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FULL-STATE CONSTRAINTS AND COMMAND FILTERING-BASED ADAPTIVE FUZZY CONTROL FOR PERMANENT MAGNET SYNCHRONOUS MOTORS WITH REDUCED ORDER OBSERVER

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Abstract. *In this article, a command filtering-based adaptive fuzzy controller is proposed for speed-sensorless permanent magnet synchronous motors (PMSMs) with full-state constraints. Firstly, aiming at the problem that the traditional backstepping method cannot constrain the state variables, the barrier Lyapunov function is employed to guarantee that the rotor position, stator current and other states of PMSMs drive system runs in a given range. Then, the adaptive fuzzy technology is used to deal with unknown parameters and load disturbance difficulty, and a fuzzy reduced-order observer is constructed to evaluate the rotor angular velocity of the PMSMs. In addition, in order to deal with the problem of "complexity of differentiation" in conventional backstepping, the command filtering technology is used to filter the virtual control signals to obtain their derivative. The error compensation mechanism is further combined with backstepping command filtering to eliminate the adverse effect of accumulated filtering errors on control performance. Finally, the simulation results verify the effectiveness of the controller.*
Keywords: Adaptive fuzzy control, Command filtering control, Barrier Lyapunov functions, Full-state constraints, Speed-sensorless PMSMs

1. **Introduction.** In recent years, PMSMs have been widely used in the field of high precision servo system because of its high efficiency, strong robustness, high torque inertia ratio, superior power density and low rotating inertia [1]. With the development of control theory, a large number of new non-linear control methods have been studied and applied to motor systems, such as backstepping control [2], sliding mode control [3] and adaptive control [4]. In addition, backstepping adaptive control technology has attracted much attention because it can overcome the disturbance problems caused by unknown parameters and load torque [5]. However, when the order of the system increases or the form of the virtual control function is more complex, the derivation process will become very complicated [6]. To this end, in the tracking controller design for PMSMs [7], by using fuzzy logic system (FLS) to approximate the derivative of virtual control function, a more concise controller form is obtained, but the tracking effect is markedly reduced.

In order to overcome the above problem of "complexity of differentiation" [8], Swaroop et al. have proposed a dynamic surface control method [9] to approximate the derivative of virtual control. However, the uncertainty of the system increases. Farrell et al. [10] proposed a backstepping method based on second-order command filter, which used the filter to realize the approximation of virtual signal and its derivative. In addition, the filter error compensation loop [11,12] is designed to improve the tracking performance.

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Although the control strategy based on command filtering control (CFC) ensures the accuracy of position tracking control, the safety problems caused by excessive speed, current and other state variables of PMSMs in the staring stage are not considered.

Inspired by the above surveys, a command filtering-based adaptive fuzzy controller is proposed for speed-sensorless PMSMs with full-state constraints. The controller has the following advantages.

1) Compared with the adaptive backstepping method in [11], the full-state constraints are further considered for PMSMs systems, and the control signals are devised based on a new log-type barrier Lyapunov function (BLF), which can assure tracking effect without violating state constraints.

2) Distinct from [11,12], CFC technology with error compensation mechanism overcomes the "complexity of differentiation" difficulty of backstepping method and eliminates the adverse effect of accumulated filtering error on the control system, which will further improve the tracking performance of the system.

3) By designing reduced-order observer, the developed scheme need not measure the value of angle speed signal, which will reduce hardware complexity and increase reliability for PMSMs.

The rest of sections are organized as follows. In Section 2, the system statement is given. In Section 3, the observer is designed. In Section 4, command filtering-based full-state constrained adaptive fuzzy controller is devised and the stability analysis is presented. Numerical simulation results and conclusions are shown in Sections 5 and 6, respectively.

2. System Statement.

In the *d-q* rotating coordinate, the system model of PMSMs can be described as follows [13]:

$$\begin{cases} \dfrac{d\Theta}{dt} = w \\ J\dfrac{dw}{dt} = \dfrac{3}{2}n_p\left[(L_d - L_q)i_d i_q + \Phi i_q\right] - Bw - T_L \\ L_q\dfrac{di_q}{dt} = -R_s i_q - n_p w L_d i_d - n_p w \Phi + u_q L_d \\ \dfrac{di_d}{dt} = -R_s i_d + n_p w L_q i_q + u_d \end{cases} \tag{1}$$

where the physical meaning of symbols is shown in Table 1.

