*ICIC Express Letters*
Volume **11**, Number **1**, January **2017**

ICIC International ©2017 ISSN 1881-803X
pp. 231–237

# FUZZY APPROXIMATION-BASED ADAPTIVE DISCRETE-TIME DYNAMIC SURFACE CONTROL FOR INDUCTION MOTORS

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Received June 2016; accepted September 2016

Abstract. *Considering the problems of parameter uncertainties and load disturbance appearing in induction motor drive systems, a discrete-time speed regulation control method is proposed in this paper. First, Euler method is used to describe the discrete-time model of IMs. Next, fuzzy approximation technique is employed to approximate the unknown nonlinear functions. Furthermore, the problem of explosion of complexity emerged in traditional backstepping design is eliminated by dynamic surface control technique. Finally, simulation results prove that tracking error can converge to a small area of the origin and illustrate the effectiveness of the proposed approach.*

**Keywords:** Discrete-time, Induction motor, Dynamic surface control, Backstepping, Fuzzy approximation

1. **Introduction.** Induction motors (IMs) are intensively used in industrial applications because of their low maintenance, high performances and ruggedness, which stimulate research in advanced motion control to achieve high performance. However, it is still a challenging problem to control IMs to get the perfect dynamic performance owing to that its dynamic model is usually multivariable, coupled and highly nonlinear. What is 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 sliding mode control [1], Hamiltonian control [2], dynamic surface control [3], backstepping [4] and some other control methods [5, 6]. Unfortunately, all those methods mentioned above were developed for continuous-time IM drive systems and implemented on digital devices. Nonlinear discrete-time control design techniques for IM drive system were seldom discussed. The discrete-time control system is regarded as typically superior to the continuous-time control system in terms of stability and achievable performances [7].

The backstepping control is considered to be one of the popular techniques for controlling the nonlinear systems with linear parametric uncertainty. However, during the backstepping design procedure, the problem of "explosion of complexity" arises. To overcome this issue, a dynamic surface control (DSC) method was proposed by introducing a first-order filtering of the virtual input at each step of the conventional backstepping approach. However, the DSC technique has not been applied to nonlinear discrete-time systems with unknown parameters. Recently, fuzzy-approximation [8] method has attracted great attention in induction motor drive systems because of its inherent capability for modeling and controlling highly uncertain, nonlinear and complex systems.

From the above observations, the adaptive fuzzy DSC control method is proposed to speed regulation for IMs based on discrete-time technique in this paper. The simulation results are provided to demonstrate the effectiveness of the proposed discrete-time adaptive speed tracking control method.

The rest of the paper is organized as follows. Section 2 describes the mathematical model of IM drive system. The dynamic surface adaptive backstepping control is designed in Section 3. Section 4 shows stability analysis. In Section 5, the simulation results are given. Finally, some conclusions are presented.

2. **Mathematical Model of the IM Drive System.** Induction motor's dynamic mathematical model can be described in the well known ($d$-$q$) frame as follows [9]:

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

where $\sigma = 1 - \frac{L_m^2}{L_s L_r}$. $\omega$, $L_m$, $n_p$, $J$, $T_L$ and $\psi_d$ denote the rotor angular velocity, mutual inductance, pole pairs, inertia, load torque and rotor flux linkage, respectively. $i_d$ and $i_q$ stand for the $d$-$q$ axis currents. $u_d$ and $u_q$ are the $d$-$q$ axis voltages. $R_s$ and $L_s$ mean the resistance, inductance of the stator. $R_r$ and $L_r$ denote the resistance, inductance of the rotor. By using the Euler method, the dynamic model of IM drivers can be described by the following equations:

