Design of a Hybrid Controller for Voice Coil Motors with Simple Self-Learning Fuzzy Control

Chun-Fei Hsu
Department of Electrical Engineering, Tamkang University,
No. 151, Yingzhuan Rd., Tamsui Dist., New Taipei City
25137, Taiwan
fei@ee.tku.edu.tw

Kai-Yi Wong
Department of Electrical Engineering, Tamkang University,
No. 151, Yingzhuan Rd., Tamsui Dist., New Taipei City
25137, Taiwan
400500111@s00.tku.edu.tw

***Abstract*—The voice coil motor (VCM) has many excellent features such as high-starting thrust force, silence, low-cost and so on. In this paper, the dynamics of a VCM with the introduction of a lumped uncertainty is studied. It shows that the dynamic characteristics and motor parameters of the VCM are non-linear and time-varying. To resolve this problem, this paper proposes a hybrid control system, which comprised of a PD controller and simple self-learning fuzzy controller (SSFC), for the position tracking control of a VCM. The SSFC contains two sets of fuzzy inference system. One is the fuzzy controller and the other is the rule modifier. The modification value of each fuzzy rule is based on the fuzzy firing weight of each fuzzy rule to achieve satisfactory learning performance, thus it is suitable for on-line VCM control. Finally, the proposed hybrid control system is implemented on a 32-bit microcontroller for possible low-cost and high-performance industrial applications. The experimental results show that the proposed hybrid control system can achieve favorable tracking performance and is robust against payload variations of a VCM.**

***Keywords*—voice coil motor; fuzzy control; rule modifier; microcontroller.**

I. Introduction

The read/write heads of a hard disk drive are very sensitive to external shock and vibration. Shock and vibration dynamics can cause head/disk impact. Disk drives will typically see higher shock levels during the nonoperational state primarily resulting from shipping and handling. Since the voice coil motor (VCM) has many excellent features such as high-starting thrust force, alleviation of gear between motor and the motion devices, reduction of mechanical losses and the size of motion devices, high-speed operation, silence, low-cost and so on, the VCM has been widely used to the read/write heads of a hard disk [2, 3]. However, the dynamic model of the VCM actuator is difficult to obtain due to the nonlinear and time-varying motor behaviors under the effect of the friction and gas flow force disturbance in VCM actuator operating conditions.

Recently, several methods for VCM position control have been proposed [4-7]. In [4], a PID control is proposed with its simple design affordable price and effectiveness but the PID control cannot adapt for wide range of operating conditions due to the controller gain is fixed. In [5], a PID control with velocity feed-forward and disturbance observer is proposed. However, the disturbance observer requires one low-pass filter which cannot compensate for the control system effectively. In [6], a hybrid control based on disturbance observer and sliding-model control is proposed to achieve high accuracy motion and high frequency response. However, the controller results in chattering control inputs. In [7], an intelligent VCM control with neural network learning ability is proposed. Though the favorable control performance can be achieved, the design procedure is overly complex and requires a heavy computation loading.

Since the fuzzy control does not need a mathematical model and is more insensitive to plant parameter variations and noise disturbance, fuzzy controller has been proven to be a powerful tool many previous published papers [8, 9]. 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. To overcome the trail-and-error tuning of the membership functions and fuzzy rules, the fuzzy control scheme has been combined with many different methods to tune the fuzzy control rules [10-16]. In [10-12], the adaptive fuzzy control approach is designed to online tune the fuzzy rules in the Lyapunov stability theory; however, the approximation error between the system uncertainty and fuzzy uncertainty observer may cause instability of the closed-loop system. In [13, 14], the fuzzy neural network approach with parameter learning are proposed by using backpropagation learning algorithm, but it is based on gradient descents that is easily trapped at local minima. In [15, 16], the evolution algorithm has been successfully applied to solve many optimization problems. However, it always leads to heavy computational costs and the convergence speed may be slow.

