

# Fuzzy Sliding Mode Control of a Magnetic Ball Suspension System

Chien-An Chen, Huann-Keng Chiang, and Jing-Chung Shen

## Abstract

**This paper presents an adaptive fuzzy estimator sliding mode position control design for robust stabilization and disturbance rejection for a magnetic ball suspension system (MBSS). In general, the conventional sliding mode control design assumes that the upper boundary of the parameter variations and external disturbances is known and the sign function is used. It causes high frequency chattering and high gain phenomenon. In this paper, we propose a novel adaptive fuzzy estimator sliding mode control for the MBSS to avoid the high gain and reduce the chattering magnitude. The parameter variation and external disturbance estimator is designed to estimate the unknown lumped uncertainty values in real-time. This is different from the conventional fuzzy sliding mode control which estimates the unknown upper boundary uncertainty. This method utilizes a Lyapunov function candidate to guarantee convergence and asymptotically track the MBSS position commands. We employ experiments to validate the proposed method.**

**Keywords:** Adaptive estimation, Fuzzy systems, Sliding mode control, Magnetic ball suspension system.

## 1. Introduction

In recent years, magnetic levitation systems [1-12] have been successfully implemented in many applications, such as high-speed maglev passenger trains, magnetic frictionless bearings and vibration isolation tables. The magnetic levitation system is open-loop unstable and inherently nonlinear electro-mechanical dynamic. It is therefore an interesting and impressive system for engineers and researchers.

In [1-2], a feedback linearization controller was discussed. The feedback linearization method utilizes a complete nonlinear description and yields consistent performance largely independent of the operating point.

However, feedback linearization control does not guarantee robustness in the presence of modeling errors. In [3],  $H^\infty$  control and sliding mode control was proposed.  $H^\infty$  control is a computation expensive method that presents good disturbance attenuation performance. In [4], sliding mode control and PID controller was discussed. In [5], the PID controller was discussed. The PID controller is a simple method for operating point linearization. However, the PID controller has good performance only within a small operating range. In [6], Fuzzy learning control was proposed. The learning control is a computation expensive method. In [7], adaptive robust nonlinear controller learning was proposed that is also computationally expensive. In [8], an evolutionary programming based fuzzy sliding mode control was proposed. The evolution computation [13,14] is also a computationally expensive in tuning the neural network controller structure and parameters. In [9], an improved force model-identification method was proposed. In [10], an integral variable controller with grey prediction was proposed to reduce the chattering and steady state error.

Sliding mode control [15,16] has attracted a great deal of attention in recent years because it is proven as a powerful tool for nonlinear robust control design. It is an effective and robust technology for rejecting parameter variations and external disturbances. It has been applied in robot control, motor control and many control fields [3,10,12, 15-22]. The uncertainties, parameter variations and/or disturbances can be rejected for variable structure control when the upper boundary of the system lumped uncertainty is known. The system uncertainty boundaries are difficult to obtain in practical applications. In real applications, uncertainty boundaries can easily exceed the assumed magnitude range, under which the sliding mode can not be used. Using high gain control to improve disturbance rejection has been proposed [18]. A control system using a large constant gain is simple to implement. However, it produces unnecessary deviations from the switching manifold and causes large chattering in the control systems. Serious chattering can reduce by using the boundary layer which the signum function is replaced by the saturation function. However, it produces steady state errors. Hence, in recent years, some researchers [10,20-23] have proposed methods to find the uncertain upper boundaries and eliminate the steady state error in which the signum function is replaced by the saturation function. Their major concept estimates

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the bounded uncertainties in real-time for the controlled system. Hence, the controller signal is smaller than that of the conventional sliding mode controller and the chattering phenomenon is also reduced.

The fuzzy theory was proposed by Zadeh [24]. It has been successfully employed in the control field [6,21, 25-29]. The fuzzy controller is an effective method when the system's mathematical model is unknown, or known with uncertainties. The fuzzy logic controller has replaced the conventional controller in many control system applications over the past three decades. In order to overcome the chattering phenomenon disadvantage of the sliding mode control (SMC), many researchers [6,21,25,26,28] investigated the relationship between fuzzy logic and SMC.

In this paper, we propose the novel adaptive fuzzy estimator sliding mode control for MBSS. This novel adaptive fuzzy estimator sliding mode control is different from the conventional fuzzy sliding mode controller. The lumped uncertainty is estimated every sampling period in real-time for the controlled system. The system uses a small magnitude sign function hence this system reduces chattering magnitude and makes the response smoother.

The organization of this paper is as follows. The experimental apparatus and the model are discussed in Section 2. In Section 3, the conventional sliding mode controller is introduced. In Section 4 the design of the adaptive fuzzy estimator sliding mode controller is proposed. In Section 5, experimental results show that the proposed sliding mode controller is implemented in MBSS. Finally, our conclusions are presented in Section 6.

