Neural Networks 95 (2017) 134–142

Contents lists available at ScienceDirect

Neural Networks

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

Composite learning from adaptive backstepping neural network control

Yongping Pan [a,b], Tairen Sun [c], Yiqi Liu [d], Haoyong Yu [a,*]

[a] Department of Biomedical Engineering, National University of Singapore, Singapore 117583, Singapore
[b] National University of Singapore (Suzhou) Research Institute, Suzhou 215123, China
[c] School of Electrical and Information Engineering, Jiangsu University, Zhenjiang 212013, China
[d] School of Automation Science and Engineering, South China University of Technology, Guangzhou 510640, China

ARTICLE INFO

Article history:
Received 1 October 2016
Received in revised form 6 June 2017
Accepted 15 August 2017
Available online 22 September 2017

Keywords:
Adaptive control
Backstepping
Learning control
Mismatched uncertainty
Neural network
Parameter convergence

ABSTRACT

In existing neural network (NN) learning control methods, the trajectory of NN inputs must be recurrent to satisfy a stringent condition termed persistent excitation (PE) so that NN parameter convergence is obtainable. This paper focuses on command-filtered backstepping adaptive control for a class of strict-feedback nonlinear systems with functional uncertainties, where an NN composite learning technique is proposed to guarantee convergence of NN weights to their ideal values without the PE condition. In the NN composite learning, spatially localized NN approximation is employed to handle functional uncertainties, online historical data together with instantaneous data are exploited to generate prediction errors, and both tracking errors and prediction errors are employed to update NN weights. The influence of NN approximation errors on the control performance is also clearly shown. The distinctive feature of the proposed NN composite learning is that NN parameter convergence is guaranteed without the requirement of the trajectory of NN inputs being recurrent. Illustrative results have verified effectiveness and superiority of the proposed method compared with existing NN learning control methods.
© 2017 Elsevier Ltd. All rights reserved.

1. Introduction

Due to the universal function approximation property of neural networks (NNs), adaptive neural control (ANC) has been demonstrated to be a powerful tool for handling functional uncertainties in nonlinear systems (Narendra, 1996) and has kept great attraction in recent years, e.g. see Chemachema (2012), Esfandiari, Abdollahi, and Talebi (2015), Fairbank, Li, Fu, Alonso, and Wunsch (2014), Hamdy and Hamdan (2015), Hamdy, Abd-Elhaleem, and Fkirin (2017), Kiumarsi and Lewis (2015), Kostarigka and Rovithakis (2012), Kruger, Schnetter, Placzek, and Vorsmann (2012), Melingui, Lakhal, Daachi, Mbede, and Merzouki (2015), Modares, Lewis, and Naghibi-Sistani (2013), Modares and Lewis (2014), Pan, Yu, and Er (2014), Pan, Sun, and Yu (2015), Pan, Liu, Xu, and Yu (2016), Pan, Gou, Li, and Yu (in press), Sahoo, Xu, and Jagannathan (2016), Shojaei (2015) and Theodorakopoulos and Rovithakis (2015). The most prominent benefit of applying NN approximation is that the difficulty of system modeling in many practical control problems can be greatly alleviated resulting in the simplification of control synthesis (Narendra, 1996). By combining with integrator backstepping, mismatched uncertainties can also be handled under the ANC framework (Pan, Liu, & Yu, 2015). It is well known that integrator backstepping suffers from the "explosion of complexity" resulting from repeated derivations of virtual control inputs (Pan & Yu, 2015). Dynamic surface control (DSC) applies a first-order filter to the virtual control input at each backstepping step to relax the limitation of the integrator backstepping (Yip & Hedrick, 1998). However, it is still noise-sensitive for using first-order filters to estimate time derivatives of virtual control inputs. A solution of enhancing the DSC design is to apply second-order commend filters instead of first-order filters to estimate time derivatives of virtual control inputs, which leads to a more practical command-filtered backstepping design (Dong, Farrell, Polycarpou, Djapic, & Sharma, 2012; Farrell, Polycarpou, Sharma, & Dong, 2009; Hu & Zhang, 2013).

A major limitation of most existing ANC approaches is that the approximation ability of NNs is not fully exploited since only tracking error convergence is obtainable in those approaches. A sufficient condition for accurate NN approximation is that adjustable parameters in NNs converge to their ideal values, which is guaranteed by a well-known persistent-excitation (PE) condition (Kurdila, Narcowich, & Ward, 1995). The benefits of parameter convergence in ANC include accurate online modeling, exponential tracking, and robust adaptation without parameter drift (Farrell, 1998). However, the PE condition in the traditional adaptive control is very stringent and often infeasible in practice. A more

* Corresponding author.
E-mail addresses: biepany@nus.edu.sg (Y. Pan), suntr@ujs.edu.cn (T. Sun), aulyq@scut.edu.cn (Y. Liu), bieyhy@nus.edu.sg (H. Yu).

