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Neural network-based adaptive tracking control for nonlinearly parameterized systems with unknown input nonlinearities

Xueli Wu [a,b], Xiaojing Wu [a,*], Xiaoyuan Luo [a], Quanmin Zhu [c], Xinping Guan [a]

[a] Institute of Electrical Engineering, Yanshan University, Hebei Province, Qinhuangdao 066004, China
[b] College of Electronic Engineering and Information, Hebei University of Science and Technology, Shijiazhuang 050018, China
[c] Bristol Institute of Technology, University of the West of England, Coldharbour Lane, Bristol BS161QY, UK

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ABSTRACT

This paper presents tracking control problem of the unmatched uncertain nonlinearly parameterized systems (NLP-systems) with unknown input nonlinearities. Two kinds of nonlinearities existing in the control input are discussed, which are non-symmetric dead-zone input and continuous nonlinearly input. The smooth controller is proposed in either of these two cases by effectively integrating adaptive backstepping technique and neural networks. Some assumptions, in which the parameters with respect to the input nonlinearities are available in advance in previous works, are removed by adaptive strategy. The researches also take the arbitrary unmatched uncertainties and nonlinear parameterization into account without imposing any condition on the system. It is shown that the closed-loop tracking error converges to a small neighborhood of zero. Finally, numerical examples are initially bench tested to show the effectiveness of the proposed results.

1. Introduction

The researches on the adaptive control of various nonlinear systems with unknown parameters have advanced significantly [1–3]. In these works, the systems are required to satisfy some assumptions such as matching condition, or growth condition, and so on. To overcome these restrictions, the backstepping technique has been applied to the adaptive control of nonlinear systems, which do not satisfy the matching condition [4–8]. However, it should be noticed that all researches were concerned with the systems with linear parameterization. In practice, however, nonlinear parameterization is very common in biochemical process, fermentation process, and other related fields. The results on the adaptive backstepping control of nonlinear systems with nonlinear parameterization are very limited [9–11]. As yet, there is no report from literature for the adaptive backstepping tracking control of NLP-systems with unknown input nonlinearities.

It is well known that nonlinearities widely exist in the control input because of the actuator's physical limitations, such as dead-zone input and continuous nonlinearly input. The presence of such nonlinearities in the control input usually can deteriorate the system performance. In recent years, many scholars have tried to use different ways to improve the performance of such control systems [12–23].

After a simplified dead-zone model proposed in [12], many research results were obtained based on this simplified model [13,14] without using the dead-zone inverse technique. However, these results were only considered symmetric dead-zone inputs. To compensate this limitation, the case of non-symmetric dead-zone was taken into account in [15] using the dead-zone modeling method presented in [12]. Then, a class of pure-feedback nonlinear systems with non-symmetric dead-zone was investigated in [16] using dynamic surface control method. For the nonlinear system with matched uncertain time-delay term and non-symmetric dead-zone, the adaptive state feedback controller was designed in [17]. For the unmatched uncertain nonlinear systems with non-symmetric dead-zone, an adaptive output feedback controller was proposed in [18]. In [19], the problem of adaptive stabilization for a class of time-delay system with matched nonlinear delayed perturbation and non-symmetric dead-zone saturating input was investigated. In [20], adaptive backstepping method was developed for the unmatched uncertain nonlinear systems with non-symmetric dead-zone and linear parameterization. Moreover, the smooth controller was designed.

Another important issue encountered in practice is continuous nonlinearly input. Many significant developments have been achieved. Based on sliding mode observer, a new adaptive sliding mode controller was designed for the uncertain nonlinear systems with continuous nonlinearly input in [21]. In [22], a control

* Corresponding author.
E-mail addresses: wuxiaojing013@163.com (X. Wu), xpguan@ysu.edu.cn, xpguan@sjtu.edu.cn (X. Guan).

