Neurocomputing 174 (2016) 597–604

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Neural network-based adaptive control for a class of chemical reactor systems with non-symmetric dead-zone

Shu Li, MingZhe Gong*, YanJun Liu

College of Science, Liaoning University of Technology, Jinzhou, Liaoning 121001, China

ARTICLE INFO

Article history:
Received 8 August 2015
Received in revised form
10 September 2015
Accepted 19 September 2015
Communicated by: Dr. D. Zhang
Available online 21 October 2015

Keywords:
Discrete-time system
CSTR control
Adaptive control
The neural networks
Nonlinear systems

ABSTRACT

In this paper, an adaptive predictive control algorithm is employed to controlling a class of continuous stirred tank reactor (CSTR) system. The main contribute of this paper is that the CSTR system are in discrete-time form and non-symmetric dead-zone inputs are considered here. The design parameters of control algorithm for the CSTR systems are not so much than before, such that the calculated amount of the control algorithm is less than before. By considering the Radial basis function neural networks (RBFNN), the unknown functions are approximated, the mean value theorem is utilized in the algorithm design process. Based on the Lyapunov analysis method, and choosing the design parameters appropriately, all the signals in the closed-loop system are proved to be semi-global uniformly ultimately bounded (SGUUB) and the tracking error is converged to a small compact set. A simulation example for CSTR systems is studied to demonstrate the effectiveness of the proposed approach.

1. Introduction

A great development of intelligent control theory have happened in recent years. In these achievements, NNs or FLS are utilized to approximate the unknown nonlinear functions in the discrete-time or the continuous systems developed quickly. Specially, in system with time-varying input delays or fault [1–4], with the help of the Takagi–Sugeno (T–S) fuzzy model, a pseudo-predictor feedback approach method, or even the augmented sliding mode observer approach method, appropriate controllers are established, then the stability of the systems are proved [5–11,53]. In comparison with the intelligent control without adaptive, with the help of approximators, the adaptive control could deal with the uncertain of the systems better [12–15]. With the certain conditions, several approximation methods have been proven that, such as fuzzy systems, polynomials [16,17], splines [18] and NNs [19–22] have function approximation abilities and have been constantly used as function approximators. In [23], in order to obtain the nominal closed-loop system, a nonlinear state feedback controller [24,25] is computed by exact linearization of the process model. By approximately linearizing the process model, a nonlinear gain-scheduled controller [26] is designed.

Whereas the previous works mainly focus on the nonlinear systems in continuous-time form. But the systems we often run across in the industrial production are always in discrete-time form. The algorithms of the continuous systems cannot be used directly to stabilize the systems in discrete-time form.

The study of discrete system has scored important achievements, and some adaptive control algorithms were introduce in [27–32], with the help of neural network the unknown functions of these discrete-time systems could be approximated, then, the appropriate controllers are introduced, and the stability of the closed-loop discrete-time systems are guaranteed. But, because of these algorithms need to satisfy the strict feedback form or matching condition [33–36,52], so they could not satisfy the stabilization of the systems of pure feedback form [37,38].

In the past few years, the development of CSTR system has made remarkable achievements. In [39], an adaptive tracking control is considered for a class of general nonlinear systems using multilayer neural networks [40], and the controller is illustrated through an application to composition control in CSTR systems. A nonlinear adaptive tracking controller for a class of general time-variant nonlinear systems is applied to controlling CSTR systems in [41], and the asymptotic convergence condition [42] of the nonlinear adaptive control system is guaranteed by the Lyapunov direct method. An adaptive fuzzy temperature controller is proposed for a class of CSTRs based on input–output feedback linearization in [43], and the concentration dependent terms and other unknown system parameters in the control law are

* Corresponding author.
E-mail addresses: li_shu43@hotmail.com (S. Li), gongmingzhe8023@hotmail.com (M. Gong), liuyanjun@live.com (Y. Liu).

http://dx.doi.org/10.1016/j.neucom.2015.09.072
0925-2312/

estimated by a fuzzy logic system [44]. Using temperature measurement, an adaptive fuzzy controller, based on backstepping technique [45] and the observability concept is proposed in [46] for temperature control of a general class of CSTRs. Considering adaptive backstepping and neural network (NN) approximation techniques, an adaptive nonlinear controller is investigated for the CSTR systems in [47]. Based on the conventional Luenberger observer, a variable structure observer is introduced in [48], with the help of a nonlinear controller, the stability of the CSTR system is proved. An uncertainty observer based on the differential algebraic techniques is introduced to deal with the problem of the online estimation of the reaction heat in a CSTR from temperature measurements in [49,50]. In [51] an adaptive predictive control algorithm is applied to control a class of SISO CSTR system in discrete time. The CSTR discrete-time system in this paper is considered with dead-zone, but the amount of the calculation of the control algorithm is too large, so it need a long to reach the stability.

In this paper, the CSTR discrete-time systems with dead-zone in pure-feedback form will be studied. Considering the fact that, some functions and the dead-zone in the system are unknown, so the system is transformed into a prediction form firstly, in this way the quantity of calculation will be reduced. Then, with the help of RBFNN, the unknown function and dead-zone are estimated. Furthermore, an appropriate controller and adaptive law are constructed for the transformed system. Finally, the closed-loop system is stable in the sense that SGUUB and the output tracking errors converge to a bounded compact set. The feasibility of the proposed method is verified by a simulation example.

