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Position tracking control for chaotic permanent magnet synchronous motors via indirect adaptive neural approximation

Jinpeng Yu [a,b,*], Bing Chen [a], Haisheng Yu [a], Chong Lin [a], Zhijian Ji [a], Xiaoqing Cheng [b]

[a] The College of Automation Engineering, Qingdao University, Qingdao 266071, PR China
[b] State Key Laboratory of Rail Traffic Control and Safety, Beijing Jiaotong University, PR China

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ABSTRACT

Position tracking control for the chaotic permanent magnet synchronous motor drive system is addressed in this paper. Neural networks are used to approximate the nonlinearities and indirect adaptive backstepping technique is employed to construct controllers. The designed indirect adaptive neural controllers can suppress chaos in the permanent magnet synchronous motor and guarantee that the position tracking error converges to a small neighborhood of the origin. Compared with the classical backstepping method, the proposed neural controllers' structure is very simple. Simulation results illustrate its effectiveness.

1. Introduction

Permanent magnet synchronous motors (PMSMs) are intensively used in industrial applications because of their high efficiency, high speed, large torque to inertia ratio and high power density [1]. However, it is still a challenging problem to control the PMSMs to get high performance and stable operation because their dynamic models are usually multivariable, coupled, highly nonlinear and even emerging chaotic attractors and limit cycles with systemic parameters dropping into a certain area. The bifurcations and chaos in a PMSM was first presented by Li et al. in [2]. The chaotic behavior in PMSM is undesirable because it can break the stability of the driver and even make the controlled system collapse. In order to achieve high performance of PMSMs, many researchers have aimed to develop nonlinear control methods for the PMSMs, various algorithms have been proposed and references therein [3–8].

Backstepping-based [9–13] nonlinear adaptive control method has been paid considerable attention to control the nonlinear systems where the uncertainties do not satisfy matching conditions. The classical backstepping is successfully applied to the control of PMSM drivers recently by Ge and Harb [3,8]. But a major problem with backstepping approaches is called "explosion of complexity" caused by the repeated differentiations of virtual input [14,15]. Theoretically, the calculation of virtual control signal derivatives is simple, but it can be quite tedious and complicated in practice applications when n is greater than three because the real control signal u will include the derivative of α_n, which requires the second derivative of α_{n-1}, which requires the third derivative of α_{n-2}, and so on. For instance, the classical backstepping controller proposed in [16] to control PMSMs is overly cumbersome, which is the representative problem of "explosion of complexity".

Neural network (NN) approximation method has attracted considerable attention during the past decades because of its inherent capability for modelling and controlling highly uncertain, complex and nonlinear systems [17–19]. A new robust backstepping speed controller for induction motors using NNs was presented by Kwan and Lewis [14], where a two-layer NN was utilized to construct the fictitious controller, and a second NN was used to realize the fictitious NN signals. The radial basis function (RBF) NN is considered as a two-layer network, which contains the output layer and the hidden layer [20,21]. The neural networks can be utilized to deal with uncertain information, and can be applied to control ill-defined and complex systems. It has been one of the classical tools in function approximation and an efficient method to design control system in the area of engineering applications [22].

Motivated by the earlier works [23,24], an approximation-based indirect adaptive neural control approach is proposed for suppressing chaos in PMSM drive systems. Unlike the direct adaptive results in [23], the RBF neural networks are utilized to approximate the unknown nonlinearities rather than the desired control input signals. Compared with the existent results of neural

* Corresponding author. Tel.: +86 532 85953697; fax: +86 532 85953672.
E-mail address: yjp1109@hotmail.com (J. Yu).

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control method for PMSM drive system, the main contributions of this paper are that (i) the proposed approximation-based neural controller has a simpler structure and the problem of "explosion of complexity" is overcome; (ii) the number of adaptive parameters is considerably reduced to only one which is independent of the number of system state variables and the neural basis function. As a result, the computational burden of the scheme is alleviated, it will make the designed scheme more suitable for practical applications by reducing the on-line computational burden of the system. Simulation results show the effectiveness and the robustness against the parameter variation in chaotic PMSM drive system.

