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Observer-Based Adaptive Finite-Time Tracking Control for a Class of Switched Nonlinear Systems With Unmodeled Dynamics

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ABSTRACT This paper investigates the adaptive finite-time tracking control problem for a class of switched nonlinear systems with unmodeled dynamics. In practical applications, switched systems usually possess unfavourable factors, such as unmeasured states and unmodeled dynamics both of which are taken into account in this paper. A dynamic signal defined with a special property is introduced in this paper to improve control performance while garanteeing stability of the controlled system. By designing an observer, a finite-time adaptive output-feedback tracking controller is constructed via the backstepping technique. Then, the finite-time stability problem of the considered systems is studied. It is shown that all the signals in the closed-loop system are semi-globally uniformly finite-time bounded (SGFUB), and the observer errors and tracking errors can be regulated to a small neighborhood of the origin by choosing appropriate parameters. It is noted that, the design process is less complex than some existing results on tackling control problems of nonlinear systems with unmodeled dynamics. In the example, the simulation result testifies the effectiveness of the proposed method.

INDEX TERMS Switched systems, adaptive control, observer, finite-time control, unmodeled dynamics.

I. INTRODUCTION

Switched systems are a type of hybrid systems, which contain a family of subsystems and a switching signal. Switched systems own many special features different from general linear systems. For example, subsystems of a switched system may be continuous-time or discrete-time systems, and even if all subsystems are unstable, a switched system can be stable by designing a suitable switching signal. In recent practical applications, switched systems are usually used to describe many complex systems. In the past decades, studies on switched systems have received more and more attention, and numerous excellent works have been reported in [1]–[19]. The authors in [1] has solved asymptotic tracking control problem for a class of uncertain switched nonlinear systems by constructing a non-smooth Lyapunov function and introducing a novel discontinuous controller with dynamic feedback compensator, and the local asymptotic tracking performance of the systems with proposed controller was verified. The stability problem for a class of switched interconnected nonlinear systems has been studied in [4], and based on average dwell time method and the small gain technique, an effective state-feedback controller is designed. Further, different form traditional definition of ADT, a new concept of ADT is proposed in [6], and the authors finished the study of switching stabilization for a class of switched nonlinear systems. However, the above mentioned results do not consider the influence of unmodeled dynamics, which widely exist in practical applications.

Unmodeled dynamics may be caused by many factors, and it can be classified into state unmodeled dynamics and input unmodeled dynamics. State unmodeled dynamics denote the parts of invalid modeling during the parameterization, and input unmodeled dynamics mean modeling errors or external disturbances acting upon controllers. The presence of unmodeled dynamics significantly affect the stability of

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systems. In order to solve this problem, many researchers have put a lot of effort to it, and got many achievements, such as [20]–[27]. In [21], an adaptive output-feedback control method has been developed by using stochastic small-gain theory and the input-state practically stable method, and to guarantee the stability of the systems under consideration. A similar method for unmodeled dynamics was used in [23], to get good performances. The authors in [24] have introduced a dynamic signal to deal with the unmodeled dynamics, and accomplished the investigation of adaptive neural control problem for nonlower triangular nonlinear systems with unmodeled dynamics and dynamic disturbances. The proposed method can ensure semi-global boundedness of all signals. It is worth mentioning that the control schemes proposed in above mentioned references need a long time to reach a steady state. However, it is often significant to ensure the stability of systems in finite-time.

In recent years, researchers have been looking for a better way to stabilize a system faster. Hence, the finite-time stability problem has received increasingly attention and became a hot issue. Finite-time stability is not only a need, but also a trend. The investigations about finite-time stability are more interesting but challenging than other types of stability, which inspired many scholars to make great achievements [28]–[41]. For example, the authors in [28] have investigated the global finite-time stabilization for a class of nonlinear systems with parametric uncertainties, and an adaptive finite-time control law is obtained by using the global practical finite-time stability theory, which however did not work for the case that system functions are unknown. Therefore, a novel finite-time stability criteria called semi-global practical finite-time stability (SGPFS) were presented in [29] and [30] for strict-feedback nonlinear systems. In [42], the tracking control problem for a class of nonstrict-feedback nonlinear systems with the actuator faults has been addressed. Besides, the authors have studied the adaptive finite-time fault-tolerant control problem for nonlinear systems with multiple faults in [43]. In a word, the control methods proposed in [42], [43] ensure that all signals in the closed-loop system are semi-globally practically finite-time stable. In summary, it is a meaningful and challenging topic to investigate adaptive finite-time control problems for switched nonlinear systems, which motives us to carry out this paper.

Motivated by the above mentioned references, this paper studies the adaptive finite-time tracking control problem for a class of switched nonlinear systems with unmodeled dynamics. The unknown functions are approximated by RBF neural networks, and the unmeasured states are estimated via introducing a state observer. Compared with the existing literatures, the contributions and advantages of this paper are listed as follows.

1. The unmodeled dynamics are settled by introducing a dynamic signal. In contrast with the existing results, the advantage is that the dynamic signal has some special properties, which makes the design process less complex.

2. Based on the SGPFS theory and the backstepping technique, an adaptive finite-time tracking control problem for a class of switched nonlinear systems with unmodeled dynamics is proposed firstly. The proposed control method and controller ensure that the system output can track a desired trajectory in finite-time.

The remainder of this paper is designed as follows: The preliminaries and problem formulation are given in section 2. The design of controller and stability analysis are addressed in section 3. In section 4, the validity of proposed method is verified by a simulation example. Section 5 concludes this paper.