Table 1. The physical meaning of symbols

Θ: the angular position	w: the angular velocity
n_p: the pole pair	B: the viscous friction velocity
J: the rotor moment of inertia	T_L: the load torque
R_s: the stator resistance	Φ: the flux linkage
i_d and i_q: the stator currents	u_d and u_q: the stator voltages

In order to simplify the control model, the following notations are introduced: $x_1 = \Theta$, $x_2 = w$, $x_3 = i_q$, $x_4 = i_d$, $a_1 = \frac{3n_p\Phi}{2}$, $a_2 = \frac{3n_p(L_d - L_q)}{2}$, $b_1 = -\frac{R_s}{L_q}$, $b_2 = -\frac{n_p L_d}{L_q}$, $b_3 = -\frac{n_p\Phi}{L_q}$, $b_4 = \frac{1}{L_q}$, $c_1 = -\frac{R_s}{L_d}$, $c_2 = \frac{n_p L_q}{L_d}$, $c_3 = \frac{1}{L_d}$. Thus, we can get

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = \dfrac{a_1}{J}x_3 + \dfrac{a_2}{J}x_3 x_4 - \dfrac{B}{J}x_2 - \dfrac{T_L}{J} \\ \dot{x}_3 = b_1 x_3 + b_2 x_2 x_4 + b_3 x_2 + b_4 u_q \\ \dot{x}_4 = c_1 x_4 + c_2 x_2 x_3 + c_3 u_d \end{cases} \tag{2}$$

The control goal of PMSMs is to construct the controller u_q and u_d to realize the tracking of rotor position signal x_1 to the given signal x_d. Meanwhile, make sure that all closed loop signals are bounded, and the full-state constraints of the system are not violated, i.e., $|x_i| \leq k_{c_i}$, where k_{c_i} is a constant, $i = 1, 2, 3, 4$.

Lemma 2.1. [11] *The command filter is defined as*

$$\begin{aligned} \dot{p}_1 &= \eta_n p_2, \\ \dot{p}_2 &= -2\xi\eta_n p_2 - \eta_n (p_1 - \alpha_1) \end{aligned} \tag{3}$$

where α_1 and p_i $(i = 1, 2)$ stand for the input and output signals of the filter, respectively. And if α_1 satisfies $|\dot{\alpha}_1| < \rho_1$, $|\ddot{\alpha}_1| < \rho_2$ for all $t \geq 0$, where $\rho_1 > 0$, $\rho_2 > 0$ and $p_1(0) = \alpha_1(0)$, $p_2(0) = 0$, then for any $\mu > 0$, there exist $\eta_n > 0$ and $\xi \in (0, 1]$ such that $|p_1 - \alpha_1| \leq \mu$, and $|\dot{p}_1|$, $|\ddot{p}_1|$, $|\dddot{p}_1|$ are bounded.

3. **Reduced-Order Observer Design.** Second-order observer is designed to estimate the rotor angular velocity of PMSMs. From the system (2), we can obtain that

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = f_2(Z) + x_3 \\ y = x_1 \end{cases} \tag{4}$$

where the unknown nonlinear functions $f_2(Z) = -x_3 + \frac{1}{J}a_1 x_3 - \frac{T_L}{J} + \frac{a_2}{J}x_3 x_4 - \frac{B}{J}x_2$, $Z = [x_1, \hat{x}_2, x_3, x_4, x_{1d}, \dot{x}_{1d}]^T$. Define $U_2 = \pi_2$ and $H_2(Z) = \varphi(Z)$. The FLS is employed to approximate $f_2(Z)$. For any given $\tau_2 > 0$, there always exists an FLS $\pi_2^T \varphi(Z)$ such that $f_2(Z) = \pi_2^T \varphi(Z) + \mu_2(Z)$, where the approximation error $\mu_2(Z)$ satisfies $|\mu_2(Z)| < \tau_2$. So Equation (4) can be rewritten as

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = \pi_2^T \varphi(Z) + \mu_2(Z) + x_3 \end{cases} \tag{5}$$

Then the reduced-order observer is designed as

$$\begin{cases} \dot{\hat{x}}_1 = \hat{x}_2 + d_1 (y - \hat{y}) \\ \dot{\hat{x}}_2 = \hat{\pi}_2^T \varphi(Z) + d_2 (y - \hat{y}) + x_3 \\ \hat{y} = \hat{x}_1 \end{cases} \tag{6}$$

where $\hat{\pi}_2 = \pi_2 - \tilde{\pi}_2$ is the estimation of π_2.

