Applied Soft Computing 47 (2016) 415–423

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

On-line constructive fuzzy sliding-mode control for voice coil motors

Chun-Fei Hsu*, Kai-Yi Wong

Department of Electrical Engineering, Tamkang University, No. 151, Yingzhuan Rd., Tamsui Dist., New Taipei City 25137, Taiwan

ARTICLE INFO

Article history:
Received 1 September 2015
Received in revised form 22 March 2016
Accepted 30 May 2016
Available online 22 June 2016

Keywords:
Exponential reaching time
Fuzzy sliding-mode control
Structure learning
Parameter learning
Voice coil motor

ABSTRACT

In this paper, a voice coil motor (VCM) featuring fast dynamic performance and high position repeatability is developed. To achieve robust VCM control performance under different operating conditions, an on-line constructive fuzzy sliding-mode control (OCFSC) system, which comprises of a main controller and an exponential compensator, is proposed. In the main controller, a fuzzy observer is used to on-line approximate the unknown nonlinear term in the system dynamics with on-line structure learning and parameter learning using a gradient descent algorithm. According to the structure learning mechanism, the fuzzy observer can either increase or decrease the number of fuzzy rules based on tracking performance. The exponential compensator is applied to ensure the system stability with a nonlinear exponential reaching law. Thus, the chattering signal can be alleviated and the convergence of tracking error can be speed up. Finally, the experimental results show that not only the OCFSC system can achieve good position tracking accuracy but also the structure learning ability enables the fuzzy observer to evolve its structure on-line.

1. Introduction

The high-precision quick-response linear motion is often required in modern testing systems. If the linear motion is realized using the rotary motors with a mechanical transmission, the mechanical transmission will introduce the backlash and large friction. A voice coil motor (VCM) for automated manufacturing processes is a direct drive motor that uses a permanent magnetic field and coil winding to produce a force proportional to the current applied to the coil winding [1,2]. The fixed part is permanent magnet field and the moving part is coil winding. Because of the characteristics of small size and high-response speed, VCM has been widely used in high-frequency response DDV drives or auto-focus modules of digital cameras [3]. Recently, several control methods for VCMs have been proposed [4–9].

Oboe et al. proposed a PI control with its simple design [1]. Since the control gains of PI control are fixed, the control performance is influenced by the system uncertainties, friction, and load changes of movable parts. Yu et al. proposed an adaptive fuzzy logic PID control to achieve a short response time with fuzzy tuning the control gains [4]. The fuzzy rules should be pre-constructed to achieve the design performance by trial-and-error; however, this trial-and-error tuning procedure is time-consuming. A fuzzy sliding-mode controller was designed to achieve favorable position control performance [5]; however, it has difficulty in determining suitable membership functions and fuzzy rules. Wu et al. proposed a sliding-mode control system with a state-space observer to improve the control accuracy and robustness [6]; however, the control signal results in the chattering phenomena. Recently, several neural-network-based intelligent control systems had been proposed for VCM control [7–9]. The developed adaptive tuning law only considers the on-line parameter learning of neural networks but doesn't consider the structure adjustment of neural networks. It implies that tracking accuracy would be not satisfied if inadequate hidden nodes of neural network, i.e. too many or too few, are predefined.

Whether a control system is robust against system uncertainties is an important issue for controller performance assessment. It is known that sliding mode control (SMC) system is an effective control approach due to its excellent advantage of strong robustness against model uncertainties, parameter variations and external disturbances [10,11]. However, the chattering problem is one of the most critical handicaps for applying the SMC system to real applications. On the other hand, based on the fuzzy rules base of fuzzy controller having skew-symmetric property, a fuzzy sliding-mode controller (FSMC) system is proposed to offer a significant reduction in rule inferences and simplify the tuning of control parameter [12–14]. Since only one variable (sliding surface) is defined as the input variable for fuzzy rules, the number of the fuzzy rules for

* Corresponding author.
E-mail addresses: fei@ee.tku.edu.tw (C.-F. Hsu), 400500111@s00.tku.edu.tw (K.-Y. Wong).

http://dx.doi.org/10.1016/j.asoc.2016.05.050
1568-4946/

FSMC is smaller than that for fuzzy control which uses the error and change of error as the input variables. However, obtaining appropriate membership functions and fuzzy rules for the design of FSMC system remains a challenge.

To tune the control parameters including the membership functions and fuzzy rules, some researchers focused on the adaptive fuzzy control (AFC) schemes with on-line parameter learning [15–18]. The AFC systems can tune its controller parameters to achieve favorable performance by designing parameter adaptation laws rather than requiring expert experience. Additionally, by combining the advantages of FSMC system and AFC system, some researchers proposed the adaptive fuzzy sliding-mode control (AFSMC) design methods [19,20]. Thus, not only the controller parameters of AFSMC system can be on-line tuned to achieve favorable performance but also the total number of fuzzy rules in AFSMC systems is greatly reduced compared to existing AFC systems.

Though the control performance in [15–20] is acceptable after controller parameters learning, the number of fuzzy rules should be determined by trial-and-error. It is not an easy task to determine an appropriate number of fuzzy rules. To overcome this problem, some researchers focused on the learning which consists of both structure learning and parameter learning [21–27]. The structure learning is responsible for on-line rule generation and the parameter learning is designed to achieve favorable learning performance. Thus, the number of fuzzy rules can dynamically vary to achieve an economical rule size.