II. PROBLEM STATEMENT AND MAIN RESULTS

A. SYSTEM DESCRIPTION AND BASIC ASSUMPTIONS

In this paper, the considered switched nonlinear systems with unmodeled dynamics have the following form:

$$\begin{aligned} \dot{s} &= q(z_1, s, t) \\ \dot{x}_i &= x_{i+1} + f_{i,\sigma(t)}(\bar{x}_i) + \Delta_i(x, s, t) \\ 1 &\leq i \leq n-1 \\ \dot{x}_n &= u + f_{n,\sigma(t)}(\bar{x}_n) + \Delta_n(x, s, t) \\ & y = x_1 \end{aligned} \tag{1}$$

where $\bar{x}_i = [x_1, x_2, \ldots, x_i]^T \in \mathcal{R}^i, i = 1, 2, \ldots, n$ are the system states. u and y are the actual input and output of the system, respectively. $\sigma(t) : [0, +\infty) \to \Xi = \{1, 2, \ldots, \mathcal{N}\}$ is the switching signal, which is assumed to be a piecewise constant function. $f_{i,k}(\cdot)$, $i = 1, 2, \ldots, n, k \in \Xi$, are unknown smooth nonlinear functions. s denotes the unmodeled dynamics; $\Delta_i(x, s, t), i = 1, 2, \ldots, n$, are the dynamic disturbances, which are unknown Lipschitz continuous functions. In addition, it is assumed that only output y is measurable in this paper.

The objective of this paper is to design an effective controller for system (1), and the stability can be guaranteed in finite time.

Definition 1 : The equilibrium point $\chi = 0$ of nonlinear system $\dot{\chi} = f(\chi, u)$ is semi-globally uniformly finite-time bounded (SGFUB), if for all $\dot{\chi}(t_0) = \chi_0$, there exists a constant $\jmath > 0$ and a setting time $T(\jmath, \chi_0)$ such that $\|\chi(t)\| < \jmath$, for all $t \geq t_0 + T$.

Assumption 1 : The n^{th} derivative of the reference signal y_r is bounded and available.

Assumption 2 : Consider $\dot{s} = q(z_1, s, t)$ and $\Delta_i(x, s, t)$ in (1), it is supposed that:

• The equilibrium $s = 0$ of $\dot{s} = q(t, s, 0) - q(t, 0, 0)$ is stable, and dynamic signal r satisfies

$$\begin{aligned} & w_1\|P\|^2 \leq r \leq w_2\|P\|^2 \\ & \frac{\partial r}{\partial t} + \frac{\partial r}{\partial s}\left(q(t, s, 0) - q(t, 0, 0)\right) \leq -w_3\|s\|^2, \\ & \left|\frac{\partial r}{\partial s}\right| \leq w_4 \|s\|, \\ & \|q(t, 0, 0)\| \leq w_5 \end{aligned}$$

where w_1, w_2, w_3, w_4 and w_5 are unknown positive constants.

• q and Δ_i satisfy the following inequalities

$$\|q(t,s,z_1)-q(t,s,0)\|\le\vartheta_0\iota_0,\ \|\Delta_i\|\le\vartheta_i\delta_{i1}+\vartheta_i\|s\|\delta_{i2}$$

where ϑ_0 and $\vartheta_i(i=1,\ldots,n)$ are unknown positive constants, $\iota_0\in C_1$ is unknown continuous function, $\iota_0(0)=0$; δ_{i1} and δ_{i2} are unknown positive continuous functions.

Remark 1 : Compared with the existing results [44], ι_0, δ_{i1} and δ_{i2} are completely unknown functions. Therefore, the proposed control method is more applicable to real systems.

Lemma 1: For $a_\hbar\in R$, $\hbar=1,\ldots,n$, $0<\eta\le1$, we have

$$\left(\sum_{\hbar=1}^{n}|a_\hbar|\right)^\eta\le\sum_{\hbar=1}^{n}|a_\hbar|^\eta\le n^{1-\eta}\left(\sum_{\hbar=1}^{n}|a_\hbar|\right)^\eta \tag{2}$$

Lemma 2: There exist positive constants α,β,γ, such that for any real variable x and y, the following inequality holds:

$$|x|^\alpha|y|^\beta\le\frac{\alpha}{\alpha+\beta}\gamma|x|^{\alpha+\beta}+\frac{\beta}{\alpha+\beta}\gamma^{-\frac{\alpha}{\beta}}|y|^{\alpha+\beta} \tag{3}$$

Lemma 3: Consider the system $\dot\chi=f(\chi,u)$ and a smooth positive defined function $V(\chi)$. If there exist constants $c>0$, $d>0$ and $0<\eta<1$ such that

$$\dot V(\chi)\le-cV^\eta(\chi)+d,\ t\ge0 \tag{4}$$

then the nonlinear system $\dot\chi=f(\chi,u)$ is SGUFB.

Proof: It follows from (4) that for any $0<\zeta<1$, one has

$$\dot V(\chi)\le-\zeta cV^\eta(\chi)-(1-\zeta)cV^\eta(\chi)+d \tag{5}$$

Define $\Omega_\chi=\left\{\chi\,|\,V^\eta(\chi)\le\frac{d}{(1-\zeta)c}\right\}$ and $\bar\Omega_\chi=\left\{\chi\,|\,V^\eta(\chi)>\frac{d}{(1-\zeta)c}\right\}$. There are two cases as following:

Case 1: If $\chi(t)\in\bar\Omega_\chi$, one can get from (5) that

$$\dot V(\chi)\le-\zeta cV^\eta(\chi) \tag{6}$$

Integrating inequality (6) in the interval $[0,T]$, it becomes that

$$\int_0^T\frac{\dot V(\chi)}{V^\eta(\chi)}dt\le-\int_0^T\zeta c dt \tag{7}$$

Furthermore, the following inequality is satisfied:

$$\frac{1}{1-\eta}V^{1-\eta}(\chi(T))-\frac{1}{1-\eta}V^{1-\eta}(\chi(0))\le-c\zeta T \tag{8}$$

where $V(\chi(0))$ is the initial value of $V(\chi)$.

Next, define

$$T_r=\frac{1}{(1-\eta)c\zeta}\left[V^{1-\eta}(\chi(0))-\left(\frac{d}{(1-\zeta)c}\right)^{\frac{1-\eta}{\eta}}\right] \tag{9}$$

Then (9) indicates that $\chi(t)\in\Omega_\chi,\forall T\ge T_r$.

Case 2: If $\chi(t)\in\Omega_\chi$, review the operations in Case 1, the trajectory of $\chi(t)$ does not exceed the set Ω_χ.

In conclusion, the time to reach the set Ω_χ is bounded as T_r, the solution of $\dot\chi=f(\chi,u)$ is bounded in a finite time.