## 2. Dynamic Analysis of Magnetic Ball Suspension System

The single-axis magnetic ball suspension system (MBSS) diagram is shown in Figure 1 which consists of a levitation object, an electromagnetic coil, a sensor system, a current driver and a controller. The levitation object is a ping-pong ball with a permanent magnet attached inside it to provide an attractive force. The sensor system includes a light source and a light receiver to determine the height of the ball. The attraction force of the magnetic ball is controlled by the electromagnetic currents from the current driver which is computed by the controller.

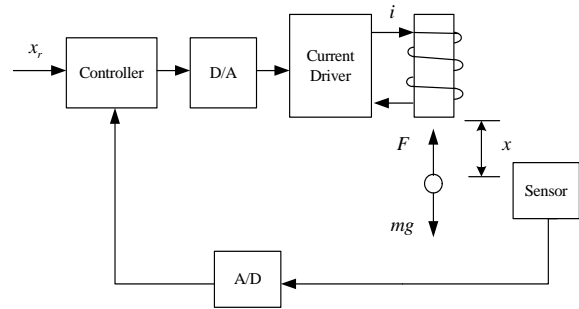


Figure 1. Schematic diagram of MBSS.

According to Newton motion law, we have

$$m\ddot{x} = mg - F - F_d \quad (1)$$

where  $x$  is the distance from upper edge the ball to the electromagnetic in milli-meter,  $m$  is the mass of levitation ball in gram,  $g$  is the gravity of  $9.8 \text{ m/sec}^2$ ,  $F$  is the magnetic control force in milli-newton and  $F_d$  is the external load disturbances. The ideal expression of force in an electromagnet is  $F = k\left(\frac{i}{x}\right)^2$  [5,11,12]. This is affected by leakage flux etc. In recent years, a linearized expression of magnetic force has been modeled by five methods [2,3,5,9-12]. In this paper, the magnetic force  $F$  [3,10] is expressed in terms of the magnetic coil current  $i$  and magnetic ball position  $x$  using

$$F = \frac{i}{a_2 x^2 + a_1 x + a_0} \quad (2)$$

Therefore, the magnetic force characteristic is experimentally determined as a function of the current and the position using the least-square fitting. This experiment consists of determining the minimum current required to pick up the magnetic ball at various positions. The experimental measurements between distances and currents are shown in Table 1.

Table 1. The relationship between distances and currents.

Distance $x$ (mm)	Current $i$ (A)	Distance $x$ (mm)	Current $i$ (A)
23	0.289	33	0.816
24	0.319	34	0.884
25	0.372	35	0.982
26	0.425	36	1.081
27	0.446	37	1.158
28	0.496	38	1.255
29	0.562	39	1.324
30	0.630	40	1.486
31	0.670	41	1.595
32	0.752	42	1.685

In order to measure the ball height ( $x$ ), a sensor system is used. However, the ball height ( $x$ )

relationship of the voltage ( $v$ ) which is generated by the light receiver is nonlinear and complex. Hence, the relation is also determined using experimental data. The voltage ( $v$ ) of the position sensor (light receiver) and magnetic ball position  $x$  can be expressed as

$$x(v) = p_4 v^4 + p_3 v^3 + p_2 v^2 + p_1 v + p_0 \quad (3)$$

where  $p_4 = 41.07$ ,  $p_3 = -185.2$ ,  $p_2 = 309.4$ ,  $p_1 = -234.7$ ,  $p_0 = 101.3$ . Table 2 shows the experimental measure data.

Table 2. The relationship between voltages and distances.

Voltage $v$ (Volt)	Distance $x$ (mm)	Voltage $v$ (Volt)	Distance $x$ (mm)
1.618	28.2	0.706	34.7
1.266	29.66	0.639	36.1
1.088	31.0	0.585	37.5
0.928	32.2	0.549	38.6
0.811	33.5	0.518	40

The state variables are defined as  $x_1 = x$ ,  $x_2 = \dot{x}$ , equation (1) can be rewritten as:

$$\begin{aligned} \dot{x}_1(t) &= x_2(t) \\ \dot{x}_2(t) &= g - bu(t) - d(t) = g - b_o(u(t) + E) \end{aligned} \quad (4)$$

where

$$b \equiv \frac{1}{m(a_2 x^2 + a_1 x + a_0)} = b_o + \Delta b$$

$$m = 1.2617g$$

$$a_2 \equiv a_{2o} + \Delta a_2$$

$$a_1 \equiv a_{1o} + \Delta a_1$$

$$a_0 \equiv a_{0o} + \Delta a_0$$

$$a_{2o} = 0.001893, a_{1o} = -0.006371, a_{0o} = 0.07048.$$

$$b_o \equiv \frac{1}{m(a_{2o} x^2 + a_{1o} x + a_{0o})}$$

$$E = \frac{-1}{b_o} (\Delta b u(t) + d(t))$$

The subscript index ‘‘o’’ indicates nominal system value; ‘‘ $\Delta$ ’’ symbol expresses uncertainty, and  $E$  is the lumped uncertainty,  $u(t)$  denotes the electromagnet current  $i$ ,  $d(t)$  denotes external disturbances.