http://dx.doi.org/10.1016/j.neunet.2017.08.005
0893-6080/© 2017 Elsevier Ltd. All rights reserved.

practical PE condition based on NNs was established in Wang and Hill (2006), where it is shown that for radial basis function (RBF)-NNs constructed on a regular lattice, any recurrent trajectory of NN inputs that stays within the regular lattice can lead to a partial PE condition. An NN learning control (NNLC) method was also developed in Wang and Hill (2006), where practical exponential stability of the closed-loop system is established to ensure tracking error convergence and accurate NN approximation within a local region along recurrent trajectories. However, *in this NNLC method and its variations such as* (Pan & Yu, 2017; Wang, Wang, & Liu, 2014; Wang, Wang, Liu, & Hill, 2012)*, the requirement on the trajectory of NN inputs being recurrent limits the applicable scope, and the high dependence of the parameter convergence rate on the PE strength results in a generally slow learning speed.* How to relax the limitation of existing NNLC methods is still an open question.

Composite adaptive control is an integrated direct and indirect adaptive control strategy which aims to achieve higher tracking accuracy and better parameter convergence via faster and smoother parameter adaptation (Slotine & Li, 1989). The superior performance of composite ANC has been verified in many recent results, e.g. (Naso, Cupertino, & Turchiano, 2010; Pan, Sun, & Yu, 2016; Pan, Zhou, Sun, & Er, 2013; Patre, Bhasin, Wilcox, & Dixon, 2010). Yet, the PE condition still has to be satisfied to guarantee NN parameter convergence in the composite ANC. Composite learning is an emerging technique to achieve exponential parameter convergence in adaptive control without the PE condition (Pan, Er, Liu, Pan, & Yu, 2016; Pan & Yu, 2016; Pan, Zhang, & Yu, 2016). In the composite learning, online historical data (OHD) are employed together with instantaneous data to generate prediction errors, both tracking errors and prediction errors are applied to update parameter estimates, and exponential stability of the closed-loop system, i.e. exponential convergence of both tracking errors and parameter estimation errors, is guaranteed by an interval-excitation (IE) condition which significantly relaxes the PE condition. In (Pan et al., 2016), a model reference composite learning control approach was proposed for a class of nonlinear systems with matched parametric uncertainties. In (Pan et al., 2016), the approach of Pan et al. (2016) was extended to a class of nonlinear systems with matched functional uncertainties via fuzzy approximation. In (Pan & Yu, 2016), the approach of Pan et al. (2016) was extended to a class of strict-feedback nonlinear systems with mismatched parametric uncertainties via command-filtered backstepping.

Motivated by our previous composite learning works (Pan et al., 2016; Pan & Yu, 2016; Pan et al., 2016), this paper proposes an NN composite learning control (NNCLC) strategy for a class of strict-feedback nonlinear systems with functional uncertainties such that NN parameter convergence is guaranteed without the PE condition. The procedure of the control design is as follows: Firstly, a command-filtered backstepping ANC law is proposed to govern the controlled plant; secondly, spatially localized NN approximation is applied to handle functional uncertainties; thirdly, a composite learning law is developed to update NN weights; finally, practical exponential stability of the closed-loop system is established under the IE condition and a proper choice of control parameters. The silent feature of the proposed NNCLC is that it is able to achieve fast convergence of NN weights to their ideal values without the requirement on the trajectory of NN inputs being recurrent.

The rest of this paper is organized as follows: The control problem is formulated in Section 2; preliminaries are given in Section 3; the NNCLC is designed in Section 4; an illustrative example is provided in Section 5; conclusions are drawn in Section 6. Throughout this paper, $\mathbb{R}$, $\mathbb{R}^+$ and $\mathbb{R}^n$ denote the spaces of real numbers, positive real numbers and real n-vectors, respectively, L_∞ denotes the space of bounded signals, $\|\mathbf{x}\|$ denotes the Euclidean norm of $\mathbf{x}$, $\min\{\cdot\}$, $\max\{\cdot\}$ and $\sup\{\cdot\}$ denote the minimum, maximum and supremum operators, respectively, $\Omega_c := \{\mathbf{x} \mid \|\mathbf{x}\| \leq c\}$ is the ball of radius c, and $\mathcal{C}^k$ represents the space of functions for which all k-order derivatives exist and are continuous, where $c \in \mathbb{R}^+$, $\mathbf{x} \in \mathbb{R}^n$, and n and k are positive integers.

2. Problem formulation

Consider a class of nth-order strict-feedback nonlinear systems with functional uncertainties as follows:

$$\begin{cases} \dot{x}_i = f_i(\mathbf{x}_i) + x_{i+1} \ (i = 1, 2, \ldots, n-1) \\ \dot{x}_n = f_n(\mathbf{x}_n) + u \end{cases} \tag{1}$$

in which $u(t) \in \mathbb{R}$ and $x_1(t) \in \mathbb{R}$ are the control input and the controlled output, respectively, $\mathbf{x}_i(t) := [x_1(t), x_2(t), \ldots, x_i(t)]^T \in \mathbb{R}^i$ ($\mathbf{x}(t) = \mathbf{x}_n(t)$) are the measurable state vectors, $f_i(\mathbf{x}_i) : \mathbb{R}^i \mapsto \mathbb{R}$ are some unknown functions, and $i = 1, 2, \cdots, n$. Let $x_d(t) \in \mathbb{R}$ be a desired output. The following assumptions are made for the convenience of the control design (Farrell et al., 2009).

