed for this simulation. The adaptive control scheme is given by (12), (3), and (16) where $\hat{\xi} = [\hat{\xi}_1, \hat{\xi}_2, \hat{\xi}_3, \hat{\xi}_4]^\top$, $L = [3 \times 10^2, 9 \times 10^4, 8 \times 10^6, 5 \times 10^8]^\top$, $K = [0.4698, 66.0563, 5037.4, 115292]^\top$, and $\hat{\theta} = [\chi_0, \chi_1, \chi_2, 1]\hat{\xi}$ with $\chi_0 = 10$, $\chi_1 = 40$, $\chi_2 = 80$, $a = 3$, and $k_c = 10$. The adaptive laws for $\hat{W}_o$ and $\hat{W}_c$ are given by (13) and (17) with $\lambda_o = \lambda_c = 0.1$ and $\sigma_o = \sigma_c = 0.001$. Fig. 1 illustrates the switching signal on non-affine nonlinearities. The tracking result and error are shown in Figs. 2(a) and 2(b), respectively. The L_2 norms of weights $\|\hat{W}_o\|$ and $\|\hat{W}_c\|$ of neural networks, and the control input u are shown in Fig. 3. From these figures, we can see that the system output y remains within the predefined output constraints for all $t \geq 0$ in the presence of the arbitrarily switched unknown non-affine nonlinearities.

5.2. Example 2

In this example, we consider the electromechanical system as a practical example. Its dynamics is given by [26,27]

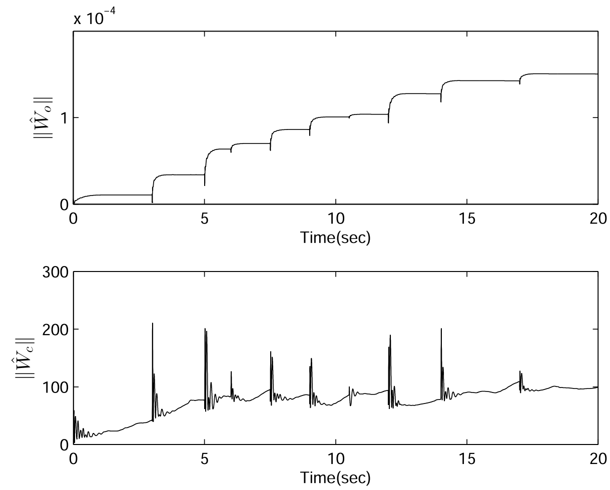
$$\begin{aligned} &D\ddot{q} + E\dot{q} + N\sin(q) = \tau, \\ &\bar{L}\dot{\tau} + R\tau = u - K_m\dot{q}, \end{aligned} \tag{33}$$

where $D = J/K_\tau + ml_0^2/(3K_\tau) + 2M_0R_0^2/(5K_\tau)$, $N = ml_0G/(2K_\tau) + M_0l_0G/K_\tau$, and $E = E_0/K_\tau$. J is the rotor inertia, m is the link mass, M_0 is the load mass, l_0 is the link length, R_0 is the radius of the load, G is the gravity coefficient, E_0 is the coefficient of viscous friction at the joint, q is the angular motor position (and hence the position of the load), τ is the motor armature current, K_τ is the coefficient which characterizes the electromechanical conversion of armature current to torque, $\bar{L}$ is the armature inductance, R is the armature resistance, K_m is the back-emf coefficient, and u is the input control voltage. Their values are chosen as $J = 1.625$ Kg$\cdot$m^2, $m = 0.506$ Kg, $R_0 = 0.023$ m, $M_0 = 0.434$ Kg, $l_0 = 0.305$ m, $E_0 = 16.25 \times 10^{-3}$ N$\cdot$m$\cdot$s/rad, $\bar{L} = 25.0 \times 10^{-3}$ H, $R = 5.0\ \Omega$, and $K_\tau = K_m = 0.90$ N$\cdot$m/A.

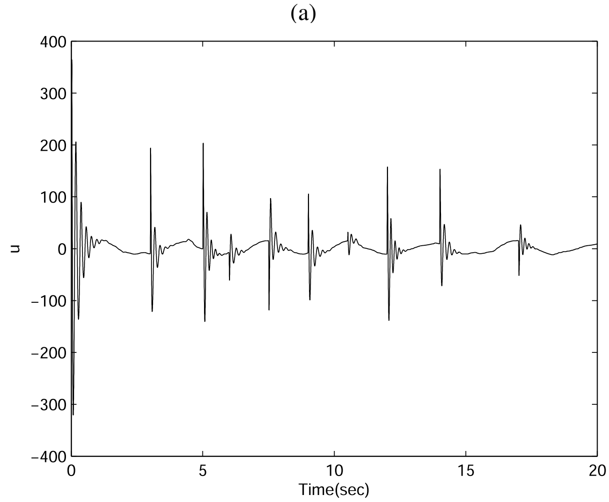
Defining $x_1 = q$, $x_2 = \dot{q}$, and $x_3 = \tau$, the electromechanical system (33) can be viewed as a non-affine nonlinear system in the following form