### 3. Conventional sliding mode controller

The position tracking error in the conventional sliding mode controller is defined as follows

$$e(t) = x_r(t) - x_1(t) \quad (5)$$

where  $x_r$  is the position command. The sliding function  $S(t)$  is combined with the error integration as

$$S(t) = \dot{e}(t) + c_{s1} e(t) + c_{s2} \int_{-\infty}^t e(\tau) d\tau, \quad c_{s1}, c_{s2} > 0 \quad (6)$$

The input control  $u(t)$  (the magnetic coil current  $i$ ) can be defined as

$$u(t) = u_{eq}(t) + u_n(t) \quad (7)$$

where  $u_{eq}(t)$  is used to control the overall system behavior and  $u_n(t)$  is used to suppress the parameter uncertainties and reject disturbances. To satisfy the equivalent control concept  $\dot{S}(e) = 0$ , we get

$$\begin{aligned} \dot{S} &= \ddot{x}_r - g + b_o(u(t) + E) + c_{s1} \dot{e} + c_{s2} e \\ &= (\ddot{x}_r - g + c_{s1} \dot{e} + c_{s2} e + b_o u_{eq}) + b_o(u_n + E) \end{aligned} \quad (8)$$

We set

$$u_{eq} = -\frac{1}{b_o} (\ddot{x}_r - g + c_{s1} \dot{e} + c_{s2} e) \quad (9)$$

To satisfy the reaching condition  $S(e)\dot{S}(e) \leq -\eta|S|$ , we have

$$S\dot{S} = S[b_o(u_n + E)] \quad (10)$$

The uncertain nonlinear switch control input can be defined as

$$u_n = -(K + \frac{\eta}{b_o}) \text{sign}(S) \quad (11)$$

where

$$|E| \leq K \quad \text{and} \quad \text{sign}(S) = \begin{cases} 1, & \text{for } S > 0 \\ 0, & \text{for } S = 0 \\ -1, & \text{for } S < 0 \end{cases} \quad (12)$$

Hence, the reaching condition  $S(e)\dot{S}(e) \leq -\eta|S|$  can be guaranteed. To avoid the chattering phenomenon, the  $\text{sign}(\cdot)$  is replaced by the saturation function  $\text{sat}(\cdot)$ . Therefore,  $u_n$  becomes

$$u_{nM} = -(K + \frac{\eta}{b_o}) \text{sat}(S) \quad (13)$$

where

$$\text{sat}(S) = \begin{cases} 1, & \text{for } S > \Phi \\ \frac{\Phi}{S}, & \text{for } |S| \leq \Phi \\ -1, & \text{for } S < -\Phi \end{cases}, \quad \Phi \text{ is the boundary layer.} \quad (14)$$

### 4. Adaptive fuzzy estimator sliding mode controller

In general, the conventional sliding mode control design is assumed that the lumped upper boundary of parameter variations and external disturbances is known and the sign function is used. However, the system lumped uncertainty boundary is difficult to obtain in practical applications. The conventional fuzzy sliding mode control [21,25] estimates the unknown uncertainty upper boundary in which chattering phenomenon exists. Therefore, we adopt this novel method to estimate the lumped unknown uncertainty. It reduces the chattering

magnitude or steady state error phenomenon. The design method for the proposed controller is as follows. First, the Lyapunov function  $V_1$  is selected as

$$V_1 = \frac{1}{2}S^2 > 0 \quad (15)$$

The derivative of  $V_1$  is

$$\dot{V}_1 = S(\ddot{x}_r - g + b_0(u(t) + E) + c_{s1}\dot{e} + c_{s2}e) \quad (16)$$

We can choose control input  $u$  as

$$u = -\frac{1}{b_0}(\ddot{x}_r - g + b_0E + c_{s1}\dot{e} + c_{s2}e + k_v S), \quad k_v > 0 \quad (17)$$

Hence, (16) becomes

$$\dot{V}_1 = -k_v S^2 \leq 0 \quad (18)$$

According to the Lyapunov second method, the control system stability is guaranteed. However, in (17), the lumped uncertainty  $E(t)$  exists, which is difficult to obtain in practical applications. The fuzzy law of the estimator is designed to estimate the unknown lumped uncertainty  $E$ . We utilize the fuzzy system IF-THEN rules as

$$R^{(j)} : \text{IF } S \text{ is } A^j \text{ THEN } E_{Fuzzy} \text{ is } B^j \quad (19)$$