This paper proposes an on-line constructive fuzzy sliding-mode control (OCFSC) system for a VCM to track a periodical position reference with robust characteristics. A fuzzy observer is utilized to on-line approximate the unknown nonlinear term of VCM system dynamics. The structure learning mechanism not only helps automate fuzzy rule generation but also locates good initial rule positions for parameter learning. All adjustable parameters of the OCFSC system are on-line tuned by the gradient descent learning method. Meanwhile, an exponential compensator is applied to ensure the system stability based on a Lyapunov function. Finally, the OCFSC system is implemented on an ARM Cortex-m4 microcontroller for high-performance industrial applications. The experimental results show that not only the fuzzy observer has the admirable property of small fuzzy rules size but also the OCFSC system can achieve favorable control performance such as good parameter variation rejection and good tracking accuracy. Thus, the proposed OCFSC system with low implementation complexity is suitable for real-time VCM control applications.

2. Problem formulation of VCM

VCM possesses the advantages of a simple structure, a fast response, and high accuracy. The dynamic equation, which satisfies the Kirchhoff's voltage law and Newton's second law of motion, can be obtained as follows [1,3]

$$v_a(t)=R_a i_a(t)+K_b\dot{x}(t)+L_a\dot{i}_a(t) \tag{1}$$

$$F_t(t)-F_f(t)=(m+M)\ddot{x}(t)+B\dot{x}(t) \tag{2}$$

where $x(t)$ is the position of the coil winding, $v_a(t)$ is the input voltage, R_a is the coil resistance, $i_a(t)$ is the coil current, K_b is the back electromotive force coefficient, K_t is the thrust force coefficient, L_a is the coil inductance, M is the mass of the coil winding, m is the mass of the payload, B is the viscous coefficient, $F_f(t)$ is the lumped friction force, and $F_t(t)=K_t i_a(t)$ is the thrust force. Due to the term L_a can be neglected; the dynamic equation of VCM represents as

$$\ddot{x}(t)=f(t)+g(t)u(t)+d(t) \tag{3}$$

where $f(t)=\frac{-(K_tK_b+R_aB)}{(m+M)R_a}\dot{x}(t)$ is the system dynamic, $g(t)=K_t/(m+M)R_a$ is the control gain, $d(t)=(-F_f(t))/m+M$ is the external disturbance, and $u(t)=v_a(t)$ is the input voltage. The control objective is to design the position of coil winding $x(t)$ can track the position command $x_c(t)$. Define a tracking error as

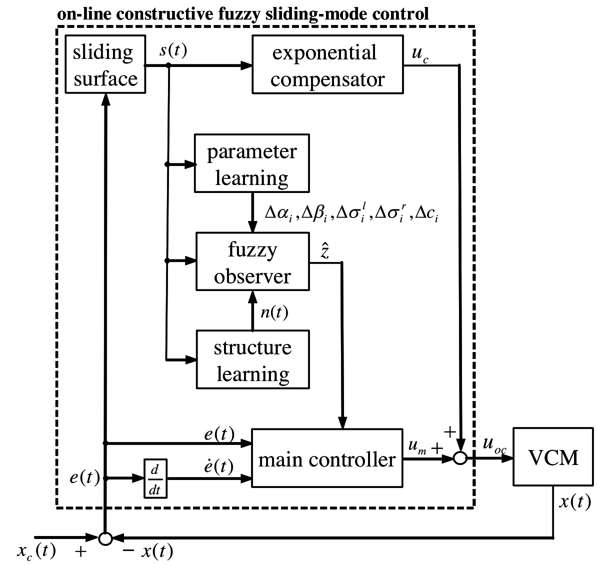

Fig. 1. The OCFSC system for a VCM.

$$e(t)=x_c(t)-x(t) \tag{4}$$

Substituting (4) into (3) yields

$$\ddot{e}(t)=z(t)-u(t) \tag{5}$$

where the nonlinear term $z(t)$ is defined as $z(t)=\ddot{x}_c(t)-(1-(1)/g(t))\ddot{x}(t)-(f(t)+d(t))/g(t)$. Assuming that all the parameters in the nonlinear term $z(t)$ are known, an ideal controller is assumed to take the following form [28]

$$u^*(t)=z(t)+k_1\dot{e}(t)+k_2e(t) \tag{6}$$

where k_1 and k_2 are positive constants. Imposing the control law $u(t)=u^*(t)$ upon (5), it follows that

$$\ddot{e}(t)+k_1\dot{e}(t)+k_2e(t)=0 \tag{7}$$

It can be seen that (7) is a Hurwitz polynomial. Thereby, it confirms that the tracking error $e(t)$ converges to zero asymptotically for any initial condition [28]. Because of the nonlinear term $z(t)$ is unknown or perturbed, the ideal controller cannot be implemented in real-time VCM control.

3. OCFSC system design

This paper proposes an OCFSC system as shown in Fig. 1, i.e.

$$u_{oc}(t)=u_m(t)+u_c(t)=\hat{z}+k_1\dot{e}(t)+k_2e(t)+u_c(t) \tag{8}$$

where $u_m(t)$ is the main controller, $u_c(t)$ is the exponential compensator, the fuzzy observer $\hat{z}$ is designed to approximate the unknown nonlinear term $z(t)$. A sliding surface, which includes an additional integral term, is defined as

$$s(t)=\dot{e}(t)+k_1e(t)+k_2\int_0^t e(\tau)d\tau \tag{9}$$

Assuming that there are $n(t)$ fuzzy rules in the fuzzy observer at time t, each fuzzy rule is described as

$$\text{Rule}\,i:\ \text{IF}\ s(t)\ \text{is}\ F_i,\ \text{THEN}\ \hat{z}\ \text{is}\ \alpha_i s(t)+\beta_i \tag{10}$$

where F_i represents fuzzy sets of $s(t)$ and $z_i=\alpha_i s(t)+\beta_i$ is the Takagi-Sugeno-Kang (TSK) type consequent part that is learned