Article ID: 1000-8152(2001)06-0833-05

Research on Fuzzy Self-learning Sliding Mode Variable Structure Control and Its Application to Linear AC Servo System

SUN Yibiao, GUO Qingding and LIU Yang

(Electrical Engineering Institute, Shenyang University of Technology · Shenyang, 110023, P.R.China)

Abstract: Sliding mode variable structure control (SMVSC) is a special nonlinear control strategy, which has strong robustness against parameter variations, load disturbances and uncertainty of system. Nevertheless, the control precision and stability of system will be affected by the chattering, caused by sliding mode switch control. To address the problem, this paper proposes that the chattering can be effectively minimized by introducing fuzzy self-learning in conventional sliding mode control, without sacrificing the strong robustness of SMVSC. Simulation research on a direct-drive AC linear servo system is also presented in the paper.

Key words: sliding mode variable structure control; fuzzy self-learning; chattering; linear servo system

Document code: A

模糊自学习滑模变结构控制的研究及在直线 AC 伺服系统中的应用

孙宜标　郭庆鼎　刘　洋

(沈阳工业大学电气工程学院·沈阳,110023)

摘要: 滑模变结构控制(SMSVC)是一种特殊的非线性控制策略,它对参数变化,负载扰动以及系统的不确定性有强的鲁棒性.然而,系统的控制精度和稳定性受到由滑模开关控制所引起的抖振的影响.在本文给出的方法中,抖振可以通过在传统的滑模控制中引入模糊自学习加以有效的抑制,而对 SMVSC 的强鲁棒性不产生影响.对于直接驱动的 AC 直线伺服系统的仿真结果显示了这种方法是有效的.

关键词: 滑模变结构控制; 模糊自学习; 抖振; 直线伺服系统

1 Introduction

Sliding mode variable structure control is a special discontinuous nonlinear control strategy, which has strong robustness against parameter variations, load disturbances and uncertainty of system, with the advantage of rapidness and easy realization. However, the control precision and stability of the system are affected by the chattering. The normal method to minimize the chattering is to replace the switch control with continued saturated nonlinear control to smooth the discontinuous variables. This method can eliminate the chattering, but at the same time minimizes the robustness of the sliding mode structure control system[1]. Another method is proposed in Ref. [2] to control the tendency rate of the sliding mode, which minimizes the chattering through the control of the approaching speed of the state variables to the switch line of sliding modes, without the loss of the robustness of the system. But it is difficult to decide the approaching speed in practice. Ref. [4] introduces the fuzzy theory to minimize the chattering, but it is as hard to establish the exact fuzzy rule.

The strategy of fuzzy self-learning sliding mode control is presented in this paper. Based on the conventional sliding mode control, a fuzzy self-learning control is introduced. It has the ability of online self-learning and adjusting the output accurately and timely. It has a vice-control effect, which ensures the kinematic state parameters to surpass the super-surface of the sliding mode at a low speed, and thus provides the possibility to minimize the chattering, at least in theory.

* Foundation item: supported by Natural Science Foundation of China (59815061).
Received date: 2000-05-31; Revised date: 2001-02-27

Since it needs no PMLSM (Permanent magnet linear synchronous motor), the mechanical switch from rotational motion to line motion, PMLSM becomes the best choice of the high precision and micro-input servo system. However, owing to the direct driving of the load, the variations of the load and outer disturbance will directly affect the performance of the servo system. The parameter variations of the motor under different working states and the nonlinear factors will have bad influence on the servo system. In this paper, as the controlled object, the simulation results of the motor are given.

2 Sliding mode equivalent control

Supposing the single input controlled system in the following form

$$X(t) = (A + \Delta A)X(t) + (B + \Delta B)u(t) + f(t) = AX(t) + Bu(t) + \Delta AX(t) + \Delta Bu(t) + f(t), \quad (X \in \mathbb{R}^n, U \in \mathbb{R}, f \in \mathbb{R}^l.) \tag{1}$$

where A, B are certain parameters of the system, ΔA, ΔB unknown parameters (offset), $f(t)$ the outer disturbance. Define the general disturbance as

$$F(t) = \Delta AX(t) + \Delta Bu(t) + f(t), \tag{2}$$

Eq. (1) can be written as

$$\dot{X}(t) = AX(t) + Bu(t) + F(t). \tag{3}$$

Let the switch function be

$$\sigma(X) = CX = c_1x_1 + c_2x_2 + \cdots + c_nx_n, \tag{4}$$

where $C = (c_1\ c_2 \cdots c_n)$ is the parameter of switch function, $X = [x_1\ x_2 \cdots x_n]^{\mathrm{T}}$ the state vector of the system.