Define the observer error $e = [e_1, e_2]^T$, where $e_1 = x_1 - \hat{x}_1$, $e_2 = x_2 - \hat{x}_2$. By subtracting the expressions on both sides of the equal sign of Equations (5) and (6), one has

$$\dot{e} = De + \varepsilon + \omega \tag{7}$$

where $D = \begin{pmatrix} -d_1 & 1 \\ -d_2 & 0 \end{pmatrix}$, $\varepsilon = [0, \mu_2(Z)]^T$, $\omega = \left[0, \tilde{\pi}_2^T \varphi(Z)\right]^T$. Select the appropriate d_1 and d_2 to guarantee that D is a strict Hurwitz matrix. Thus, for any given $Q^T = Q > 0$, there always exists $G^T = G > 0$ satisfying that $D^T G + GD = -Q$.

Construct a Lyapunov function candidate as $V_0 = e^T Ge$ and differentiate it with respect to e.

$$\dot{V}_0 = \dot{e}^T Ge + e^T G\dot{e} = -e^T Qe + 2e^T G(\varepsilon + \omega) \tag{8}$$

Utilizing the Young's inequality: $2e^T G\varepsilon \leq \|e\|^2 + \|G\|^2 \tau_2^2$, $2e^T G\omega \leq \|e\|^2 + \|G\|^2 \tilde{\pi}_2^T \tilde{\pi}_2$, we can conclude that

$$\dot{V}_0 \leq -\lambda_{\min}(Q) e^T e + 2\|e\|^2 + \|G\|^2 \tau_2^2 + \|G\|^2 \tilde{\pi}_2^T \tilde{\pi}_2 \tag{9}$$

4. **Command Filtering-Based Full-State Constrained Adaptive Fuzzy Controllers Study.** The following system tracking error z_i and the compensated tracking error s_i are defined:

$$\begin{aligned} &z_1 = x_1 - x_d,\ z_2 = \hat{x}_2 - x_{1,m},\ z_3 = x_3 - x_{2,m},\ z_4 = x_4 \\ &s_1 = z_1 - \varsigma_1,\ s_2 = z_2 - \varsigma_2,\ s_3 = z_3 - \varsigma_3,\ s_4 = z_4 - \varsigma_4 \end{aligned} \tag{10}$$

where x_d stands for the given reference signal, α_i and $x_{i,m}$ $(i = 1, 2)$ are the input and output signals of the filter, respectively. The filtering errors $x_{i,m} - \alpha_i$ are handled by error compensation mechanism and ς_i represent the error compensation signals. Then, define a compact set $\Omega_s := \{|s_i| < k_{b_i}, i = 1, \ldots, 4\}$, where k_{b_i} is a positive constant.

Step 1: Consider the BLF $V_1 = \log \frac{k_{b_1}^2}{k_{b_1}^2 - s_1^2} + V_0$. Then, the time derivative of V_1 can be obtained as

$$\dot{V}_1 = \dot{V}_0 + K_{s_1}(z_2 + (x_{1,m} - \alpha_1) + \alpha_1 + e_2 - \dot{x}_d - \dot{\varsigma}_1) \tag{11}$$

where $K_{s_1} = s_1 \big/ \left(k_{b_1}^2 - s_1^2\right)$ and $K_{s_i} = s_i \big/ \left(k_{b_i}^2 - s_i^2\right)$ with $i = 2, 3, 4$, which will be used in the following steps. Choose the virtual control function and the compensating signal as

$$\begin{aligned} \alpha_1 &= -k_1 z_1 + \dot{x}_d - \frac{1}{2} K_{s_1} \\ \dot{\varsigma}_1 &= -k_1 \varsigma_1 + \varsigma_2 + (x_{1,m} - \alpha_1) \end{aligned} \tag{12}$$

where the control gain $k_1 > 0$ and $\varsigma(0) = 0$. Substituting Equation (12) into Equation (11) results in

$$\dot{V}_1 \leq \dot{V}_0 - k_1 K_{s_1} s_1 + K_{s_1} s_2 + \frac{\|e\|^2}{2} \tag{13}$$