B. RBF NEURAL NETWORKS

In this part, the radial basis function neural networks (RBFNNs) will be given to approximate the unknown functions, which are defined on a compact set $\Omega\in\mathcal{R}^n$. For instance, $f(x)$ is a smooth continuous functions over a compact set $\Omega\in\mathcal{R}^n$, and there exists an NN $\theta^T\varphi(x)$ for a positive constant ε such that

$$f(x)=\theta^T\varphi(x)+\varepsilon$$

where $x\in\mathcal{R}^n$ is the input vector. $\theta=[\theta_1,\theta_2,\ldots,\theta_l]^T\in\mathcal{R}^l$ is the ideal weight vector, $l>1$ is the NN node number; ε is the approximation error, and $\varphi(x)=[\varphi_1,\varphi_2,\ldots,\varphi_l]\in\mathcal{R}^l$ is the basis function vector, which is generally chosen as an Gaussian function. In this paper, the Gaussian basis function will be utilized:

$$\varphi_i(x)=\exp[-\frac{(x-\xi_i)^T(x-\xi_i)}{\omega_i}],\quad i=1,2,\ldots,l$$

where $\xi=[\xi_1,\xi_2,\ldots,\xi_n]$ denotes the center of the receptive field, and ω_i represents the width of Gaussian function.

Defining the ideal constant weight vector $\theta_i{}^*$ as:

$$\theta_i^*=\arg\min_{\theta_i\in R^l}\left\{\sup_{x\in\Omega}\left|f_i(\bar x_i)-\theta_i^T\varphi_i\right|\right\}$$

where $\theta_i^*=\hat\theta_i+\tilde\theta_i$.

III. MAIN RESULTS

In this section, a detailed design process is provided. First, an observer is constructed in subsection 3.1. As we all know, the Backstepping technique has unique advantages in dealing with nonlinear control problems, it eliminates the constraint that a system uncertainty should satisfy the matching condition. Therefore, it is used in this paper. An effective actual controller is designed by combining the Lyapunov function method and the Backstepping technique. Finally, stability analysis is given in subsection 3.3.

A. OBSERVER DESIGN

The observer is designed in this subsection. Construct the observer with the following form:

$$\begin{aligned}\dot{\hat x}_i&=\hat x_{i+1}+\hat f_{i,k}\left(\hat{\bar x}_i\middle|\hat\theta_i\right)+\Delta_i\\ \dot{\hat x}_n&=u+\hat f_{n,k}\left(\hat{\bar x}_n\middle|\hat\theta_n\right)+\Delta_n\end{aligned} \tag{10}$$

The error is defined as:

$$e=x-\hat x \tag{11}$$

The derivative of e is

$$\begin{aligned}\dot e&=Ae+\sum_{j=1}^{n}B_jf_{i,\sigma(t)}(\bar x_i|\theta_i)-\sum_{j=1}^{n}B_j\hat f_{i,\sigma(t)}\left(\hat{\bar x}_i\middle|\hat\theta_i\right)\\ &=Ae+\sum_{j=1}^{n}B_j\tilde\theta_j\varphi_j+\varepsilon\end{aligned} \tag{12}$$

where $\varepsilon=[\varepsilon_1,\ldots,\varepsilon_n]^T$, $\tilde\theta_j=\theta_j^*-\hat\theta_j$.

Considering the Lyapunov function candidate as

$$V_0 = e^T Pe \tag{13}$$

The differential operator of V_0 is

$$\begin{aligned}\dot{V}_0 &= \dot{e}^T Pe + e^T P\dot{e} \\ &= e^T(-Q)e + 2e^T P\left(\sum_{j=1}^{n} B_j\tilde{\theta}_j\varphi_j + \varepsilon\right)\end{aligned} \tag{14}$$

By using the Youngs inequality, we get

$$2e^T P\sum_{j=1}^{n} B_j\tilde{\theta}_j\varphi_j \le n\|e\|^2 + \|P\|^2\sum_{j=1}^{n}\vartheta_j\varphi_j{}^T\varphi_j \tag{15}$$

where $\vartheta_j = \tilde{\theta}_j^T\tilde{\theta}_j$.

$$2e^T P\varepsilon \le \|e\|^2 + \|P\|^2\varepsilon^{*2} \tag{16}$$

where ε^* is a positive constant.

Substituting (15) and (16) into (14), one can get

$$\dot{V}_0 \le -(\lambda_{\min} - n - 1)\|e\|^2 + \|P\|^2\sum_{j=1}^{n}\vartheta_j\varphi_j{}^T\varphi_j + \psi_0 \tag{17}$$

where $\psi_0 = \|P\|^2\varepsilon^{*2}$.

B. THE DESIGN OF CONTROLLER

In this part, we will give the design process of actual controller. First, we introduce a signal r, which has the property in Assumption 2. Then, we construct an adaptive neural finite-time tracking controller by using the backstepping technique. Since backstepping technique need n steps, we give the coordinate transformation of each step as follows:

$$\begin{aligned}z_1 &= y - y_r \\ z_i &= \hat{x}_i - \alpha_{i-1}, 2 \le i \le n\end{aligned}$$

Step 1: Construct the Lyapunov function as:

$$V_1 = V_0 + \frac{1}{\gamma_0}r + \frac{1}{2}z_1{}^2 + \frac{1}{2\mu_1}\tilde{\vartheta}_1^T\tilde{\vartheta}_1 \tag{18}$$

where μ_1 is a known constant.

According to Assumption 2, the derivative of r is

$$\begin{aligned}\dot{r} &= \frac{\partial r}{\partial t} + \frac{\partial r}{\partial s}\upsilon(t,s,z_1) \\ &= \frac{\partial r}{\partial t} + \frac{\partial r}{\partial s}(\upsilon(t,s,z_1) - \upsilon(t,s,0)) + \frac{\partial r}{\partial s}\upsilon(t,0,0) \\ &\quad + \frac{\partial r}{\partial s}(\upsilon(t,s,0) - \upsilon(t,0,0)) \\ &\le -w_3\|s\|^2 + w_4w_5\|s\| + w_4\|s\|\nu_0\iota_0\end{aligned} \tag{19}$$