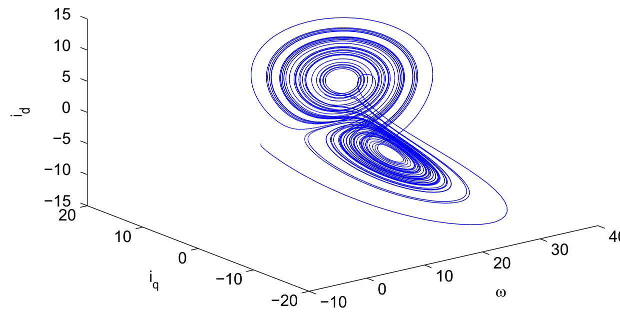

Fig. 1. Typical chaotic attractor in PMSM.

2. Mathematical model of chaotic PMSM drive system

The dimensionless mathematical model of PMSM drive system with the smooth air gap is shown as follows [2]:

$$\begin{aligned}
\frac{d\Theta}{dt} &= \omega,\\
\frac{d\omega}{dt} &= \sigma(i_q-\omega),\\
\frac{di_q}{dt} &= -i_q - i_d\omega + \gamma\omega + u_q,\\
\frac{di_d}{dt} &= -i_d + i_q\omega + u_d
\end{aligned} \tag{1}$$

where Θ, i_d, i_q and ω are state variables of PMSM drive system, which denote the rotor position, the $d-q$ axis currents and angle speed, respectively. γ and σ are system operating parameters, which are unknown positive. u_d and u_q stand for the $d-q$ axis voltages.

Li et al. found that the PMSM was experiencing chaotic behavior when the system parameters σ and γ fall into a certain area [2] and the external inputs were set to zero. For instance, the PMSM drive system begins to display chaos with $\sigma = 5.46$ and $\gamma = 14.93$, which is shown in Fig. 1. In order to suppress chaos of PMSM drive system, an indirect adaptive neural control approach is proposed via backstepping in this paper. For simplicity, the following notations are introduced: $x_1 = \Theta, x_2 = \omega, x_3 = i_q, x_4 = i_d$. Thus the dynamic model of PMSM drive system can be redescribed as follows:

$$\begin{aligned}
\dot{x}_1 &= x_2,\\
\dot{x}_2 &= \sigma(x_3 - x_2),\\
\dot{x}_3 &= -x_3 - x_2x_4 + \gamma x_2 + u_q,\\
\dot{x}_4 &= -x_4 + x_2x_3 + u_d.
\end{aligned} \tag{2}$$

3. Indirect adaptive neural controller design and stability analysis

This section is devoted to provide an indirect adaptive NN control approach to suppress chaos in PMSM drive system via backstepping.

Step 1: For the reference signal x_d, define the tracking error variable as $z_1 = x_1 - x_d$. From the first differential equation of (2), the error dynamic system is given by $\dot{z}_1 = x_2 - \dot{x}_d$.

Choose Lyapunov function candidate as $V_1 = \frac{1}{2}z_1^2$, then the time derivative of V_1 is computed by

$$\dot{V}_1 = z_1\dot{z}_1 = z_1(x_2 - \dot{x}_d). \tag{3}$$

Construct the virtual control law α_1 as

$$\alpha_1(x_1, x_d, \dot{x}_d) = -k_1z_1 + \dot{x}_d \tag{4}$$

with $k_1 > 0$ being a design parameter and $z_2 = x_2 - \alpha_1$. By using (4), (3) can be rewritten of the following form:

$$\dot{V}_1 = -k_1z_1^2 + z_1z_2.$$

Step 2: Differentiating z_2 gives

$$\dot{z}_2 = \dot{x}_2 - \dot{\alpha}_1 = \sigma(x_3 - x_2) - \dot{\alpha}_1. \tag{5}$$