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

where $\Delta_t$ is the sampling period and

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

The control objective is to design an adaptive fuzzy controller such that the state variable $x_i(k)$ ($i = 1, 2, 3, 4$) follows the given reference signal $x_{id}(k)$ and all the closed-loop signals are bounded. The approximation property of the fuzzy logic systems (FLSs) can be found in [2]. By using the FLSs, given a compact set $z = [z_1, z_2, \ldots, z_n] \in \Omega_z$, the unknown smooth function $\varphi(z)$ can be expressed as $\varphi(z) = W^T S(z) + \varepsilon(z)$, where $W \in R^N$ is the optimal parameter vector, $S(z) = \left[s^1(z), s^2(z), \ldots, s^N(z)\right]^T$ is a fuzzy basis function vector with $s^l(z) = \Pi_{i=1}^n \mu_{\phi_i^l}(z_i) / \Sigma_{l=1}^N \Pi_{i=1}^n \mu_{\phi_i^l}(z_i)$, and then $S(z)$ has the following properties: $\lambda_{\max}\left[S(z)S^T(z)\right] < 1$. And $\varepsilon(z) \in R$ is the approximation error satisfying $|\varepsilon(z)| \leq \bar{\varepsilon}$ with the constant $\bar{\varepsilon} > 0$. $\mu_{\phi_i^l}(z_i)$ is the fuzzy membership function and $\phi_i^l$ is fuzzy sets in $R$.

3. **Adaptive Fuzzy Controller Design with Backstepping.** In this section, we will design the controllers for the approximate discrete-time IM drive system via backstepping.

**Step 1:** For the reference signal $x_{1d}$, define the tracking error variable as $e_1(k) = x_1(k) - x_{1d}(k)$. From the first equation of (1), we can obtain $e_1(k+1) = x_1(k) + a_1\Delta_t x_2(k)x_3(k) - a_2\Delta_t T_L - x_{1d}(k+1)$. Choose the Lyapunov function candidate as $V_1(k) = \frac{1}{2}e_1^2(k)$, and then the difference of $V_1(k)$ is computed by $\Delta V_1(k) = \frac{1}{2}\big[x_1(k) + a_1\Delta_t x_2(k)x_3(k) - a_2\Delta_t T_L - x_{1d}(k+1)\big]^2 - \frac{1}{2}e_1^2(k)$. Construct the virtual control law $\alpha_1(k)$ as

$$\alpha_1(k) = \frac{[-x_1(k) + x_{1d}(k+1) + a_2\Delta_t T_L]}{a_1\Delta_t x_3(k)} \tag{3}$$

$$\varsigma_1\left[\alpha_{1d}(k+1) - \alpha_{1d}(k)\right] + \Delta_t\alpha_{1d}(k) = \Delta_t\alpha_1(k), \quad \alpha_{1d}(0) = \alpha_1(0) \tag{4}$$

Define $e_2(k) = x_2(k) - \alpha_{1d}(k)$. By using (3), $\Delta V_1(k)$ can be rewritten as

$$\Delta V_1(k) = \frac{1}{2}a_1^2\Delta_t^2\left[e_2(k) + \alpha_{1d}(k) - \alpha_1(k)\right]^2 x_3^2(k) - \frac{1}{2}e_1^2(k) \tag{5}$$

**Step 2:** From the second equation of (1), we can obtain $e_2(k+1) = f_2(k) + b_5\Delta_t u_q(k)$, where $f_2(k) = (1+b_1\Delta_t)x_2(k) + b_2\Delta_t x_1(k)x_3(k) - b_3\Delta_t x_1(k)x_4(k) - b_4\Delta_t\frac{x_2(k)x_4(k)}{x_3(k)} - \alpha_{1d}(k+1)$. Choose the Lyapunov function candidate as $V_2(k) = \frac{1}{2}e_2^2(k) + V_1(k)$. Furthermore, differencing $V_2(k)$ yields

$$\Delta V_2(k) = \frac{1}{2}[f_2(k) + b_5\Delta_t u_q(k)]^2 - \frac{1}{2}e_2^2(k) + \Delta V_1(k) \tag{6}$$

By using the approximation property of the FLS, for any given $\varepsilon_2 > 0$, there exists a fuzzy logic system $W_2^T S_2(z_2(k))$ such that $f_2(k) = W_2^T S_2(z_2(k)) + \varepsilon_2$ where $\varepsilon_2$ is the approximation error. At this present stage, choose the following control law $u_q(k)$ and adaptive law $\hat{\eta}_2(k+1)$ as

$$u_q(k) = -\frac{1}{b_5\Delta_t}\hat{\eta}_2(k)\|S_2(z_2(k))\| \tag{7}$$

$$\hat{\eta}_2(k+1) = \hat{\eta}_2(k) + \gamma_2\|S_2(z_2(k))\|e_2(k+1) - \delta_2\hat{\eta}_2(k) \tag{8}$$

where $\gamma_2$ and $\delta_2$ are positive paramenters. In general, $W_2$ is bounded and unknown and let $\|W_2\| = \eta_2$ where $\eta_2 > 0$ is unknown constant. Let $\hat{\eta}_2(k)$ estimate $\eta_2$ and the estimate error is $\tilde{\eta}_2(k) = \eta_2 - \hat{\eta}_2(k)$.