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scheme was presented for the uncertain unified chaotic systems with continuous nonlinearly input. In [23], a sliding mode controller with adaptive laws was proposed to synchronize two different n-dimensional chaotic systems with unknown bounded uncertainty and continuous nonlinearly input. For the uncertain large-scale time-varying delayed systems with continuous nonlinearly input, a memoryless decentralized adaptive sliding mode controller was developed in [24].

However, aforementioned results either require knowing some knowledge of input nonlinearities in advance [15,16,18,20–24] or can only be applied to the systems with linear parameterization and matched uncertainties [15,17,19,20,22–24]. There are still some limitations in these research results, which will be illustrated in Remarks after the text.

In this paper, the tracking control problem for the unmatched nonlinear systems with unknown input nonlinearities and nonlinear parameterization is investigated via adaptive backstepping technology. By approximating the unknown nonlinear functions by neural networks, we incorporate the backstepping technique into the parameter separation method based on the adaptive control design framework. The controllers are designed, respectively, either in non-symmetric dead-zone input case or in continuous nonlinearly input case. Promisingly the control strategy removes the assumptions that some parameters on non-symmetric dead-zone input or continuous nonlinearly input are needed to know in advance. Correspondingly, the arbitrary unmatched uncertainties and nonlinear parameterization are well considered in the controller design procedure. Moreover, the designed controller is smooth without chattering phenomenon by choosing appropriate design parameters. Finally, two simulated examples are conducted to shown the effectiveness of development.

2. Problem formulations

In this paper, the unmatched uncertain NLP-systems with input nonlinearities are modeled as follows:

$$\begin{cases} \dot{x}_1 = x_2 + f_1(\bar{x}_1,\rho_1) + g_1(\bar{x}_1) \\ \dot{x}_i = x_{i+1} + f_i(\bar{x}_i,\rho_i) + g_i(\bar{x}_i), \quad i = 2,\ldots,n-1 \\ \dot{x}_n = \Gamma(u) + f_n(\bar{x}_n,\rho_n) + g_n(\bar{x}_n) \end{cases} \tag{1}$$

where $x = (x_1,\ldots,x_n)^T \in R^n$ are the system states, $\bar{x}_i = (x_1,\ldots,x_i)$. $f_i(\bar{x}_i,\rho_i)$ is the smooth function with unknown parameters ρ_i, and the unknown parameter ρ_i appears nonlinearly in the system. Smooth function $g_i(\bar{x}_i)$ denotes the possible modeling error and neglected dynamics. The function $\Gamma(u)$ represents the actuator input–output characteristics, which is a nonlinear function, and is not precisely known.

Remark 1. Many results have been obtained for the linearly parameterized systems, in which the nonlinear function can be described as the product of an unknown parameter and a nonlinear function, such as $\rho f(x)$ [4,5,15,18]. In practice, however, some dynamic systems cannot be modeled as the aforementioned form since it may lead to overparameterizion, such as Mass-spring mechanical system used in the next simulation. Motivated by this, the study is intended to investigate the NLP-systems.

In order to facilitate the controller design, firstly, the following assumptions and lemmas are given:

Assumption 1. [11]: For $i = 1,\ldots,n$

$$|f_i(\bar{x}_i,\rho_i)| \le (|x_1| + \ldots |x_i|) b_i(x_1,\ldots,x_i,\rho_i) \tag{2}$$

where $b_i(\cdot)$ is nonnegative continuous function.

Lemma 1. [11] *For any real-valued continuous function $f(x,y)$, where $x \in R^n$ and $y \in R^n$, there are smooth scalar functions $a(x) \ge 0$, $b(y) \ge 0$, $c(x) \ge 1$ and $d(y) \ge 1$, such that*

$$\begin{aligned} |f(x,y)| &\le a(x) + b(y) \\ |f(x,y)| &\le c(x) d(y) \end{aligned} \tag{3}$$

Lemma 2. [25]*The following inequality holds for any $\delta > 0$ and any $\xi \in R$*

$$0 \le |\xi| - \xi \tanh(\xi/\delta) \le \kappa\delta \tag{4}$$

where κ is a constant that satisfies $\kappa = e^{-(\kappa+1)}$, i.e. $\kappa = 0.2785$.