Step 2: Consider Lyapunov function as $V_2 = V_1 + \frac{1}{2} \log \frac{k_{b_2}^2}{k_{b_2}^2 - s_2^2} + \frac{1}{2r_1} \tilde{\pi}_2^T \tilde{\pi}_2$ with $r_1 > 0$, and then its time derivative can be presented as

$$\begin{aligned} \dot{V}_2 = \dot{V}_1 &+ K_{s_2}\left(z_3 + x_{2,m} + d_2 e_1 + \hat{\pi}_2^T \varphi(Z) - \dot{x}_{1,m} - \dot{\varsigma}_2\right) - K_{s_2} \tilde{\pi}_2^T \varphi(Z) \\ &+ \frac{\tilde{\pi}_2^T}{r_1}\left(r_1 K_{s_2} \varphi(Z) - \dot{\hat{\pi}}_2\right) \end{aligned} \tag{14}$$

Adopt the virtual control function, the compensating signal and the adaptive law as

$$\begin{aligned} &\alpha_2 = -k_2 z_2 - d_2 e_1 - \hat{\pi}_2^T \varphi(Z) + \dot{x}_{1,m} - \frac{K_{s_2}}{2} - K_{s_1}\left(K_{b_2}^2 - s_2^2\right) \\ &\dot{\varsigma}_2 = -k_2 \varsigma_2 + \varsigma_3 + (x_{2,m} - \alpha_2) \\ &\dot{\hat{\pi}}_2 = r_1 K_{s_2} \varphi(Z) - m_1 \hat{\pi}_2 \end{aligned} \tag{15}$$

Substituting Equation (15) into Equation (14), one has

$$\dot{V}_2 \leq \dot{V}_0 - k_1 K_{s_1} s_1 - k_2 K_{s_2} s_2 + K_{s_2} s_3 + \frac{\|e\|^2}{2} + \frac{\tilde{\pi}_2^T \tilde{\pi}_2}{2} + \frac{m_1}{r_1} \tilde{\pi}_2^T \hat{\pi}_2 \tag{16}$$

Step 3: Premeditate the following candidate as $V_3 = V_2 + \frac{1}{2} \log\left(\frac{k_{b_3}^2}{k_{b_3}^2 - s_3^2}\right)$ and the time derivative V_3 is

$$\begin{aligned} \dot{V}_3 \leq \dot{V}_0 &- k_1 K_{s_1} s_1 - k_2 K_{s_2} s_2 + K_{s_3} s_2 + K_{s_3}\left(b_4 u_q - \dot{\varsigma}_3 + f_3(Z) - \dot{x}_{2,m}\right) \\ &+ \frac{\|e\|^2}{2} + \frac{\tilde{\pi}_2^T \tilde{\pi}_2}{2} + \frac{m_1}{r_1} \tilde{\pi}_2^T \hat{\pi}_2 \end{aligned} \tag{17}$$

Design the real control law u_q and the compensating signal as

$$\begin{aligned} u_q &= \frac{1}{b_4}\left(-k_3 z_3 - \frac{1}{2l_3^2} K_{s_3} \hat{\chi} H_3^T H_3 + \dot{x}_{2,m} - \frac{K_{s_3}}{2} - K_{s_2}\left(k_{b_3}^2 - s_3^2\right)\right) \\ \dot{\varsigma}_3 &= -k_3 \varsigma_3 \end{aligned} \tag{18}$$

Then, one has

$$\dot{V}_3 \leq \dot{V}_0 - \sum_{i=1}^{3} k_i K_{s_i} s_i + \frac{1}{2l_3^2} K_{s_3}^2 \left(\|U_3\|^2 - \hat{\chi}\right) H_3^T H_3 + \frac{\|e\|^2}{2} + \frac{\tilde{\pi}_2^T \tilde{\pi}_2}{2} + \frac{m_1}{r_1} \tilde{\pi}_2^T \hat{\pi}_2 + \frac{l_3^2 + \tau_3^2}{2} \tag{19}$$