By using Equality (7), we can obtain

$$\begin{aligned}\Delta V_2(k) \le{}& 4\eta_2^2\|S_2(z_2(k))\|^2 + \tilde{\eta}_2^2(k)\|S_2(z_2(k))\|^2 - \frac{1}{2}e_2^2(k)\\ &+ \frac{1}{2}a_1^2\Delta_t^2 x_3^2(k)\left[e_2(k) + \alpha_{1d}(k) - \alpha_1(k)\right]^2 - \frac{1}{2}e_1^2(k) + \varepsilon^2\end{aligned} \tag{9}$$

**Step 3:** For the reference signal $x_{3d}$, define the tracking error variable as $e_3(k) = x_3(k) - x_{3d}(k)$. From the third equation of (1), we can obtain $e_3(k+1) = (1 + c_1\Delta_t)x_3(k) + b_4\Delta_t x_4(k) - x_{3d}(k+1)$. Choose the Lyapunov function candidate as $V_3(k) = \frac{1}{2}e_3^2(k) + V_2(k)$. Furthermore, differencing $V_3(k)$ yields

$$\Delta V_3(k) = \frac{1}{2}\left[(1 + c_1\Delta_t)x_3(k) - x_{3d}(k+1) + b_4\Delta_t x_4(k)\right]^2 - \frac{1}{2}e_3^2(k) + \Delta V_2(k)$$

Construct the virtual control law $\alpha_2(k)$ as

$$\alpha_2(k) = \frac{1}{b_4\Delta_t}\left[-(1 + c_1\Delta_t)x_3(k) + x_{3d}(k+1)\right] \tag{10}$$

$$\varsigma_2\left[\alpha_{2d}(k+1) - \alpha_{2d}(k)\right] + \Delta_t\alpha_{2d}(k) = \Delta_t\alpha_2(k), \quad \alpha_{2d}(0) = \alpha_2(0)$$

Using (8), $\Delta V_3(k)$ can be rewritten as:

$$\Delta V_3(k) \le \tilde{\eta}_2^2(k)||S_2(z_2(k))||^2 + 4\eta_2^2(k)||S_2(z_2(k))||^2$$

$$+\frac{1}{2}b_4^2\Delta_t^2\left[e_4(k)+\alpha_{2d}(k)-\alpha_2(k)\right]^2-\frac{1}{2}e_3^2(k)-\frac{1}{2}e_2^2(k)$$
$$+\frac{1}{2}a_1^2\Delta_t^2x_3^2(k)\left[e_2(k)+\alpha_{1d}(k)-\alpha_1(k)\right]^2-\frac{1}{2}e_1^2(k)+\varepsilon_2^2 \quad (11)$$

with $e_4(k)=x_4(k)-\alpha_2(k)$.

**Step 4:** From the fourth equation of (1), we have $e_4(k+1)=f_4(k)+b_5\Delta_t u_d(k)$, where $f_4(k)=(1+b_1\Delta_t)x_4(k)+c_2\Delta_t x_3(k)+b_3\Delta_t x_1(k)x_2(k)+b_4\Delta_t\frac{x_2^2(k)}{x_3(k)}-\alpha_{2d}(k+1)$. Choose the Lyapunov function candidate as $V_4(k)=\frac{P}{2}e_4^2(k)+V_3(k)$ with $P>0$, and then the difference of $V_4(k)$ is computed by

$$\Delta V_4(k)=\frac{P}{2}\left[f_4(k)+b_5\Delta_t u_d(k)\right]^2-\frac{P}{2}e_4^2(k)+\Delta V_3(k) \quad (12)$$