System uncertainties, including unmodeled system dynamics and external disturbances, unavoidably exist in real VCM control applications. Motivated by the previous discussions, this paper proposes a hybrid controller system which is composed of a PD controller and a simple self-learning fuzzy controller (SSFC) to achieve high accuracy motion and high frequency response for a VCM. The proposed SSFC contains a fuzzy controller and a rule modifier, where the modification value of each fuzzy control rule is tuned based on its fuzzy firing weight. Finally, the hybrid control system is implemented on a 32-bit microcontroller for possible low-cost and high-performance industrial applications. The experimental results verify that the proposed hybrid control system can achieve favorable control performance such as good parameter variation rejection and good tracking accuracy due to the SSFC can online tuned the fuzzy rules to achieve satisfactory performance.

II. PROBLEM FORMULATION

The VCM has lightweight moving parts, high dynamic characteristics and good linearity between thrust force and coil current. The moving equation of a VCM can be simplified as [4]

$$F_t - F_f = (m+M)\ddot{x} + B\dot{x} \tag{1}$$

where x is the position of the moving table, M is the mass of the moving table, m is the mass of the payload, B is the viscous coefficient, F_t is the thrust force, and F_f is the lumped friction force. The thrust force F_t is defined as

$$F_t = K_t i_a \tag{2}$$

where K_t is the thrust force coefficient and i_a is the coil current. The electric equation of a VCM can be simplified as [4]

$$v_a = R_a i_a + K_b \dot{x} + L_a \frac{di_a}{dt} \tag{3}$$

where R_a is the coil resistance, K_b is the back electromotive force coefficient, L_a is the coil inductance and v_a is the applied voltage. Since the coil inductance L_a can be negligible, the dynamics of the VCM can be represented in the following form

$$\ddot{x} = f + gu + d \tag{4}$$

where $f = \frac{-(K_t K_b + R_a B)}{(m+M)R_a}\dot{x}$ and $g = \frac{K_t}{(m+M)R_a}$ are system dynamics, $d = \frac{-F_f}{m+M}$ is the external disturbance, and $u = v_a$ is the control input. The control objective is to find a control law so that the table position x can track a position command x_c under the occurrence of the external disturbance. Define a tracking error as

$$e = x - x_c \tag{5}$$

Substituting (4) into (5) yields

$$\ddot{e} = z + u \tag{6}$$

where the nonlinear term z is defined as $z = -\ddot{x}_c + (1-\frac{1}{g})\ddot{x} + \frac{f+d}{g}$. Assuming that all the parameters in the nonlinear term z are known, we can construct an ideal controller as [17]

$$u^* = -k_1\dot{e} - k_2 e - z \tag{7}$$

where k_1 and k_2 are positive constants. Imposing the control law $u = u^*$ upon (6), it follows that

$$\ddot{e} + k_1\dot{e} + k_2 e = 0\,. \tag{8}$$

If k_1 and k_2 are chosen to correspond to the coefficients of a Hurwitz polynomial, it implies that $\lim_{t\to\infty} e = 0$ [17]. Since the nonlinear term z may be unknown or perturbed in real-time applications, the ideal controller cannot be precisely obtained. The nonlinear term z has a significant impact on the performance of a position controller for a VCM.

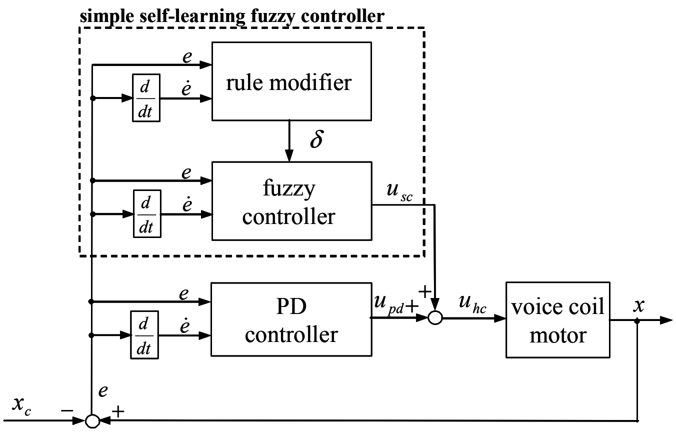

Fig. 1 The block diagram of the of the hybrid control system for a VCM

III. HYBRID CONTROLLER DESIGN

Whether a position control system is robust against the nonlinear term z is an important issue for a tracking performance assessment. In this paper, the proposed hybrid control system for a VCM is designed as shown in Fig. 1, i.e.

