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Neural network-based discrete-time command filtered adaptive position tracking control for induction motors via backstepping

Zhencheng Zhou, Jinpeng Yu*, Haisheng Yu, Chong Lin

College of Automation and Electrical Engineering, Qingdao University, Qingdao, Shandong 266071, China

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ABSTRACT

Considering the problems of parameter uncertainties and load disturbance appeared in induction motor drive systems, a discrete-time command filtered adaptive position tracking control method based on neural networks is proposed in this paper. First, Euler method is used to describe the discrete-time dynamic mathematical model of induction motors (IMs). Next, the neural networks technique is employed to approximate the unknown nonlinear functions. Furthermore, the "explosion of complexity" problem and noncausal problem, which emerged in traditional backstepping design, are eliminated by command filtered control technique. Simulation results prove that tracking error converges to a small neighborhood of the origin and the effectiveness of the proposed approach is illustrated.

1. Introduction

In recent years, induction motors (IMs) have been intensively used in industrial applications for their advantages as low maintenance, high performances and ruggedness, which has inspired many scholars for the study of the high-performance motion controller. However, because the dynamic model of induction motor is generally coupled, multivariable and highly nonlinear, getting the perfect dynamic performance is very difficult. What's more, it can be easily influenced by parameter variations and external load disturbances. To solve the above problems, many control methods have been proposed for IMs, such as dynamic surface control [1,2] Hamiltonian control [3], sliding mode control [4–6] backstepping [7–9], fuzzy logic control [10–13], and some other control methods [14–16]. Unfortunately, all these methods mentioned above were designed for continuous-time IM drive systems. And the design techniques of discrete-time control for IM were seldom mentioned. Considering stability and achievable performances of methods, the discrete-time control systems are generally regarded as superior to continuous-time control systems [14].

The backstepping control is considered to be one of the most popular techniques for controlling the nonlinear systems with linear parametric uncertainty. However, during the backstepping design procedure, the "explosion of complexity" problem [17] and noncausal problem [18–20] arise. Recently, one method to overcome the noncausal problem in [21] is that transforming the system equation into a special form, but it will make the controller more complex. And several new techniques are proposed to solve this problem of "explosion of complexity" inherent in traditional backstepping such as dynamic surface control (DSC) [22–24] and command filtered backstepping control [25,26]. A novel adaptive fuzzy control combined DSC technology proposed in [27] eliminates the "explosion of complexity" problem by introducing first-order filters for the backstepping approach which will produce the filtering error. In order to resolve this issue, a command filtered backstepping control method is proposed by introducing a second-order filtering of the virtual input at each step in the conventional backstepping approach. Though "explosion of complexity" problem and noncausal problem can be got over by the command filter technique, the command filter technique has not been applied to nonlinear discrete-time systems with unknown parameters.

In another research front line, many adaptive control methods are proposed in [28–31] to solve the uncertain nonlinear functions. The adaptive control methods via approximation theories are presented to cope with the nonlinear systems with parametric uncertainty based on fuzzy logic system (FLS) [32] or neural networks (NNs) [33–35] approximation. The uncertain information can be approximated by NNs, which can be employed to control ill-defined or complex systems. And the RBF NN is widely used to approximate the uncertain nonlinearities [36–39].

Compared with the existing achievements, the main merits of the developed scheme can be summed up as follows: 1) The

* Corresponding author.
E-mail address: yjp1109@hotmail.com (J. Yu).

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neural network command filtered backstepping control can solve the problem of “explosion of complexity” to alleviate the online calculational burden; 2) the noncausal problem can be got over by command filtering technique without transforming the system model into a predictor form; 3) the command filtered method can overcome the drawback of traditional method and gain a smaller overshoots. From the above facts, a discrete-time command filtered adaptive control method is developed for position tracking of IMs based on neural network. And the simulation results are provided to illustrate the effectiveness and robustness against the parameter uncertainties and load disturbances.