Similarly, the fuzzy logic system $W_4^TS_4(z_4(k))$ is utilized to approximate the nonlinear function $f_4(k)$ such that for given $\varepsilon_4>0$, $f_4(k)=W_4^TS_4(z_4(k))+\varepsilon_4$. Now choose the following control law $u_d(k)$ and adaptive law $\hat{\eta}_4(k+1)$ as

$$u_d(k)=-\frac{1}{b_5\Delta_t}\hat{\eta}_4(k)\left\|S_4(z_4(k))\right\| \quad (13)$$

$$\hat{\eta}_4(k+1)=\hat{\eta}_4(k)+\gamma_4\left\|S_4(z_4(k))\right\|e_4(k+1)-\delta_4\hat{\eta}_4(k) \quad (14)$$

where $\gamma_4$ and $\delta_4$ are positive paramenters. In general, $W_4$ is bounded and unknown and let $\|W_4\|=\eta_4$, where $\eta_4>0$ is an unknown constant. Let $\hat{\eta}_4(k)$ estimate $\eta_4$ and we have $\tilde{\eta}_4(k)=\eta_4-\hat{\eta}_4(k)$. Substituting (13) into (12) results in

$$\Delta V_4(k)\le 4P\eta_4^2(k)\|S_4(z_4(k))\|^2+p\tilde{\eta}_4^2(k)\|S_4(z_4(k))\|^2-\frac{1}{2}Pe_4^2(k)+P\varepsilon_4^2-\frac{1}{2}e_2^2(k)$$
$$+\frac{1}{2}b_4^2\Delta_t^2\left[e_4(k)+\alpha_{2d}(k)-\alpha_2(k)\right]^2+\frac{1}{2}a_1^2\Delta_t^2x_3^2(k)\left[e_2(k)+\alpha_{1d}(k)-\alpha_1(k)\right]^2$$
$$-\frac{1}{2}e_1^2(k)+4\eta_2^2(k)\left\|S_2\left(z_2\left(k\right)\right)\right\|^2+\tilde{\eta}_2^2(k)\left\|S_2\left(z_2\left(k\right)\right)\right\|^2+\varepsilon_2^2-\frac{1}{2}e_3^2(k) \quad (15)$$

4. **Stability Analysis.** To address the stability of the closed-loop system, choose the Lyapunov function candidate as $V(k)=V_4(k)+\frac{1}{2}y_1^2(k)+\frac{1}{2}y_2^2(k)+\frac{1}{2\gamma_2}\tilde{\eta}_2^2(k)+\frac{P}{2\gamma_4}\tilde{\eta}_4^2(k)$, where $y_i(k)=\alpha_{id}(k)-\alpha_i(k)$ and $\gamma_3$, $\gamma_4$, $P$ are positive paramenters. Furthermore, differencing $V(k)$ yields

$$\Delta V(k)=\Delta V_4(k)+\frac{1}{2\gamma_2}\left[\tilde{\eta}_2^2(k+1)-\tilde{\eta}_2^2(k)\right]+\frac{P}{2\gamma_4}\left[\tilde{\eta}_4^2(k+1)-\tilde{\eta}_4^2(k)\right]$$
$$+\frac{1}{2}\left[y_1^2(k+1)-y_1^2(k)\right]+\frac{1}{2}\left[y_2^2(k+1)-y_2^2(k)\right] \quad (16)$$

By using (4), we can obtain

$$y_i(k+1)=\left(-\frac{\Delta_t}{\varsigma_i}+1\right)y_i(k)+\kappa_i(k),\quad (i=1,2)$$

$$y_i^2(k+1)-y_i^2(k)\le\left(\frac{\Delta_t^2}{\varsigma_i^2}-\frac{3\Delta_t}{\varsigma_i}+1\right)y_i^2(k)+\left(2-\frac{\Delta_t}{\varsigma_i}\right)\kappa_i^2(k),\quad (i=1,2)$$

where $\kappa_i(k)=\alpha_i(k)-\alpha_i(k+1)$. As defined before, it can be computed that

$$\tilde{\eta}_i^2(k+1)-\tilde{\eta}_i^2(k)=\eta_i^2+\hat{\eta}_i^2(k+1)-2\eta_i\hat{\eta}_i(k+1)-\tilde{\eta}_i^2(k) \quad (17)$$

$$\hat{\eta}_i^2(k+1)=\gamma_i^2e_i^2(k+1)\left\|S_i(z_i(k))\right\|^2+\left(1-\delta_i\right)^2\hat{\eta}_i^2(k)$$
$$+2(1-\delta_i)\gamma_i\left\|S_i(z_i(k))\right\|e_i(k+1)\hat{\eta}_i(k) \quad (18)$$