It is well known that RBF NN is widely used as a tool for modeling nonlinear functions because of its good capability in function approximation. In structure, the RBF NN takes the form $\Theta^T \Psi(z)$ where $z \in \Omega_z \subset R^q$, q is the NN input dimension, weight vector$\Theta = [\Theta_1,\ldots,\Theta_l]^T$. The NN node number $l > 1$, and $\Psi(z) = [\Psi_1,\ldots,\Psi_l]^T$, with Ψ_1 being chosen as the commonly used Gaussian functions, which is in the following form:

$$\Psi_i = \exp(-(z-\mu_i)^T (z-\mu_i)/\chi_i^2) \tag{5}$$

where $\mu_i = [\mu_{i1},\ldots,\mu_{iq}]$ is the center of the receptive field and χ_i is the width of the Gaussian function.

It has been proved that the NN can approximate any continuous function over a compact set $\Omega_x \subset R^q$ to arbitrary accuracy as

$$g_i(\bar{x}_i) = \theta_{iN}^{*T} \varphi_i(\bar{x}_i) + w_i \tag{6}$$

where ideal weight vector $\theta_{iN}^* = [\theta_{i1N}^*,\ldots,\theta_{ilN}^*]^T$; Gaussian function $\varphi_i(\bar{x}_i) = [\varphi_{i1},\ldots,\varphi_{il}]^T$; w_i is the approximation error. There exists an unknown constant ε_i satisfying $\|w_i\| \le \varepsilon_i$ by $|w_i| \le \varepsilon_i$.

The ideal weight vector θ_{iN}^* is an artificial quantity required for analytical purpose. θ_{iN}^* is defined as the value of θ_{iN} that minimizes $|\varepsilon_i|$ for all $\bar{x}_i \in \Omega_{\bar{x}_i}$ in a compact region, i.e.

$$\theta_{iN}^* = \arg\min_{\theta_{iN} \in R^l} \{\sup |g_i(\bar{x}_i) - \theta_{iN}^T \varphi_i(\bar{x}_i)|\} \tag{7}$$

2.1. Non-symmetric dead-zone input descriptions

Actuator dead-zone is common in mechanical connections, hydraulic servo valves, piezoelectric translators, and electric servomotors. The presence of such nonlinearities usually deteriorates the system performance. In this section, the characteristics of non-symmetric dead-zone input will be introduced.

The function $\Gamma(u)$ shown in Fig. 1, represents actuator output with non-symmetric dead-zone, and can be expressed as

$$\Gamma(u) = \begin{cases} m_r(u - b_r) & \text{if} \quad u \ge b_r \\ 0 & \text{if} \quad -b_l \le u \le b_r \\ m_l(u + b_l) & \text{if} \quad u \le -b_l \end{cases} \tag{8}$$

where the parameters m_r and m_l stand for the right and left slopes of the dead-zone characteristic, respectively. The parameters b_r and b_l represent the breakpoint of the actuator dead-zone input.

The actuator non-symmetric dead-zone can be modeled as a combination of a line and a disturbance-like term [15].

$$\Gamma(u) = m(t)u + d(t) \tag{9a}$$

where

$$m(t) = \begin{cases} m_l, & u \le 0 \\ m_r, & u > 0 \end{cases}, \quad d(t) = \begin{cases} -m_r b_r, & u \ge b_r \\ -m(t)u, & -b_l < u < b_r \\ m_l b_l, & u \le -b_l \end{cases} \tag{9b}$$

Assumption 2. Parameters m_l, m_r, b_l and b_r are positive but unknown. There exists an enough small unknown parameter η such that $0 < \eta \le m_l$; $0 < \eta \le m_r$. And the upper bound $\bar{d}$ of the disturbance $d(t)$ is also an unknown constant.