Step 4: Select barrier Lyapunov function $V_4 = V_3 + \frac{1}{2}\log\left(\frac{k_{b_4}^2}{k_{b_4}^2 - s_4^2}\right)$. Then the derivation of V_4 is

$$\dot{V}_4 = \dot{V}_3 + K_{s_4}\left(c_3 u_d + f_4(Z) - \dot{\varsigma}_4\right) \tag{20}$$

Design the control function u_d and the compensating signal ς_4 as

$$\begin{aligned} u_d &= \frac{1}{c_3}\left(-k_4 z_4 - \frac{1}{2l_4^2}K_{s_4}\hat{\chi}H_4^T H_4 - \frac{K_{s_4}}{2}\right) \\ \dot{\varsigma}_4 &= -k_4\varsigma_4 \end{aligned} \tag{21}$$

Define $\chi = \max\left\{\|U_3\|^2, \|U_4\|^2\right\}$ and $\tilde{\chi} = \chi - \hat{\chi}$. Then, we can certify

$$\dot{V}_4 \le \dot{V}_0 - \sum_{i=1}^{4} k_i K_{s_i} s_i + \sum_{i=3}^{4}\frac{1}{2l_i^2}K_{s_i}^2\tilde{\chi}H_i^T H_i + \frac{\|e\|^2}{2} + \frac{\tilde{\pi}_2^T\tilde{\pi}_2}{2} + \frac{m_1}{r_1}\tilde{\pi}_2^T\hat{\pi}_2 + \sum_{i=3}^{4}\frac{l_i^2 + \tau_i^2}{2} \tag{22}$$

Step 5: The Lyapunov function of the whole system is chosen as $V = V_4 + \frac{1}{2r_2}\tilde{\chi}^2$. Then, the $\dot{V}$ is given by

$$\begin{aligned} \dot{V} \le{}& \dot{V}_0 - \sum_{i=1}^{4} k_i K_{s_i} s_i + \frac{\tilde{\chi}}{r_2}\left(\sum_{i=3}^{4}\frac{1}{2l_i^2}r_2 K_{s_i}^2 H_i^T H_i - \dot{\hat{\chi}}\right) + \frac{\|e\|^2}{2} + \frac{\tilde{\pi}_2^T\tilde{\pi}_2}{2} + \frac{m_1}{r_1}\tilde{\pi}_2^T\hat{\pi}_2 \\ &+ \sum_{i=3}^{4}\frac{l_i^2 + \tau_i^2}{2} \end{aligned} \tag{23}$$

Then we choose the adaptive laws as

$$\dot{\hat{\chi}} = \sum_{i=3}^{4}\frac{1}{2l_i^2}r_2 K_{s_i}^2 H_i^T H_i - m_2\hat{\chi} \tag{24}$$

Then, we can certify

$$\begin{aligned} \dot{V} \le{}& -\left(\lambda_{\min}(Q) - \frac{5}{2}\right)e^T e - \sum_{i=1}^{4}\log\frac{k_{b_i}^2}{k_{b_i}^2 - s_i^2} - \left(\frac{m_1}{2r_1} - \frac{1}{2} - \|G\|^2\right)\tilde{\pi}_2^T\tilde{\pi}_2 \\ &- \frac{m_2}{2r_2}\tilde{\chi}^2 + \|G\|^2\tau_2^2 + \frac{m_1}{2r_1}\pi_2^T\pi_2 + \frac{m_2}{2r_2}\chi^2 + \sum_{i=3}^{4}\frac{l_i^2 + \tau_i^2}{2} \\ \le{}& -a_0 V(t) + b_0 \end{aligned} \tag{25}$$

where $\lambda_{\min}(Q) - \frac{5}{2} > 0$, $\frac{m_1}{2r_1} - \frac{1}{2} - \|G\|^2 > 0$, and $a_0 = \min\left\{\frac{\lambda_{\min}(Q) - \frac{5}{2}}{\lambda_{\max}(G)}, 2r_1\left(\frac{m_1}{2r_1} - \frac{1}{2} - ||G||^2\right), 2k_1, 2k_2, 2k_3, 2k_4, m_2\right\}$, $b_0 = \|G\|^2\tau_2^2 + \frac{m_1}{2r_1}\pi_2^T\pi_2 + \frac{m_2}{2r_2}\chi^2 + \sum_{i=3}^{4}\frac{l_i^2 + \tau_i^2}{2}$.