Replacing (18) into (17) yields

$$\tilde{\eta}_i^2(k+1)-\tilde{\eta}_i^2(k)=\eta_i^2+(1-\delta_i)^2\hat{\eta}_i^2(k)+\gamma_i^2e_i^2(k+1)\|S_i(z_i(k))\|^2$$

$$-2(1-\delta_i)\eta_i\hat{\eta}_i(k)+2(1-\delta_i)\gamma_i\|S_i(z_i(k))\|e_i(k+1)\hat{\eta}_i(k)-\tilde{\eta}_i^2(k)-2\gamma_i\|S_i(z_i(k))\|e_i(k+1)\eta_i \tag{19}$$

Then, with $\|S_i(z_i(k))\|^2 \le 1$ and according to the Young's inequality [6], we have

$$\begin{aligned}\tilde{\eta}_i^2(k+1)-\tilde{\eta}_i^2(k) \le\ & \left(16\gamma_i^2-8\gamma_i^2\delta_i+9\gamma_i-\delta_i+2\right)\eta_i^2+\left(\delta_i^2-4\delta_i+3\right)\hat{\eta}_i^2(k)\\ &+\left(4\gamma_i^2-2\gamma_i^2\delta_i+2\gamma_i-1\right)\tilde{\eta}_i^2(k)\\ &+\left(4\gamma_i^2-2\gamma_i^2\delta_i+2\gamma_i\right)\varepsilon_i^2, \quad (i=2,4)\end{aligned} \tag{20}$$

Define $x_3^2(k) \le M$, where $M$ is a positive constant. Substituting (20) and (15) into (16), one has

$$\begin{aligned}\Delta V \le\ & -\frac{P}{2}e_4^2(k)+b_4^2\Delta_t^2e_4^2(k)+b_4^2\Delta_t^2y_2^2(k)-\frac{1}{2}e_3^2(k)-\frac{1}{2}e_2^2(k)-\frac{1}{2}e_1^2(k)\\ &-\frac{1}{2}\left[\left(-\frac{\Delta_t^2}{\varsigma_1^2}+\frac{3\Delta_t}{\varsigma_1}-1\right)y_1^2(k)+\left(\frac{\Delta_t}{\varsigma_1}-2\right)\kappa_1^2(k)\right]+a_1^2\Delta_t^2Me_2^2(k)\\ &-\frac{1}{2}\left[\left(-\frac{\Delta_t^2}{\varsigma_2^2}+\frac{3\Delta_t}{\varsigma_2}-1\right)y_2^2(k)+\left(\frac{\Delta_t}{\varsigma_2}-2\right)\kappa_2^2(k)\right]+a_1^2\Delta_t^2My_1^2(k)\\ &+\frac{1}{2\gamma_2}\left[\left(\delta_2^2-4\delta_2+3\right)\hat{\eta}_2^2(k)+\beta_2+\left(4\gamma_2^2-2\gamma_2^2\delta_2+4\gamma_2-1\right)\tilde{\eta}_2^2(k)\right]\\ &+\frac{P}{2\gamma_4}\left[\left(\delta_4^2-4\delta_4+3\right)\hat{\eta}_4^2(k)+\beta_4+\left(4\gamma_4^2-2\gamma_4^2\delta_4+4\gamma_4-1\right)\tilde{\eta}_4^2(k)\right]\end{aligned}$$

$$\beta_i=\left(4\gamma_i^2-2\gamma_i^2\delta_i+4\gamma_i\right)\varepsilon_i^2+\left(16\gamma_i^2-8\gamma_i^2\delta_i+17\gamma_i-\delta_i+2\right)\eta_i^2, \quad (i=2,4)$$