We adopt the Gaussian membership function, singleton fuzzifier product inference engine and center average defuzzifier. The input and output membership functions are defined in Figures 2 and 3. The fuzzy system output is expressed as

$$E_{Fuzzy}(S) = \frac{\sum_{j=1}^m B^j(\mu_{A_1^j}(S))}{\sum_{j=1}^m (\mu_{A_1^j}(S))} = \alpha^T W(S) \quad (20)$$

where

$$\mu_{A_1^j}(S) = \exp\left(-\frac{(S - c_j)^2}{2\sigma^2}\right), \quad \sigma = 500\pi, \quad c_1 = -\frac{2000}{6\pi}, \quad c_2 = -\frac{2000}{12\pi},$$

$$c_3 = 0, \quad c_4 = \frac{2000}{12\pi}, \quad c_5 = \frac{2000}{6\pi}$$

$$\alpha = [B^1, \dots, B^m]^T, \quad W(S) = [w^1(S), \dots, w^m(S)]^T,$$

$$w^i(S) = \frac{(\mu_{A_1^i}(S))}{\sum_{j=1}^m (\mu_{A_1^j}(S))}, \quad \text{for } i = 1, \dots, m = 5.$$

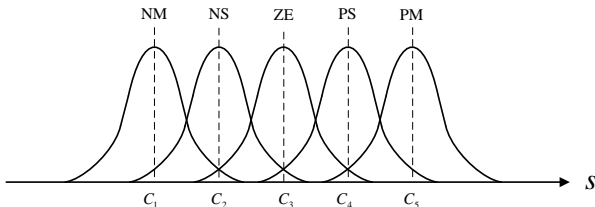


Figure 2. Input membership function of the fuzzy estimator.

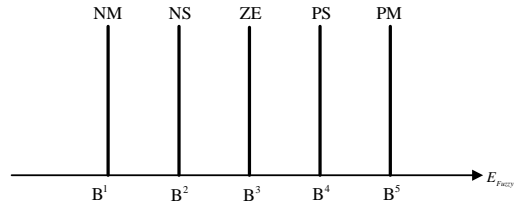


Figure 3. Output membership function of the fuzzy estimator.

However, the parameter  $\alpha = [B^1, \dots, B^m]^T$  is difficult to set in practical applications. Assuming the lumped uncertainty  $E = E_{Fuzzy}^*(S | \alpha^*) + \delta = \alpha^{*T}W(S) + \delta$  is a constant during the sampling period. The  $E_{Fuzzy}^*$  is the nearest orthogonal projection of  $E(t)$  and  $\alpha^*$  is the parameter vector of the  $E_{Fuzzy}^*$  in finite dimension  $W(S) = [w^1(S), \dots, w^m(S)]^T$  which has the initial parameter  $\alpha = [B^1, \dots, B^m]^T = [-0.2, -0.1, 0, 0.1, 0.2]^T$  and  $\delta$  is the distance between  $E$  and  $E_{Fuzzy}^*$ . Assuming  $\delta$  is less than a small positive constant  $\varepsilon$ , i.e.,  $|\delta| < \varepsilon$ . Let  $\hat{E}_{Fuzzy} = \hat{\alpha}^T W(S)$  is the estimated value of the lumped uncertainty and  $\tilde{E}_{Fuzzy} = E_{Fuzzy}^* - \hat{E}_{Fuzzy} = (\alpha^* - \hat{\alpha})^T W(S) = \tilde{\alpha}^T W(S)$ , where  $\tilde{\alpha}$  is the estimated error between the parameter vector  $\alpha^*$  and the estimated parameter vector  $\hat{\alpha}$  of the lumped uncertainty. Equation (15) can be rewritten as

$$V_2 = \frac{1}{2}S^2 + \frac{1}{2r}\tilde{\alpha}^T\tilde{\alpha} > 0 \quad (21)$$

where  $r$  is a positive constant. The derivative of  $V_2$  is  $\dot{V}_2 = S[\ddot{x}_r - g + b_0(u + \hat{\alpha}^T W(S) + \delta) + c_{s1}\dot{e} + c_{s2}e] - \tilde{\alpha}^T \left(\frac{1}{r}\dot{\tilde{\alpha}} - Sb_0 W(S)\right)$

We choose control input  $u$  as

$$u = -\frac{1}{b_0}(\ddot{x}_r - g + b_0\hat{\alpha}^T W(S) + b_0\varepsilon \text{sgn}(S) + c_{s1}\dot{e} + c_{s2}e + k_v S) \quad (23)$$

Substituting (23) into (22), we can obtain

$$\dot{V}_2 = -k_v S^2 - b_0\varepsilon|S| + b_0\delta S - \tilde{\alpha}^T \left(\frac{1}{r}\dot{\tilde{\alpha}} - Sb_0 W(S)\right) \quad (24)$$

We choose  $\dot{\tilde{\alpha}} = rSb_0 W(S)$ , the estimated value  $\hat{E}$  of the lumped uncertainty can be expressed as

$$\hat{E} = \hat{\alpha}^T W(S) = \left(\int_0^t rSb_0 W(S) dt\right)^T W(S) \quad (25)$$