Assumption 1. $f_i(\mathbf{x}_i)$ are of $\mathcal{C}^1$ for $i = 1, 2, \cdots, n$.

Assumption 2. $x_d(t)$ and $\dot{x}_d(t)$ are continuous and of L_∞.

Let $\alpha_i(t) \in \mathbb{R}$ and $\alpha_i^c(t) \in \mathbb{R}$ with $i = 1, 2, \ldots, n-1$ be virtual control inputs and their filtered counterparts, respectively. Define tracking errors $e_i(t) := x_i(t) - \alpha_{i-1}^c(t)$ with $\alpha_0^c(t) = x_d(t)$ for $i = 1$ to n . Let $\mathbf{e}(t) := [e_1(t), e_2(t), \ldots e_n(t)]^T$, and $\mathbf{x}_d(t) := [x_d(t), \dot{x}_d(t)]^T \in \Omega_{c_d} \subset \mathbb{R}^2$, where the existence of a finite $c_d \in \mathbb{R}^+$ is guaranteed by the boundedness of x_d and $\dot{x}_d$ in Assumption 2.

According to (Farrell et al., 2009), a command-filtered backstepping control law for the system (1) is given as follows:

$$\begin{cases} \alpha_i = -k_{ci} e_i + \dot{\alpha}_{i-1}^c - f_i(\mathbf{x}_i) - v_{i-1} \\ \qquad (i = 1, 2, \ldots, n-1) \\ u = -k_{cn} e_n + \dot{\alpha}_{n-1}^c - f_n(\mathbf{x}_n) - v_{n-1} \end{cases} \tag{2}$$

with $v_0 = 0$, where for $i = 1, 2, \ldots, n$, $k_{ci} \in \mathbb{R}^+$ are control gain parameters, $v_i(t) := e_i(t) - \xi_i(t)$ are compensated tracking errors, and $\xi_i(t) \in \mathbb{R}$ are compensating signals generated by

$$\dot{\xi}_i = -k_{ci}\xi_i + \xi_{i+1} - \xi_{i-1} + \tilde{\alpha}_i \tag{3}$$

with $\tilde{\alpha}_i := \alpha_i^c - \alpha_i$ and $\xi_0 = \xi_{n+1} = \tilde{\alpha}_n = 0$. The terms α_i^c and $\dot{\alpha}_i^c$ in (2) are generated by a command filter (Farrell et al., 2009):

$$\begin{cases} \dot{z}_1 = z_2 \\ \dot{z}_2 = -2\varsigma\omega z_2 + \omega^2(\alpha_i - z_1) \end{cases} \tag{4}$$

with $z_1(0) = \alpha_i(0)$, $z_2(0) = 0$, $\alpha_i^c = z_1$ and $\dot{\alpha}_i^c = z_2$, in which $\omega \in \mathbb{R}^+$ is a natural frequency, $\varsigma \in \mathbb{R}^+$ is a damping ratio, and $i = 1, 2, \ldots, n-1$.

The stability and convergence of the system (1) driven by the control law composed of (2)–(4) have been established in Farrell et al. (2009). However, the above control law is unrealizable as $f_1(\mathbf{x}_1)$ to $f_n(\mathbf{x}_n)$ are unknown in this study. Therefore, it is necessary to use NNs for the approximation of $f_1(\mathbf{x}_1)$ to $f_n(\mathbf{x}_n)$. The objective of this study is to design a backstepping-based ANC law for the system (1) such that convergence of both tracking errors and NN weights is guaranteed under certain conditions.

3. Preliminaries

3.1. Radial-Basis-Function neural network

Let $\Omega_{c_w} \subset \mathbb{R}^N$ with $c_w \in \mathbb{R}^+$. The RBF-NN can be represented by (Farrell & Polycarpou, 2006)

$$\hat{f}(\mathbf{x}, \hat{W}) = \Phi^T(\mathbf{x})\hat{W} \tag{5}$$

in which $\hat{W} = [\hat{w}_1, \hat{w}_2, \ldots, \hat{w}_N]^T \in \Omega_{c_w}$ is an adjustable weight vector, $\Phi(\mathbf{x}) = [\phi_1(\mathbf{x}), \phi_2(\mathbf{x}), \ldots, \phi_N(\mathbf{x})]^T \in \mathbb{R}^N$ is a regressor, N is

Download English Version:

https://daneshyari.com/en/article/4946592

Download Persian Version:

https://daneshyari.com/article/4946592

Daneshyari.com