$$u_{hc} = u_{pd} + u_{sc} \tag{9}$$

where the PD controller $u_{pd} = -k_1\dot{e} - k_2 e$ is the main control and the SSFC u_{sc} is designed to estimate the unknown nonlinear term z . The SSFC contains two sets of fuzzy inference system. One is the fuzzy controller and the other is the rule modifier. For fuzzy controller using the error and the change-of-error as fuzzy input variables, there are m fuzzy rules in the fuzzy controller can be described in the following form

$$\text{Rule } i: \text{IF } e \text{ is } F_e^i \text{ and } \dot{e} \text{ is } F_{\dot{e}}^i, \text{ THEN } u_{sc} \text{ is } \alpha_i \tag{10}$$

where, in the i-th fuzzy rule, F_e^i and $F_{\dot{e}}^i$ represent the fuzzy sets of e and $\dot{e}$, respectively, and α_i are the singleton control actions. The output of the fuzzy controller is accomplished by the method of center-of-gravity as

$$u_{sc} = \frac{\sum_{i=1}^{m} w_i \times \alpha_i}{\sum_{i=1}^{m} w_i} \tag{11}$$

where w_i is the firing weight of the i-th fuzzy rule. In this paper, the fuzzy rules in (10) are initiated from zero ($\alpha_i = 0$, $i = 1,2,..,m$) and are learned from the rule modifier. For the fuzzy rule learning, there are n fuzzy rules in the rule modifier can be described in the following form

$$\text{Rule } j: \text{IF } e \text{ is } F_e^j \text{ and } \dot{e} \text{ is } F_{\dot{e}}^j, \text{ THEN } \delta \text{ is } \beta_i \tag{12}$$

where, in the j-th fuzzy rule, F_e^j and $F_{\dot{e}}^j$ represent the fuzzy sets of e and $\dot{e}$, respectively, and β_i are the singleton control actions. The output of the rule modifier is accomplished by the method of center-of-gravity as

$$\delta = \frac{\sum_{j=1}^{n} v_j \times \beta_j}{\sum_{j=1}^{n} v_j} \tag{13}$$

where v_i is the firing weight of the j-th fuzzy rule. For the k-th time interval, the modification algorithm is designed as follows

$$\alpha_i(k+1) = \alpha_i(k) + \eta\delta(k) \cdot \frac{w_i}{\sum_{i=1}^{m} w_i} \tag{14}$$

where η is the positive learning rate, $\Delta\alpha_i(k)$ is a modification value to be added to the i-th fuzzy rule in (10). Equation (14) shows that the modification value of each fuzzy rule is proportional to its firing weight of fuzzy inference. Thus, the SSFC can automatically tune the fuzzy control rules base to achieve satisfactory performance.

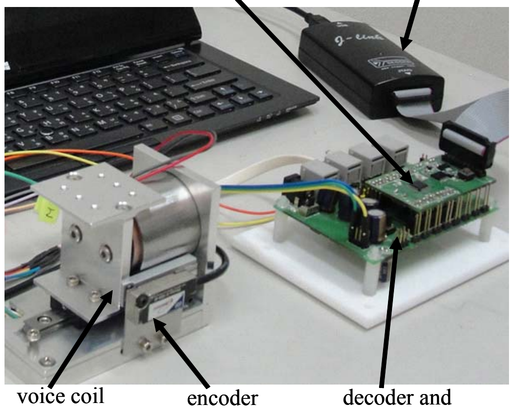

Fig. 2 Microcontroller-based experimental setup

IV. EXPERIMENTAL RESULTS

This paper proposed a microcontroller-based experimental setup for a VCM as shown in Fig. 2. The used 32-bit microcontroller (LPC1114FBD48) is an ARM Cortex-M0 microcontroller and it can operate up to 50 MHz [18]. On the software side, the µVision IDE from Keil combines project management, make facilities, source code editing, program debugging, and complete simulation in one powerful environment [19]. Two conditions are tested here. One is the nominal condition and the other one is the payload condition by adding a payload on the moving table. To investigate the effectiveness of the proposed control system, a comparison among the PD control and the proposed hybrid control system is made. A second-order transfer function is chosen as the reference model as follow

$$\frac{w_n^2}{s^2 + 2\xi w_n s + w_n^2} = \frac{225}{s^2 + 30s + 225} \tag{15}$$

where s is the Laplace operator, ξ and w_n are the damping ratio and undamped natural frequency.