Substituting (23) and  $\dot{\tilde{\alpha}} = rSb_0 W(S)$  into (22), we can obtain

$$\dot{V}_2 = -k_v S^2 - b_0(\varepsilon|S| - \delta S) \leq -k_v S^2 - b_0(\varepsilon|S| - |\delta||S|) \quad (26)$$

$$= -k_v S^2 - b_0|S|(\varepsilon - |\delta|) \leq 0$$

Defining  $\xi(t)$  as

$$\xi(t) = -k_v S^2 - b_0|S|(\varepsilon - |\delta|) \quad (27)$$

The integration of (27) can be expressed as



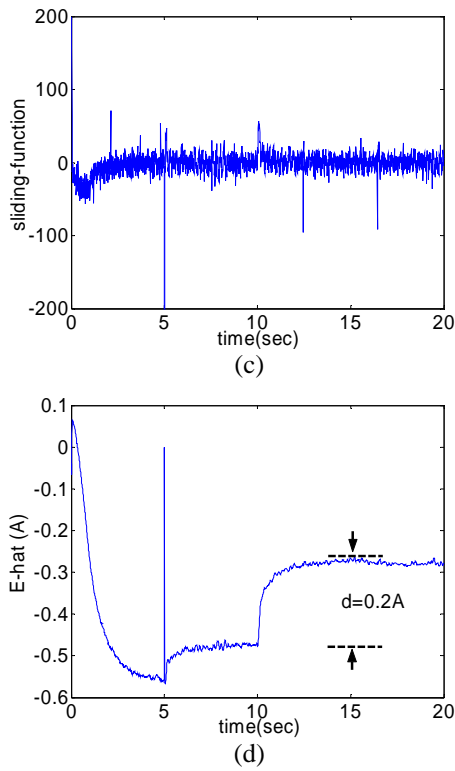


Figure 5. Experimental results of  $x_r = 37$  mm at  $0 \leq t \leq 5$  sec,  $x_r = 35$  mm at  $t > 5$  sec and a step load disturbance  $d(t) = 0.2A$  is added at  $t = 10$  sec with initial position  $x_1(0) = 40$  mm in Case1. (a) position response (b) control input (c) sliding function (d) estimated value  $\hat{E}(t)$ .

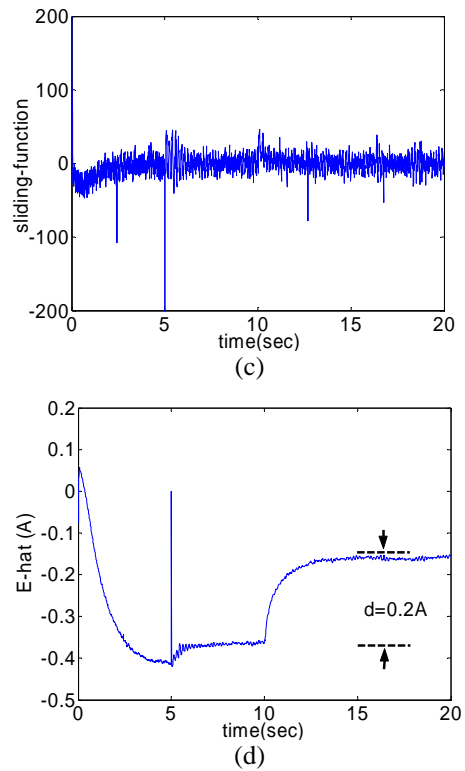
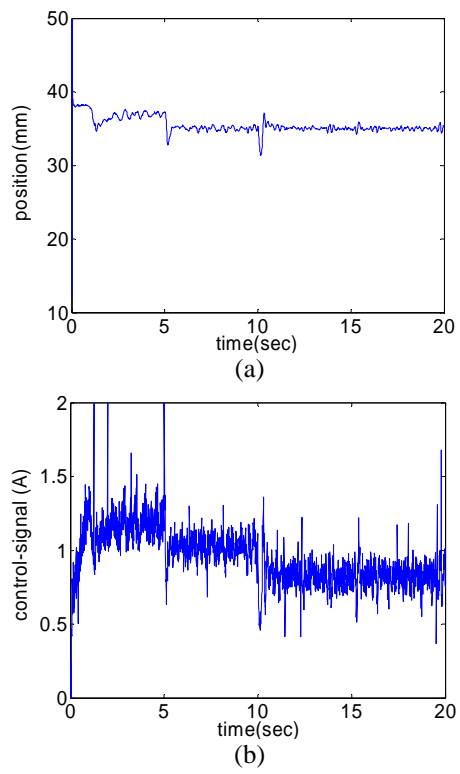
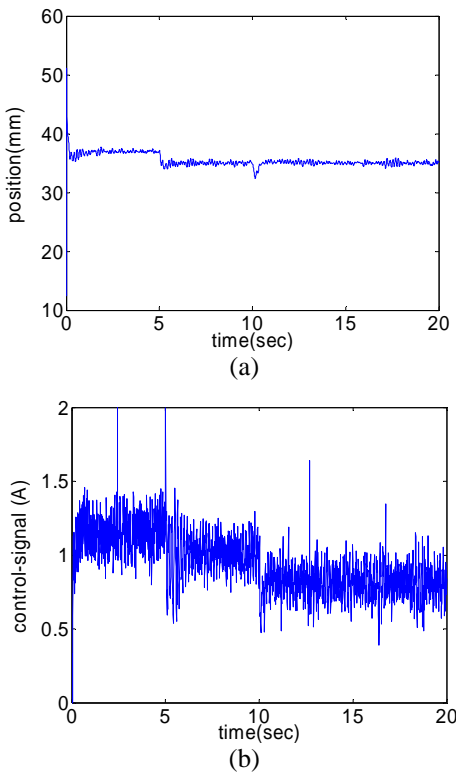