Multiplying both side by $e^{a_0 t}$, Equation (25) can be represented as $\mathrm{d}(Ve^{a_0 t})/\mathrm{d}t \le b_0 e^{a_0 t}$ and integrating it over $(0, t]$, we can certify that

$$V(t) \le \left(V(0) - \frac{b_0}{a_0}\right)e^{-a_0 t} + \frac{b_0}{a_0} \le V(0) + \frac{b_0}{a_0}, \quad \forall t \ge t_0 \tag{26}$$

It can be concluded from the above formula that $\lim_{t\to\infty}\log\left(\frac{k_{b_i}^2}{k_{b_i}^2 - s_i^2}\right) \le \frac{2b_0}{a_0} \Rightarrow \lim_{t\to\infty}|s_1| \le k_{b_1}\sqrt{1 - e^{(-2b_0/a_0)}}$.

Next, choose the Lyapunov function as $\bar{V} = \frac{1}{2}\varsigma_1^2 + \frac{1}{2}\varsigma_2^2 + \frac{1}{2}\varsigma_3^2 + \frac{1}{2}\varsigma_4^2$. Then, one has

$$\begin{aligned} \dot{\bar{V}} &= \varsigma_1\dot{\varsigma}_1 + \varsigma_2\dot{\varsigma}_2 + \varsigma_3\dot{\varsigma}_3 + \varsigma_4\dot{\varsigma}_4 \\ &= -k_1\varsigma_1^2 + \varsigma_1\varsigma_2 + \varsigma_1(x_{1,m} - \alpha_1) - k_2\varsigma_2^2 + \varsigma_2\varsigma_3 + \varsigma_2(x_{2,m} - \alpha_2) - k_3\varsigma_3^2 - k_4\varsigma_4^2 \end{aligned} \tag{27}$$

According to Lemma 2.1, $|x_{i,m} - \alpha_i| \le \psi$, $i = 1, 2$. By using $|\varsigma_i|\psi \le \frac{1}{2}\varsigma_i^2 + \frac{1}{2}\psi^2$ and $\varsigma_i\varsigma_{i+1} \le \frac{1}{2}\varsigma_i^2 + \frac{1}{2}\varsigma_{i+1}^2$ with $i = 1, 2$, we can obtain

$$\dot{\bar{V}} \leq -(k_1 - 1)\varsigma_1^2 - \left(k_2 - \frac{3}{2}\right)\varsigma_2^2 - \left(k_3 - \frac{1}{2}\right)\varsigma_3^2 - k_4\varsigma_4^2 + \psi^2 \leq -a_1\bar{V} + b_1 \tag{28}$$

where $a_1 = \min\{2k_1 - 2, 2k_2 - 3, 2k_3 - 1, 2k_4\}$, $b_1 = \psi^2$. Thus, we can get $\lim_{t\to\infty} |\varsigma_i| \leq \sqrt{\frac{2\psi^2}{a_1}}$. According to the constructed system error, it can be concluded that $|z_1| \leq |s_1| + |\varsigma_1| < k_{b_1}\sqrt{1 - e^{(-2b_0/a_0)}} + \sqrt{\frac{2\psi^2}{a_1}}$, when t tends to ∞.

Remark 4.1. *In the light of the definition of a_0, a_1, b_0 and b_1, after the parameters m_1 and m_2 are selected, the sufficiently large k_1, r_1, r_2 and sufficiently small l_i can guarantee that z_1 converges to the small neighborhood of the origin.*

5. **Simulation Results.** The parameters of PMSM are selected in Table 2.

Table 2. The parameters of PMSMs

$J = 0.003798$ Kg·m^2	$B = 0.001158$ N·m/(rad/s)	$\Phi = 0.1245$ Wb
$L_q = 0.00315$ H	$L_d = 0.00285$ H & $n_p = 3$	$R_s = 0.68\ \Omega$

Choosing the reference signal as $x_{1d} = \sin(t) + 0.5 * \sin(0.5 * t)$, the initial condition is $[0.2, 0, 0, 0]$, load torque $T_L = \begin{cases} 5.0, & 0 \leq t < 15 \\ 7.1, & t \geq 15 \end{cases}$ and the fuzzy membership functions $\mu_{F_i^j} = \exp\left[\frac{-(x+n)^2}{2}\right]$ where $j = 1, 2, 3, \ldots, 11$, $i = 2, 3, 4$ and $n = -5, -4, -3, \ldots, 5$.

