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Robust Adaptive Dynamic Surface Control of Uncertain Nonlinear Systems

Ming-Zhe Hou and Guang-Ren Duan

Abstract: This paper studies the robust adaptive dynamic surface control of a class of nonlinear systems with unmatched uncertainties. The unmatched uncertainties consist of not only the linearly parameterized terms but also the nonlinearly parameterized terms. The bound of each nonlinearly parameterized uncertainty term is supposed to be expressed by a known nonnegative function multiplied by a constant called bound parameter. According to whether the bound parameters are known or not, two different kinds of robust adaptive dynamic surface control algorithms are proposed. It is proved that in each case all the states of the closed-loop system are kept uniformly ultimately bounded, and the output is driven to track a feasible desired output trajectory with an arbitrarily small error. An example is also employed to indicate the effect of the proposed methods.

Keywords: Dynamic surface control, nonlinear system, robust adaptive control, unmatched uncertainty.

1. INTRODUCTION

Feedback control of uncertain nonlinear systems by robust or adaptive control techniques is a problem of paramount importance in the field of control and has received considerable attention, since nonlinearities and uncertainties exist inherently in many real systems [1,2]. A powerful tool for solving such a problem is the backstepping technique. This control design methodology was first proposed for parametric strict-feedback systems with linearly parameterized uncertainties [3,4], and then extended to deal with nonlinearly parameterized uncertainties [5,6]. After nearly twenty years of development, it has become one of the most popular design methods for a large class of nonlinear systems with uncertainties, especially with unmatched uncertainties [7,8].

However, the backstepping technique suffers from the problem of explosion of complexity arising from the repeated differentiations of the virtual controls. As a result, the complexity of controller grows drastically as the order of the system increases. In addition, it requires certain system functions to be C^n. To avoid these problems, the dynamic surface control (DSC) technique was proposed in [9] and [10] for nonlinear systems with unmatched uncertainties by introducing a first-order filtering of the synthetic input at each step of the traditional backstepping approach. So far, this control method has been implemented successfully in many practical applications such as friction compensation [11], anti-lock brake system [12], formation control [13], magnetic levitation system [14], underactuated mechanical system [15], and so on. More details about how to synthesize the design parameters in DSC can be found in [16]. In [17] the DSC method was applied to a class of nonlinear systems with linearly parameterized uncertainties. However, if this linear parameterization assumption is not satisfied, the adaptive dynamic surface control design will become more difficulty and challenging. For this problem, some results have been obtained combining with fuzzy control [18] or neural network control [19]. For more developments about DSC incorporating with intelligent control, the interested readers can see [20] and the references therein.

In the current paper, we further consider the output tracking problem of nonlinear systems with unmatched uncertainties, which include both of the linearly parameterized parts and the nonlinearly parameterized parts. Specifically, we consider a class of single-input-single-output uncertain nonlinear systems of the form

$$\begin{cases} \dot{x}_i = x_{i+1} + \theta_i f_i(\vec{x}_i) + \delta_i(x), i = 1, 2, \cdots, n-1 \\ \dot{x}_n = u + \theta_n f_n(x) + \delta_n(x) \\ y = x_1, \end{cases} \tag{1}$$

where $x = [x_1 \quad x_2 \quad \cdots \quad x_n]^{\mathrm{T}} \in R^n$, $u \in R$ and $y \in R$ are the state, the input and the output of the system, respectively; for $i = 1, 2, \cdots, n$, θ_i are all unknown constants, $\vec{x}_i = [x_1 \quad x_2 \quad \cdots \quad x_i]^{\mathrm{T}}$, $f_i(\vec{x}_i) : R^i \to R$ are C^1 functions, $\delta_i(x) : R^n \to R$ are continuous functions, the terms $\theta_i f_i(\vec{x}_i)$ represent the linearly parameterized uncertainties, and the terms $\delta_i(x)$ represent the nonlinear parameterized uncertainties and are supposed to satisfy the following assumption.

Assumption 1: There exist a set of possibly unknown constants $\rho_i \geq 0$, $i = 1, 2, \cdots, n$, which are called as

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bound parameters, and a set of known nonnegative C^1 functions $\varphi_i(\vec{x}_i)$ such that

$$\left|\delta_i(x)\right| \le \rho_i \varphi_i(\vec{x}_i). \tag{2}$$

The main objective of this paper is to develop the robust adaptive dynamic surface control (RADSC) methods for system (1) under Assumption 1 to make the output track a desired output trajectory x_{1d} and keep the other states bounded. Here, the feasible desired output trajectories are supposed to satisfy the assumption below.

Assumption 2: The desired output trajectory x_{1d} is a sufficiently smooth function and available, and satisfies that

$$[x_{1d}\ \dot{x}_{1d}\ \ddot{x}_{1d}]^{\mathrm{T}} \in B_0 = \{[z_1\ z_2\ z_3]^{\mathrm{T}} : z_1^2 + z_2^2 + z_3^2 \le r_0\},$$

where r_0 is a known constant.

In this paper, two different kinds of robust adaptive dynamic surface controllers are proposed according to whether the bound parameters ρ_i are known or not. It is proved that by using the proposed robust adaptive controllers with proper design parameters, the output of the closed-loop system can track the desired output trajectory with arbitrary small tracking error, and the other states are kept bounded simultaneously. As a result, a systematic design procedure is established to handle the output regulation problem of a large class of nonlinear systems with unmatched uncertainties. Throughout this paper, $|\cdot|$ represents the absolute value of a real number, $\|\cdot\|$ represents the Euclidean norm of a vector or the spectral norm of a matrix. For convenience, we denote a vector $[v_1\quad v_2\quad \cdots\quad v_i]^{\mathrm{T}}$ by $\vec{v}_i$.

2. ROBUST ADAPTIVE DYNAMIC SURFACE CONTROL DESIGN

This section first presents the robust adaptive dynamic surface control for system (1) under Assumption 1 when the bound parameters are known, and then gives the result when the bound parameters are unknown.