Figure 6. Experimental results of  $x_r = 37$  mm at  $0 \leq t \leq 5$  sec,  $x_r = 35$  mm at  $t > 5$  sec and a step load disturbance  $d(t) = 0.2A$  is added at  $t = 10$  sec with initial position  $x_1(0) = 40$  mm in Case2. (a) position response (b) control input (c) sliding function (d) estimated value  $\hat{E}(t)$ .



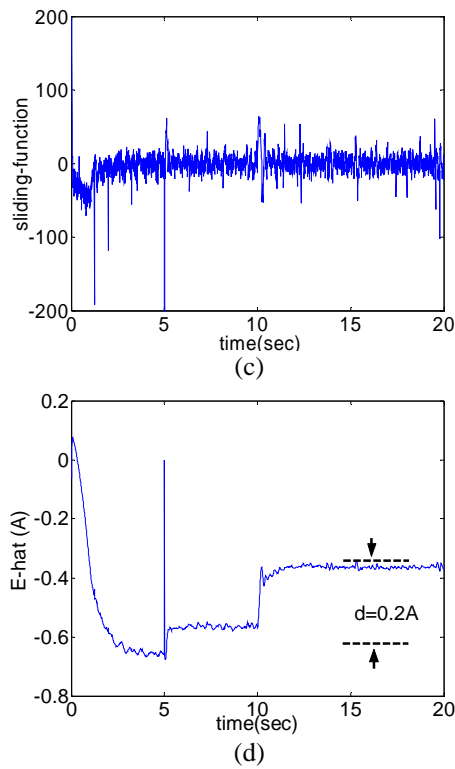


Figure 7. Experimental results of  $x_r = 37$  mm at  $0 \leq t \leq 5$  sec,  $x_r = 35$  mm at  $t > 5$  sec and a step load disturbance  $d(t) = 0.2$  A is added at  $t = 10$  sec with initial position  $x_1(0) = 40$  mm in Case3. (a) position response (b) control input (c) sliding function (d) estimated value  $\hat{E}(t)$ .

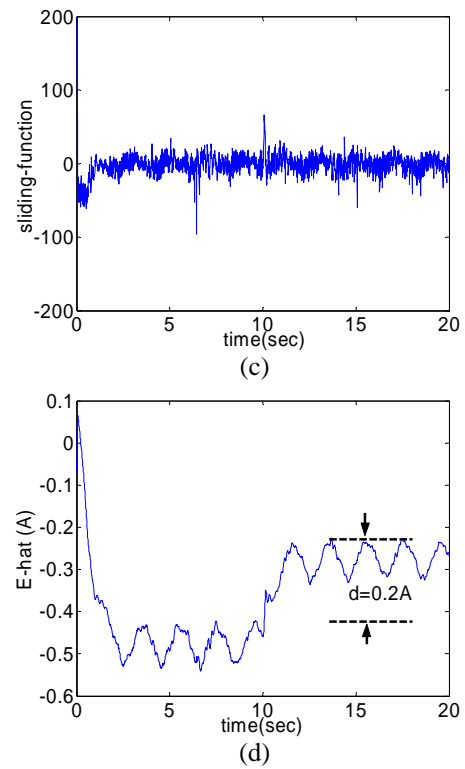
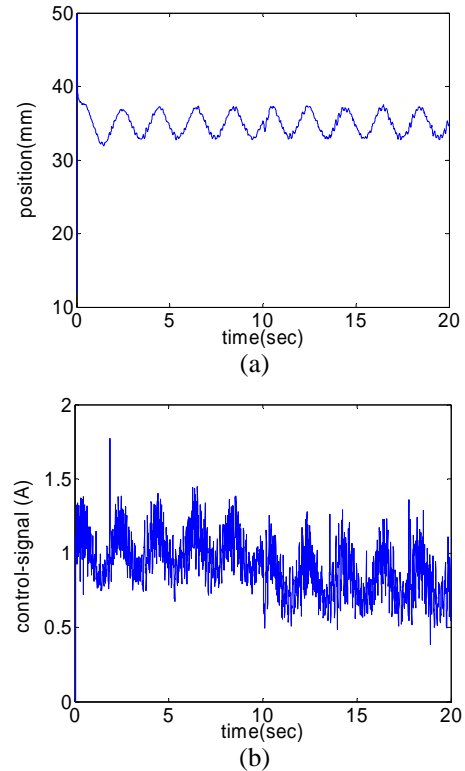
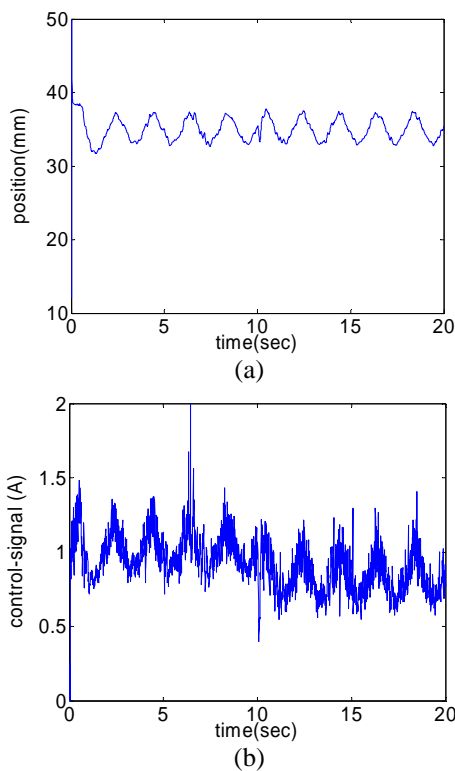


