Adaptive Neural DSC for Nonlinear Switched Systems With Prescribed Performance and Input Saturation

Wenjie Si and Xunde Dong

Abstract—**This paper solves the problem of an adaptive neural dynamic surface control for a class of uncertain strict-feedback nonlinear systems with guaranteed transient and steady-state performance under arbitrary switchings. First, by utilizing the prescribed performance control, the prescribed tracking control performance can be ensured, while the requirement for the initial error is removed. Second, radial basis function (RBF) neural networks (NNs) are used to handle unknown nonlinear functions, the Gaussian error function is employed to represent a continuous differentiable asymmetric saturation model and the dynamic surface control (DSC) technique is used to overcome the problem of 'explosion of complexity' inherent in the control design. At last, by using the common Lyapunov function method in combination with the backstepping technology, a common adaptive neural controller is constructed. The designed controller overcomes the problem of the over-parameterization, and further alleviates the computational burden. Under the proposed common adaptive controller, all the signals in the closed-loop system are bounded, and the prescribed transient and steady tracking control performance are guaranteed under arbitrary switchings. Simulation studies demonstrate the effectiveness of the proposed method.**

Index Terms—**Adaptive neural control, common Lyapunov function, dynamic surface control (DSC), input saturation, nonlinear switched systems, prescribed performance control (PPC)**

I. INTRODUCTION

Switched systems have drawn a lot of attention during past decades, due to their wide engineering application such as chemical reactor, heat exchanger, flight control, robot operating system and electric power systems [1]−[4]. A common Lyapunov function approach was presented in [5] to solve the stability problem for nonlinear switched systems under arbitrary switching. Subsequently, several studies were investigated via common Lyapunov functions and then stabilizing controllers for nonlinear switched systems were designed in [6]−[8]. However, the above-mentioned methods cannot be applied to unknown nonlinear systems. Therefore, to ensure the system stability and control performance, this paper studies the neural tracking control scheme for a class of nonlinear systems under arbitrary switchings with unknown system dynamics and input constraint.

For the systems with unknown system dynamics, both fuzzy logic systems (FLSs) and neural networks (NNs) have been proved to be useful in the control design, where their universal approximation properties are utilized to model unknown nonlinear functions. In the past decades, many approximation-based adaptive control methods have also been developed in [9], [10]. Adaptive fuzzy/neural control approaches for multi-input and multi-output (MIMO) were studied by [11]−[14]. For uncertain stochastic nonlinear systems, [15]−[17] designed adaptive fuzzy/neural control methods. When immeasurable states were considered, in [18], the tracking control was studied based on fuzzy logic system for airbreathing hypersonic flight vehicle. Recently, by using the approximation property of the neural network or fuzzy logic system, many control methods for switched nonlinear uncertain systems have been presented in [19]−[22]. Furthermore, stochastic disturbances are also considered in the switched systems. In [23]−[25], the fuzzy/neural adaptive control methods for the switched stochastic nonlinear systems were investigated. However, for the above-mentioned control schemes, the computational complexity drastically increases with the order of the system increases.

To overcome the 'explosion of complexity' caused in the traditional backstepping design, the dynamic surface control (DSC) technology has been proposed in [26] and a first-order low-pass filter is introduced at each step during the backstepping control design. In [27], the DSC technique was incorporated into the decentralized adaptive control for a class of large-scale nonlinear time-delay systems. Based on DSC technology, [13], [28] presented adaptive neural tracking control schemes subject to input saturation. In [29], the adaptive tracking control method was proposed by using the Nussbaum function and dynamic surface control for a class of MIMO non-affine nonlinear systems. By using using DSC technique, [30] presented an adaptive fuzzy output-feedback backstepping control approach. In [31], the DSC technique was extended to the control of the stochastic nonlinear and then an adaptive neural control scheme was investigated. Furthermore, when the states were unmeasured, the problem of adaptive neural observer-based dynamic surface control was addressed in [32] for a class of the nonstrict-feedback nonlinear systems. However, for nonlinear switched systems, to guarantee the tracking control performance is difficult and challenging. In

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this paper, we try to solve the tracking control problem for nonlinear switched systems with prescribed performance and unknown input saturation.

In the control process, the system output error is only required to converge to a small residual set, noting that the transient and stead-state performance are not considered. In practice, the industrial systems often meet certain prespecified overshoot and convergence rate. More recently, the problem was solved in [33] with prescribed performance control (PPC). This method was further applied to the robot position tracking control in [34], [35]. Combining PPC with dynamic surface control, fuzzy logic control schemes were studied in [36]−[38] to guarantee the tracking control performance. When states were unmeasurable, an observer-based control was proposed in [39] for large-scale nonlinear time-delay systems. The prescribed performance control technology was extended to MIMO nonlinear systems [40]−[42]. To the best of the authors' knowledge, by designing a new performance function, there exist few tracking control methods for nonlinear switched systems without the need for the initial error conditions.

Motivated by the aforementioned discussion, we will develop a common adaptive neural tracking controller for a class of strict-feedback nonlinear switched systems with prescribed performance technique and the dynamic surface control subject to input constraint. RBF neural networks are employed to approximate the unknown nonlinearities. A novel prescribed performance function is designed to guarantee the prespecified tracking performance, which does not need to consider the initial error values. Then, based on the backstepping design technique and the common Lyapunov function, we propose an adaptive neural tracking control method to guarantee the boundedness of the closed-loop system under arbitrary switchings.

Compared with previous works, the main advantages of this paper are summarized as follows: 1) A performance function is given to ensure the tracking control performance, and the requirement for the exact initial values is removed. 2) By using the DSC technique, the designed control scheme can overcome the defect of 'explosion of complexity'. Furthermore, the norm of the unknown weight vector themselves is estimated in this paper, and thus the online computation burden is greatly alleviated.

The rest of the paper is organized as follows. Section II presents the preliminaries and problem formulation. In section III, an adaptive neural tracking control scheme is given for nonlinear switched system with prescribed performance control. The simulation example is presented in Section IV to illustrate the effectiveness of the proposed method in this paper. Section V concludes this paper.