Using sliding mode equivalent control strategy, the output of the controller is

$$u = u_{eq} + \Delta u, \tag{5}$$

in which u_{eq} is the equivalent part of the sliding mode control, i.e. the necessary known part of the control system when $d\sigma(X)/dt = 0$ and $F(t) = 0$, the sliding switch control Δu, through high frequency switch control, makes the system state approach to the super-surface of the sliding mode and ensures the system state point approaches the stable point along the super-surface. Therefore, the kinematic state will not be affected by the uncertain parts of the system and the outer disturbance, and thus the system shows strong robustness. When the system runs into the sliding mode, the main characteristic of the system is decided by the super-surface $\sigma(X) = 0$.

According to the sliding mode equivalent control condition $d\sigma(X)/dt = 0$ and $F(t) = 0$, the equivalent control can be derived from Eqs. (3) and (4) as

$$u_{eq} = -(CB)^{-1}CAX. \tag{6}$$

3 Fuzzy self-learning sliding control

The fuzzy self-learning sliding control strategy are adopted in this paper to design the Δu for minimizing the chattering of the sliding mode control system.

3.1 Fuzzy basis functions

In order to solve the problem of the convergent speed of learning algorithm, a special fuzzy control – fuzzy basic function is introduced in this paper. The system is treated as a nonlinear function. It is expanded based on a series of basic functions and accomplishes self-learning through the correction of the weight of the basic function according to the error between the input and feedback. The convergence is superior to the Nerve Net(NN)[4]. The fuzzy control (FC) consists of fuzzy, rule base, fuzzy deduction and anti-fuzzy (Fig. 1).

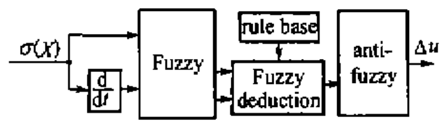


Fig. 1 Structure of the fuzzy controller

The distance between the kinematic state point $P(X)$ and the super-surface of sliding mode $\sigma(X) = 0$ is $R = \sigma(X)/\sqrt{\sum_{i=1}^{n} c_i^2}$, its derivative $dR/dt = \dot{\sigma}(X)/\sqrt{\sum_{i=1}^{n} c_i^2}$ is just the speed at which the point $P(X)$ approaches the super-surface. So we used switch function $\sigma(X)$ and its derivative as the input of the fuzzy controller and substituted the sliding switch Δu with the output of fuzzy control. Assuming that the input of the fuzzy controller has seven level language variables, its membership function is shown in Fig. 2.

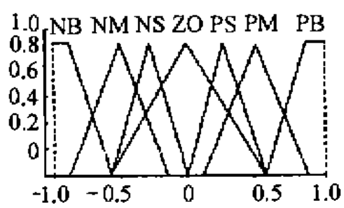


Fig. 2 Membership function of input variables

Two-input-one-output structure is adopted in fuzzy controller. The relation between $\sigma(X)$, $\dot{\sigma}(X)$ and Δu can be seen as a nonlinear function with two input and one output and naturally can make fuzzy basic function expansion. Supposing that the input variables $\sigma(X) = s_1$, $\dot{\sigma}(X) = s_2$, the fuzzy rule in the rule base can be expressed as

Rule j: If s_1 is A_1^j and s_2 is A_2^j, then Z is B^j, (7)

where $j = 1, \cdots, m (m = 7 \times 7 = 49)$ is the number of the fuzzy rule, $s_i (i = 1,2)$ is the input of the fuzzy controller, $Z = \Delta u$ is the output, A_i^j and B^j are the input and output language variables with the membership function $\mu_{A_i^j}(s_i)$ and $\mu_{B^j}(z)$, respectively. The corresponding expression is

$$\mu_{A_1^j A_2^j \to B^j}(s_1, s_2, z) = \mu_{A_1^j}(s_1) * \mu_{A_2^j}(s_2) * \mu_{B^j}(z), \tag{8}$$

where $*$ means multiplying, not getting minimum as in the traditional fuzzy controller. The Eq. (8) can be transformed into

$$\mu_{A_i \cdot B_j}(z) = \mu_{B^j}(z) * \prod_{i=1}^{2} \mu_{A_i^j}(s_i). \tag{9}$$