2.1. Control design for known bound parameters

2.1.1 Control algorithm

When the bound parameters $\rho_i,\ i = 1,2,\cdots,n$ are known, the RADSC algorithm for system (1) is described as follows.

Algorithm 1:

Step $i\,(1 \le i \le n-1)$**:**

$$\begin{aligned}
&S_i = x_i - x_{id}\\
&\overline{x}_{i+1} = \dot{x}_{id} - K_i S_i - \hat{\theta}_i f_i(\vec{x}_i) - \rho_i^2 \varphi_i^2(\vec{x}_i) S_i\\
&\tau_{i+1}\dot{x}_{i+1d} + x_{i+1d} = \overline{x}_{i+1},\ x_{i+1d}(0) = \overline{x}_{i+1}(0)
\end{aligned}$$

Step n**:**

$$\begin{aligned}
&S_n = x_n - x_{nd}\\
&u = \dot{x}_{nd} - K_n S_n - \hat{\theta}_n f_n(x) - \rho_n^2 \varphi_n^2(x) S_n,
\end{aligned}$$

where the design parameters $K_1,\cdots,K_n$ are called as surface gains; $\tau_2,\cdots,\tau_n$ are called as filter time constants; and $\hat{\theta}_i$ is the estimate of the unknown parameter θ_i and satisfies the following update law

$$\dot{\hat{\theta}}_i = \lambda_i\left[S_i f_i(\vec{x}_i) + \pi_i(\theta_{i0} - \hat{\theta}_i)\right],\ i = 1,2,\cdots,n,$$

where λ_i, π_i and θ_{i0} are all design parameters, and θ_{i0} is the predictive value of the unknown parameter θ_i.

2.1.2 Stability analysis

Define the boundary layer errors as

$$y_i = x_{id} - \overline{x}_i,\ i = 2,\cdots,n,$$

and the estimate errors as

$$\tilde{\theta}_i = \theta_i - \hat{\theta}_i,\ i = 1,2,\cdots,n.$$

Then the closed-loop dynamics can be expressed in terms of the surfaces (S_i), the boundary layer errors (y_i) and the estimate errors ($\tilde{\theta}_i$). The dynamics of the surfaces are expressed as, for $i = 1,2,\cdots,n-1$,

$$\begin{aligned}
\dot{S}_i &= \dot{x}_i - \dot{x}_{id}\\
&= x_{i+1} + \theta_i f_i(\vec{x}_i) + \delta_i(x) - \dot{x}_{id}\\
&= S_{i+1} + y_{i+1} + \overline{x}_{i+1} + \theta_i f_n(\vec{x}_i) + \delta_i(x) - \dot{x}_{id}\\
&= S_{i+1} + y_{i+1} - K_i S_i + \tilde{\theta}_i f_i(\vec{x}_i) - \rho_i^2 \varphi_i^2(\vec{x}_i) S_i + \delta_i(x),
\end{aligned}$$

and

$$\begin{aligned}
\dot{S}_n &= \dot{x}_n - \dot{x}_{nd}\\
&= u + \theta_n f_n(x) + \delta_n(x) - \dot{x}_{nd}\\
&= -K_n S_n + \tilde{\theta}_n f_n(x) - \rho_n^2 \varphi_n^2(x) S_n + \delta_n(x).
\end{aligned}$$

The dynamics of the boundary layer errors are expressed as, for $i = 2,\cdots,n$,

$$\dot{y}_i = -\frac{1}{\tau_i} y_i - \dot{\overline{x}}_i.$$

The dynamics of the estimate errors are expressed as, for $i = 1,\cdots,n$,

$$\dot{\tilde{\theta}}_i = -\dot{\hat{\theta}}_i = -\lambda_i\left[S_i f_i(\vec{x}_i) + \pi_i\left(\theta_{i0} - \hat{\theta}_i\right)\right].$$

Let

$$V = \sum_{i=1}^{n} V_{is} + \sum_{i=2}^{n} V_{iy} + \sum_{i=1}^{n} V_{i\theta},$$

where

$$V_{is} = \frac{1}{2} S_i^2,\qquad V_{iy} = \frac{1}{2} y_i^2,\qquad V_{i\theta} = \frac{1}{2\lambda_i} \tilde{\theta}_i^2,$$

then one has

$$\begin{aligned}
\dot V_{is} &= S_i \dot S_i \\
&= S_i S_{i+1} + S_i y_{i+1} - K_i S_i^2 + \tilde\theta_i S_i f_i(\vec x_i) \\
&\quad -\rho_i^2 \varphi_i^2(\vec x_i) S_i^2 + S_i \delta_i(x) \\
&\le (1-K_i) S_i^2 + \frac{1}{2} S_{i+1}^2 + \frac{1}{2} y_{i+1}^2 + \tilde\theta_i S_i f_i(\vec x_i) \\
&\quad -\rho_i^2 \varphi_i^2(\vec x_i) S_i^2 + |S_i| \rho_i \varphi_i(\vec x_i) \\
&\le (1-K_i) S_i^2 + \frac{1}{2} S_{i+1}^2 + \frac{1}{2} y_{i+1}^2 + \tilde\theta_i S_i f_i(\vec x_i) + \frac{1}{4}, \\
&\quad i = 1,\cdots,n-1, \\
\dot V_{ns} &= S_n \dot S_n \\
&= -K_n S_n^2 + \tilde\theta_n S_n f_n(x) - \rho_n^2 \varphi_n^2(x) S_n^2 + S_n \delta_n(x) \\
&\le -K_n S_n^2 + \tilde\theta_n S_n f_n(x) - \rho_n^2 \varphi_n^2(x) S_n^2 + |S_n| \rho_n \varphi_n(x) \\
&\le -K_n S_n^2 + \tilde\theta_n S_n f_n(x) + \frac{1}{4}, \\
\dot V_{i\theta} &= \frac{1}{\lambda_i} \tilde\theta_i \dot{\tilde\theta}_i \\
&= -\tilde\theta_i \left[S_i f_i(\vec x_i) + \pi_i(\theta_{i0} - \hat\theta_i) \right] \\
&= -\tilde\theta_i \left[S_i f_i(\vec x_i) + \pi_i(\theta_{i0} - \theta_i + \theta_i - \hat\theta_i) \right] \\
&= -\tilde\theta_i S_i f_i(\vec x_i) - \frac{\pi_i}{2} \tilde\theta_i^2 + \frac{\pi_i}{2} (\theta_{i0} - \theta_i)^2, \ i = 1,\cdots,n,
\end{aligned}$$

and

$$\dot V_{iy} = y_i \dot y_i = -\frac{1}{\tau_i} y_i^2 - y_i \dot{\bar x}_i, \ i = 2,\cdots,n.$$