II. Preliminary Knowledge and System Formulation

A. System Representation

Consider a class of uncertain nonlinear switched systems with input saturation in the following form

$$\begin{cases} \dot{x}_i = x_{i+1} + f_{i,\sigma(t)}(x_1,\ldots,x_i) \\ \dot{x}_n = u(v) + f_{n,\sigma(t)}(x) \\ \;y = x_1 \quad i = 1,2,\ldots,n-1 \end{cases} \tag{1}$$

where $x = [x_1, x_2, \ldots, x_n]^T \in \mathbb{R}^n$, $u \in \mathbb{R}$ and $y \in \mathbb{R}$ are the system state variables, system input and output, respectively. $\sigma(t) : [0, +\infty] \to M = [1, 2, \ldots, m]$ is the switching signal. $\sigma(t) = k$ $(k \in M)$ means that the kth subsystem is active. $f_i(\cdot)$: $\mathbb{R}^i \to \mathbb{R}$ is the unknown locally Lipschitz smooth function. $v \in \mathbb{R}$ and $u \in \mathbb{R}$ are the input and output of the saturation nonlinearity to be expressed as follows

$$u(v) = \mathrm{Sat}[v] = \begin{cases} u^-, v < u^- \\ v, u^- \le v \le u^+ \\ u^+, v > u^+ \end{cases} \tag{2}$$

where u^+ and u^- the upper and lower bounds of the actuator u.

The main goal of this control scheme is to present a common adaptive NN tracking controller such that the system output y can track the desired signal y_d under arbitrary switchings, and all signals in the closed-loop system remain bounded.

Assumption 1: The desired signal y_d and its nth order y_d^n are continuous and bounded.

lemma 1: (Young's inequality [43]) For $\forall(x, y) \in \mathbb{R}^2$, the following inequality holds:

$$xy \le \frac{\varepsilon^p}{p}|x|^p + \frac{1}{q\varepsilon^q}|y|^q \tag{3}$$

where $\varepsilon > 0$, $p > 1$, $q > 1$, $(p-1)(q-1) = 1$.

B. Asymmetric Saturation Model

In this paper, according to [28], an asymmetric saturation nonlinearity with smooth form is employed as

$$u(v) = u_M \times \mathrm{erf}(\frac{\sqrt{\pi}}{2u_M}v) \tag{4}$$

where $u_M = u^+ + u^-/2 + u^+ - u^-/2\mathrm{sign}(v)$, $u^+$and u^- are the upper and lower bounds. $\mathrm{sign}(\cdot)$ is the standard sign and $\mathrm{erf}(\cdot)$ is a Gaussian error function defined as.

$$\mathrm{erf}(x) = \frac{2}{\sqrt{\pi}}\int_0^x e^{-t^2}dt \tag{5}$$

shows different output results using the saturation model (2) and (4), and (4) indeed guarantees the saturation limitation with smooth form, where $u^- = 2$, $u^+ = 2.5$, and the input signal $v(t) = 5\sin(t)$.

The following function is defined as

$$d(v) = u - cv \tag{6}$$

where c is a positive constant, u and v are the functions of time t. Then, for the following control design, the saturation model (4) can be written as,

$$u = cv + d(v) \tag{7}$$

For the following control design, we need make the following assumptions:

Assumption 2: There exist positive constants $\bar{\Delta}$, $\underline{c}$, $\bar{c}$ such that $d(v) \le d^*$, $c \in [\underline{c}, \bar{c}]$.

C. Prescribed Performance

A performance function is given, which will be used in the following control design.

Definition 1: [33] A smooth function $\rho(t) : \mathbb{R}^+ \to \mathbb{R}^+$ satisfies the following conditions, which will be called a performance function:

1) $\rho(t)$ is a strictly positive and decreasing function;

2) $\lim_{t\to+\infty} \rho(t) = \rho_\infty > 0$

where ρ_∞ is a positive constant.

According to Definition 1, a performance function in this paper is chosen as:

$$\rho(t) = \coth(\kappa t + \iota) - 1 + \rho_\infty \tag{8}$$

where κ, ι and ρ_∞ are design parameters.

Based on the above description of the performance function $\rho(t)$, the performance bound for the tracking error $\nu_1 = y - y_d$ is given by.

$$-\underline{\delta}\rho(t) < \nu_1(t) < \bar{\delta}\rho(t) \tag{9}$$

where $\underline{\delta}$, $\bar{\delta}$ are positive constants.

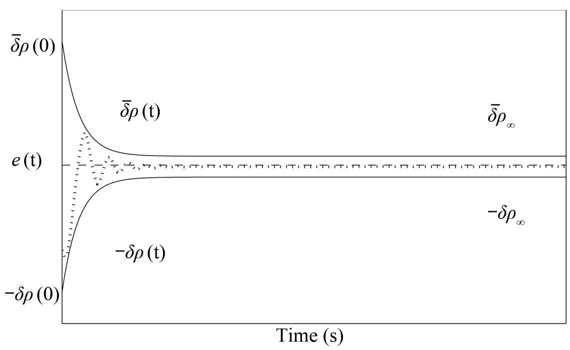

Fig. 1. Prescribed performance on the error $\nu_1(t)$.

Fig. 1 shows the tracking error curve with the designed prescribed performance function (8). Apparently, for the initial error $\nu_1(0)$, one has the following inequality

$$-\underline{\delta}\rho(0) < \nu_1(0) < \bar{\delta}\rho(0) \tag{10}$$

Therefore, the initial error $\nu_1(0)$ covers the positive and negative values.

To represent (9) by an unconstrained form, the following state transformation is employed as [33]

$$\nu_1(t) = \rho(t)R(\zeta_1) \tag{11}$$

where

$$R(\zeta_1) = \frac{\bar{\delta}e^{\zeta_1} - \underline{\delta}e^{-\zeta_1}}{e^{\zeta_1} + e^{-\zeta_1}} \tag{12}$$

where ζ_1 is called as the transformed error. According to (12), $R(\zeta_1)$ has the following properties

1) $R(\zeta_1)$ is smooth and strictly increasing function;

2) $\lim_{\zeta_1\to-\infty} R(\zeta_1) = -\underline{\delta}$ and $\lim_{\zeta_1\to+\infty} R(\zeta_1) = -\bar{\delta}$.