Figure 8. Experimental results of  $x_r = 35 + 2\sin(\pi t)$  mm and a step load disturbance  $d(t) = 0.2$  A is added at  $t = 10$  sec with initial position  $x_1(0) = 40$  mm in Case1. (a) position response (b) control input (c) sliding function (d) estimated value  $\hat{E}(t)$ .



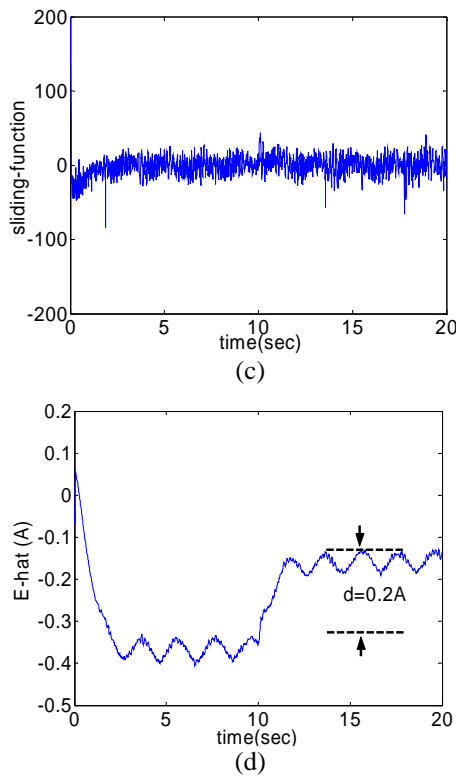


Figure 9. Experimental results of  $x_r = 35 + 2\sin(\pi t)$  mm and a step load disturbance  $d(t) = 0.2A$  is added at  $t = 10$  sec with initial position  $x_1(0) = 40$  mm in Case2. (a) position response (b) control input (c) sliding function (d) estimated value  $\hat{E}(t)$ .