It is not hard to get the following inequalities:

$$\frac{1}{\gamma_0}w_4w_5\|s\| \le \frac{w_3}{8\gamma_0}\|s\|^2 + \frac{2}{w_3\gamma_0}w_4{}^2w_5{}^2 \tag{20}$$

$$\begin{aligned}\frac{1}{\gamma_0}\|s\|\nu_0\iota_0 &\le \frac{w_3}{8\gamma_0}\|s\|^2 + \frac{2}{w_3\gamma_0}w_4{}^2\nu_0{}^2\iota_0{}^2 \\ &\le \frac{w_3}{8\gamma_0}\|s\|^2 + \frac{1}{w_3{}^2\gamma_0{}^2}w_4{}^4\nu_0{}^4 + \iota_0{}^4\end{aligned} \tag{21}$$

Putting together (19), (20) and (21) gives

$$\dot{r} \le -\frac{3w_3}{4\gamma_0}\|s\|^2 + \frac{2}{w_3\gamma_0}w_4{}^2w_5{}^2 + \frac{1}{w_3{}^2\gamma_0{}^2}w_4{}^4\nu_0{}^4 + \iota_0{}^4 \tag{22}$$

The derivative with respect to V_1 is:

$$\begin{aligned}\dot{V}_1 &= \dot{V}_0 + \frac{1}{\gamma_0}\dot{r} + z_1\dot{z}_1 - \frac{1}{\mu_1}\tilde{\vartheta}\dot{\hat{\vartheta}} \\ &\le -(\lambda_{\min} - n - 1)\|e\|^2 + \|P\|^2\sum_{j=1}^{n}\vartheta_j\varphi_j{}^T\varphi_j - \frac{3w_3}{4\gamma_0}\|s\|^2 \\ &\quad + z_1\left(x_2 + f_{1,k}(x_1) + p_1 - \dot{y}_d\right) + \frac{1}{\gamma_0{}^2w_3{}^2}w_4{}^4\nu_0{}^4 \\ &\quad + \frac{2}{\gamma_0w_3}w_4{}^2w_5{}^2 + \iota_0{}^4 - \frac{1}{\mu_1}\tilde{\vartheta}\dot{\hat{\vartheta}} + \psi_0\end{aligned} \tag{23}$$

According to Lemma 2, one gets

$$\begin{aligned}|z_1||p_1| &\le |z_1|(\nu_1\delta_{11} + \nu_1\|s\|\delta_{12}) \\ &\le \frac{z_1{}^2\delta_{11}{}^2}{2\tau_{11}{}^2} + \frac{\tau_{11}{}^2}{2}\nu_1{}^2 + \frac{w_3}{4\gamma_0}\|s\|^2 \\ &\quad + \frac{\gamma_0{}^2z_1{}^4\delta_{12}{}^4}{2w_3{}^2\rho_{11}{}^2} + \frac{\rho_{11}{}^2\nu_1{}^4}{2}\end{aligned} \tag{24}$$

Substituting (24) into (23), the result is:

$$\begin{aligned}\dot{V}_1 \le &-(\lambda_{\min} - n - 1)\|e\|^2 + \|P\|^2\sum_{j=1}^{n}\vartheta_j\varphi_j{}^T\varphi_j + \frac{1}{2}z_2{}^2 \\ &+ z_1\alpha_1 + z_1\widehat{f}_{1,k} + \psi_1 - \frac{w_3}{2\gamma_0}\|s\|^2 - \frac{1}{\mu_1}\tilde{\vartheta}\dot{\hat{\vartheta}}\end{aligned} \tag{25}$$

where

$$\widehat{f}_{1,k} = \frac{1}{2}z_1 + f_{1,k} - \dot{y}_d + \frac{z_1{}^2\delta_{11}{}^2}{2\tau_{11}{}^2} + \frac{\gamma_0{}^2z_1{}^4\delta_{12}{}^4}{2w_3{}^2\rho_{11}{}^2} \tag{26}$$

$$\begin{aligned}\psi_1 &= \psi_0 + \frac{2}{\gamma_0w_3}w_4{}^2w_5{}^2 + \frac{1}{\gamma_0{}^2w_3{}^2}w_4{}^4\nu_0{}^4 \\ &\quad + \iota_0{}^4 + \frac{\tau_{11}{}^2}{2}\nu_1{}^2 + \frac{\rho_{11}{}^2\nu_1{}^4}{2}\end{aligned} \tag{27}$$

There are many unknown items in $\widehat{f}_{1,k}$, so the RBF neural networks are used to approximate $\widehat{f}_{1,k}$.

$$\widehat{f}_{1,k} = \theta^*{}_1\varphi_1 + \varepsilon_1 \tag{28}$$

Then, we can get the following inequality

$$z_1\widehat{f}_{1,k} \le \tfrac{1}{2}z_1{}^2 + \tfrac{z_1{}^2\vartheta_1\varphi_1{}^T\varphi_1}{2\omega_1{}^2} + \tfrac{\omega_1{}^2}{2} + \tfrac{1}{2}\varepsilon^{*2} \tag{29}$$

Substituting (29) into (25), one gets

$$\begin{aligned}\dot{V}_1 \le &-(\lambda_{\min} - n - 1)\|e\|^2 + \|P\|^2\sum_{j=1}^{n}\vartheta_j\varphi_j{}^T\varphi_j + \frac{1}{2}z_2{}^2 \\ &+ \frac{\omega_1{}^2}{2} + \frac{1}{2}\varepsilon^{*2} + z_1\left(\alpha_1 + \frac{z_1\hat{\vartheta}\varphi_1{}^T\varphi_1}{2\omega_1{}^2} + \frac{1}{2}z_1\right)\end{aligned}$$

$$+\frac{\tilde{\vartheta}_1}{\mu_1}\left(\frac{\mu_1 z_1{}^2\varphi_1{}^T\varphi_1}{2\omega_1{}^2}-\dot{\vartheta}_1\right)+\Delta_1+\psi_1 \tag{30}$$

The virtual controller α_1 and adaptive law ϑ_1 are designed as:

$$\alpha_1=-\frac{z_1\hat{\vartheta}\varphi_1{}^T\varphi_1}{2\omega_1{}^2}-\frac{1}{2}z_1-c_1z_1{}^{2\eta-1} \tag{31}$$

$$\dot{\vartheta}_1=\frac{\mu_1z_1{}^2\varphi_1{}^T\varphi_1}{2\omega_1{}^2}-l_1\vartheta_1 \tag{32}$$

where c_1 and l_1 are design parameters.