The role of the anti-fuzzy is to map from the fuzzy aggregate in output space R to the exact point in the R. When gravity center anti-fuzzy method is used, we have

$$Z = \sum_{j=1}^{m} \underline{Z}^j \mu_{A_i \cdot B_j}(\underline{Z}^j) \Big/ \sum_{j=1}^{m} \mu_{A_i \cdot B_j}(\underline{Z}^j), \tag{10}$$

where $\underline{Z}^j$ is the value when $\mu_B(Z)$ is the maximum. In general, let $\mu_B(\underline{Z}^j) = 1$. Substituting Eq. (9) into (10), the expansion form of the fuzzy controller output is

$$\Delta u = f(S) = \sum_{j=1}^{m} p_j(S) w_j, \tag{11}$$

where

$$p_j(S) = \prod_{i=1}^{n} \mu_{A_i^j}(s_i) \Big/ \sum_{j=1}^{m} \prod_{i=1}^{n} \mu_{A_i^j}(s_i), \tag{12}$$

in which $n = 2$ is the number of input, $w_j = \underline{Z}^j$ is the weight, decided by the following learning algorithm. Eq. (12) is called the fuzzy basic function (FBF). The expansion of Eq. (11) can approaches arbitrary nonlinear function with arbitrary accuracy[5].

3.2 Learning algorithm

The task of the learning algorithm is to justify the weight w_j to ensure the state point sliding on the super-surface. According to the sliding mode condition $\sigma \cdot \dot{\sigma} < 0$ and the principle of minimizing the chattering, the justification of the weight should make $\sigma \cdot \dot{\sigma}$ decrease, that is, under the condition of sliding mode, the switch function converges to zero and the state point slides to the stability point along the sliding mode super-surface. Gradient descend method is used to justify the weight w_j

$$\Delta w_j = -\Gamma \nabla_{w_j} \sigma(X)\dot{\sigma}(X) = -\Gamma \frac{\partial \sigma(X)\dot{\sigma}(X)}{\partial w_j(t)}, \tag{13}$$

where $\Gamma > 0$ is the rate of learning. Eq. (13) can be written as

$$\Delta w_j = -\Gamma \frac{\partial \sigma(X)\dot{\sigma}(X)}{\partial u(t)} \frac{\partial u(t)}{\partial w_j(t)} = -\Gamma \frac{\partial \sigma(X)\dot{\sigma}(X)}{\partial u(t)} \frac{\partial (u_{eq} + \Delta u)}{\partial w_j}. \tag{14}$$

From Eq. (6) we can see that u_{eq} is decided by the state variable X but has nothing to do with weight $w_j(t)$, so $\partial u_{eq}/\partial w_j = 0$. According to Eq. (3) and Eq. (4)

$$\frac{\partial \sigma(X)\dot{\sigma}(X)}{\partial u(t)} = \sigma(X)\frac{\partial \dot{\sigma}(X)}{\partial u(t)} = \sigma(X)\frac{\partial (C\dot{X})}{\partial u} = \sigma(X)\frac{\partial}{\partial u}[C(A\dot{X} + Bu + F)] = CB\sigma(X). \tag{15}$$

Combine Eqs. (14) and (15), we get the learning rule of the weight w_j

$$\Delta w_j = -\Gamma CB\sigma(X)\frac{\partial \Delta u(t)}{\partial w_j(t)} = -\Gamma CB\sigma(X)\frac{\partial \Sigma p_j w_j}{\partial w_j} = -\Gamma CB\sigma(X) p_j(\sigma, \dot{\sigma}), \tag{16}$$

where $j = 1, \cdots, m$.

4 The application in linear AC servo system

The basic structure of PMLSM and the working principles of AC linear servo system were proposed in [6]. The directional vector control is used in the inner circle of the system. Let $i_d = 0$, the simplified model of the controlled object is

$$F_e = \frac{\pi}{\tau}\phi_f i_q = K_f i_q = M\frac{dv}{dt} + Bv + F_l + F_d, \tag{17}$$

$$s = \int v dt, \tag{18}$$

where M is the mass of the mover, B is the viscous frictional coefficient, F_l is the load resistance, F_e is the electromagnetic thrust, F_d is the equivalent resistance caused by the top effects, K_f is the thrust coefficient, s is the mechanical displacement of mover, v is the linear speed of mover, ϕ_f is the effective flux of permanent magnet, τ is polar distance.