Based on the analysis of $R(\zeta_1)$, it implies

$$-\underline{\delta} < R(\zeta_1) < \bar{\delta} \tag{13}$$

Then, one can obtain

$$-\underline{\delta}\rho < \rho R(\zeta_1) < \rho\bar{\delta} \tag{14}$$

Thus, the equivalent unconstrained condition (11) can be obtained by the constrained tracking error one (9). Then, the transformed error ζ_1 can be expressed as

$$\zeta_1 = \mathbb{R}^{-1}\Big(\frac{\nu_1}{\rho}\Big) = \frac{1}{2}\ln\left(\frac{\frac{\nu_1}{\rho} + \underline{\delta}}{\bar{\delta} - \frac{\nu_1}{\rho}}\right) \tag{15}$$

Its derivative is

$$\dot{\zeta}_1 = \varrho_1\Big(\dot{\nu}_1 - \frac{\dot{\rho}}{\rho}\nu_1\Big) \tag{16}$$

where

$$\varrho_1 = \frac{1}{2\rho}\left(\frac{1}{\frac{\nu_1}{\rho} + \underline{\delta}} - \frac{1}{\frac{\nu_1}{\rho} - \bar{\delta}}\right) > 0 \tag{17}$$

$$\dot{\rho} = \kappa - \kappa(\coth(\kappa t + \iota))^2 \tag{18}$$

D. RBF Neural Networks

It has been proved in [44] that neural networks are useful to model unknown nonlinear functions in control design. In this paper, RBF NNs will be used to approximate any continuous function $f(Z) : \mathbb{R}^q \to \mathbb{R}$ over a compact set $\Omega_Z \subset \mathbb{R}^q$ as follows

$$f(Z) = W^{*\mathrm{T}}S(Z) + \epsilon(Z) \tag{19}$$

where $Z \in \Omega_Z$ is the input vector with q being the NNs input dimension. $W = [w_1, w_2, \ldots, w_l]^T \in \mathbb{R}^l$ is the NNs weight vector with $l > 1$ being the neural network node number, and W^* denotes the ideal constant weight vector. $\epsilon(Z)$ is the approximation error, $\|\epsilon(Z)\| \le \epsilon^*$. $S(Z) = [s_1(Z), s_2(Z), \ldots, s_l(Z)]^T$ is the basis function vector with $s_i(Z)$ being commonly used Gaussian function of the form

$$s_i(Z) = \exp\Big[\frac{-(Z-\xi_i)^{\mathrm{T}}(Z-\xi_i)}{\eta^2}\Big],\ i = 1, \ldots, l \tag{20}$$

where $\xi_i = [\xi_{i1}, \xi_{i2}, \ldots, \xi_{iq}]^T$ is the center of the receptive field and η is the width of Gaussian function [44].

The ideal constant weight vector is defined as

$$W^* := \arg\min_{\hat{W}\in\mathbb{R}^l}\Big\{\sup_{Z\in\Omega_Z}|f(Z) - \hat{W}^TS(Z)|\Big\} \tag{21}$$

where $\hat{W}$ denotes the estimate of W^*.

In fact, in the ith step of the backstepping design, as the ideal constant weight vector, $W^*_{i,k}$ needs to be estimated by $\hat{W}_{i,k}$. However, in this paper, we do not directly update the value of $W^*_{i,k}$ but the norm of $W^*_{i,k}$. Noting that $\|W^*_{i,\max}\|^2$ is an unknown constant, a positive constant θ^*_i is used to express as $\|W^*_{i,\max}\|^2 = b_i\theta^*_i$, where $W^*_{i,\max} = \max\{W_{i,k} : k \in M\}$. $\hat{\theta}_i$ denotes the estimate of θ^*_i, and the resulting estimation error $\tilde{\theta}_i$ is defined as $\tilde{\theta}_i = \hat{\theta}_i - \theta^*_i$.

III. Adaptive Dynamic Surface Control Design With Prescribed Performance

In this section, an adaptive control scheme will be presented and the recursive design procedure contains n steps with DSC and backstepping technology.

The n-step backstepping design is based on the following coordinate changes:

$$z_1 = \zeta_1$$
$$z_i = x_i - \pi_i, \chi_i = \pi_i - \alpha_{i-1},\ i = 2, \ldots, n \quad (22)$$

where α_{i-1} is the common virtual control signal, which is defined later. π_i is the output of the following first order filter with the time constant ς_i

$$\varsigma_i \dot{\pi}_i + \pi_i = \alpha_{i-1}, \pi_i(0) = \alpha_{i-1}(0),\ i = 2, \ldots, n. \quad (23)$$

Step 1: For the nonlinear switched systems (1), one has

$$\dot{z}_1 = \varrho_1\Big(x_2 + f_{1,k}(x) - \dot{y}_d - \frac{\dot{\rho}}{\rho}\nu_1\Big). \quad (24)$$

Introduce a new variable π_2 as the output of a first-order filter, and let the virtual control α_1 pass through it with time constant ς_2

$$\varsigma_2 \dot{\pi}_2 + \pi_2 = \alpha_1, \pi_2(0) = \alpha_1(0). \quad (25)$$

Since $\chi_2 = \pi_2 - \alpha_1$, one has $\dot{\pi}_2 = -\chi_2/\varsigma_2$. The differential of χ_2 is

$$\dot{\chi}_2 = -\frac{\chi_2}{\varsigma_2} + B_2(x_1, \chi_2, \hat{\theta}_1, y_d, \dot{y}_d, \ddot{y}_d) \quad (26)$$

where B_2 is a smooth functions and have its maximum value denoted by M_2 (please refer to [31] for details).

Consider the following Lyapunov function candidate as

$$V_1 = \frac{1}{2}z_1^2 + \frac{1}{2}\chi_2^2 + \frac{\tilde{\theta}_1^2}{2r_1} \quad (27)$$

where r_1 is a positive parameter.

