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Brief Papers

Neural network control-based adaptive design for a class of DC motor systems with the full state constraints

Rui Bai

School of Electrical Engineering, Liaoning University of Technology, Jinzhou, Liaoning 121001, China

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ABSTRACT

In the paper, an adaptive neural controller for the tracking problem of a direct-current (DC) motor is investigated. Because the unknown functions are included in the systems, the neural networks are used to estimate the unknown functions. In this study, the state variables of DC motor are required to be constrained in the compact set. The main contribution of this paper is that the proposed scheme is successfully to integrate barrier Lyapunov function to avoid the violation of the constraints. Based on Lyapunov analysis, it is proved that the output of the DC motor follows a desired trajectory and all the signals of the systems are guaranteed to be bounded. A simulation result is shown to confirm the effectiveness of the proposed scheme.

1. Introduction

In the control community, the stability of the systems with the uncertainties has received many regards. A lot of research methods were one after the other proposed, such as *T–S* fuzzy control [1,2], adaptive implementation [3], an integration of neural network [4,5], fault-tolerant control [6,7], Interval Type-2 Fuzzy [8,9], big data [10], switched nonlinear systems [40,41] and flexible system [42,43]. Specially, the intelligent control-based adaptive control of nonlinear systems with unknown functions has been a broad research field. A lot of significant works were made for multifarious nonlinear systems. For example, the adaptive control fuzzy or neural design was proposed for nonlinear multiagent time-delay systems [11], switched nonlinear systems [12], nonlinear stochastic systems [13–15], nonlinear MIMO systems [16–22,48] and nonlinear discrete-time systems [23–26,44–47]. In addition, robust adaptive controllers were designed in [27–30] for uncertain nonlinear systems. However, these adaptive control strategies do not consider the constraints of the output and the states.

In [31], the controller designs for nonlinear SISO systems in strict-feedback with an output constraint were investigated. A Barrier Lyapunov Function (BLF) is used to prevent the violation of constraint. An adaptive neural algorithm was presented in [32] for a class of output constraint nonlinear feedback systems with only output measurements based the BLF. In [33], an adaptive indirect fuzzy design was presented for a class of uncertain input and output constraint nonlinear systems. A BLF and an auxiliary system were utilized to avoid the output and input constraints. The problem of control design for nonlinear systems with constraints on the partial states was discussed in [34] and it is to prevent violating the constraints by utilizing a BLF. For nonlinear systems with the full state constraints, the authors in [35] propose an adaptive control technique to overcome the violation of the full states. However, these methods only focus on the theoretical research, and do not take some practical applications into consideration.

In the recent years, the control problem of DC motor is an important problem and many industry applications need to solve this problem. In [36], a deadzone fuzzy compensator was constructed for a DC motor with unknown function. An adaptive tuning design was given for the fuzzy parameters such that the adaptive parameter and the tracking errors are bounded. The control of DC servo system with dead-zone was considered in [37] and a robust adaptive by framing a deadzone compensation was proposed. In [38], a position sensorless control was proposed for four switch three phase brushless DC drives. The works in [36–38] do not consider the effect of the output and the state constraints. In [39], an adaptive neural control algorithm was given for a DC motor with both unknown dead-zone and output constraint. However, the full state constraints are not considered. When the full state constraints are required in the DC motor, the current methods cannot be implemented. This paper will try to solve this problem.

In this paper, an adaptive strategy for the tracking control of a DC motor system was studied. The systems contain unknown function and it is required that the full states are constrained in the corresponding compact set. The unknown function is

E-mail address: broffice@126.com

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approximated by using the neural networks and the BLFs are employed in the stability analysis for the controller and the adaptation law. The proposed control scheme is to guarantee that the tracking error can converge to a small compact set, all the signals of the systems are bounded, and the constraints are not transgressed. A simulation example is given to verify the effectiveness of the approach.

2. Problem and formulation

2.1. A. system description

Consider a DC motor without vibratory modes as follows [37]:

$$\begin{cases} \dot{\alpha}_1 = \alpha_2 \\ J\dot{\alpha}_2 + B\dot{\alpha}_1 + T_f + d(t) = T \\ y = \alpha_1 \end{cases} \tag{1}$$

where $\alpha_1(t)$ is motor angular position; J means the inertia and it is not equal to zero; B and T_f are unmeasured viscous friction and unmeasured nonlinear friction, respectively; $d(t)$ is unknown but bounded disturbance with $\|d(t)\| \le d_M$; $y \in R$ is the output; and T means the motor torque, which is related to the control input $u(t)$; the states of the systems are constrained in the compact sets $|\alpha_1| \le k_{c_1}$ and $|\alpha_2| \le k_{c_2}$.

The control objective is to design an adaptive neural control scheme such that the tracking error can converge to a small compact set of zero and all the signals in the closed-loop are bounded as well as the full state constraints are not violated.

Remark 1. In [36–39], several adaptive control algorithms for a DC motor have been studied. These methods are very effective to solve the stability of DC motor. However, a restriction is that the full state constraints are omitted in these algorithms. In this paper, the stability of DC motor with the full state constraints is studied. Then, the advantage of the proposed result is to guarantee that the full state constraints are not violated.