By choosing a suitable parameter $P$ and sampling period $\Delta_t$, we can get $\frac{P}{2}-b_4^2\Delta_t^2>0$, $\frac{1}{2}-a_1^2\Delta_t^2M>0$, $\frac{\Delta_t}{\varsigma_1}-2>0$. $2b_4^2\Delta_t^2+\frac{\Delta_t^2}{\varsigma_2^2}-\frac{3\Delta_t}{\varsigma_2}+1<0$, $2a_1^2\Delta_t^2M+\frac{\Delta_t^2}{\varsigma_1^2}-\frac{3\Delta_t}{\varsigma_1}+1<0$. If we choose the design parameters as follows: $\delta_i^2-4\delta_i+3<0$, $4\gamma_i^2-2\gamma_i^2\delta_i+4\gamma_i-1<0$, for $i=2,4$, then $\Delta V(k)\le 0$ once the error $|e_4(k)|>\sqrt{\frac{P\beta_4}{-2\gamma_4b_4^2\Delta_t^2+P\gamma_4}}$ and $|e_2(k)|>\sqrt{\frac{\beta_2}{\gamma_2-2\gamma_2a_1^2\Delta_t^2M}}$. $\lim\limits_{k\to\infty}\|x_1(k)-x_d(k)\|\le\sigma$ where $\sigma$ is a small positive constant.

## 5. **Simulation Results.**

To illustrate the effectiveness of the proposed control approach, the simulation is run for IM with the parameters: $J=0.0586\text{Kg}\cdot\text{m}^2$, $R_s=0.1\Omega$, $R_r=0.15\Omega$, $L_s=L_r=0.0699\text{H}$, $L_m=0.068\text{H}$, $n_p=1$. The reference signal is chosen as $x_{1d}(k)=2\cos(\Delta_t k\pi/2)$ with the load torque being $T_L=\begin{cases}0.5, & 0\le k\le 2000\\ 1.0, & k\ge 2000\end{cases}$. The sampling period is chosen as $\Delta_t=0.0025\text{s}$ considering the system efficiency and control performance. The values of the control parameters are selected as $\delta_2=0.87$, $\delta_4=0.0021$, $\varsigma_1=0.0025$, $\varsigma_2=0.002$, $\gamma_2=0.98$ and $\gamma_4=0.25$.

Simulation results in Figures 1-4 are obtained by using the proposed scheme. The trajectories of $x_1(k)$ and $x_{1d}(k)$ are given in Figure 1, in which the solid line represents $x_1(k)$, the dashed line represents $x_{1d}(k)$. It can be observed that the system output can track the desired reference signal well. The dynamics of the tracking error is shown in Figure 2 and it can be seen that the tracking error converges to a small neighborhood of the origin. The trajectories of $u_q(k)$ and $u_d(k)$ are shown in Figure 3 and Figure 4. From Figures 3 and 4, we can seen that $u_d(k)$ and $u_q(k)$ are bounded into a certain area. The controllers can guarantee the robustness against the system parameter variations and load disturbances. In this simulation, it should be remarked that when the load torque changes, the controllers can cope with the sudden change of the load torque and provide a fast tracking response.