We have

$$\dot{V}_1 = z_1\varrho_1\Big(x_2 + f_{1,k}(x) - \dot{y}_d - \frac{\dot{\rho}}{\rho}\nu_1\Big) + \frac{\tilde{\theta}_1\dot{\hat{\theta}}_1}{r_1} + \chi_2(-\frac{\chi_2}{\varsigma_2} + B_2). \quad (28)$$

Consider $z_2 = x_2 - \chi_2 - \alpha_1$ and we can obtain

$$\dot{V}_1 = z_1\varrho_1\Big(z_2 + \chi_2 + \alpha_1 + f_{1,k}(x) - \dot{y}_d - \frac{\dot{\rho}}{\rho}\nu_1\Big) + \frac{\tilde{\theta}_1\dot{\hat{\theta}}_1}{r_1} + \chi_2(-\frac{\chi_2}{\varsigma_2} + B_2). \quad (29)$$

Using the Young's inequality, the following inequalities are obtained as

$$z_1\varrho_1 z_2 \le \frac{1}{2}z_1^2\varrho_1^2 + \frac{1}{2}z_2^2 \quad (30)$$

$$z_1\varrho_1 \chi_2 \le \frac{1}{2}z_1^2\varrho_1^2 + \frac{1}{2}\chi_2^2 \quad (31)$$

$$\chi_2 B_2 \le \frac{1}{2}\chi_2^2 + \frac{1}{2}B_2^2 \le \frac{1}{2}\chi_2^2 + \frac{1}{2}M_2^2. \quad (32)$$

Design the first common virtual control function α_1 as

$$\alpha_1 = -k_1\frac{z_1}{\varrho_1} - \frac{b_1\hat{\theta}_1 z_1}{2\varrho_1 a_{1,\min}^2}S_1^T(Z_1)S_1(Z_1) + \frac{\dot{\rho}}{\rho}\nu_1 \quad (33)$$

where k_1 is a positive parameter. $a_{1,\min} = \min\{a_{1,k} : k \in M\}$.

Define the unknown function $F_{1,k}(Z_1)$:

$$F_{1,k}(Z_1) = \varrho_1 f_{1,k} - \varrho_1\dot{y}_d + z_1\varrho_1^2. \quad (34)$$

A RBF NN $W_1^{*T}S_1$ is employed to approximate the unknown function $F_{1,k}$

$$F_{1,k}(Z_1) = W_{1,k}^{*\mathrm{T}}S_{1,k}(Z_1) + \epsilon_{1,k}(Z_1), |\epsilon_{1,k}(Z_1)| \le \epsilon_{1,k}^*. \quad (35)$$

where $Z_1 = [x_1, y_d, \dot{y}_d]^T \in \mathbb{R}^3$ and $\epsilon_{1,k}(Z_1)$ is the approximation error. Because the input of RBF neural network is the same in kth subsystem, $S_{1,k}(Z_1) : k \in M$ is the same and is rewritten as $S_1(Z_1)$.

The following inequality holds:

$$z_1F_{1,k} = z_1(W_{1,k}^{*\mathrm{T}}S_{1,k}(Z_1) + \epsilon_{1,k}(Z_1)) \le \frac{b_1}{2a_{1,k}^2}z_1^2\theta_1^* S_{1,k}^T S_{1,k} + \frac{1}{2}a_{1,k}^2 + \frac{1}{2}z_1^2 + \frac{1}{2}\epsilon_{1,k}^{*2} \quad (36)$$

where $\|W_{1,\max}^*\|^2 = b_1\theta_1^*$, $W_{1,\max}^* = \max\{W_{1,k} : k \in M\}$.

Define the adaptive law as follows:

$$\dot{\hat{\theta}}_1 = \frac{b_1 r_1}{2a_{1,\min}^2}z_1^2 S_1^T(Z_1)S_1(Z_1) - \sigma_1\hat{\theta}_1 \quad (37)$$

where $\sigma_1 > 0$ is a positive parameter. $a_{1,\min} = \min\{a_{1,k} : k \in M\}$.

Substituting (30), (33), (36) and (37) into (29) results in

$$\dot{V}_1 \le \frac{1}{2}z_2^2 - \chi_2(\frac{\chi_2}{\varsigma_2} - \chi_2) + \frac{1}{2}M_2^2 + \frac{b_1}{2a_{1,k}^2}z_1^2\theta_1^* S_{1,k}^T S_{1,k} + \frac{1}{2}a_{1,k}^2 + \frac{1}{2}z_1^2 + \frac{1}{2}\epsilon_{1,k}^{*2} - k_1z_1^2 - \frac{b_1\hat{\theta}_1 z_1^2}{2a_{1,k}^2}S_1^T(Z_1)S_1(Z_1) + \frac{\tilde{\theta}_1}{r_1}(\frac{b_1r_1z_1^2}{2a_{1,k}^2}S_1^T(Z_1)S_1(Z_1) - \sigma_1\hat{\theta}_1). \quad (38)$$

Considering $\tilde{\theta}_1 = \hat{\theta}_1 - \theta_1^*$, the following inequality holds

$$-\frac{\sigma_1}{r_1}\tilde{\theta}_1\hat{\theta}_1 \le -\frac{\sigma_1\tilde{\theta}_1^2}{2r_1} + \frac{\sigma_1\theta_1^{*2}}{2r_1} \quad (39)$$

and (38) is rewritten as

$$\dot{V}_1 \le -(k_1 - \frac{1}{2})z_1^2 - \chi_2^2(\frac{1}{\varsigma_2} - 1) - \frac{\sigma_1\tilde{\theta}_1^2}{2r_1} + \frac{1}{2}z_2^2 + \frac{1}{2}M_2^2 + \frac{1}{2}a_{1,\max}^2 + \frac{1}{2}\epsilon_{1,\max}^{*4} + \frac{\sigma_1\theta_1^{*2}}{2r_1} \quad (40)$$

where $a_{1,\max} = \max\{a_{1,k} : k \in M\}$ and $\epsilon_{1,\max}^* = \max\{\epsilon_{1,k}^* : k \in M\}$.

Step i ($2 \le i \le n-1$): Choose the following Lyapunov function candidate:

$$V_i = V_{i-1} + \frac{1}{2}z_i^2 + \frac{1}{2}\chi_i^2 + \frac{\tilde{\theta}_i^2}{2r_i} \quad (41)$$

Introduce a new variable π_{i+1} as the output of a first-order filter, and let the virtual control α_i pass through it with time constant ς_{i+1}

$$\varsigma_{i+1}\dot{\pi}_{i+1} + \pi_{i+1} = \alpha_i, \pi_{i+1}(0) = \alpha_i(0). \quad (42)$$

Since $\chi_{i+1} = \pi_{i+1} - \alpha_i$, one has $\dot{\pi}_{i+1} = -\chi_{i+1}/\varsigma_{i+1}$. The differential of χ_{i+1} is

$$\dot{\chi}_{i+1} = -\frac{\chi_{i+1}}{\varsigma_{i+1}} + B_{i+1}(x_1, \ldots, x_i, \chi_2, \ldots, \chi_{i+1}, \hat{\theta}_1, \ldots, \hat{\theta}_i, y_d, \dot{y}_d, \ddot{y}_d) \quad (43)$$

where B_{i+1} is a smooth function and has its maximum value denoted by M_{i+1}.