2. Problem statement

2.1. System description

Consider the CSTR system in discrete-time form with unknown non-symmetric dead-zone:

$$\begin{cases} x_1(k+1) = \downarrow x_1(k) + \left[-x_1(k) + C_a(1-x_1(k))\downarrow \times e^{\alpha x_2(k)/(\alpha + z_2(k))}\right]T \\ x_2(k+1) = \downarrow x_2(k) + \left[-x_2(k)\downarrow + BC_a(1-x_1(k))e^{\frac{\gamma x_2(k)}{\gamma + x_2(k)}}\downarrow - C_r(x_2(k) - D(u(k)))\right]T + d_1(k) \\ y = \downarrow x_1(k) \end{cases} \tag{1}$$

where $x_1(k)$ is the dimensionless concentration at time instant k and the dimensionless temperature at time instant k is denoted by $x_2(k)$, C_a and B are Damkohler number and dimensionless heat of reaction, respectively; C_r denotes dimensionless cooling rate, and sampling period is T, $d_1(k)$ is added to represent an external disturbance, which is bounded $|d_1(k)| < \overline{d}_1$. $D(u(k))$ denotes the temperature of the dimensionless coolant, which is related to the control input $u(k)$ through the unknown non-symmetric dead-zone. The non-symmetric dead-zone $D(u(k))$ is described as

$$D(u(k)) = \begin{cases} m_r(u(k) - b_r), & \text{if } u(k) \geq b_r \\ 0, & \text{if } -b_l < u(k) < b_r \\ m_l(u(k) - b_l), & \text{if } u(k) \leq b_l \end{cases} \tag{2}$$

where m_r m_l,b_l and b_r are positive constants. The constants m_l and m_r stand for the right and left slope of the dead-zone characteristic and are known. The constants b_l and b_r represent the breakpoints of the input nonlinearity.

The dead-zone input may be written as:

$$D(u) = m(k)u(k) + b(k) \tag{3}$$

where

$$m(k) = \begin{cases} m_r(k), & \text{if } u(k) > 0 \\ m_l(k), & \text{if } u(k) \leq 0 \end{cases} \tag{4}$$

and

$$b(k) = \begin{cases} -m_r(k)b_r(k), & \text{if } u(k) \geq b_r \\ -m(k)u(k), & \text{if } -b_l < u(k) < b_r \\ m_l(k)b_l(k), & \text{if } u(k) \leq -b_l \end{cases} \tag{5}$$

It is obvious that $m(k)$ is known, let $\underline{m} = \min(m_l(k), m_r(k))$, $\overline{m} = \max(m_l(k), m_r(k))$, $\overline{b} = \max(m_r b_r, m_l b_l)$, $\underline{b} = \min(m_r b_r, m_l b_l)$. In this paper, RBFNN will be employed to approximate the unknown functions of the system and the approximation property will be given in the following subsection.

An adaptive RBFNN control algorithm will be developed in the following section, so that the tracking error converges to a small compact set and all the signals in the closed-loop are SGUUB.

2.2. RBFNN approximation property

Based on certain conditions, several methods can be used to approximate the unknown functions, such as polynomials, splines, NN, fuzzy logic etc. were well-developed. In this paper, the unknown function $y(k)$ will be approximated by the RBFNN

$$y_N(k,\tau) = \omega^T \tau(k) \tag{6}$$

where $k \in R^l$ is the input of the RBFNN, $\omega = [\omega_1, \cdots, \omega_n]^T$ is the weight vector, n denotes the number of the NN node, $\tau(k) = [\tau_1(k), \cdots, \tau_n(k)]^T$ is the smooth basis, where $\tau_i(k)$ is in the form of Gaussion function

$$\tau_i(k) = \exp\left[\frac{-(k-\zeta_i)^T(k-\zeta_i)}{\nu_i^2}\right], i = 1, \cdots, n \tag{7}$$

where $\zeta_i = [\zeta_1, \cdots, \zeta_l]^T$ denotes the center of the Gaussion functions and v_i is the width of the Gaussion functions.

Noticing the fact that any function can be approximated by Eq. (6)

$$y_i(k) = \omega_i^{*T}\tau_i(k) + \varepsilon_i(k) \tag{8}$$

where ω_i^* denotes the ideal constant weight, and the approximation error $\varepsilon_i(k)$ satisfies that $|\varepsilon_i(k)| \leq \varepsilon_M$, with $\varepsilon_M > 0$.

The ideal weight vector ω_i^*, an "artificial" quantity required for analytical purposes, is defined as

$$\omega_i^* = \arg \min_{(\omega_i \in R^l)} \left[\sup_{t \in \Omega_t} \left|\omega_i^T(k)\tau_i - y(k)\right|\right]$$

3. System transformations

In order to facilitate expression, we denote that

$$f_1(x_1(k), x_2(k)) = x_1(k) + \left[-x_1(k) + C_a \times (1 - x_1(k))e^{\frac{\alpha x_2(k)}{\alpha + x_2(k)}}\right]T \tag{9}$$

$$\begin{aligned} f_2(x_1(k), x_2(k), D(u(k))) \\ = x_2(k) + \Big[-x_2(k) + BC_a(1-x_1(k)) \\ \times e^{\frac{\alpha x_2(k)}{\alpha + x_2(k)}} - \lambda(x_2(k) - D(u(k)))\Big]T \end{aligned} \tag{10}$$

Then, (1) can be rewritten as:

$$\begin{cases} x_1(k+1) = f_1(x_1(k), x_2(k)) \\ x_2(k+1) = d_1(k) + f_2(x_1(k), x_2(k), D(u(k))) \\ y = x_1(k) \end{cases} \tag{11}$$