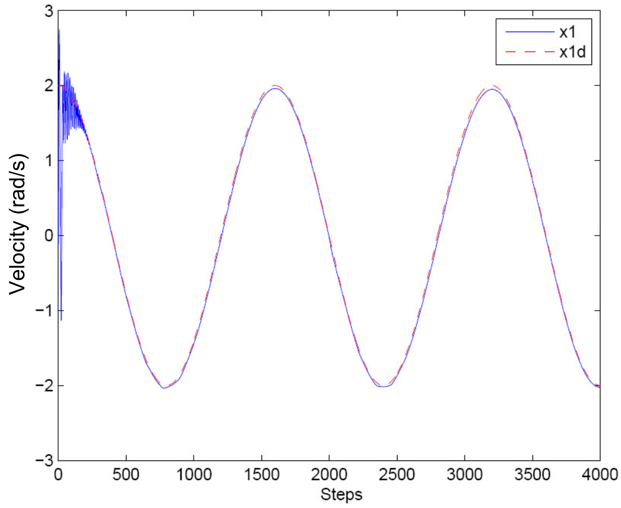


FIGURE 1. $x_1$ and $x_{1d}$

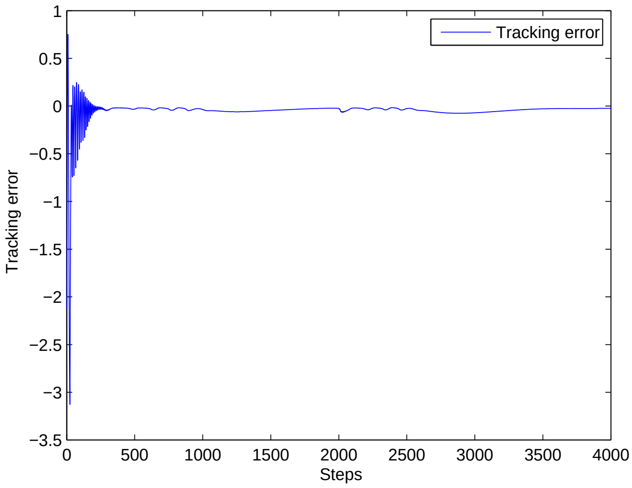


FIGURE 2. The tracking error $e$

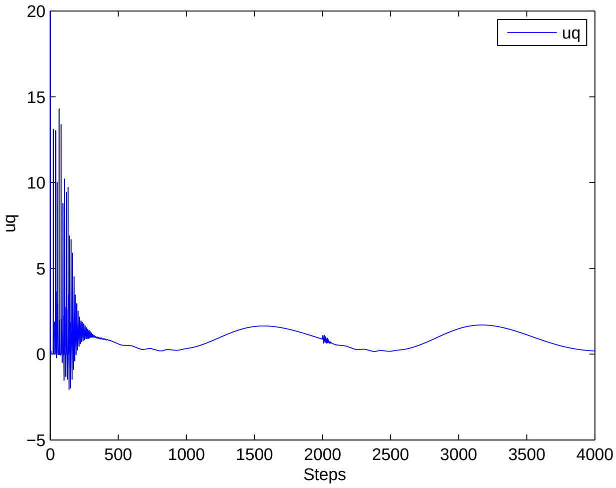


FIGURE 3. The control law $u_q$

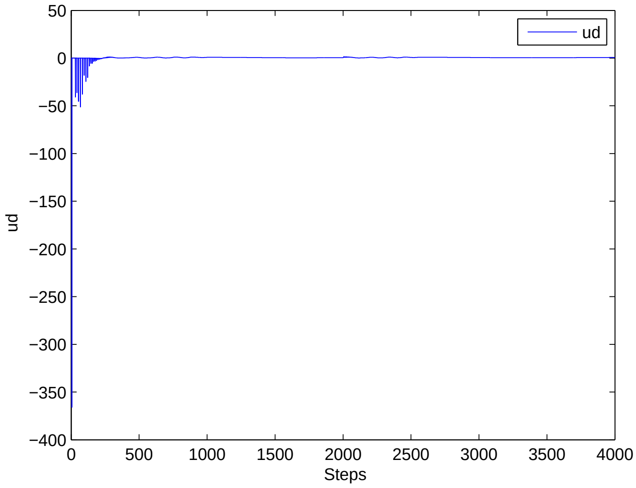


FIGURE 4. The control law $u_d$

6. **Conclusion.** In this paper, based on DSC backstepping technique, fuzzy adaptive discrete-time method is proposed to speed regulation control for IM drive system. The designed controllers guarantee that the tracking error converges to a small neighborhood of the origin. Simulation results are provided to demonstrate the effectiveness and robustness of the proposed approach. Future research will focus on adaptive fuzzy control of permanent magnet synchronous motors based on dynamic surface control.

**Acknowledgment.** This work was partially supported by the National Natural Science Foundation of China (61573204, 61573203, 61501276, 61603204), Shandong Province Outstanding Youth Fund (ZR2015JL022), the China Postdoctoral Science Foundation (2014T70620, 2013M541881, 201303062), Qingdao Postdoctoral Application Research Project, Qingdao Application Basic Research Project (16-5-1-22-jch) and Taishan Scholar Special Project Fund.

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