Define $z_i = x_i - \pi_i$ and the differential of z_i

$$\dot{z}_i = x_{i+1} + f_{i,k}(\bar{x}_i) - \dot{\pi}_i. \quad (44)$$

Considering $z_{i+1} = x_{i+1} - \chi_{i+1} - \alpha_i$, according to Itô differentiation rule, one has

$$\dot{V}_i = \dot{V}_{i-1} + z_i(z_{i+1} + \chi_{i+1} + \alpha_i + f_{i,k}(\bar{x}_i) - \dot{\pi}_i) + \frac{\tilde{\theta}_i\dot{\hat{\theta}}_i}{r_i} + \chi_{i+1}(-\frac{\chi_{i+1}}{\varsigma_{i+1}} + B_{i+1}). \quad (45)$$

Considering $\tilde{\theta}_i = \hat{\theta}_i - \theta_i^*$, the following inequality is obtained as

$$-\frac{\sigma_i}{r_i}\tilde{\theta}_i\hat{\theta}_i \le -\frac{\sigma_i\tilde{\theta}_i^2}{2r_i} + \frac{\sigma_i\theta_i^{*2}}{2r_i}. \quad (46)$$

Using the Young's inequality, we have:

$$z_i z_{i+1} \le \frac{1}{2}z_i^2 + \frac{z_{i+1}^2}{2} \quad (47)$$

$$z_i\chi_{i+1} \le \frac{1}{2}z_i^2 + \frac{1}{2}\chi_{i+1}^2 \quad (48)$$

$$\chi_{i+1}B_{i+1} \le \frac{1}{2}\chi_{i+1}^1 + \frac{1}{2}B_{i+1}^2 \le \frac{1}{2}\chi_{i+1}^2 + \frac{1}{2}M_{i+1}^2. \quad (49)$$

Define the unknown function $F_{i,k}(Z_i)$:

$$F_{i,k} = f_{i,k}(\bar{x}_i) - \dot{\pi}_i. \quad (50)$$

A RBF NN $W_{i,k}^{*T}S_{i,k}$ is employed to approximate the unknown function $F_{i,k}(Z_i)$

$$F_{i,k} = W_{i,k}^{*\mathrm{T}}S_{i,k}(Z_i) + \epsilon_{i,k}(Z_i), |\epsilon_{i,k}(Z_i)| \le \epsilon_{i,k}^* \quad (51)$$

where $Z_i = [x_1, \ldots, x_i, \dot{\pi}_i]^T \in \mathbb{R}^{i+1}$.

Similar to the derivation (36), we have

$$z_iF_{i,k} = z_i(W_{i,k}^{*\mathrm{T}}S_{i,k}(Z_i) + \epsilon_{i,k}(Z_i)) \le \frac{b_i}{2a_{i,k}^2}z_i^2\theta_i^*S_{i,k}^TS_{i,k} + \frac{1}{2}a_{i,k}^2 + \frac{1}{2}z_i^2 + \frac{1}{2}\epsilon_{i,k}^{*2} \quad (52)$$

where $\|W_{i,\max}^*\|^2 = b_i\theta_i^*$, and $W_{i,\max}^* = \max\{W_{i,k} : k\}$. During the ith step, note that the input of RBF neural network is the same in kth subsystem, and thus $S_{i,k}(Z_i) : k \in M$ is also the same and can be rewritten as $S_i(Z_i)$ for concision purposes.

Define the adaptive law $\hat{\theta}_i$ as

$$\dot{\hat{\theta}}_i = \frac{b_ir_iz_i^2}{2a_{i,\min}^2}S_i^T(Z_i)S_i(Z_i) - \sigma_i\hat{\theta}_i \quad (53)$$

where $\sigma_i > 0$ is a positive parameter. $a_{i,\min} = \min\{a_{i,k} : k \in M\}$.

The intermediate common virtual control function α_i is defined as

$$\alpha_i = -k_iz_i - \frac{b_i\hat{\theta}_iz_i}{2a_{i,\min}^2}S_i^T(Z_i)S_i(Z_i) \quad (54)$$

where k_i is a positive parameter.

Substituting (53) and (54) into (45), one has

$$\begin{aligned}\dot{V}_i \le{}& \dot{V}_{i-1} + z_i^2 + \frac{z_{i+1}^2}{2} - k_iz_i^2 - \frac{b_i\hat{\theta}_iz_i^2}{2a_{i,\min}^2}S_i^T(Z_i)S_i(Z_i) \\ &+\chi_{i+1}(-\frac{\chi_{i+1}}{\varsigma_{i+1}} + \chi_{i+1}) + \frac{1}{2}M_{i+1}^2 \\ &+\frac{b_i}{2a_{i,k}^2}z_i^2\theta_i^*S_i^TS_i + \frac{1}{2}a_{i,k}^2 + \frac{1}{2}z_i^2 + \frac{1}{2}\epsilon_{i,k}^{*2} \\ &+\frac{\tilde{\theta}_i}{r_i}(\frac{b_ir_iz_i^2}{2a_{i,\min}^2}S_i^T(Z_i)S_i(Z_i) - \sigma_i\hat{\theta}_i) \\ \le{}& -(k_1 - \frac{1}{2})z_1^2 - \sum_{j=2}^{i}(k_j - 2)z_j^2 + \frac{z_{i+1}^2}{2} \\ &-\sum_{j=1}^{i}\frac{\sigma_j\tilde{\theta}_j^2}{2r_j} - \sum_{j=1}^{i}\chi_{j+1}^2(\frac{1}{\varsigma_{j+1}} - 1) \\ &+\sum_{j=1}^{i}(\frac{1}{2}M_{j+1}^2 + \frac{1}{2}a_{j,\max}^2 + \frac{1}{2}\epsilon_{j,\max}^{*2} + \frac{\sigma_j\theta_j^{*2}}{2r_j})\end{aligned} \quad (55)$$

where $a_{i,\max} = \max\{a_{i,k} : k \in M\}$, $\epsilon_{i,\max}^* = \max\{\epsilon_{i,k}^* : k \in M\}$.