Because the unknown functions are included in the systems, they are not directly used in the controller. Thus, it needs to approximate them based on the neural networks. The neural approximation property is described in the following subsection.

2.2. B. The neural network approximation

Under certain conditions, it has been proven that the neural networks have function approximation abilities and have been frequently used as function approximators. In this paper, the NNS are used to approximate the unknown function $f(z)$

$$f^{NN}(z,\theta) = \theta^T \phi(z) \tag{2}$$

where $z \in R^q$ is the input variable of the neural networks with q being a positive constant, $\theta = [\theta_1, \cdots, \theta_l]^T$ is the weight vector with the NN node number l, $\phi(z)$ is the smooth basis vector to be $\phi(z) = [\phi_1(z), \cdots, \phi_l(z)]^T$ and $\phi_i(z)$ is chosen as the commonly used Gaussion functions

$$\phi_i(z) = \exp\left[\frac{-(z-\mu_i)^T(z-\mu_i)}{\tau_i^2}\right], i = 1, \cdots, l \tag{3}$$

where $\mu_i = [\mu_{i1}, \cdots, \mu_{iq}]^T$ and τ_i are the center and the width of the Gaussion functions, respectively.

For the system (1), it is necessary for the reference trajectory to satisfy the following assumption.

Assumption 1 [34,35]:. The reference trajectory $y_d(t)$ and it time derivatives $\dot{y}_d(t)$ and $\ddot{y}_d(t)$ are bounded, i.e., $|y_d(t)| \le Y_0$, $|\dot{y}_d(t)| < Y_1$ and $|\ddot{y}_d(t)| < Y_2$ where Y_0, Y_1 and Y_2 are constants.

3. Adaptive NN controller design

In this section, we extend the method to investigate state feedback adaptive control for an actual DC motor system as described in (1). The design procedure is as follows:

Step 1: Design the tracking error as $e_1 = \alpha_1 - y_d(t)$ and its time derivative is

$$\dot{e}_1 = \dot{\alpha}_1 - \dot{y}_d(t) \tag{4}$$

Based on (1), we have

$$\dot{e}_1 = \alpha_2 - \dot{y}_d(t) \tag{5}$$

By introducing $e_2 = \alpha_2 - v_1$ where v_1 is the designed virtual control to be designed later on, we have

$$\dot{e}_1 = e_2 + v_1 - \dot{y}_d(t) \tag{6}$$

Choose the following Barrier Lyapunov function candidate

$$V_1 = \frac{1}{2}\log\frac{k_{b_1}^2}{k_{b_1}^2 - e_1^2} \tag{7}$$

where $\log(\cdot)$ denotes the natural logarithm and k_{b_1} is a positive constant.

The time derivative of V_1 is

$$\dot{V}_1 = \frac{e_1\dot{e}_1}{k_{b_1}^2 - e_1^2} \tag{8}$$

Using (6) and (8) becomes

$$\dot{V}_1 = \frac{e_1[e_2 + v_1 - \dot{y}_d(t)]}{k_{b_1}^2 - e_1^2} \tag{9}$$

Choose the virtual control v_1 as

$$v_1 = -k_1\left(k_{b_1}^2 - e_1^2\right)e_1 + \dot{y}_d \tag{10}$$

Then, one has

$$\dot{V}_1 = -k_1 e_1^2 + \frac{e_1 e_2}{k_{b_1}^2 - e_1^2} \tag{11}$$

where $e_1 e_2 / k_{b_1}^2 - e_1^2$ will be canceled in the following step.

Step 2: In the second step, the actual control input will be described. The time derivative of the error variable $e_2 = \alpha_2 - v_1$ is

$$\dot{e}_2 = \dot{\alpha}_2 - \dot{v}_1 \tag{12}$$

where

$$\dot{v}_1 = \frac{\partial v_1}{\partial \alpha_1}\dot{\alpha}_1 + \frac{\partial v_1}{\partial y_d}\dot{y}_d + \frac{\partial v_1}{\partial \dot{y}_d}\ddot{y}_d.$$

From (1), we obtain

$$\dot{e}_2 = [u - T_f - d(t) - B\alpha_2]/J - \dot{v}_1 \tag{13}$$

When $d(t) = 0$, design a desired control input as

$$u^* = -k_2 J e_2 - T_f - B\alpha_2 + J\dot{v}_1 \tag{14}$$

Because the parameters T_f and B are not available, u^* cannot be implemented in practice. To solve this problem, the neural networks are used to approximate the unknown part of u^* as

$$M(z) = \theta^{*T}\phi(z) + \varepsilon(z) \tag{15}$$

where $M(z) = (T_f + B\alpha_2)/J + \dot{v}_1$ and $z = [\alpha_1, \alpha_2, y_d, \dot{y}_d]^T$.

By substituting (15) into (13), we have

$$\dot{e}_2 = u/J - \theta^{*T}\phi(z) - d(t)/J \tag{16}$$

Choose the following Barrier Lyapunov function candidate

$$V_2 = V_1 + \frac{1}{2}\log\frac{k_{b_2}^2}{k_{b_2}^2 - e_2^2} + \frac{1}{2}\tilde{\theta}^T\tilde{\theta} \tag{17}$$

where $\tilde{\theta} = \hat{\theta} - \theta^*$ and $\hat{\theta}$ is the estimation of θ^*.