2. Mathematical model of the IM drive system

Induction motor’s dynamic mathematical model is described in the well known $(d-q)$ frame as:

$$\begin{cases} \frac{d\Theta}{dt} = \omega, \\ \frac{d\omega}{dt} = \frac{n_p L_m}{L_r J}\psi_d i_q - \frac{T_L}{J}, \\ \frac{di_q}{dt} = -\frac{L_m^2 R_r + L_r^2 R_s}{\sigma L_s L_r^2} i_q - \frac{L_m n_p}{\sigma L_s L_r}\omega\psi_d - n_p\omega i_d - \frac{L_m R_r}{L_r}\frac{i_q i_d}{\psi_d} + \frac{1}{\sigma L_s}u_q, \\ \frac{d\psi_d}{dt} = -\frac{R_r}{L_r}\psi_d + \frac{L_m R_r}{L_r} i_d, \\ \frac{di_d}{dt} = -\frac{L_m^2 R_r + L_r^2 R_s}{\sigma L_s L_r^2} i_d + \frac{L_m R_r}{\sigma L_s L_r^2}\psi_d + n_p\omega i_q + \frac{L_m R_r}{L_r}\frac{i_q^2}{\psi_d} + \frac{1}{\sigma L_s}u_d, \end{cases}$$

where $\sigma = 1 - \frac{L_m^2}{L_s L_r}$. n_p, T_L, J, L_m, ω, Θ and ψ_d represent the mutual inductance, load torque, inertia, pole pairs, rotor angular velocity, rotor position and rotor flux linkage. i_d and i_q stand for the $d-q$ axis currents. u_d and u_q are the $d-q$ axis voltages. L_s and R_s mean the inductance, resistance of the stator. R_r and L_r denote the resistance, inductance of the rotor.

By using the Euler method, the induction motor drivers’ dynamic model can be written as:

$$\begin{aligned} x_1(k+1) &= x_1(k) + \Delta_t x_2(k), \\ x_2(k+1) &= x_2(k) + a_1\Delta_t x_3(k)x_4(k) - a_2\Delta_t T_L, \\ x_3(k+1) &= (1 + b_1\Delta_t)x_3(k) + b_2\Delta_t x_2(k)x_4(k) \\ &\quad - b_3\Delta_t x_2(k)x_5(k) - b_4\Delta_t\frac{x_3(k)x_5(k)}{x_4(k)} + u_q(k)b_5\Delta_t, \\ x_4(k+1) &= b_4\Delta_t x_5(k) + x_4(k)(1 + c_1\Delta_t), \\ x_5(k+1) &= (1 + b_1\Delta_t)x_5(k) + c_2\Delta_t x_4(k) + b_4\Delta_t\frac{x_3^2(k)}{x_4(k)} \\ &\quad + b_3\Delta_t x_2(k)x_3(k) + u_d(k)b_5\Delta_t, \end{aligned} \tag{1}$$

where Δ_t is the sampling period and

$$\begin{aligned} & x_1(k) = \Theta(k), x_2(k) = \omega(k), x_3(k) = i_q(k), \\ & x_4(k) = \psi_d(k), x_5(k) = i_d(k), \\ & a_1 = \frac{n_p L_m}{L_r J}, a_2 = \frac{1}{J}, b_1 = -\frac{L_m^2 R_r + L_r^2 R_s}{\sigma L_s L_r^2}, \\ & b_2 = -\frac{L_m n_p}{\sigma L_s L_r}, b_3 = n_p, b_4 = \frac{L_m R_r}{L_r}, \\ & b_5 = \frac{1}{\sigma L_s}, c_1 = -\frac{R_r}{L_r}, c_2 = \frac{L_m R_r}{\sigma L_s L_r^2}. \end{aligned} \tag{2}$$

Lemma 1 ([11]). The command filter is defined as

$$z_1(k+1) = \omega_n z_2(k)\Delta_t + z_1(k)$$
$$z_2(k+1) = \{-2\zeta\omega_n z_2(k) - \omega_n(z_1(k) - \alpha_1(k))\}\Delta_t + z_2(k)$$

the input signal $\alpha_1(k)$ satisfies $|\alpha_1(k+1) - \alpha_1(k)| \le \rho_1$, $|\alpha_1(k+2) - 2\alpha_1(k+1) + \alpha_1(k)| \le \rho_2$ for all $k \ge 0$, where ρ_1, ρ_2 are positive constants. And $z_1(0) = \alpha_1(0), z_2(0) = 0$, then for any $\mu > 0$, there exist $\zeta \in (0, 1]$, and $\omega_n > 0$, so we have $|z_1(k) - \alpha_1(k)| \le \mu$ and $\Delta z_1(k) = |z_1(k+1) - z_1(k)|$ is bounded.