Step n: Consider $z_n = x_n - \pi_n$ and choose the Lyapunov function V_n as

$$V_n = V_{n-1} + \frac{1}{2}z_n^2 + \frac{1}{2r_n}\tilde{\theta}_n^2. \quad (56)$$

According to Itô differentiation rule, one has

$$\dot{V}_n = \dot{V}_{n-1} + z_n(u + f_{n,k} - \dot{\pi}_n) + \frac{\tilde{\theta}_n\dot{\hat{\theta}}_n}{r_n}. \quad (57)$$

Define the adaptive law

$$\dot{\hat{\theta}}_n = \frac{b_nr_n}{2a_{n,\min}^2}z_n^2S_n^T(Z_n)S_n(Z_n) - \sigma_n\hat{\theta}_n \quad (58)$$

where $\sigma_n > 0$ is a positive parameter. $a_{n,\min} = \min\{a_{n,k} : k \in M\}$.

Consider $\tilde{\theta}_n = \hat{\theta}_n - \theta_n^*$, and the following inequality

$$-\frac{\sigma_n}{r_n}\tilde{\theta}_n\hat{\theta}_n \le -\frac{\sigma_n\tilde{\theta}_n^2}{2r_n} + \frac{\sigma_n\theta_n^{*2}}{2r_n} \quad (59)$$

(57) is rewritten as:

$$\dot{V}_n \le \dot{V}_{n-1} + z_n(c\upsilon(t) + d(\upsilon)) + z_nF_{n,k} + \frac{\tilde{\theta}_n}{r_n}(\frac{b_nr_nz_n^2}{2a_{n,\min}^2}S_n^T(Z_n)S_n(Z_n) - \sigma_n\hat{\theta}_n) \quad (60)$$

where the unknown nonlinear function $F_n(Z_n)$ is defined as:

$$F_{n,k} = f_{n,k} - \dot{\pi}_n. \quad (61)$$

A RBF NN $W_{n,k}^{*T}S_{n,k}$ is employed to approximate the unknown function $F_{n,k}$

$$F_{n,k} = W_{n,k}^{*\mathrm{T}}S_{n,k}(Z_n) + \epsilon_{n,k}(Z_n), |\epsilon_{n,k}(Z_n)| \le \epsilon_{n,k}^* \quad (62)$$

where $Z_n = [x_1, \ldots, x_n, \dot{\pi}_n]^T \in \mathbb{R}^{n+1}$, and $\epsilon_{n,k}(Z_n)$ is the approximation error.

Similar to the deviation in (36) and (52), the following inequality holds

$$\begin{aligned} z_n F_{n,k} &= z_n(W_{n,k}^{*\mathrm{T}} S_{n,k}(Z_n) + \epsilon_{n,k}(Z_n)) \\ &\le \frac{b_n}{2a_{n,k}^2} z_n^2 \theta_n^* S_{n,k}^T S_{n,k} + \frac{1}{2}a_{n,k}^2 + \frac{1}{2}z_n^2 + \frac{1}{2}\epsilon_{n,k}^{*2} \end{aligned} \quad (63)$$

where $\|W_{n,\max}^*\|^2 = b_n \theta_n^*$, with $W_{n,\max}^* = \max\{W_{n,k}^* : k \in M\}$.

$$z_n d(v) \le \frac{1}{2}z_n^2 + \frac{1}{2}d^{*2}. \quad (64)$$

The common control input u is defined as

$$v = \frac{1}{g_n}\big(- k_n z_n - \frac{b_n \hat{\theta}_n z_n}{2a_{n,\min}^2} S_n^T(Z_n) S_n(Z_n)\big) \quad (65)$$

where $g_n = \underline{c}$ is a positive design parameter, and k_n is a positive parameter.

Substituting (63) and (65) into (60) yields

$$\begin{aligned} \dot{V}_n &\le \dot{V}_{n-1} - (k_n - 1)z_n^2 - \frac{\sigma_n \tilde{\theta}_n^2}{2r_n} + \frac{\sigma_n \theta_n^{*2}}{2r_n} \\ &\quad + \frac{1}{2}a_n^2 + \frac{1}{2}\epsilon_n^{*2} + \frac{1}{2}d^{*2} \\ &\le -(k_1 - \frac{1}{2})z_1^2 - \sum_{i=2}^{n-1}(k_i - 2)z_i^2 - (k_n - \frac{3}{2})z_n^2 \\ &\quad - \sum_{i=1}^{n} \frac{\sigma_i \tilde{\theta}_i^2}{2r_i} + \sum_{i=1}^{n}\big(\frac{1}{2}a_{i,\max}^2 + \frac{1}{2}\epsilon_{i,\max}^{*2} + \frac{\sigma_i \theta_i^{*2}}{2r_i}\big) \\ &\quad + \frac{1}{2}d^{*2} + \sum_{j=1}^{n-1}\big(\frac{1}{2}M_{j+1}^2 - \chi_{j+1}^2(\frac{1}{\varsigma_{j+1}} - 1)\big) \end{aligned} \quad (66)$$

Given $l_i > 0$ $(i = 1, 2, \ldots, n)$ and $\xi_i > 0$ $(i = 2, \ldots, n)$, such that

$$\begin{aligned} l_1 &= k_1 - \frac{1}{2} \\ l_i &= k_i - 2, \quad i = 2, \ldots, n-1 \\ l_n &= k_n - \frac{3}{2} \\ \xi_i &= \frac{1}{\varsigma_i} - 1, \quad i = 2, \ldots, n. \end{aligned} \quad (67)$$

Let $a_0 = \min\{2l_1,\ 2l_i,\ 2\xi_i,\ \sigma_1,\ \sigma_i\}$, $n = 2, \ldots, n$, and $b_0 = \sum_{i=1}^{n}(1/2a_{i,\max}^2 + 1/2\epsilon_{i,\max}^{*2} + \sigma_i\theta_i^{*2}/2r_i) + \sum_{j=1}^{n-1} 1/2M_{j+1}^2 + 1/2d^{*2}$, such that (66) is rewritten as:

$$LV \le -a_0 V + b_0, \quad t \ge 0. \quad (68)$$

Theorem 1: Considering the closed-loop system consisting of plant (1), the common controller (65) together with the common virtual control signal (33), (54) and adaptive laws (37), (53) and (58). There exist suitable parameters l_i, ξ_i, σ_i such that all signals of the closed-loop system remain bounded under arbitrary switchings, and the error boundary can be arbitrarily reduced by the designed parameters (l_i, ξ_i, σ_i), but also achieves the prescribed performances.