First, the PD control is applied to the VCM. The PD control is given in the following form

$$u_{pd} = -0.2\dot{e} - 0.8e \tag{16}$$

where these parameters are chosen to achieve a desired system response in additional to the requirement of the system stability. The experimental results of the PD control are shown in Fig. 3. Under the nominal condition, the tracking performance of the table position x and the control input u are shown in Figs. 3(a) and 3(b), respectively. Meanwhile, under the payload condition, these terms are shown in Figs. 3(c) and 3(d), respectively. The experimental results show that favorable control performance can be achieved even under frequency change of the position command for the nominal condition. However, the tracking performance will be gradually deteriorated under the payload condition because of the PD control cannot adapt for wide range of operating conditions with its fixed control gains.

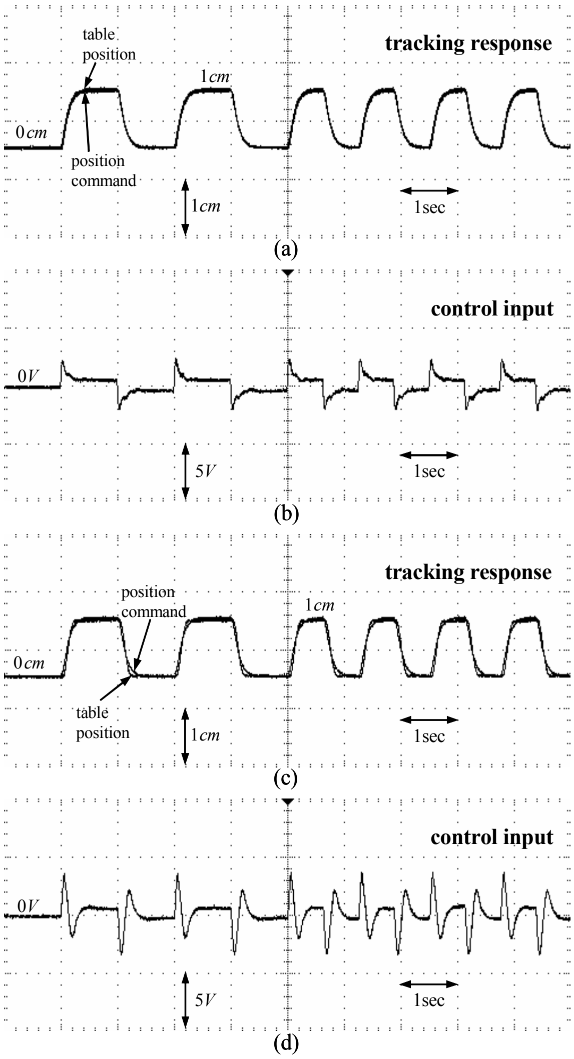

Fig. 3 Experimental results of the PD control

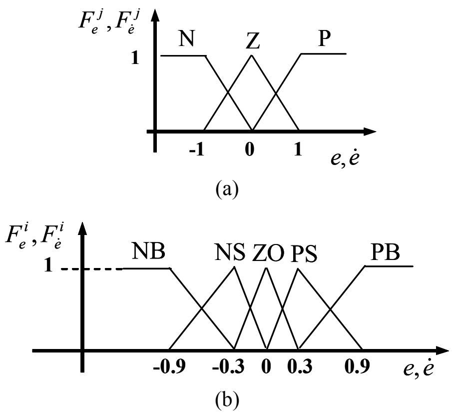

Fig. 4 (a) fuzzy sets of rule modifier. (b) fuzzy sets of fuzzy controller.