$$\begin{aligned} \dot{x}_1 &= f_1(x_1, x_2) + x_2, \\ \dot{x}_2 &= f_2(x_1, x_2, x_3) + x_3, \\ \dot{x}_3 &= f_3(x_1, x_2, x_3, u) + u, \\ y &= x_1, \end{aligned} \tag{34}$$

where $f_1(x_1, x_2) = 0$, $f_2 = -\frac{N}{D}\sin(x_1) - \frac{E}{D}x_2 + \frac{1}{D}x_3 - x_3$, and $f_3(x_1, x_2, x_3, u) = -\frac{K_m}{\bar{L}}x_2 - \frac{R}{\bar{L}}x_3 + \frac{u}{\bar{L}} - u$ are unknown



(a)



(b)

Fig. 3. (a) $\|\hat{W}_o\|$ and $\|\hat{W}_c\|$ for example 1 (b) Control input u for example 1.

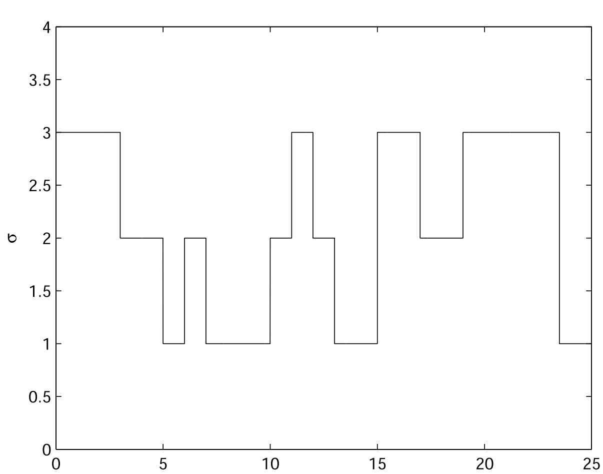
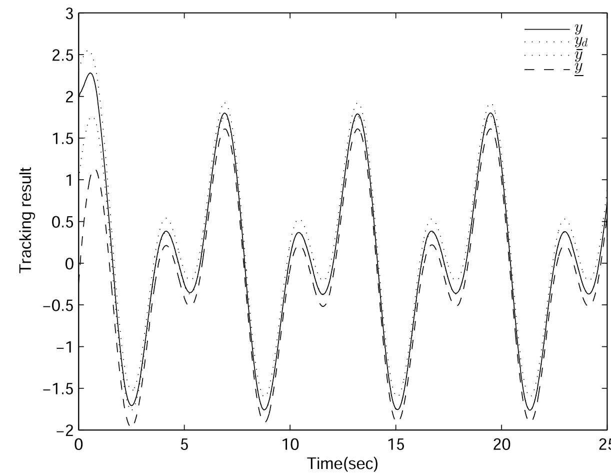
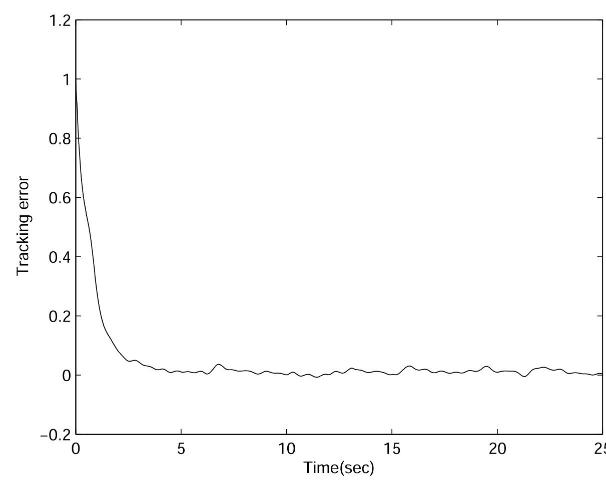


Fig. 4. Switching signal σ for example 2.