The block diagram of the discrete-time neural network command filtered controller for induction motor control system is shown as Fig. 1. In this paper, the RBF NNs [21] are employed to approximate the continuous function $\varphi(z)$: $R^q \to R$ as $\hat{\varphi}(z) = \phi^{*T}P(z)$, where $z \in \Omega_z \subset R^q$ is the input variable of the NNs and q is the input dimension, $\phi^* = [\Phi_1^*, \ldots, \Phi_l^*]^T$, is the weight vector with l being the NN node number. The define of NN and parameters are shown in [21]. From [21], we know $||P_i(z_i(k))||^2 \le l_i$, $(i = 1, \ldots, n)$.

3. Discrete-time command filtered neural network controller design

In this section, the discrete-time controllers are designed for the IM drive system with backstepping. At each step, one commend filter is needed to filter the virtual control. For $i = 1, 2, 4$, the commend filter is defined as:

$$z_{i,1}(k+1) = \omega_n z_{i,2}(k)\Delta_t + z_{i,1}(k) \tag{3}$$

$$z_{i,2}(k+1) = \{-2\zeta\omega_n z_{i,2}(k) - \omega_n(z_{i,1}(k) - \alpha_i(k))\}\Delta_t + z_{i,2}(k) \tag{4}$$

where $\alpha_i(k)$ is the input and $z_{i,1}(k)$ is the output of the filter. The initial condition of the filter is $z_{i,1}(0) = \alpha_i(0)$, and $z_{i,2}(0) = 0$.

Step 1: The tracking error variable is defined as $e_1(k) = x_1(k) - x_{1d}(k)$ with the desired signal $x_{1d}(k)$. According to Eq. (1), we can obtain $e_1(k+1) = \Delta_t x_2(k) + x_1(k) - x_{1d}(k+1)$. Define the Lyapunov function as $V_1(k) = \frac{1}{2}e_1^2(k)$, and the difference of $V_1(k)$ can be written as

$$\Delta V_1(k) = -\frac{1}{2}e_1^2(k) + \frac{1}{2}[x_1(k) + \Delta_t x_2(k) - x_{1d}(k+1)]^2$$

The virtual control law $\alpha_1(k)$ is chosen as

$$\alpha_1(k) = \frac{-x_1(k) + x_{1d}(k+1)}{\Delta_t} \tag{5}$$

Define $e_2(k) = x_2(k) - x_{1c}(k)$, where $x_{ic}(k) = z_{i,1}(k)$, $(i = 1, 2, 4)$ as the outputs of command filters. By using (5), $\Delta V_1(k)$ can be given as

$$\Delta V_1(k) = \frac{1}{2}[e_2(k) + x_{1c}(k) - \alpha_1(k)]^2\Delta_t^2 - \frac{1}{2}e_1^2(k)$$

Step 2: By use of Eq. (1), $e_2(k+1)$ is obtained as $e_2(k+1) = a_1\Delta_t x_3(k)x_4(k) + x_2(k) - a_2\Delta_t T_L - x_{1c}(k+1)$. Define the Lyapunov function as $V_2(k) = V_1(k) + \frac{1}{2}e_2^2(k)$. Furthermore, differencing $V_2(k)$ yields

$$\begin{aligned} \Delta V_2(k) &= -\frac{1}{2}e_1^2(k) + \frac{1}{2}[x_2(k) + a_1\Delta_t x_3(k)x_4(k) \\ &\quad - a_2\Delta_t T_L - x_{1c}(k+1)]^2 + \Delta V_1(k) \end{aligned}$$

In this paper, due to the parameter T_L being bounded in practice system, we assume the T_L is unknown, but its upper bound is $d > 0$. Namely, $|T_L| \le d$, and we have $-a_2\Delta_t T_L \le \frac{a_2^2\Delta_t^2}{2} + \frac{d^2}{2}$. The virtual control law $\alpha_2(k)$ is constructed as

$$\alpha_2(k) = \frac{-x_2(k) + x_{1c}(k+1) - \frac{a_2^2\Delta_t^2}{2} - \frac{d^2}{2}}{a_1\Delta_t x_4(k)} \tag{6}$$

where $x_{1c}(k+1)$ can be calculated by (3).

Remark 1. It can be seen that the virtual controller $\alpha_2(k)$ contains variable $x_{1c}(k+1)$, which covers future information. And the