Then, the hybrid control system with SSFC is applied to the VCM again. The controller parameters are selected as $k_1 = 0.2$, $k_2 = 0.8$, $\eta = 0.01$, 25 fuzzy rules in the fuzzy controller and 9 fuzzy rules in the rule modifier. To show the self-learning ability, the fuzzy rules in (10) are initiated from zero and are learned from the rule modifier. Table 1 is derived by the basic idea for converging the tracking error and its derivative to zeros. The triangular-typed functions are used to define the membership functions of IF-part for rule modifier and fuzzy controller, which are shown in Figs. 4(a) and 4(b), respectively. The fuzzy labels are negative (N), zero (Z) and big (P) for rule modifier, and the fuzzy labels are negative big (NB), negative small (NS), zero (ZO), positive small (PS) and positive big (PB) for fuzzy controller.

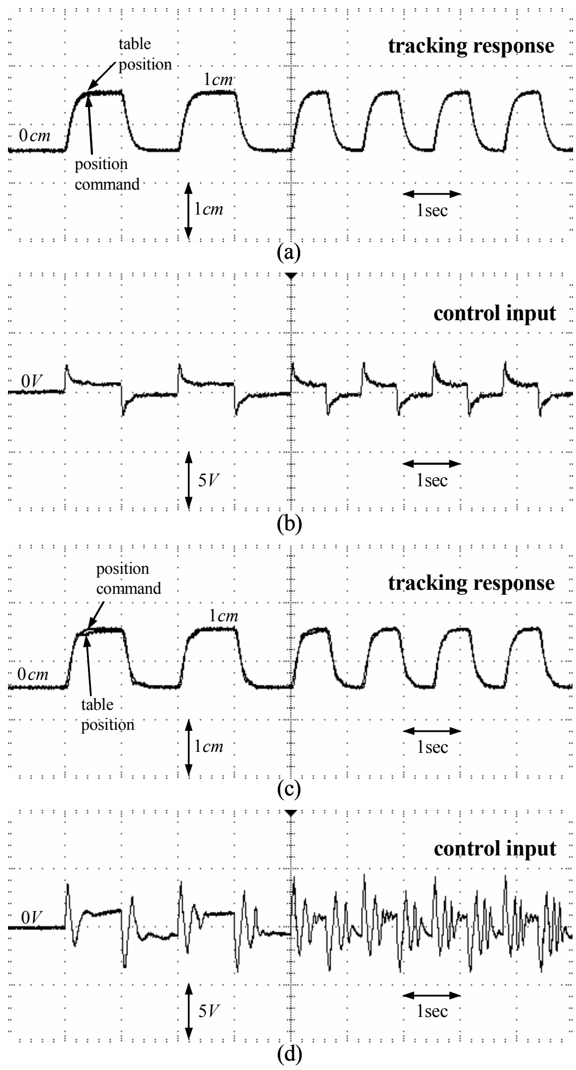

Fig. 5 Experimental results of the of the hybrid control system with SSFC

The experimental results of the hybrid control are shown in Fig. 5. The tracking responses x are shown in Figs. 5(a) and 5(c), and the control inputs u are shown in Figs. 5(b) and 5(d). To show the self-learning ability, the fuzzy rules are initiated from zero and are learned from the rule modifier. The learned fuzzy rules are shown in Tables 2(a) and 2(b) for nominal condition and payload condition, respectively. From the experimental results, accurate position tracking control performance of the VCM can be obtained after fuzzy rules learning and robust characteristics also can be achieved. Meanwhile, the hybrid control system with learned SSFC is applied to the VCM again. The experimental results of the hybrid control system with learned SSFC are shown in Fig. 6. The tracking responses x are shown in Figs. 6(a) and 6(c), and the control inputs u are shown in Figs. 6(b) and 6(d) for nominal condition and payload condition. From the experimental results, the hybrid control system with learned SSFC can achieve favorable position tracking control performance and is robust against payload variations.