Define state variables: assuming that s^* is known, s is the actual displacement of mover, $e_1 = s^* - s$, $e_2 = \dot{e}_1$, from Eqs. (17) and (18) we get the error state equation of PMLSM

$$\begin{bmatrix} \dot{e}_1 \\ \dot{e}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & -a_n \end{bmatrix}\begin{bmatrix} e_1 \\ e_2 \end{bmatrix} + \begin{bmatrix} 0 \\ -b_n \end{bmatrix} u + \begin{bmatrix} 0 \\ d_n \end{bmatrix} f, \tag{19}$$

where $a = B/M$, $b = K_f/M$, $d = 1/M$, $u = i_q$ is the control element, a, b, d are the limited time variable parameters with rated value a_n, b_n, d_n respectively.

$$f = F_1 + \Delta M \mathrm{d}v/\mathrm{d}t + \Delta B v + F_d$$

is the defined general loading disturbance, ΔM and ΔB are the offset of system parameters M and B, respectively.

According to Eq. (4), the switch function of sliding mode variable structure is $\sigma(e) = ce_1 + e_2$. From Eq. (6), we have

$$u_{eq} = (c - a_n) e_2 / b_n. \tag{20}$$

The input of the fuzzy controller is $s_1 = \sigma(e)$, $s_2 = \dot{\sigma}(e)$. From Eq. (11), the fuzzy switch control of sliding mode

$$\Delta u = f(S) = \sum_{j=1}^{m} p_j(S) w_j, \tag{21}$$

where

$$p_j(S) = \prod_{i=1}^{n} \mu_{A_i^j}(s_i) \Big/ \sum_{j=1}^{m} \prod_{i=1}^{n} \mu_{A_i^j}(s_i).$$

According to Eq. (16), the weight learning algorithm

$$\Delta w_j = -\Gamma(-b_n\sigma(e)) \frac{\partial u_{fz}(t)}{\partial w_j(t)} = -\Gamma(-b_n\sigma(e)) \frac{\partial \Sigma p_j w_j}{\partial w_j} = -\Gamma b_n \sigma(e) p_j(\sigma, \dot{\sigma}), \tag{22}$$

where $j = 1, \cdots, m$. From Eqs. (20) and (21), the output of the sliding mode controller

$$u = u_{eq} + \Delta u = (c - a) e_2 / b_n + \sum_{j=1}^{m} p_j(S) w_j. \tag{23}$$

The block diagram of linear servo system with self-learning fuzzy sliding mode control (SFSMC) is given in Fig. 3. The dash part is self-learning fuzzy sliding mode control (SFSMC), including sliding mode control (SMC) and fuzzy self-learning control (FSLC).

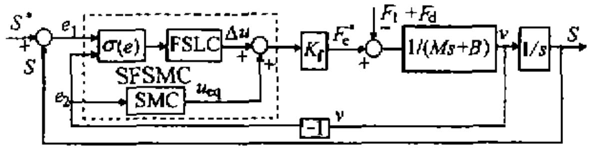


Fig. 3 Block diagram of linear servo system with self-learning fuzzy sliding mode control

5 Simulation and analysis

Based on the PMLSM servo system developed by ourselves, we simulated the self-learning fuzzy sliding mode control by using MATLAB 5.1 (fuzzy toolbox, controltoolbox, simulinkbox). The parameters are:

$M_n = 11.0\text{kg}$, $B_n = 8.0\text{N}\cdot\text{s/m}$,

$K_{fn} = 28.5\text{N/A}$, $F_{en} = 100\text{N}$, $v_n = 1.0\text{m/s}$.

The emulation of the traditional PI and sliding mode control is also carried out. The parameters of PI control are $K_p = 46$, $K_i = 5.6$, and the parameter of sliding mode control is $c = 12$. Let the dimensional factors of the input parameters of self-learning fuzzy sliding mode control $\sigma(e)$, $\dot{\sigma}(e)$ be $k_1 = 12$, $k_2 = 50$, respectively, the proportional factor of the output parameter Δu is $k_3 = 10$, learning rate is $\Gamma = 1000$, sample period is $T = 0.5\text{ms}$.

5.1 Constant disturbance

As constant disturbance $F_1 = 60\text{N}(t > 0.6\text{ms})$, $M = M_n$. The simulational curves of PI and self-learning fuzzy sliding mode control are shown in Fig.4, marked with 1 and 2, respectively. It can be seen that the speed descending amplitude of PI is greater than that of self-learning fuzzy control. Algorithm and the respondent time are longer. Therefore, self-learning fuzzy sliding mode control has good tracking ability.