Proof: Based on the comparison principle, (68) is expressed as

$$\dot{V}(t) \le -a_0 V(t) + b_0. \quad (69)$$

It satisfies

$$0 \le V(t) \le \big(V(0) - \frac{b_0}{a_0}\big)e^{-a_0 t} + \frac{b_0}{a_0} \quad (70)$$

and

$$V(t) \le V(0) + \frac{b_0}{a_0}, \forall t > 0 \quad (71)$$

where $V(0) = \sum_{i=1}^{n} 1/2z_i^2(0) + \sum_{i=2}^{n} 1/2\chi_i^2(0) + \sum_{i=1}^{n} 1/2r_i\tilde{\theta}_i^2(0)$. Thus, based on the inequality (71) and the definition of V, all the signals in the closed-loop system are bounded under arbitrary switchings.

Furthermore, from (70), one has

$$V(t) \le \frac{b_0}{a_0}, \quad t \to \infty \quad (72)$$

with (71) and (72), we have

$$\sum_{i=1}^{n} z_i^2 \le 2V(t) \le \frac{2b_0}{a_0}. \quad (73)$$

Therefore, z_i can eventually converge to the compact set Ω. Ω is defined as

$$\Omega := \{z_i \Big| \|z_i\| \le \sqrt{\frac{2b_0}{a_0}}\}. \quad (74)$$

■

IV. Simulation Study

Consider the following second-order nonlinear switched system:

$$\begin{cases} \dot{x}_1 = x_2 + f_{1,\sigma(t)}(x_1), \\ \dot{x}_2 = u(v) + f_{2,\sigma(t)}(x_1, x_2) \\ y = x_1 \end{cases} \quad (75)$$

where $\sigma(t) : [0, \infty] \to \{1, 2\}$. $f_{1,1} = x_1^2$, $f_{2,1} = x_1^2\cos^2(x_2)$. $f_{1,2} = 0.8x_1\sin(x_1)$, $f_{2,2} = \cos(x_1)x_2^2$.

The control objective is to design a common adaptive neural control scheme such that all signals in closed-loop system remain bounded under arbitrary switchings, and for guaranteed prescribed performance, the system output y follows the ideal reference trajectory $y_d = 0.5(\sin(t) + \sin(0.5t))$ with no need of the initial error under arbitrary switchings.

The initial conditions of the closed-loop system are shown as: The saturation parameters $u^- = 32$, $u^+ = 28$. $[x_1(0), x_2(0)]^T = [0.3, 0.1]^T$, $[\hat{\theta}_1(0), \hat{\theta}_2(0)]^T = [0, 0]^T$, $z_1 = x_1(0) - y_d(0) = 0.3 - 0 > 0$. To verify the effectiveness of the designed controller with no need of the initial error, we make a comparative study, in which initial conditions $[x_1(0), x_2(0)]^T = [-0.25, 0.2]^T$ and $z_1 = x_1(0) - y_d(0) = -0.25 - 0 < 0$.

The performance function is given as

$$\rho(t) = \coth(0.6t + 0.4) - 1 + \rho_\infty \quad (76)$$

where $\bar{\delta} = \underline{\delta} = 0.2$, $\rho_\infty = 0.1$.

In the simulation study, the design parameters are taken as: $k_1 = 17$, $k_2 = 18$, $r_1 = 1$, $r_2 = 1.2$, $a_{1,\min} = 2$,

$a_{2,\min} = 2$, $\sigma_1 = 0.1$, $\sigma_2 = 0.3$. $\varsigma_2 = 0.01$. Based on the control design, we construct the Gaussian RBF network $\hat{W}_1^T S_1(Z_1)$ using 5^3nodes with the centers evenly spaced on $[-2, 2]\times[-2, 2]\times[-2, 2]$ and the width being 0.95; The neural network $\hat{W}_2^T S_2(Z_2)$ contains 3^3 nodes with the centers evenly spaced on $[-1.5, 1.5]\times[-1.5, 1.5]\times[-1.5, 1.5]$ and the width being 1.49.

Figs. 2−9 show the simulation results. Fig. 2 provides the tracking performance of the closed-loop system under arbitrary switchings and Fig. 3 shows the curves of the tracking errors with prescribed performance control (PPC) and without prescribed performance control. When the initial error $\nu_1 < 0$,

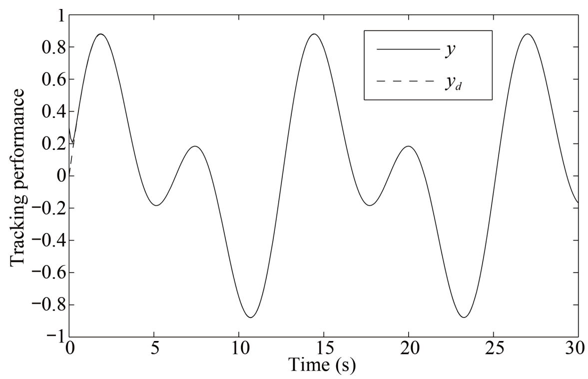

Fig. 2. System output y and reference signal y_d with the positive initial error $\nu_1(0) > 0$.

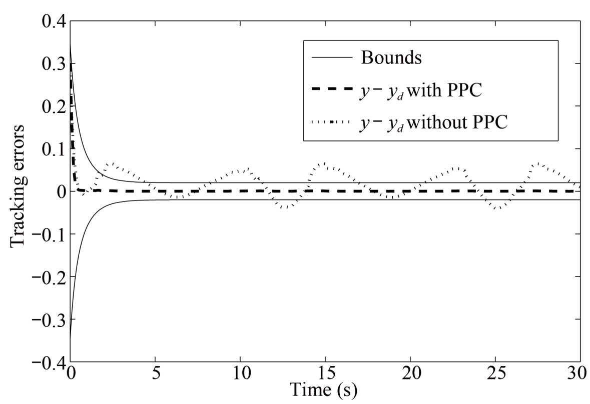

Fig. 3. Tracking error z_1 and prescribed performance bounds with the positive initial error $\nu_1(0) > 0$.