Simple computations show

$$\begin{aligned}
x_1 &= S_1 + x_{1d} \\
&= \psi_1(S_1, x_{1d}), \\
x_2 &= S_2 + y_2 + \dot x_{1d} - K_1 S_1 - \hat\theta_1 f_1(x_1) - \rho_1^2 \varphi_1^2(x_1) S_1 \\
&= \psi_2(S_1, S_2, y_2, \tilde\theta_1, x_{1d}, \dot x_{1d}, K_1), \\
x_i &= S_i + y_i + \dot x_{i-1d} - K_{i-1} S_{i-1} - \hat\theta_{i-1} f_{i-1}(\vec x_{i-1}) \\
&\quad -\rho_{i-1}^2 \varphi_{i-1}^2(\vec x_{i-1}) S_{i-1} \\
&= \psi_i(\vec S_i, \vec y_i, \vec{\tilde\theta}_{i-1}, x_{1d}, \dot x_{1d}, \vec K_{i-1}, \vec\tau_{i-1}), \ i = 3,\cdots,n,
\end{aligned}$$

where ψ_i, $i = 1,\cdots,n,$ are continuous functions,

$$\begin{aligned}
\vec y_i &= [y_2 \ \cdots \ y_i]^{\mathrm T}, \\
\vec\tau_{i-1} &= [\tau_2 \ \cdots \ \tau_{i-1}]^{\mathrm T}.
\end{aligned}$$

In addition,

$$\begin{aligned}
|\dot S_1| &= \left| S_2 + y_2 - K_1 S_1 + \tilde\theta_1 f_1(x_1) - \rho_1^2 \varphi_1^2(x_1) S_1 + \delta_1(x) \right| \\
&\le \phi_1(S_1, S_2, y_2, \tilde\theta_1, x_{1d}, K_1), \\
|\dot S_2| &= \left| S_3 + y_3 - K_2 S_2 + \tilde\theta_2 f_2(\vec x_2) - \rho_2^2 \varphi_2^2(\vec x_2) S_2 + \delta_2(x) \right| \\
&\le \phi_2(\vec S_3, \vec y_3, \vec{\tilde\theta}_2, x_{1d}, \dot x_{1d}, \vec K_2), \\
|\dot S_i| &= \left| S_{i+1} + y_{i+1} - K_i S_i + \tilde\theta_i f_i(\vec x_i) - \rho_i^2 \varphi_i^2(\vec x_i) S_i + \delta_i(x) \right| \\
&\le \phi_i(\vec S_{i+1}, \vec y_{i+1}, \vec{\tilde\theta}_i, x_{1d}, \dot x_{1d}, \vec K_i, \vec\tau_{i-1}), \ i = 3,\cdots,n-1, \\
|\dot S_n| &= \left| -K_n S_n + \tilde\theta_n f_n(x) - \rho_n^2 \varphi_n^2(x) S_n + \delta_n(x) \right| \\
&\le \phi_n(\vec S_n, \vec y_n, \vec{\tilde\theta}_n, x_{1d}, \dot x_{1d}, \vec K_n, \vec\tau_{n-1}),
\end{aligned}$$

where $\phi_i, i = 1,\cdots,n,$ are continuous functions. Further, considering that $f_i(\vec x_i)$ and $\varphi_i(\vec x_i)$ are all C^1 functions, and

$$\begin{aligned}
\dot x_1 &= \dot S_1 + \dot x_{1d}, \\
\dot x_i &= \dot S_i + \dot y_i + \dot{\bar x}_i,
\end{aligned}$$

then from

$$\begin{aligned}
\dot{\bar x}_2 &= \ddot x_{1d} - K_1 \dot S_1 - \dot{\hat\theta}_1 f_1(x_1) - \hat\theta_1 \frac{\partial f_1}{\partial x_1} \dot x_1 - \rho_1^2 \varphi_1^2(x_1) \dot S_1 \\
&\quad -2\rho_1^2 \varphi_1(x_1) S_1 \frac{\partial \varphi_1}{\partial x_1} \dot x_1
\end{aligned}$$

one can easily obtain that

$$\left| \dot{\bar x}_2 \right| \le \eta_2(S_1, S_2, y_2, x_{1d}, \dot x_{1d}, \ddot x_{1d}, \tilde\theta_1, K_1, \lambda_1, \pi_1, \theta_{10}),$$

and by induction, it is easy from

$$\begin{aligned}
\dot{\bar x}_i &= \ddot x_{i-1d} - K_{i-1} \dot S_{i-1} - \dot{\hat\theta}_{i-1} f_{i-1}(\vec x_{i-1}) - \hat\theta_{i-1} \sum_{j=1}^{i-1} \frac{\partial f_{i-1}}{\partial x_j} \dot x_j \\
&\quad -\rho_{i-1}^2 \varphi_{i-1}^2(\vec x_{i-1}) \dot S_{i-1} - 2\rho_{i-1}^2 S_{i-1} \varphi_{i-1}(\vec x_{i-1}) \sum_{j=1}^{i-1} \frac{\partial \varphi_{i-1}}{\partial x_j} \dot x_j \\
&= \frac{y_{i-1}}{\tau_{i-1}^2} + \frac{\dot{\bar x}_{i-1}}{\tau_{i-1}} - K_{i-1} \dot S_{i-1} - \dot{\hat\theta}_{i-1} f_{i-1}(\vec x_{i-1}) - \hat\theta_{i-1} \sum_{j=1}^{i-1} \frac{\partial f_{i-1}}{\partial x_j} \dot x_j \\
&\quad -\rho_{i-1}^2 \varphi_{i-1}^2(\vec x_{i-1}) \dot S_{i-1} - 2\rho_{i-1}^2 S_{i-1} \varphi_{i-1}(\vec x_{i-1}) \sum_{j=1}^{i-1} \frac{\partial \varphi_{i-1}}{\partial x_j} \dot x_j,
\end{aligned}$$