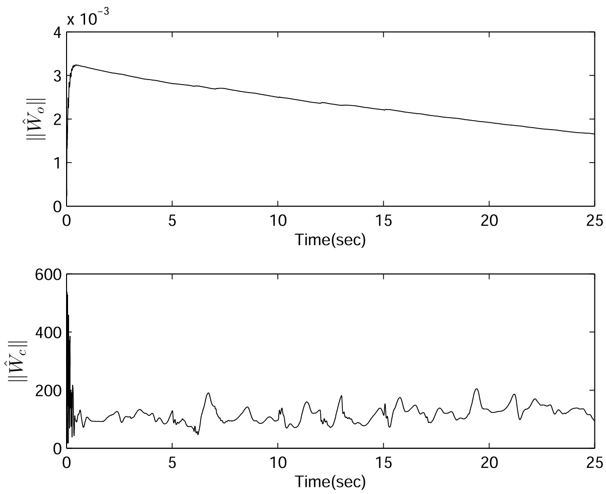
(a)



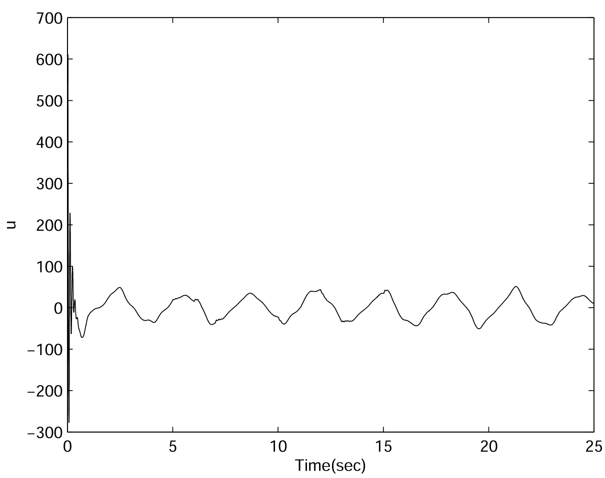
(b)

Fig. 5. Tracking result and error for example 2 (a) Tracking result (b) Tracking error $y - y_d$.

function. To describe system (34) as a switched nonlinear system, the load mass and armature resistance are assumed to be switched according to the load change (i.e., $M_{0,\sigma(t)}$ and $R_{\sigma(t)}$). Then, system (34) is represented by a switched non-affine nonlinear system with $n = 3$, $\sigma(t) : [0,\infty) \to M = \{1,2,3\}$, $M_{0,1} = 0.434$ Kg and $R_1 = 5.0\ \Omega$ at $\sigma(t) = 1$, $M_{0,2} = 0.658$ Kg and $R_2 = 6.5\ \Omega$ at $\sigma(t) = 2$, and $M_{0,3} = 0.821$ Kg and $R_3 = 8.0\ \Omega$ at $\sigma(t) = 3$. The desired signal y_d is given by $y_d = \cos(t) + \sin(2t)$. The initial conditions of the state variables are set to $x_1(0) = 2$ and $x_2(0) = x_3(0) = 0$. The lower and upper bounds of output constraints are given by $\underline{y} = -1.1\exp(-1.2t) - 0.15 + y_d$ and $\bar{y} = 1.16\exp(-1.1t) + 0.16 + y_d$. The adaptive control scheme is given by (12), (3), and (16) where $\hat{\xi} = [\hat{\xi}_1, \hat{\xi}_2, \hat{\xi}_3, \hat{\xi}_4]^\top$, $L = [3\times 10^2, 5\times 10^4, 2\times 10^6, 1\times 10^8]^\top$, $K = [0.3659, 34.8262, 1758.4, 43028]^T$, and $\hat{\theta} = [\chi_0, \chi_1, \chi_2, 1]\hat{\xi}$ with $\chi_0 = 120$, $\chi_1 = 180$, $\chi_2 = 20$, $a = 1$, and $k_c = 3$. The design parameters for the adaptive laws (13) and (17) are set to $\lambda_o = \lambda_c = 1.5$ and $\sigma_o = \sigma_c = 0.01$.



(a)



(b)

Fig. 6. (a) $\|\hat{W}_o\|$ and $\|\hat{W}_c\|$ for example 2 (b) Control input u for example 2.

Fig. 4 shows the switching signal for this simulation. The tracking result and error are displayed in Figs. 5(a) and 5(b), respectively. Figs. 6(a) and 6(b) show the norm of weights of neural networks and the control input, respectively. These figures reveal that the system output y evolves within preassigned time-varying output constraints for all $t \geq 0$.

6. CONCLUSION

This paper has investigated an adaptive approximation-based output-constrained tracking problem of uncertain switched pure-feedback systems with arbitrary switchings. The output constraints have been utilized as the control performance bounds. From the system transformation and the common Lyapunov function method, an adaptive output-constrained control scheme using only two neural networks has been designed regardless of the order of the systems. We have shown that the stability of the controlled closed-loop system and the constraint satisfaction have been analyzed in the Lyapunov sense. Finally, simulation examples have successfully verified the theoretical result.

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