Substituting (31) and (32) into (30) concludes that

$$\dot{V}_1\leq-(\lambda_{\min}-n-1)\|e\|^2+\|P\|^2\sum_{j=1}^{n}\vartheta_j\varphi_j{}^T\varphi_j+\frac{1}{2}z_2{}^2 -c_1z_1{}^{2\eta}+\frac{l_1}{\mu_1}\tilde{\vartheta}_1\hat{\vartheta}_1+\psi_1+\frac{w_3}{2\gamma_0}\|s\|^2+\frac{\omega_1{}^2}{2}+\frac{1}{2}\varepsilon^{*2} \tag{33}$$

Step i (i=2, 3, …, n-1): In this step, the change of coordinates equality is

$$z_i=\hat{x}_i-\alpha_{i-1}$$

The derivative of z_i is

$$\begin{aligned}\dot{z}_i&=\dot{\hat{x}}_i-\dot{\alpha}_{i-1}\\&=z_{i+1}+\alpha_i-\sum_{j=2}^{i-1}\frac{\partial\alpha_{i-1}}{\partial x_j}\left(x_{j+1}+f_{j,k}(x_j)+p_j\right)\\&\quad+\hat{f}_{i,k}(\bar{x}_i)+p_i-\sum_{j=2}^{i-1}\left(\frac{\partial\alpha_{i-1}}{\partial\hat{\vartheta}_j}\dot{\hat{\vartheta}}_j+\frac{\partial\alpha_{i-1}}{\partial y_d{}^{(j-1)}}y_d{}^{(j)}\right)\end{aligned} \tag{34}$$

Choosing the Lyapunov function candidate as

$$V_i=V_{i-1}+\frac{1}{2}z_i{}^2+\frac{1}{2\mu_i}\tilde{\vartheta}_i^T\tilde{\vartheta}_i \tag{35}$$

where μ_i is a known constant.

Combining (33), (34) with (35), the derivative of V_i is

$$\begin{aligned}\dot{V}_i&\leq-(\lambda_{\min}-n-1)\|e\|^2+\|P\|^2\sum_{j=1}^{n}\vartheta_j\varphi_j{}^T\varphi_j\\&\quad-\sum_{j=1}^{i-1}c_jz_j{}^{2\eta}+\sum_{j=1}^{i-1}\frac{l_j}{\mu_j}\tilde{\vartheta}_j\hat{\vartheta}_j+\psi_{i-1}+\frac{i-4}{4\gamma_0}w_3\|s\|^2\\&\quad+\sum_{j=1}^{i-1}\frac{\omega_j^2}{2}+\frac{i-1}{2}\varepsilon^{*2}+\frac{1}{2}z_i{}^2+\frac{1}{2}z_i{}^2+\frac{1}{2}z_{i+1}{}^2\\&\quad+z_i\alpha_i+z_if_i+z_ip_i-z_i\sum_{j=2}^{i-1}\frac{\partial\alpha_{i-1}}{\partial x_j}\left(x_{j+1}+f_{j,k}(\bar{x}_j)\right)\\&\quad-z_i\sum_{j=2}^{i-1}\frac{\partial\alpha_{i-1}}{\partial x_j}p_j-z_i\sum_{j=2}^{i-1}\left(\frac{\partial\alpha_{i-1}}{\partial\hat{\vartheta}_j}\dot{\hat{\vartheta}}_j+\frac{\partial\alpha_{i-1}}{\partial y_d{}^{(j-1)}}y_d{}^{(j)}\right)\\&\quad-\frac{1}{\mu_i}\tilde{\vartheta}_i^T\dot{\hat{\vartheta}}_i\end{aligned} \tag{36}$$

Similar to the procedures in Step 1, we can obtain

$$\begin{aligned}|z_i|\,|p_i|&\leq\sum_{j=2}^{i-1}\frac{2\gamma_0{}^2}{w_3{}^2\rho_{j1}{}^2}\left(\frac{\delta_{j2}z_j\partial\alpha_{i-1}}{\partial x_j}\right)^4+\frac{\rho_{j1}{}^2\nu_1{}^4}{2}\\&\quad+\sum_{j=2}^{i-1}\left(\frac{\partial\alpha_{i-1}}{\partial x_j}\right)^2\frac{z_j{}^2\delta_{j1}{}^2}{2\tau_{j1}{}^2}+\frac{\tau_{j1}{}^2\nu_1{}^2}{2}+\frac{w_3}{8\gamma_0}\end{aligned} \tag{37}$$

Substituting (37) into (36), the following inequality is obtained

$$\begin{aligned}\dot{V}_i&\leq-(\lambda_{\min}-n-1)\|e\|^2+\|P\|^2\sum_{j=1}^{n}\vartheta_j\varphi_j{}^T\varphi_j\\&\quad-\sum_{j=1}^{i-1}c_jz_j{}^{2\eta}+\sum_{j=1}^{i-1}\frac{l_j}{\mu_j}\tilde{\vartheta}_j\hat{\vartheta}_j+\psi_{i-1}+\frac{i-4}{4\gamma_0}w_3\|s\|^2\\&\quad+\sum_{j=1}^{i}\frac{\omega_j^2}{2}+\frac{i}{2}\varepsilon^{*2}+z_i\left(\alpha_i+\frac{z_i\hat{\vartheta}_i\varphi_i{}^T\varphi_i}{2\omega_i^2}+\frac{1}{2}z_i\right)\\&\quad+\frac{\tilde{\vartheta}_i}{\mu_i}\left(\frac{\mu_iz_i{}^2\varphi_i{}^T\varphi_i}{2\omega_i^2}-\dot{\hat{\vartheta}}_i\right)+\frac{w_3}{4\gamma_0}\|s\|^2+\frac{\tau_{i1}{}^2\nu_1{}^2}{2}\\&\quad+\frac{\rho_{i1}{}^2\nu_1{}^4}{2}\end{aligned} \tag{38}$$

From the inequality (38), we design the intermediate control function α_i and the adaptive law $\hat{\vartheta}_i$ as follows

$$\alpha_i=-\frac{z_i\hat{\vartheta}_i\varphi_i{}^T\varphi_i}{2\omega_i^2}-\frac{1}{2}z_i-c_iz_i{}^{2\eta-1} \tag{39}$$

$$\dot{\hat{\vartheta}}_i=\frac{\mu_iz_i{}^2\varphi_i{}^T\varphi_i}{2\omega_i^2}-l_i\hat{\vartheta}_i \tag{40}$$

where c_i and l_i are known constants.