to conclude that for $i = 3,\cdots,n,$

$$\left| \dot{\bar x}_i \right| \le \eta_i(\vec S_i, \vec y_i, x_{1d}, \dot x_{1d}, \ddot x_{1d}, \vec{\tilde\theta}_{i-1}, \vec K_{i-1}, \vec\lambda_{i-1}, \vec\pi_{i-1}, \vec\tau_{i-1}, \vec\theta_{i-10}),$$

where η_i, $i = 2,\cdots,n$ are a set of nonnegative continuous functions.

Given any r, the set

$$B_r = \left\{ (S_1,\cdots,S_n, y_2,\cdots,y_n, \tilde\theta_1,\cdots,\tilde\theta_n)^{\mathrm T} : V \le r \right\}$$

is a compact set. Clearly, B_0 is also a compact set, hence so is $B_r \times B_0$. Therefore, the continuous function η_i has maximum, called M_i on $B_r \times B_0$, where M_i depends on $\vec K_{i-1}$, $\vec\lambda_{i-1}$, $\vec\pi_{i-1}$, $\vec\theta_{i-10}$ and $\vec\tau_{i-1}$ (M_2 depends on K_1, λ_1, θ_{10} and π_1). Hence, one has

$$\begin{aligned}
\dot V_{iy} &\le -\frac{1}{\tau_i} y_i^2 + |y_i| M_i \\
&\le \left(M_i^2 - \frac{1}{\tau_i} \right) y_i^2 + \frac{1}{4}.
\end{aligned}$$

Therefore,

$$\begin{aligned}
\dot{V} &= \sum_{i=1}^{n}\dot{V}_{is} + \sum_{i=2}^{n}\dot{V}_{iy} + \sum_{i=1}^{n}\dot{V}_{i\theta} \\
&\le \sum_{i=1}^{n-1}\left[\left(1-K_i\right)S_i^2 + \frac{1}{2}S_{i+1}^2 + \frac{1}{2}y_{i+1}^2 + \tilde{\theta}_i S_i f_i\left(\vec{x}_i\right) + \frac{1}{4}\right] \\
&\quad -K_n S_n^2 + \tilde{\theta}_n S_n f_n\left(x\right) + \frac{1}{4} + \sum_{i=2}^{n}\left[\left(M_i^2 - \frac{1}{\tau_i}\right)y_i^2 + \frac{1}{4}\right] \\
&\quad +\sum_{i=1}^{n}\left[-\tilde{\theta}_i S_i f_i\left(\vec{x}_i\right) - \frac{\pi_i}{2}\tilde{\theta}_i^2 + \frac{\pi_i}{2}\left(\theta_{i0}-\theta_i\right)^2\right] \\
&\le \sum_{i=1}^{n}\left(\frac{3}{2}-K_i\right)S_i^2 + \sum_{i=2}^{n}\left(M_i^2 + \frac{1}{2} - \frac{1}{\tau_i}\right)y_i^2 - \sum_{i=1}^{n}\frac{\pi_i}{2}\tilde{\theta}_i^2 \\
&\quad +\sum_{i=1}^{n}\frac{\pi_i}{2}\left(\theta_{i0}-\theta_i\right)^2 + \frac{2n-1}{4},
\end{aligned}$$

where

$$\beta = \sum_{i=1}^{n}\tfrac{\pi_i}{2}\left(\theta_{i0}-\theta_i\right)^2 + \tfrac{2n-1}{4}.$$

Let

$$K_i = \frac{\alpha+3}{2}, \quad \frac{1}{\tau_i} = M_i^2 + \frac{\alpha+1}{2}, \quad \lambda_i = \frac{\alpha}{\pi_i},$$

where α is a positive scalar, then one has

$$\dot{V} \le -\alpha V + \beta. \tag{3}$$

If $V = r$ and $\alpha \ge \frac{\beta}{r}$, then $\dot{V} \le 0$. This implies that if $V(0) \le r$, then $V(t) \le r$ for all $t \ge 0$, that is, B_r is a invariant set. By comparison principle [2], it is easy from (3) to conclude that

$$0 \le V\left(t\right) \le \frac{\beta}{\alpha} + \left[V\left(0\right) - \frac{\beta}{\alpha}\right]e^{-\alpha t}.$$

Therefore, $S_1,\cdots,S_n$, $y_2,\cdots,y_n$ and $\tilde{\theta}_1,\cdots,\tilde{\theta}_n$ are all uniformly ultimately bounded. Furthermore, $x_1,\cdots,x_n$, $x_{2d},\cdots,x_{nd}$, $\bar{x}_2,\cdots,\bar{x}_n$ and $\hat{\theta}_1,\cdots,\hat{\theta}_n$ are all uniformly ultimately bounded. In addition, it is easy to see that for any given π_i and θ_{i0}, β is a unknown but bounded constant which is independent of α. So $\frac{\beta}{\alpha}$ can be made arbitrary small by choosing proper α. This implies that the tracking error S_1 can be made arbitrary small ultimately.

Based on the above analysis, we have the following theorem.

Theorem 1: Consider the uncertain nonlinear system (1) satisfying Assumption 1. If the bound parameters ρ_i, $i = 1,2,\cdots,n$ are known, then the robust adaptive dynamic surface control algorithm 1 with appropriate design parameters can keep all the states of the closed-loop system bounded and drive the actual output to track a feasible desired output trajectory with an arbitrary small tracking error.