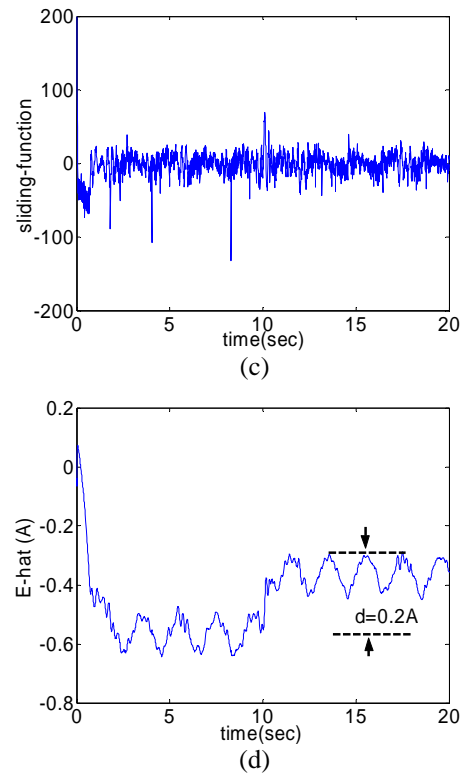
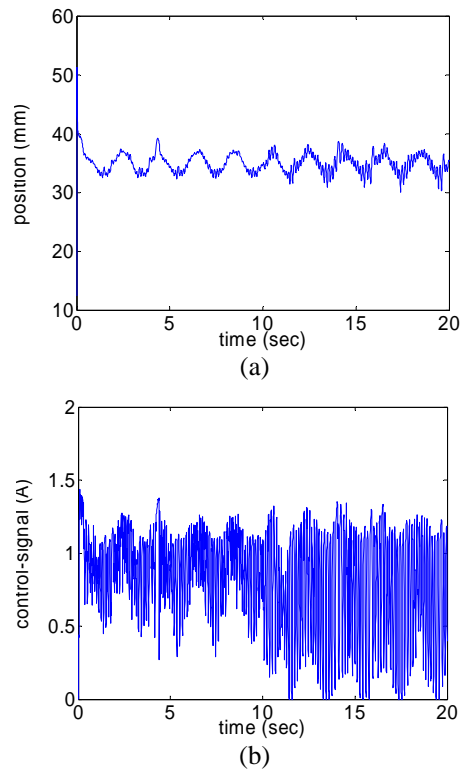
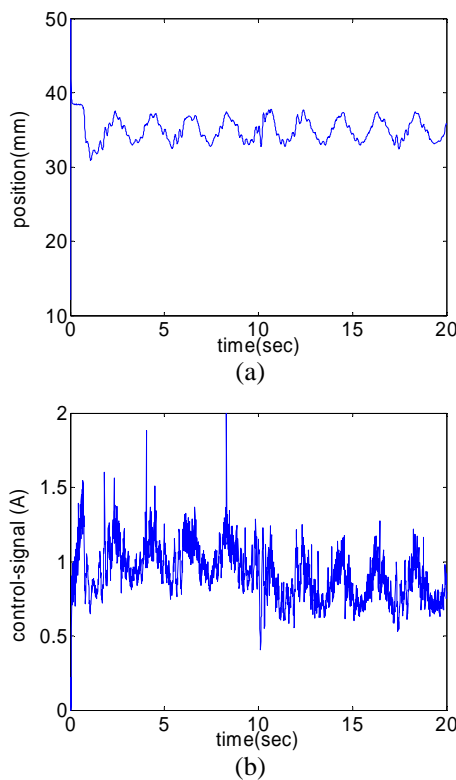


Fig. 10 Experimental results of  $x_r = 35 + 2\sin(\pi t)$  mm and a step load disturbance  $d(t) = 0.2A$  is added at  $t = 10$  sec with initial position  $x_1(0) = 40$  mm in Case3. (a) position response (b) control input (c) sliding function (d) estimated value  $\hat{E}(t)$ .



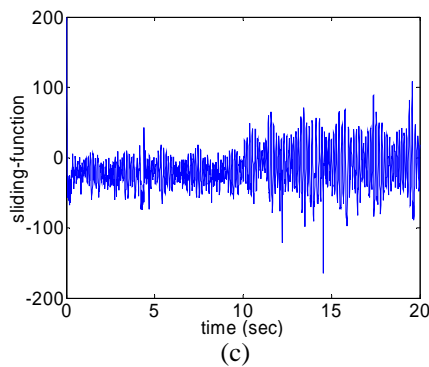


Fig. 11 Experimental results of the conventional sliding mode control for  $x_r = 35 + 2\sin(\pi t)$  mm trajectory tracking and a step load disturbance  $d(t) = 0.2 A$  is added at  $t = 10$  sec with initial position  $x_1(0) = 40$  mm in Case2. (a) position response (b) control input (c) sliding function.

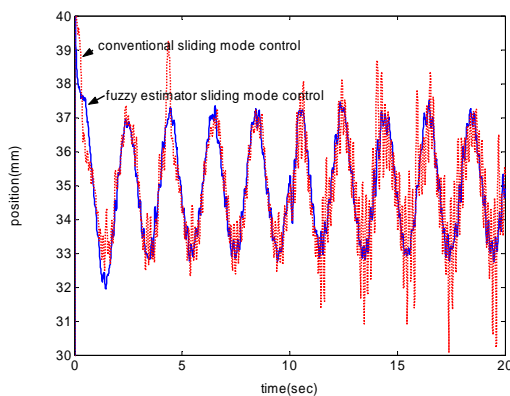


Figure 12. The comparative position responses of Figure 9 and Figure 11.

## 6. Conclusions

This paper proposed an adaptive fuzzy estimator to estimate the lumped uncertainty in real time. It successfully demonstrated the design, experimental results for the position control of MBSS. The MBSS stabilizing control law is simple in which the adaptive control provides on-line estimation values for the system lumped uncertainty. Hence, the proposed controller does not require high accuracy to know the maximum uncertain boundary for the lumped uncertainty. It shows good performance and reduces the chattering magnitude. This method utilizes a Lyapunov function candidate to guarantee convergence and asymptotically track the MBSS position commands. The validity of the proposed controller was demonstrated experimentally.

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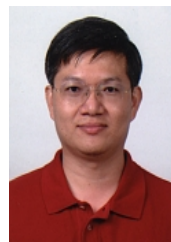
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