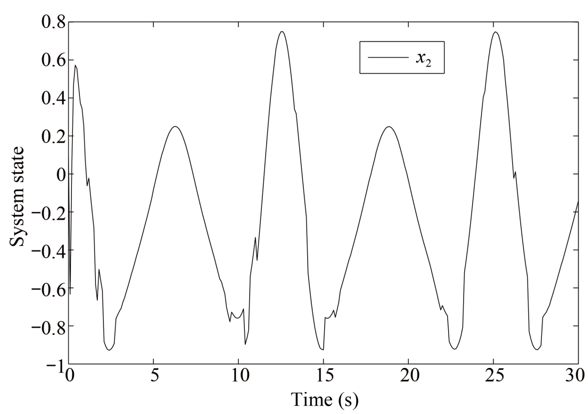

Fig. 4. System state x_2.

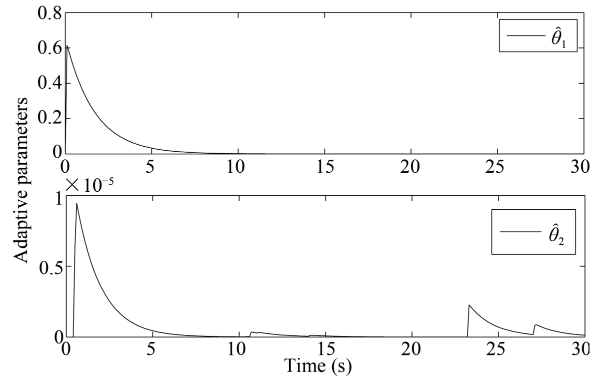

Fig. 5. Adaptive parameters $\hat{\theta}_1$ and $\hat{\theta}_2$.

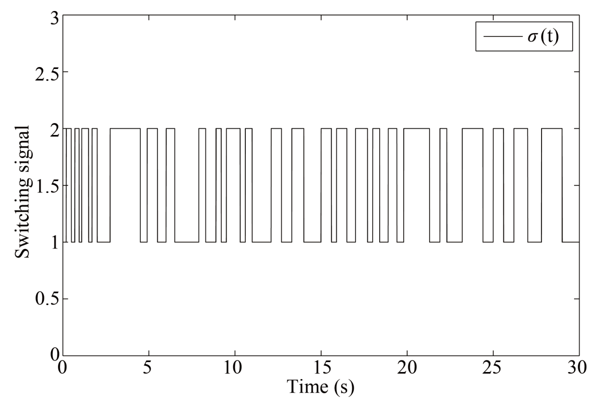

Fig. 6. Switch signal $\sigma(t)$.

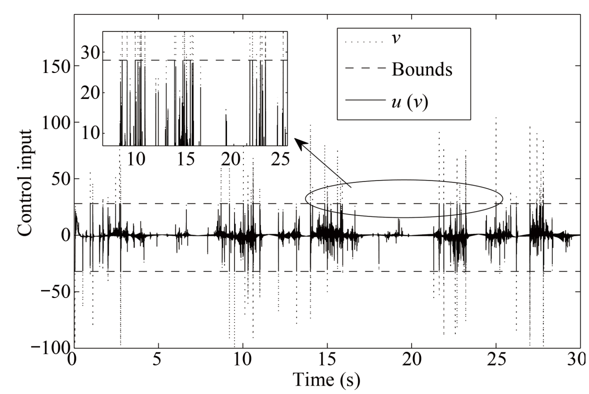

Fig. 7. The control signal u.

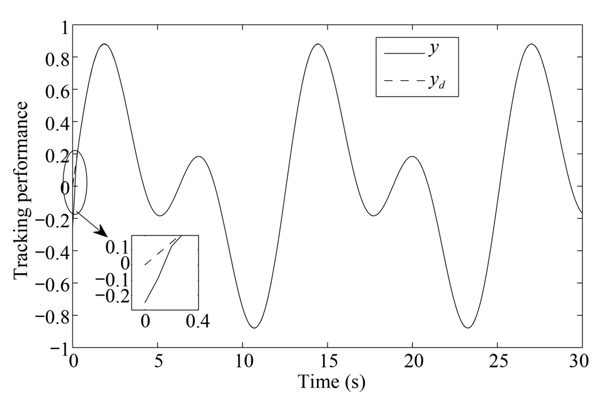

Fig. 8. System output y and reference signal y_d with the negative initial error $\nu_1(0) < 0$.

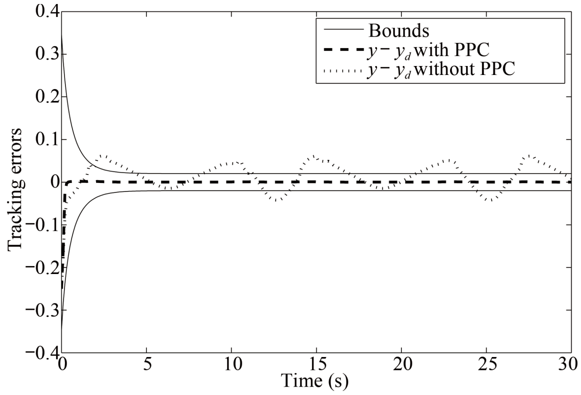

Fig. 9. Tracking error z_1 and prescribed performance bounds with the negative initial error $\nu_1(0) < 0$.

Figs. 8 and 9 show the tracking performance and tracking errors with the same design parameters, respectively. It is obvious that the initial error ν_1 does not need to be known in advance. Figs. 4 and 5 illustrate the time trajectory of the state variable x_2, the adaptive laws $\hat{\theta}_1$ and $\hat{\theta}_2$, which are shown that these signals are bounded. Fig. 6 shows the evolution of switching signal. The output u and input v of the saturation are shown in Fig. 7.

V. CONCLUSION

This paper investigates the problem of adaptive neural PPC for a class of nonlinear systems with the smooth differentiable saturation nonlinearity under arbitrary switchings. By using the DSC method, the problem of “explosion of complexity”can be eliminated. RBF neural networks are used to model the unknown nonlinear functions, and a performance function is designed with no requirement for the exact initial error. In this paper, the norm of the NN weight vector is estimated to reduce the number of the learning parameters. It has been shown that the proposed common controller can guarantee that all signals in the closed-loop systems are semi-globally uniformly bounded under arbitrary switchings and tracking error converges to a predefined small neighborhood of zero. The future researches include its extension to the interconnected MIMO case of such stochastic nonlinear switched systems with unmeasured states and unknown time delays.

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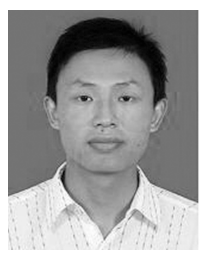

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