2.2. Control design for unknown bound parameters

2.2.1 Control algorithm

In the RADSC algorithm 1, the bound parameters of the uncertainties $\rho_i, i = 1,2,\cdots,n$ must be known a priori. In practice, however, sometimes the bound parameters may not be easily obtained due to the complexity of the uncertainties. One way to overcome this difficulty is to estimate these bound parameters by simple adaptation laws and to design an adaptive controller using these updated bound parameters. Based on this idea, the modified RADSC algorithm is stated below.

Algorithm 2:

Step i $(1 \le i \le n-1)$**:**

$$\begin{aligned}
&S_i = x_i - x_{id} \\
&\bar{x}_{i+1} = \dot{x}_{id} - K_i S_i - \hat{\theta}_i f_i(\vec{x}_i) - \hat{\rho}_i \varphi_i^2(\vec{x}_i) S_i \\
&\tau_{i+1}\dot{x}_{i+1d} + x_{i+1d} = \bar{x}_{i+1},\ x_{i+1d}(0) = \bar{x}_{i+1}(0)
\end{aligned}$$

Step n**:**

$$\begin{aligned}
&S_n = x_n - x_{nd} \\
&u = \dot{x}_{nd} - K_n S_n - \hat{\theta}_n f_n(x) - \hat{\rho}_n \varphi_n^2(x) S_n,
\end{aligned}$$

where $K_1,\cdots,K_n$ and $\tau_2,\cdots,\tau_n$ are all design parameters; $\hat{\theta}_i$ and $\hat{\rho}_i$ are respectively the estimates of the unknown parameters θ_i and ρ_i, and satisfy the following update laws

$$\begin{aligned}
&\dot{\hat{\theta}}_i = \lambda_i\left[S_i f_i(\vec{x}_i) + \pi_i(\theta_{i0} - \hat{\theta}_i)\right],\ i = 1,2,\cdots,n, \\
&\dot{\hat{\rho}}_i = \mu_i\left[S_i^2\varphi_i^2(\vec{x}_i) + \sigma_i(\rho_{i0} - \hat{\rho}_i)\right],\ i = 1,2,\cdots,n,
\end{aligned}$$

where λ_i, π_i, θ_{i0}, ρ_{i0}, μ_i and σ_i are all design parameters, θ_{i0} and ρ_{i0} are respectively the predictive values of the unknown parameters θ_i and ρ_i.

2.2.2 Stability analysis

Similarly, define the boundary layer errors as

$$y_i = x_{id} - \bar{x}_i,\ i = 2,\cdots,n,$$

and the estimate errors as

$$\tilde{\theta}_i = \theta_i - \hat{\theta}_i,\ i = 1,2,\cdots,n,$$

and

$$\tilde{\rho}_i = \rho_i - \hat{\rho}_i,\ i = 1,2,\cdots,n.$$

Then the closed-loop dynamics can be expressed in terms of the surfaces (S_i), the boundary layer errors (y_i) and the estimate errors ($\tilde{\theta}_i$ and $\tilde{\rho}_i$). The dynamics of the surfaces are expressed as, for $i = 1,2,\cdots,n-1$,

$$\begin{aligned}\dot{S}_i &= \dot{x}_i - \dot{x}_{id}\\ &= x_{i+1} + \theta_i f_n(x_1,\cdots,x_i) + \delta_i(x) - \dot{x}_{id}\\ &= S_{i+1} + y_{i+1} + \overline{x}_{i+1} + \theta_i f_n(\vec{x}_i) + \delta_i(x) - \dot{x}_{id}\\ &= S_{i+1} + y_{i+1} - K_i S_i + \tilde{\theta}_i f_i(\vec{x}_i) - \hat{\rho}_i\varphi_i^2(\vec{x}_i) S_i + \delta_i(x),\end{aligned}$$

and

$$\begin{aligned}\dot{S}_n &= \dot{x}_n - \dot{x}_{nd}\\ &= u + \theta_n f_n(x_1,\cdots,x_i) + \delta_n(x) - \dot{x}_{nd}\\ &= -K_n S_n + \tilde{\theta}_n f_n(x) - \hat{\rho}_n\varphi_n^2(x) S_n + \delta_n(x).\end{aligned}$$

The dynamics of the boundary layer errors are expressed as, for $i = 2,\cdots,n,$

$$\dot{y}_i = -\frac{1}{\tau_i} y_i - \dot{\overline{x}}_i.$$

The dynamics of the estimate errors are expressed as, for $i = 1,\cdots,n,$

$$\dot{\tilde{\theta}}_i = -\dot{\hat{\theta}}_i = -\lambda_i\left[S_i f_i(\vec{x}_i) + \pi_i(\theta_{i0} - \hat{\theta}_i)\right],$$

and

$$\dot{\tilde{\rho}}_i = -\dot{\hat{\rho}}_i = -\mu_i\left[S_i^2\varphi_i^2(\vec{x}_i) + \sigma_i(\rho_{i0} - \hat{\rho}_i)\right].$$

Let

$$V = \sum_{i=1}^{n} V_{is} + \sum_{i=2}^{n} V_{iy} + \sum_{i=1}^{n} V_{i\theta} + \sum_{i=1}^{n} V_{i\rho},$$

where

$$V_{is} = \frac{1}{2}S_i^2,\quad V_{iy} = \frac{1}{2}y_i^2,\quad V_{i\theta} = \frac{1}{2\lambda_i}\tilde{\theta}_i^2,\quad V_{i\rho} = \frac{1}{2\mu_i}\tilde{\rho}_i^2.$$