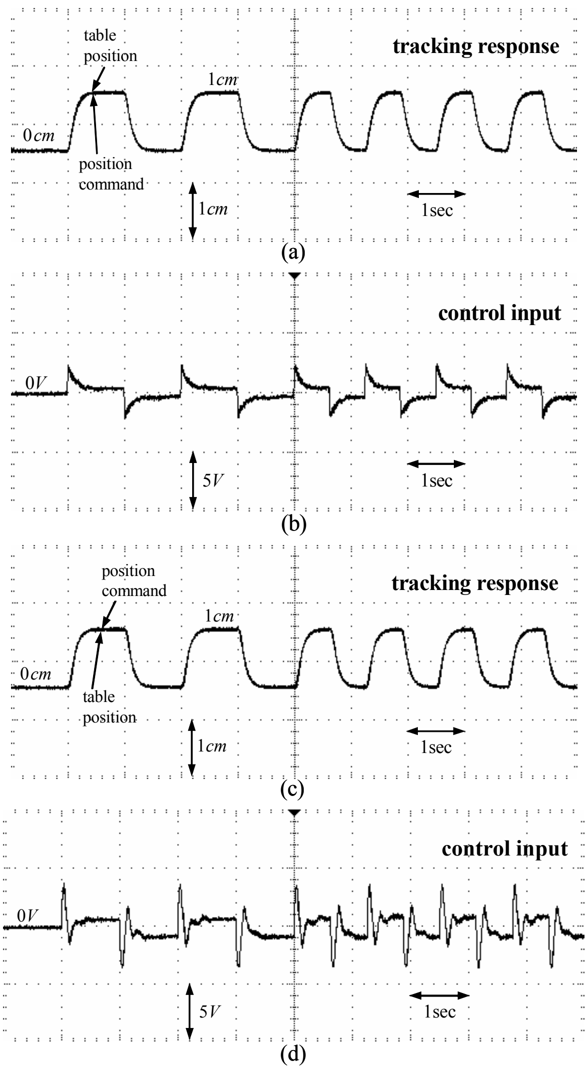

Fig. 6 Experimental results of the hybrid control system with learned SSFC

Table 1 Fuzzy rules for rule modifier

$\dot{e}$ \ e	**N**	**Z**	**P**
N	2	1	0
Z	1	0	-1
P	0	-1	-2

Table 2 (a) Modification fuzzy rules for nominal condition; (b) Modification fuzzy rules for payload condition

(a)

$\dot{e}$ \ e	**NB**	**NS**	**ZO**	**PS**	**PB**
NB	0.0387	0.0004	0.0001	0.0000	0.0000
NS	0.1691	0.0105	0.0017	-0.0077	-0.0997
ZO	1.6321	0.1998	0.0001	-0.3586	-1.1626
PS	0.1339	0.0056	-0.0019	-0.0141	-0.1379
PB	-0.0001	-0.0001	-0.0001	-0.0006	-0.0239

(b)

$\dot{e}$ \ e	**NB**	**NS**	**ZO**	**PS**	**PB**
NB	0.1145	0.0017	0.0006	0.0001	-0.0075
NS	0.5150	0.0276	0.0140	-0.0054	-0.1458
ZO	2.0721	0.2363	0.0016	-0.4024	-1.2538
PS	0.2073	0.0040	-0.0044	-0.0185	-0.3715
PB	0.0101	-0.0002	-0.0008	-0.0036	-0.0907

V. CONCLUSIONS

In this paper, a hybrid control system is designed to possess high-accuracy motion performance for a VCM. The hybrid control system is composed of a PD controller and a rule-based SSFC. The SSFC contains two sets of fuzzy inference system. One is the fuzzy controller and the other is the rule modifier. The contribution of this paper is an SSFC scheme for handling the effects of a nonlinear motor parameter and payload variations with a simple but powerful learning algorithm. In addition, the modification value of each rule is based on the fuzzy firing weight, so the learning algorithm can proceed reasonably. Finally, to show the effectiveness of the proposed control method, a comparison among the PD control and the hybrid control system is made. The experimental results demonstrate that the proposed hybrid control system can indeed attain satisfactory position control performance and is robust against payload variations of a VCM.