The control parameters are selected as $k_1 = 5$, $k_2 = 20$, $k_3 = 100$, $k_4 = 50$, $m_1 = m_2 = 1$, $r_1 = r_2 = 10$, $l_2 = l_3 = 1$. Besides, the parameters of the command filters are $\xi = 0.5$, $\eta_n = 500$, $k_{b_1} = 0.3$, $k_{b_2} = k_{b_3} = k_{b_4} = 2$. The states of PMSMs are restricted in $|x_1| \leq 1.5$, $|x_2| \leq 10$, $|x_3| \leq 10$, $|x_4| \leq 10$.

Figure 1 shows the tracking curve of rotor position. It can be seen from Figure 1 that the control schemes can track the given signal quickly and accurately. Figure 2 shows the observation results of the reduced-order observer. It can be seen from the figure that the parameters d_1 and d_2 selected in this paper can make the observer obtain good estimation.

6. **Conclusion.** For the speed sensorless PMSMs with full-state constraints, an adaptive fuzzy controller based on CFC is proposed in this chapter. BLF is introduced to design the controller to ensure that all system states are always in a given range, and a fuzzy

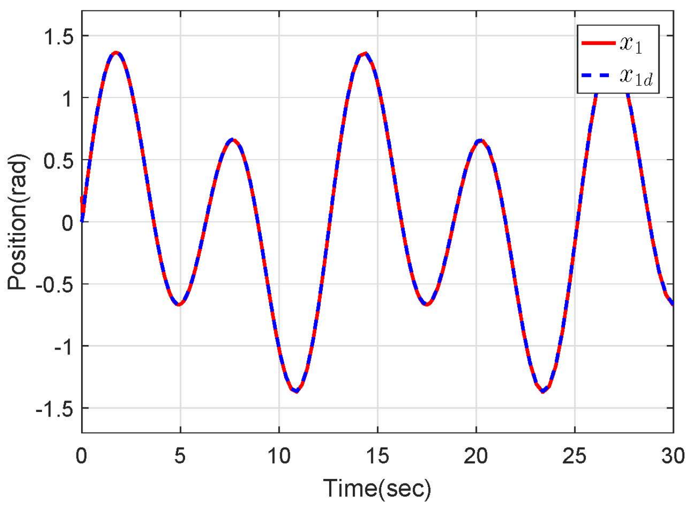

Figure 1. The trajectory of x_1 and x_{1d}

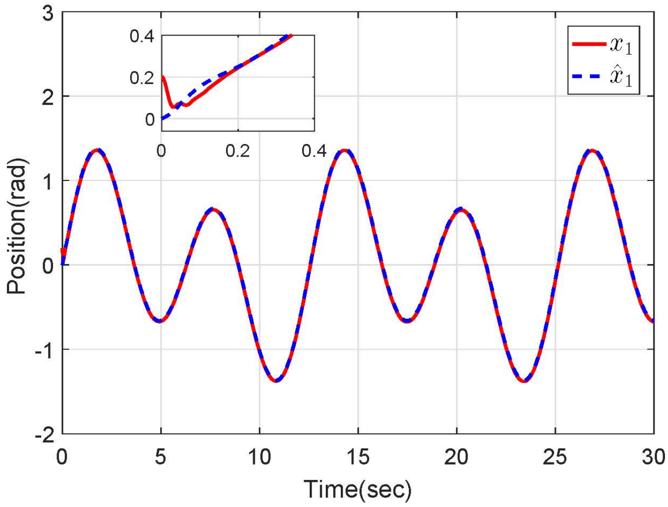

FIGURE 2. The trajectory of x_1 and $\hat{x}_1$

reduced order observer is established to estimate the PMSMs rotor angular velocity. In addition, the CFC scheme is used to solve the problem of "complexity of differentiation", and an error compensation link is constructed to eliminate the adverse effect of filtering error.

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