Then by some computations, we have

$$\begin{aligned}\dot{V}_{is} &= S_i\dot{S}_i\\ &= S_i\big(S_{i+1} + y_{i+1} - K_i S_i + \tilde{\theta}_i f_i(\vec{x}_i)\\ &\qquad - \hat{\rho}_i\varphi_i^2(\vec{x}_i) S_i + \delta_i(x)\big)\\ &\le (1 - K_i) S_i^2 + \frac{1}{2}S_{i+1}^2 + \frac{1}{2}y_{i+1}^2 + \tilde{\theta}_i S_i f_i(\vec{x}_i)\\ &\quad - \hat{\rho}_i\varphi_i^2(\vec{x}_i) S_i^2 + |S_i||\delta_i(x)|\\ &\le (1 - K_i) S_i^2 + \frac{1}{2}S_{i+1}^2 + \frac{1}{2}y_{i+1}^2 + \tilde{\theta}_i S_i f_i(\vec{x}_i)\\ &\quad + \tilde{\rho}_i\varphi_i^2(\vec{x}_i) S_i^2 + \frac{\rho_i}{4},\ i = 1,\cdots,n-1,\\ \dot{V}_{ns} &= S_n\dot{S}_n\\ &= S_n\left(-K_n S_n + \tilde{\theta}_n f_n(x) - \hat{\rho}_n\varphi_n^2(x) S_n + \delta_n(x)\right)\\ &\le -K_n S_n^2 + \tilde{\theta}_n S_n f_n(x) - \hat{\rho}_n\varphi_n^2(x) S_n^2 + |S_n||\delta_n(x)|\\ &\le -K_n S_n^2 + \tilde{\theta}_n S_n f_n(x) + \tilde{\rho}_n\varphi_n^2(x) S_n^2 + \frac{\rho_n}{4},\end{aligned}$$

$$\begin{aligned}\dot{V}_{i\theta} &= \frac{1}{\lambda_i}\tilde{\theta}_i\dot{\tilde{\theta}}_i\\ &= -\tilde{\theta}_i\left[S_i f_i(\vec{x}_i) + \pi_i(\theta_{i0} - \hat{\theta}_i)\right]\\ &= -\tilde{\theta}_i S_i f_i(\vec{x}_i) - \frac{\pi_i}{2}\tilde{\theta}_i^2 + \frac{\pi_i}{2}(\theta_{i0} - \theta_i)^2,\ i = 1,\cdots,n,\\ \dot{V}_{i\rho} &= \frac{1}{\mu_i}\tilde{\rho}_i\dot{\tilde{\rho}}_i\\ &= -\tilde{\rho}_i\left[S_i^2\varphi_i^2(\vec{x}_i) + \sigma_i(\rho_{i0} - \hat{\rho}_i)\right]\\ &\le -\tilde{\rho}_i S_i^2\varphi_i^2(\vec{x}_i) - \frac{\sigma_i}{2}\tilde{\rho}_i^2 + \frac{\sigma_i}{2}(\rho_{i0} - \rho_i)^2,\ i = 1,\cdots,n,\\ \dot{V}_{iy} &= y_i\dot{y}_i\\ &= -\frac{1}{\tau_i}y_i^2 - y_i\dot{\overline{x}}_i,\ i = 2,\cdots,n.\end{aligned}$$

Similar to the analysis in subsection 2.1.2, by straightforward calculations, we have

$$\left|\dot{\overline{x}}_2\right| \le \eta_2\left(S_1, S_2, y_2, x_{1d}, \dot{x}_{1d}, \ddot{x}_{1d}, \tilde{\theta}_1, K_1, \lambda_1, \pi_1, \mu_1, \sigma_1,\ \theta_{10}, \rho_{10}\right),$$

and for $3 \le i \le n,$

$$\left|\dot{\overline{x}}_i\right| \le \eta_i\left(\vec{S}_i, \vec{y}_i, x_{1d}, \dot{x}_{1d}, \ddot{x}_{1d}, \vec{\tilde{\theta}}_{i-1}, \vec{K}_{i-1}, \vec{\lambda}_{i-1}, \vec{\pi}_{i-1}, \vec{\tau}_{i-1},\ \vec{\mu}_{i-1}, \vec{\sigma}_{i-1}, \vec{\theta}_{i-10}, \vec{\rho}_{i-10}\right),$$

where $\eta_i,\ i = 2,\cdots,n$ are a set of nonnegative continuous functions. Given some r, the set

$$B_r = \left\{(S_1,\cdots,S_n, y_2,\cdots,y_n, \tilde{\theta}_1,\cdots,\tilde{\theta}_n, \tilde{\rho}_1,\cdots,\tilde{\rho}_n)^{\mathrm{T}} : V \le r\right\}$$

is a compact set. Hence so is $B_r \times B_0$. Therefore, the continuous function η_i has maximum, called M_i on $B_r \times B_0$, where M_i depends on $\vec{K}_{i-1}$, $\vec{\lambda}_{i-1}$, $\vec{\pi}_{i-1}$, $\vec{\tau}_{i-1}$, $\vec{\mu}_{i-1}$, $\vec{\rho}_{i-10}$, $\vec{\theta}_{i-10}$ and $\vec{\sigma}_{i-1}$ (Particularly, M_2 depends on K_1, λ_1, π_1, μ_1, θ_{10}, ρ_{10} and σ_1). As a sequence, one has

$$\begin{aligned}\dot{V}_{iy} &\le -\frac{1}{\tau_i}y_i^2 + |y_i| M_i\\ &\le \left(M_i^2 - \frac{1}{\tau_i}\right)y_i^2 + \frac{1}{4}.\end{aligned}$$