Putting (39) and (40) together with (38), one gets

$$\begin{aligned}\dot{V}_i&\leq-(\lambda_{\min}-n-1)\|e\|^2+\|P\|^2\sum_{j=1}^{n}\vartheta_j\varphi_j{}^T\varphi_j\\&\quad-\sum_{j=1}^{i}c_jz_j{}^{2\eta}+\sum_{j=1}^{i}\frac{l_j}{\mu_j}\tilde{\vartheta}_j\hat{\vartheta}_j+\sum_{j=1}^{i}\frac{\omega_j^2}{2}+\frac{i}{2}\varepsilon^{*2}\\&\quad-\frac{i-4}{4\gamma_0}w_3\|s\|^2+\frac{1}{2}z_{i+1}{}^2+\psi_i\end{aligned} \tag{41}$$

where $\psi_i=\psi_{i-1}+\frac{\tau_{i1}{}^2\nu_1{}^2}{2}+\frac{\rho_{i1}{}^2\nu_1{}^4}{2}$.

Step n: At the final step, the actual controller will be designed. Consider $z_n=\hat{x}_n-\alpha_{n-1}$, and the derivative of z_n is

$$\begin{aligned}\dot{z}_n&=u+\hat{f}_{n,k}(\bar{x}_n)-\sum_{j=2}^{n-1}\frac{\partial\alpha_{n-1}}{\partial x_j}\left(x_{j+1}+f_{j,k}(x_j)+p_j\right)\\&\quad+p_n-\sum_{j=2}^{n-1}\left(\frac{\partial\alpha_{n-1}}{\partial\hat{\vartheta}_j}\dot{\hat{\vartheta}}_j+\frac{\partial\alpha_{n-1}}{\partial y_d{}^{(j-1)}}y_d{}^{(j)}\right)\end{aligned} \tag{42}$$

Construct the final Lyapunov function as

$$V_n=V_{n-1}+\frac{1}{2}z_n{}^2+\frac{1}{2\mu_n}\tilde{\vartheta}_n^T\tilde{\vartheta}_n \tag{43}$$

where μ_n is a known constant.

According to the result in Setp i, we can get

$$\begin{aligned}\dot{V}_n \leq& -(\lambda_{\min}-n-1)\|e\|^2+\|P\|^2\sum_{j=1}^{n}\vartheta_j\varphi_j{}^T\varphi_j\\&-\sum_{j=1}^{n-1}c_jz_j{}^{2\eta}+\sum_{j=1}^{n-1}\frac{l_j}{\mu_j}\tilde{\vartheta}_j\hat{\vartheta}_j+\frac{n-5}{4\gamma_0}w_3\|s\|^2\\&+\sum_{j=1}^{n-1}\frac{\omega_j{}^2}{2}+\frac{n-1}{2}\varepsilon^{*2}+\frac{1}{2}z_n{}^2-\frac{1}{\mu_n}\tilde{\vartheta}_n^T\dot{\hat{\vartheta}}_n+z_nu\\&+z_nf_n+z_np_n-z_n\sum_{j=2}^{n-1}\frac{\partial\alpha_{n-1}}{\partial x_j}\left(x_{j+1}+f_{j,k}\left(\bar{x}_j\right)\right)\\&+\psi_{i-1}-z_n\sum_{j=2}^{n-1}\left(\frac{\partial\alpha_{n-1}}{\partial\hat{\vartheta}_j}\dot{\hat{\vartheta}}_j+\frac{\partial\alpha_{n-1}}{\partial y_d{}^{(j-1)}}y_d{}^{(j)}\right)\\&-z_i\sum_{j=2}^{n-1}\frac{\partial\alpha_{n-1}}{\partial x_j}p_j\end{aligned}\tag{44}$$

Similar to the operations in previous steps, we can obtain

$$\begin{aligned}|z_n|\,|p_n|\leq&\frac{z_n{}^2\delta_{n1}{}^2}{2\tau_{n1}{}^2}+\frac{\tau_{n1}{}^2}{2}\nu_1{}^2+\frac{w_3}{8\gamma_0}\|s\|^2\\&+\frac{\gamma_0{}^2z_n{}^4\delta_{n2}{}^4}{2w_3{}^2\rho_{n1}{}^2}+\frac{\rho_{n1}{}^2\nu_1{}^4}{2}\end{aligned}\tag{45}$$

$$\begin{aligned}-z_n\sum_{j=2}^{n-1}\frac{\partial\alpha_{n-1}}{\partial x_j}p_j\leq&\sum_{j=2}^{n-1}\frac{2\gamma_0{}^2}{w_3{}^2\rho_{j1}{}^2}\left(\frac{\delta_{j2}z_j\partial\alpha_{n-1}}{\partial x_j}\right)^4\\&+\frac{\rho_{j1}{}^2\nu_1{}^4}{2}+\sum_{j=2}^{n-1}\left(\frac{\partial\alpha_{n-1}}{\partial x_j}\right)^2\frac{z_j{}^2\delta_{j1}{}^2}{2\tau_{j1}{}^2}\\&+\frac{\tau_{j1}{}^2\nu_1{}^2}{2}+\frac{w_3}{8\gamma_0}\end{aligned}\tag{46}$$

Design the actual controller u and adaptive law $\hat{\vartheta}_n$ as

$$u=-\frac{z_n\hat{\vartheta}_n\varphi_n{}^T\varphi_n}{2\omega_n{}^2}-\frac{1}{2}z_n-c_nz_n{}^{2\eta-1}\tag{47}$$

$$\dot{\hat{\vartheta}}_n=\frac{\mu_nz_n{}^2\varphi_n{}^T\varphi_n}{2\omega_n{}^2}-l_n\hat{\vartheta}_n\tag{48}$$

By substituting (45), (46), (47) and (48) into (44), one can obtain

$$\begin{aligned}\dot{V}_n\leq&-(\lambda_{\min}-n-1)\|e\|^2+\|P\|^2\sum_{j=1}^{n}\vartheta_j\varphi_j{}^T\varphi_j\\&-\sum_{j=1}^{n}c_jz_j{}^{2\eta}+\sum_{j=1}^{n}\frac{l_j}{\mu_j}\tilde{\vartheta}_j\hat{\vartheta}_j+\sum_{j=1}^{n}\frac{\omega_j{}^2}{2}+\frac{n}{2}\varepsilon^{*2}\\&-\frac{n-5}{4\gamma_0}w_3\|s\|^2+\psi_n\end{aligned}\tag{49}$$

where $\lambda'=\lambda_{\min}-n-1$ and $\psi_n=\psi_{n-1}+\frac{\tau_{n1}{}^2\nu_1{}^2}{2}+\frac{\rho_{n1}{}^2\nu_1{}^4}{2}$.