Now, choose the Lyapunov function candidate as $V_2 = V_1 + \frac{1}{2}z_2^2$. Obviously, the time derivative of V_2 is given by

$$\begin{aligned}
\dot{V}_2 &= \dot{V}_1 + z_2\dot{z}_2\\
&= -k_1z_1^2 + z_2(z_1 + \sigma(x_3 - x_2) - \dot{\alpha}_1)\\
&= -k_1z_1^2 + (\sigma z_2x_3 + z_2f_2)
\end{aligned} \tag{6}$$

where $f_2(Z_2) = -\sigma x_2 + z_1 - \dot{\alpha}_1$, $Z_2 = [x_1, x_2, x_d, \dot{x}_d, \ddot{x}_d]^T$. Noting that f_2 contains the nonlinear term $\dot{\alpha}_1$ and the unknown parameter σ, this will make the conventional backstepping design difficult. Herein we will employ the neural networks to approximate the nonlinear function f_2 in order to avoid this trouble.

According to the RBF neural network approximation property proven in [25], for given $\varepsilon_2 > 0$, there exists RBF neural network $\phi_2^TP_2(Z_2)$ such that

$$f_2(Z_2) = \phi_2^TS_2(Z_2) + \delta_2(Z_2), \tag{7}$$

where $\delta_2(Z_2)$ is the approximation error and satisfies $|\delta_2| \le \varepsilon_2$. Consequently, a simple method computing produces the following inequality:

$$\begin{aligned}
z_2f_2 &= z_2\left(\phi_2^TS_2 + \delta_2\right)\\
&\le \frac{1}{2l_2^2}z_2^2\|\phi_2\|^2S_2^TS_2\\
&\quad + \frac{1}{2}l_2^2 + \frac{1}{2}z_2^2 + \frac{1}{2}\varepsilon_2^2
\end{aligned} \tag{8}$$

where l_2 is a positive constant.

Thus, it follows immediately from substituting (8) into (6) that

$$\dot{V}_2 \le -k_1z_1^2 + \frac{1}{2l_2^2}z_2^2\|\phi_2\|^2S_2^TS_2 + \frac{1}{2}l_2^2 + \frac{1}{2}z_2^2 + \frac{1}{2}\varepsilon_2^2 + \sigma z_2x_3. \tag{9}$$

The virtual control α_2 is constructed as

$$\alpha_2(x_1, x_2, x_d, \dot{x}_d, \ddot{x}_d) = \frac{1}{\sigma}\left(-k_2z_2 - \frac{1}{2l_2^2}z_2\hat{\theta}S_2^TS_2\right) \tag{10}$$

where $\hat{\theta}$ is the estimation of the unknown constant θ which will be specified later. Adding and subtracting α_2 in (9) show that

$$\begin{aligned}
\dot{V}_2 &\le -k_1z_1^2 + \frac{1}{2l_2^2}z_2^2\|\phi_2\|^2S_2^TS_2 + \frac{1}{2}l_2^2 + \frac{1}{2}z_2^2\\
&\quad + \frac{1}{2}\varepsilon_2^2 + \sigma z_2\left(\frac{1}{\sigma}\left(-k_2z_2 - \frac{1}{2l_2^2}z_2\hat{\theta}S_2^TS_2\right) + z_3\right)\\
&\le -k_1z_1^2 + \frac{1}{2l_2^2}z_2^2\|\phi_2\|^2S_2^TS_2 + \frac{1}{2}l_2^2 + \frac{1}{2}z_2^2 + \frac{1}{2}\varepsilon_2^2\\
&\quad - k_2z_2^2 - \frac{1}{2l_2^2}z_2^2\hat{\theta}S_2^TS_2 + \sigma z_2z_3
\end{aligned}$$