Therefore,

$$\begin{aligned}\dot{V} &= \sum_{i=1}^{n}\dot{V}_{is} + \sum_{i=2}^{n}\dot{V}_{iy} + \sum_{i=1}^{n}\dot{V}_{i\theta} + \sum_{i=1}^{n}\dot{V}_{i\rho}\\ &\le \sum_{i=1}^{n-1}\Big[(1 - K_i) S_i^2 + \frac{1}{2}S_{i+1}^2 + \frac{1}{2}y_{i+1}^2 + \tilde{\theta}_i S_i f_i(\vec{x}_i)\\ &\qquad + \tilde{\rho}_i\varphi_i^2(\vec{x}_i) S_i^2 + \frac{\rho_i}{4}\Big] - K_n S_n^2 + \tilde{\theta}_n S_n f_n(x)\end{aligned}$$

$$
\begin{aligned}
&+\tilde{\rho}_n\varphi_n^2(x)S_n^2+\frac{\rho_n}{4}+\sum_{i=2}^{n}\left[\left(M_i^2-\frac{1}{\tau_i}\right)y_i^2+\frac{1}{4}\right]\\
&+\sum_{i=1}^{n}\left[-\tilde{\theta}_iS_if_i(\vec{x}_i)-\frac{\pi_i}{2}\tilde{\theta}_i^2+\frac{\pi_i}{2}(\theta_{i0}-\theta_i)^2\right]\\
&+\sum_{i=1}^{n}\left[-\tilde{\rho}_iS_i^2\varphi_i^2(\vec{x}_i)-\frac{\sigma_i}{2}\tilde{\rho}_i^2+\frac{\sigma_i}{2}(\rho_{i0}-\rho_i)^2\right]\\
\le&\sum_{i=1}^{n}\left(\frac{3}{2}-K_i\right)S_i^2+\sum_{i=2}^{n}\left(M_i^2+\frac{1}{2}-\frac{1}{\tau_i}\right)y_i^2-\sum_{i=1}^{n}\frac{\pi_i}{2}\tilde{\theta}_i^2\\
&-\sum_{i=1}^{n}\frac{\sigma_i}{2}\tilde{\rho}_i^2+\beta,
\end{aligned}
$$

where

$$\beta=\sum_{i=1}^{n}\left[\frac{\rho_i}{4}+\frac{\pi_i}{2}\left(\theta_{i0}-\theta_i\right)^2+\frac{\sigma_i}{2}\left(\rho_{i0}-\rho_i\right)^2\right]+\frac{n-1}{4}.$$

Let

$$K_i=\frac{\alpha+3}{2},\quad \frac{1}{\tau_i}=M_i^2+\frac{\alpha+1}{2},\quad \lambda_i=\frac{\alpha}{\pi_i},\quad \mu_i=\frac{\alpha}{\sigma_i},$$

where α is a positive scalar, then one has

$$\dot{V}\le-\alpha V+\beta. \tag{4}$$

Similar to the previous analysis, it is easy from (4) to conclude that $S_1,\cdots,S_n$, $y_2,\cdots,y_n$, $\tilde{\theta}_1,\cdots,\tilde{\theta}_n$ and $\tilde{\rho}_1$, $\cdots,\tilde{\rho}_n$ are all uniformly ultimately bounded. Furthermore, $x_1,\cdots,x_n$, $x_{2d},\cdots,x_{nd}$, $\bar{x}_2,\cdots,\bar{x}_n$, $\hat{\theta}_1$, $\cdots,\hat{\theta}_n$ and $\hat{\rho}_1$, $\cdots,\hat{\rho}_n$ are all uniformly ultimately bounded. In addition, it is easy to see that for any given π_i, σ_i, ρ_{i0} and θ_{i0}, β is a unknown but bounded constant which is independent of α. So $\frac{\beta}{\alpha}$ can be made arbitrary small by choosing proper α. This leads to arbitrary small tracking error S_1.

To sum up, we have the following theorem.

Theorem 2: Consider the uncertain nonlinear system (1) satisfying Assumption 1. If the bound parameters ρ_i, $i=1,2,\cdots,n$ are unknown, then the robust adaptive dynamic surface control algorithm 2 with appropriate design parameters can keep all the states of the closed-loop system bounded and drive the actual output to track a feasible desired output trajectory with an arbitrary small tracking error.

Remark: It is noted that Theorems 1 and 2 only present the existence of the corresponding adaptive dynamic surface controllers. In fact, to achieve the design objective, one just needs to choose the design parameters K_i, λ_i and μ_i big enough and τ_i small enough. However, as shown in [9] and [10], the filter time constants can not be made arbitrarily small in real-time implementation. So theoretically speaking, the tracking error can be arbitrarily small by choosing arbitrarily small filter time constants, but this results in that the dynamic surface controller can not be implemented in practice. Therefore, the design parameters should be adjusted by considering actuator and sensor limitations and the desired the tracking accuracy simultaneously.

3. DESIGN EXAMPLE

To indicate the effect of our results, consider the following system

$$\begin{cases}\dot{x}_1=x_2+\theta_1x_1^3+\vartheta_1x_1^2\cos x_2\\ \dot{x}_2=u\\ y=x_1,\end{cases} \tag{5}$$

here θ_1 and ϑ are both constants, where θ_1 is unknown but ϑ may be unknown. If ϑ is known and equals to zero, then the output regulation problem of the above system can be solved by the result in [17]. However, to the best knowledge of the authors, when ϑ is nonzero or unknown, this problem is difficult to be solved by the existing dynamic surface control methods without incorporating with intelligent control methods. However, the intelligent control based dynamic surface control algorithms are usually complicated. Fortunately, by choosing $\rho_1=|\vartheta_1|$ and $\varphi_1(x_1)=x_1^2$, it is easy to check that system (5) satisfies Assumption 1, since $|\delta(x)|=\left|\vartheta_1x_1^2\cos x_2\right|\le\rho_1\varphi_1(x_1)$. So no matter whether the bound parameter ρ_1 is known or not, according to the results of the current paper, the robust adaptive dynamic surface controller can be constructed for system (5) to make x_1 track a given feasible desired output trajectory x_{1d} with an arbitrarily small tracking error.

When ρ_1 is known, according to Algorithm 1, the proposed robust dynamic surface controller is given as follows.