According to Lemma 2, some items in (49) can be changed as

$$\|P\|^2\sum_{j=1}^{n}\tilde{\vartheta}_j\varphi_j{}^T\varphi_j\leq\frac{n\|P\|^2}{2}+\frac{\|P\|^2}{2}\sum_{j=1}^{n}\tilde{\vartheta}_j^T\tilde{\vartheta}_j\tag{50}$$

$$\sum_{j=1}^{n}\frac{l_j}{\mu_j}\tilde{\vartheta}_j\hat{\vartheta}_j\leq\sum_{j=1}^{n}\frac{\vartheta_j{}^T\vartheta_j}{2}-\sum_{j=1}^{n}\frac{\tilde{\vartheta}_j^T\tilde{\vartheta}_j}{2}\tag{51}$$

Define $c=\min\left\{\lambda',2c_j,l_j-\|P\|^2,\frac{n-5}{4\gamma_0}w_3\right\}$, and $\dot{V}_n$ is rewritten as

$$\dot{V}_n\leq-ce^TPe-c\sum_{j=1}^{n}z_j{}^{2\eta}-c\sum_{j=1}^{n}\tilde{\vartheta}_j^T\tilde{\vartheta}_j-c\|s\|^2+d_n\tag{52}$$

where $d_n=\psi_n+\frac{n\|P\|^2}{2}+\sum_{j=1}^{n}\frac{l_j}{2\mu_j}\vartheta_j{}^T\vartheta_j$.

According to Lemma 1, the following inequalities hold

$$\left(e^TPe\right)^\eta\leq e^TPe+(1-\eta)\,\eta^{\frac{\eta}{1-\eta}}\tag{53}$$

$$c\left(\sum_{j=1}^{n}\tilde{\vartheta}_j^T\tilde{\vartheta}_j\right)^\eta\leq c\sum_{j=1}^{n}\tilde{\vartheta}_j^T\tilde{\vartheta}_j+c\,(1-\eta)\,\eta^{\frac{\eta}{1-\eta}}\tag{54}$$

$$c\left(\sum_{j=1}^{n}\tilde{\vartheta}_j^T\tilde{\vartheta}_j\right)^\eta\leq c\sum_{j=1}^{n}\tilde{\vartheta}_j^T\tilde{\vartheta}_j+c\,(1-\eta)\,\eta^{\frac{\eta}{1-\eta}}\tag{55}$$

Substituting (53), (54) and (55) into (52), the result is

$$\dot{V}_n\leq-cV_n{}^\eta+d\tag{56}$$

where $d=d_n+(1-\eta)\,\eta^{\frac{\eta}{1-\eta}}+c\,(1-\eta)\,\eta^{\frac{\eta}{1-\eta}}$.

Define a constant $\wp=\frac{d}{(1-\zeta)c}$, where ζ is a constant which satisfies $0<\zeta<1$. Then let

$$T_r=\frac{1}{(1-\eta)c\zeta}\left[V_n^{1-\eta}\left(\chi\left(0\right)\right)-\wp^{\frac{1-\eta}{\eta}}\right]\tag{57}$$

where $V_n\left(\chi\left(0\right)\right)$ represents the initial value of $V_n(\chi)$. According to Lemma 3, the time to reach the set $\chi(t)$ is bounded as T_r.

Theorem 1: For the nonlinear switched systems (1) with unmodeled dynamics, the actual controller (47), the adaptive laws (32), (39), (48), and Lemma 3, guarantee that all signals in the resulting system are SGUFB.

IV. SIMULATION RESULTS

In this section, an example will be given to expound our design scheme and verify the obtained results.

Consider the following nonlinear system with unmodeled dynamics:

$$\begin{aligned}\dot{s}&=-s+\frac{1}{8}x_1{}^2\sin(t)\\\dot{x}_1&=x_2+f_{1,k}(x_1)+\Delta_1\\\dot{x}_2&=u+f_{2,k}(\bar{x}_2)+\Delta_2\\y&=x_1,\quad k=1,2\end{aligned}$$

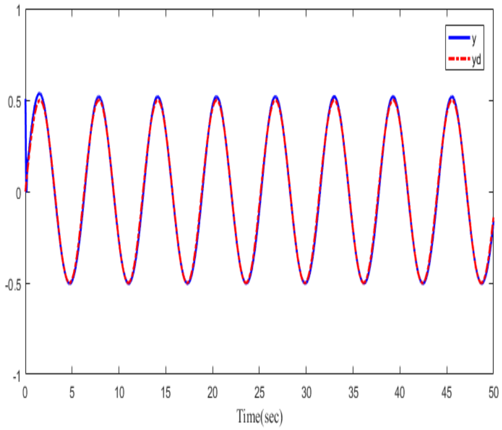

FIGURE 1. Tracking performance.

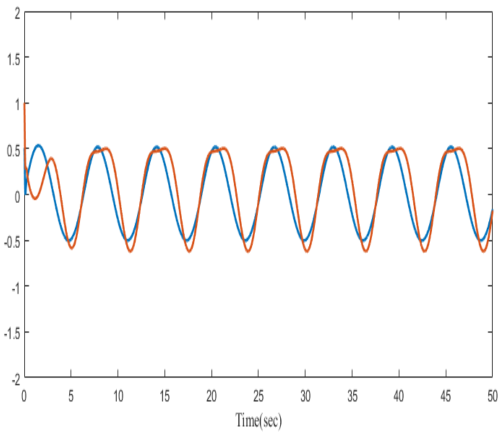

FIGURE 2. Response of x_1 and $\hat{x}_1$.