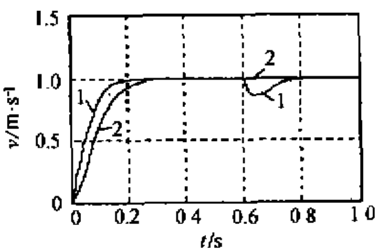
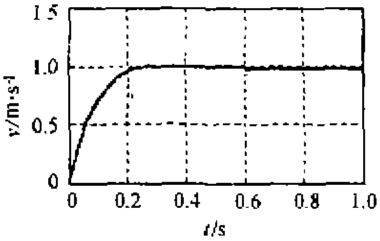


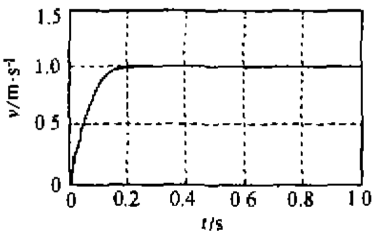
Fig. 4 Speed responses of the servo system with constant disturbance

5.2 Variational disturbance

Add $F_l = 40\sin(25t)N$, $M = M_n$. The simulational results are shown in Fig.5(a) and 5(b). From Fig. 5 (a) we can see that the conventional sliding mode control has great adaptability to the disturbance, which indicates the advantage of sliding mode control, that is, it is non-sensitive to the variation of outer disturbance. But the chattering and static error still exist to some extent. It can be seen from Fig. 5(b) that the fuzzy self-learning control minimizes the chattering remarkably and has strong robustness to the disturbance.



(a) Conventional SMC



(b) SFSMC

Fig. 5 Speed responses of the servo system with variational disturbance

5.3 Parameter perturbance

Supposing that the mass of mover, one of parameters of the linear servo system, is $M = 3M_n$. The simulational curves of PI control and fuzzy self-learning sliding mode control are given in Fig.6. The curves, marked with 1, 2 and ①, ②, are the speed responding curves when $M = M_n$ and $M = 3M_n$, respectively.

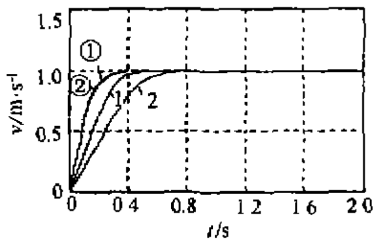


Fig. 6 Speed responses of the servo system with parameter perturbance

It can be seen that when the parameters are perturbing, PI control obviously can not fit this variation and the speed curves display delaying. However, the fuzzy self-learning sliding control is almost not affected, which means that the fuzzy self-learning sliding mode control has strong ability against parameter perturbance.

6 Conclusion

The emulational results indicate that the strategy proposed in this paper is effective. It is superior to PI and traditional sliding mode control. It has strong robustness to the parameter perturbance and outer disturbance and minimizes the chattering remarkably.

References

[1] Zhao Jin, Wan Shuyun, Sun Xiaopeng, et al. A survey to control strategies of AC servo systems based on slinding mode control [J]. Electric Drive, 1996, 26(1): 2 - 6 (in Chinese)

[2] Gao Weibing and Hung James C. Variable structure control of nonlinear systems: a new approach [J]. IEEE Trans. on Industrial Elect., 1993, 40 (1): 45 - 55

[3] Kim Duk-Heon, Kim Hack-Seong, Ryoo Hong-Je, et al. Position control system for induction motor using variable structure system with fuzzy sliding surface [A]. Proceedings ICPE'95 [C], Seoul, 1995, 200 - 210

[4] Yang Bin, Xu Dianguo and Wang Zongpei. Control of reluctance motor via fuzzy learning system [J]. Electric Machine and Control, 1998, 2(2): 100 - 103 (in Chinese)

[5] Wang Lixin and Mendel Jerry M. Fuzzy basis functions universal approximation and orthogonal least-squares learning [J]. IEEE Trans. on Neural Network, 1992, 3(5): 808 - 814

[6] Hung John Y, Gao Weibing and Hung James C. Variable structure control: a survey [J]. IEEE Trans. on Industrial Elect., 1993, 40 (1): 2 - 22

[7] Sun Yibiao, Guo Qingding and Shi Limei. Thurst observer-based sliding mode variable structure control for linear AC servo system [J]. Trans. of China Electrontechnical Society, 1998, 13(2): 1 - 5 (in Chinese)

本文作者简介

SUN Yibiao Born in 1970. He received the M.S. degree in 1997. He is a lecturer in Shenyang Polytechnic University. His research interests include AC servo system, sliding mode VSC, fuzzy control, artificial nerve network control and robust control etc.

GUO Qingding He graduated from electrical engineering department of Harbin institute of Technology in 1964. He is a professor of electrical engineering department in Shenyang university of technology presently. His main interests are AC servo system, numerical control, robust control and intelligent control.

LIU yang Born in 1977. He is a postgraduate in Shenyang University of Technology. His main interests are AC servo system, numerical control, robust control and coupling control.