RADSC-I:

$$
\begin{aligned}
&S_1=x_1-x_{1d},\\
&\bar{x}_2=\dot{x}_{1d}-K_1S_1-\hat{\theta}_1f_1(x_1)-\rho_1^2\varphi_1^2(x_1)S_1,\\
&\dot{\hat{\theta}}_1=\lambda_1\left[S_1f_1(x_1)+\pi_1(\theta_{10}-\hat{\theta}_1)\right],\\
&\tau_2\dot{x}_{2d}+x_{2d}=\bar{x}_2,\ x_{2d}(0)=\bar{x}_2(0),\\
&S_2=x_2-x_{2d},\\
&u=\dot{x}_{2d}-K_2S_2.
\end{aligned}
$$

For the numerical simulation, we choose $\theta_1=3$, $\vartheta_1=-3$, the desired output trajectory $x_{1d}=\sin t$, the initial states $x_1(0)=0$, $x_2(0)=1$ the design parameters of controller $\pi_1=0.1$, $\tau_2=0.02$, $\lambda_1=K_1=K_2=50$ and $\theta_{10}=2.5$. The simulation results are shown in Fig. 1.

When ρ_1 is unknown, the proposed robust dynamic surface controller is given below.

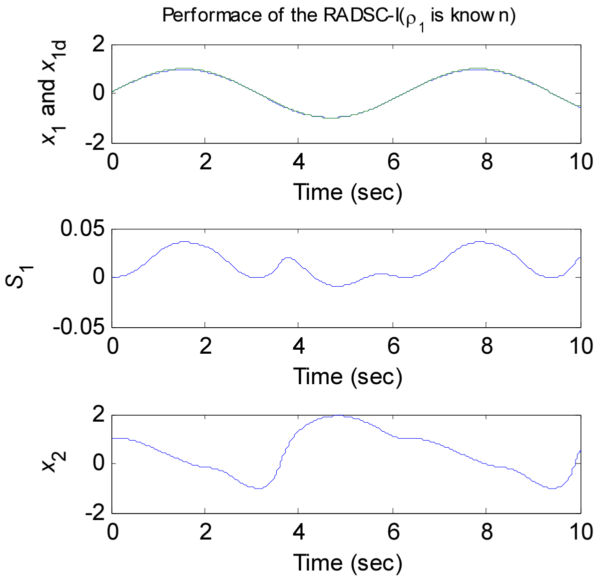

Fig. 1. Performace of the RADSC-I (ρ_1 is known).

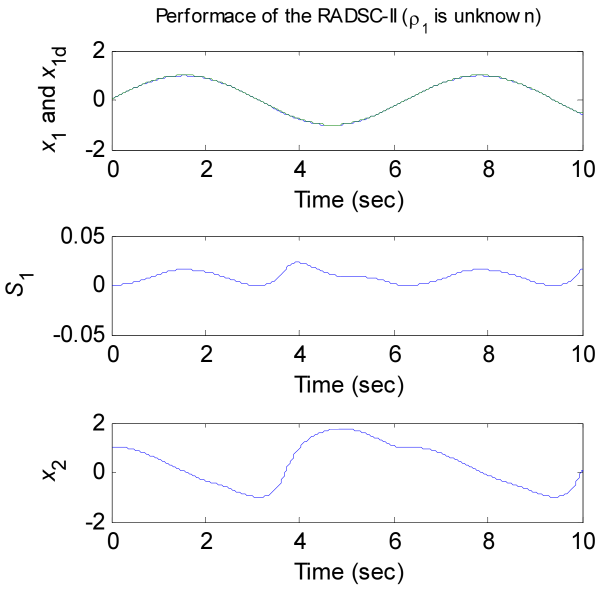

Fig. 2. Performace of the RADSC-II (ρ_1 is unknown).

RADSC-II:

$$S_1 = x_1 - x_{1d},$$
$$\bar{x}_2 = \dot{x}_{1d} - K_1 S_1 - \hat{\theta}_1 f_1(x_1) - \hat{\rho}_1 \varphi_1^2(x_1) S_1,$$
$$\dot{\hat{\theta}}_1 = \lambda_1 \left[S_1 f_1(x_1) + \pi_1(\theta_{10} - \hat{\theta}_1) \right],$$
$$\dot{\hat{\rho}}_1 = \mu_1 \left[S_1^2 \varphi_1^2(x_1) + \sigma_1(\rho_{10} - \hat{\rho}_1) \right],$$
$$\tau_2 \dot{x}_{2d} + x_{2d} = \bar{x}_2, x_{2d}(0) = \bar{x}_2(0),$$
$$S_2 = x_2 - x_{2d},$$
$$u = \dot{x}_{2d} - K_2 S_2.$$

For the numerical simulation, we choose $\theta_1 = 2$, $\vartheta_1 = -2$, the desired output trajectory $x_{1d} = \sin t$, the initial states $x_1(0) = 0$, $x_2(0) = 1$, the design parameters of controller $\pi_1 = 0.1$, $\sigma_1 = 0.1$, $\tau_2 = 0.02$, $\theta_{10} = 1$, $\rho_{10} = 3$, and $\lambda_1 = \mu_1 = K_1 = K_2 = 50$. The simulation results are shown in Fig. 2.

Obviously in each case, the actual output x_1 is driven to track the desired output trajectory x_{1d} with a small tracking error S_1, and the remained state x_2 is kept bounded. The simulation results indicate the effect of the proposed control strategies.

4. CONCLUSION

In this paper, the output tracking problem of a class of uncertain nonlinear systems is considered using robust adaptive dynamic surface control methodology. The unmatched uncertainties include both of the linearly parameterized terms and the nonlinearly parameterized terms. Under the assumption that the bound of each nonlinearly parameterized uncertainty term can be expressed by a known function multiplied by a possibly unknown parameter, two different kinds of robust adaptive dynamic surface control algorithms are proposed according to whether the bound parameters are known or not. The proofs and the design example show that each of the control algorithms with proper design parameters can make all the states of the corresponding closed-loop system uniformly ultimately bounded, and the output track a feasible desired output trajectory with a sastisfactory tracking error. These indicate the effect of our results.

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