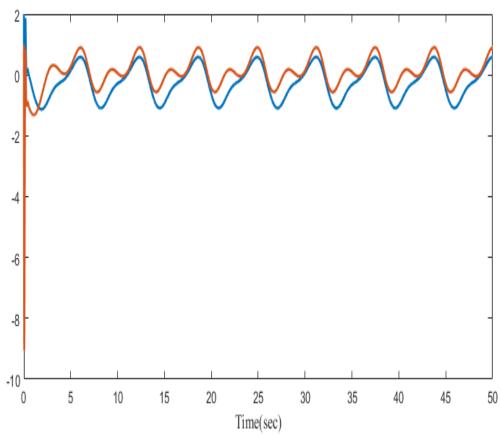

FIGURE 3. Response of x_2 and $\hat{x}_2$.

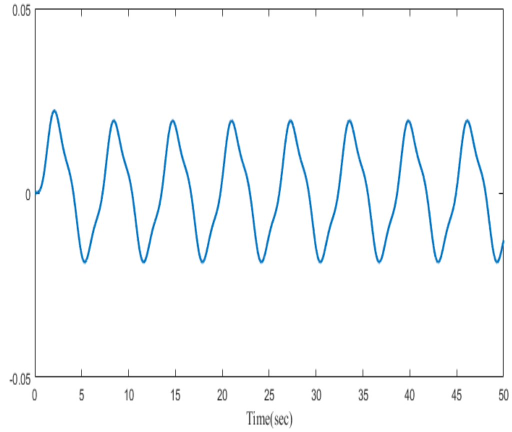

FIGURE 4. Response of the input *u*.

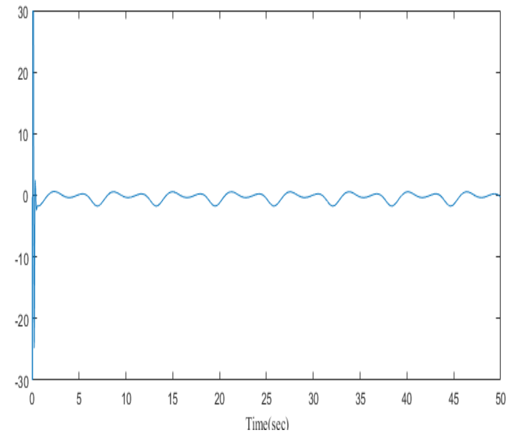

FIGURE 5. Response of the unmodeled dynamic.

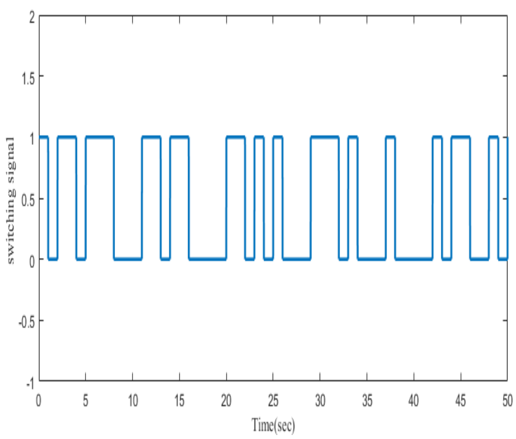

FIGURE 6. Switching signal.

where $f_{1,1}(x_1) = 2sin^2(x_1) - x_1$, $f_{1,2}(x_1) = -x_1 sin(x_1)$, $f_{2,1}(x_1) = sin(x_1 x_2) + 0.5cos(x_2)$, $f_{2,2}(x_1) = 0.5x_1 + sin(x_2{}^2)$, $\Delta_1 = s^2 + sin(x_1)$, $\Delta_2 = -2s + x_1^2$.

First of all, the reference signal is chosen as:

$$y_r = 0.5sin(t).$$

Then, the state observer is designed as:

$$\dot{\hat{x}}_1 = \hat{x}_2 + \hat{f}_{1,k}\left(\hat{\bar{x}}_1 \middle| \hat{\theta}_1\right) + \Delta_1$$
$$\dot{\hat{x}}_2 = u + \hat{f}_{2,k}\left(\hat{\bar{x}}_2 \middle| \hat{\theta}_2\right) + \Delta_2$$

Finally, RBF neural networks are used in the design of controller, and NNs have five hidden nodes with Gaussian basis function $\varphi_i(x)$. In this example, the design parameters are chosen as: $\mu_1 = \mu_2 = 10$, $l_1 = l_2 = 30$, $c_1 = c_2 = 30$, $\lambda_1 = \lambda_2 = 10$, $\eta = 0.99$. The initial values are chosen as $\left[x_{1,1}, x_{1,2}, x_{2,1}, x_{2,2}\right]^T = [0.5, 2, 1, 1]^T$. The initial values of the other parameters are taken as zero.

The simulation results are shown in Figs. 1-5. Fig. 1 shows the the trajectories of y and y_r, Fig. 2 and Fig. 3 exhibit the trajectories of x_1 and $\hat{x}_1$, x_2 and $\hat{x}_2$, respectively. Fig. 4 plots the trajectory of actual input u. Fig. 5 is the response of ζ. The switching signal is given in Fig. 6. We can draw a conclusion that the tracking error can be regulated arbitrarily small and all the sates are guaranteed to be bounded.

V. CONCLUSION

In this paper, an adaptive neural control strategy for a class of stochastic switched nonlinear systems in nonstrict-feedback form with actuator faults is considered. Actuator faults include loss of effectiveness and outage in this paper []. In the process of neural networks (NNs) being utilized to estimate the unknown functions, via the character of the Gaussian function, the problem of nonstrict-feedback form is handled. By designing the fault-tolerant control (FTC) which is obtained via backstepping technique, the problem of actuator faults is dealt with. Finally, the boundedness of all the signals in the resulting closed-loop system are achieved and the tracking error converges to a small neighborhood around the origin. A vivid simulation example is given to demonstrate the high efficiency of the proposed control method in the end.

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