ACKNOWLEDGMENT

The authors appreciate the partial financial support from the National Science Council of Republic of China under grant NSC 102-2221-E-032-052.

REFERENCES

[1] Du, C., Xie, L., and Zhang, J.: 'Compensation of VCM actuator pivot friction based on an operator modeling method', *IEEE Trans. Control Syst. Technol.*, 2010, 18, (4), pp. 918-926.

[2] Oboe, R., Marcassa, F., and Maiocchi, G.: 'Hard disk drive with voltage driven voice coil motor and model-based control', *IEEE Trans. Magn.*, 2005, 41, (2), pp. 784-790.

[3] Zheng, J., Fu, M., Wang, Y., and Du, C.: 'Nonlinear tracking control for a hard disk drive dual-stage actuator system', *IEEE/ASME Trans. Mechatronics*, 2008, 13, (5), pp. 510-518.

[4] Seok, J.K. and Kim, S.K.: 'VCM controller design with enhanced disturbance decoupling for precise automated manufacturing processes', *IET Electr. Power Appl.*, 2012, 6, (8), pp. 575-582.

[5] Ratliff, R.T. and Pagilla, P.R.: 'Design, modeling, and seek control of a voice coil motor actuator with nonlinear magnetic bias', *IEEE Trans. Magn.*, 2005, 41, (6), pp. 2180-2188.

[6] Wu, S., Jiao, Z., Yan, L., Zhang, R., Yu, J., and Chen, C.Y.: 'Development of a direct-drive servo valve with high-frequency voice coil motor and advanced digital controller', *IEEE/ASME Trans. Mechatronics*, 2014, 19, (3), pp. 932-942.

[7] Lin, C.M. and Li, H.Y.: 'Adaptive dynamic sliding-mode fuzzy CMAC for voice coil motor using asymmetric Gaussian membership function', *IEEE Trans. Ind. Electron.*, 2014, 61, (10), pp. 5662-5671.

[8] Timothy, J.R.: 'Fuzzy logic with engineering application' (NewYork: Mc-Graw Hill 1995).

[9] Wang, L.X.: 'A course in fuzzy systems and control' (Englewood Cliffs, NJ: Prentice Hall, 1997).

[10] Wong, C.C. and Chen, J.Y.: 'Fuzzy control of nonlinear systems using rule adjustment', *IEE Control Theory Appl.*, 1999, 146, (6), pp. 578-584.

[11] Tong, S., Li, Y., Li, Y., and Liu, Y.: 'Observer-based adaptive fuzzy backstepping control for a class of stochastic nonlinear strict-feedback systems', *IEEE Trans. Syst. Man Cybern. B*, 2011, 41, (6), pp. 1693-1704.

[12] Chaoui, H. and Sicard, P.: Adaptive fuzzy logic control of permanent magnet synchronous machines with nonlinear friction', *IEEE Trans. Ind. Electron.*, 2012, 59, (2), pp. 1123-1133.

[13] Mon, Y.J. and Lin, C.M.: 'Supervisory recurrent fuzzy neural network control for vehicle collision avoidance system design', *Neural Comput. Applic.*, 2012, 21, (8), pp. 2163-2169.

[14] Hsu, C.F.: 'Nonlinear system control using a self-organizing functional-linked neuro-fuzzy network', *Nonlinear Dyn.*, 2013, 73, (3), pp. 1631-1643.

[15] Ge. P., Guo, L., Zhang, R., Shao, Q., and Zhao, X.: 'Parameter optimisation of path-following fuzzy controller for a six-wheel lunar rover', *IET Intell. Transp. Syst.*, 2013, 7, (1), pp. 1-9.

[16] Lu, C.F., Hsu, C.H., and Juang, C.F.: 'Coordinated control of flexible AC transmission system devices using an evolutionary fuzzy lead-lag controller with advanced continuous ant colony optimization', *IEEE Trans. Power Syst.*, 2013, 28, (1), pp. 385-392.

[17] Slotine, J.J.E. and Li, W.P.: 'Applied nonlinear control' (Englewood Cliffs, NJ: Prentice Hall, 1991).

[18] http://www.tw.nxp.com/

[19] http://www.keil.com/