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A Fuzzy-Neural Network Control And Nonlinear Disturbance Observer-Based Cascaded Controller For Suspension Of The Active Magnetic Bearing System

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Abstract:
This paper presents a robust controller for the suspension active magnetic bearing system (SAMB), the combination of the sliding mode control (SMC), and a disturbance observer (DOB) is presented. The nonlinear disturbance observer is constructed to estimate and reduce the effect of the outside disturbance and also the variation of inside system parameters. Due to the chattering value will be dealt by the suitable control signal, this paper propose the fuzzy-neural to cover the chattering disadvantage problem. The fuzzy Elman neural network was proposed to approximate the nonlinear term of the chattering values. The fuzzy Elman neural network output is used to regulate the control signal. The Elman neural network is a recurrent neural network structure, which based on the back propagation. The input signal is stored by the cortex layer, which takes in charge of characterize the dynamic phenomenon. The controller will be chose as two sliding mode controller with two surface value. Which are input of the fuzzy neural network system. The neural network system are included four layer.
Keywords: *Suspension active magnetic bearing (SAMB), sliding mode control (SMC), disturbance observer (DOB), nonlinear disturbance observer, fuzzy neural network system.*

I. Introduction.

This control methodology is a fuzzy-neural network control and nonlinear disturbance observer-based cascaded controller for suspension of the active magnetic bearing system. This methodology is built by the presents a robust controller for the suspension active magnetic bearing system (SAMB), the combination of the sliding mode control (SMC), and a disturbance observer (DOB) is presented. The sliding mode surface is constructed by a proportional-integral-derivative (PID) surface. Due to unable to construct the disturbance mathematical model, the measured disturbance are direct feedback and filtered by a fuzzy neural logic controller will be revealed by an observer based on input and output signals.

<u>*Layer 1*</u>

Recognize the neural-fuzzy network input signal by the sliding mode surface value as net_i is the input signal, and $s_i(\mathrm{k})$ is the output signal of the node k

<u>*Layer 2.*</u>

Output signal is the context layer output signal and the connective weight between input signal and hidden layer of the neural network system.

<u>*Layer 3.*</u>

The cortex layer with a delay time signal.

<u>*Layer 4.*</u>

The output signal here are the total signal from the hidden layer.

All the structure of the fuzzy neural network is just aim to force the chattering goes to zero.

The archived results are given out by Matlab Simulink. This part is organized as (i) overview of this part, (ii) the disturbance observer-based control law, (iii) summary is given by the third section of this part.

II. Disturbance observer-based control law

A highly unstable system as AMB cannot be presented as a dynamical system or the lump of the uncertainty value is unmeasured. Furthermore, the unexpected disturbance is unable to observer, then an observer is required. Which can reveal the disturbance by the input-output time history.

2.1 Nonlinear disturbance observer-based Control Law

The Eq. system is represented as

$$\dot{x}=\begin{bmatrix}0 & I\\ B & A\end{bmatrix}x+\begin{bmatrix}0\\ C\end{bmatrix}i+\begin{bmatrix}0\\ 1\end{bmatrix}m_d \qquad (2.1)$$

or $$\dot{x}=G_1x+G_2i+G_3m_d \qquad (2.2)$$

where $x=[z(t) \quad \dot{z}(t)]^T$ is the system state vector.

This section presents the nonlinear disturbance observer as

$$\begin{cases}\dot{y}=-L(x)\cdot G_3\cdot\left[y+\rho(z)\right]-L(x)\cdot\left[G_1\cdot x+G_2\cdot i\right]\\ \hat{m}_d=y+\rho(x)\end{cases} \qquad (2.3)$$

where z is an internal state vector of the DOB, $p(x)$ is auxiliary vector of DOB, nonlinear function to make is, $L(x)=\partial\rho(x)/\partial x$ is observer gain, and $\hat{m}_d$ is estimated value of disturbance from mechanical part of the system. Nonlinear disturbance observer is used to estimate uncertain unknown disturbance under operating process. There exists a sub-function $y=H(x)\in R^m$, where $H(x)$ is smooth function, related to degree from disturbance l to y for all system states $x(t)$. The $\rho(x)$, and $\mathrm{L}(x)$ are chosen as

$$L(X)=\rho_0\frac{\partial L_f^{\rho-1}H(X)}{\partial X} \qquad (2.\ 4)$$

$$\rho(X)=\rho_0\partial L_f^{\rho-1}H(X)$$

Respectively, where p_0 is positive constant for tuning the bound of errors. Let $n_0=\left|\min_z L_{G_4}L_{G_1X}H(X)\right|$ is positive scalar.

The error of the estimated disturbance and disturbance is $\tilde{m}_d=m_d-\hat{m}_d$.

or

$$\begin{aligned}\dot{\tilde{m}}_d&=\dot{m}_d+L(x)\cdot G_4\cdot\left[y+\rho(x)\right]\\ &\quad+L(x)\cdot\left[G_1\cdot x-L(x)\cdot\dot{z}\right]\\ &=\dot{m}_d-L(x)\cdot G_4\cdot\tilde{m}_d\end{aligned} \qquad (2.5)$$

Suppose that $|m_d|\le k$ where k is positive constant given by system lump of uncertainties. The Lyapunov function are

$$V(\tilde{d})=\tilde{m}_d{}^T\tilde{m}_d \qquad (2.6)$$

will leads to

$$\begin{aligned}\dot{V}(\tilde{d})&=2\tilde{m}_d{}^T\left[\dot{m}_d-L(x)G_4\tilde{m}_d\right]\\ &=-2\tilde{m}_d{}^TL(x)G_4\tilde{m}_d+2\tilde{m}_d{}^T\dot{\tilde{m}}_d\\ &\le-2n_0\rho_0\|\tilde{m}_d\|^2+2\|\tilde{m}_d\|k\\ &\le-\rho_0n_0\|\tilde{m}_d\|^2+\frac{k}{\rho_0n_0}\end{aligned} \qquad (2.7)$$

Then, we have

$$\left\|\tilde{m}_d(t)\right\| \le \left\|\tilde{m}_d(0)\right\| \exp\left(-\rho_0 n_0 t\right) + \frac{k}{\rho_0 n_0^2} \tag{2.8}$$

$$I_{control} = I_c + \alpha \hat{m}_d \tag{2.9}$$

where I_c is the conventional control value

$$\dot{x} = G_1 \cdot x + G_2 \cdot \left[I_c + \alpha \cdot \left(l - \tilde{l}\right)\right] + G_3 \cdot m_d$$
$$= G_1 \cdot x + G_2 \cdot I_c + \left(G_2 \cdot \alpha + G_3\right) m_d - G_2 \cdot \alpha \cdot \tilde{m}_d \tag{2.10}$$

Based on the matching condition α is chosen as $\alpha = -G_2^{-1} G_4$ is in the sense that input-to-state stable.

2.2 Fuzzy-neural network control for filter design

Fuzzy logic is widely used in many industrial machine control. Fuzzy logic was first proposed by Lotfi A. Zadeh of the University of California at Berkeley in a 1965. This chapter is apply the fuzzy-neural network to improve the performance tracking. The Elman neural network based some fuzzy law is proposed. The input of the fuzzy-neural system is sliding mode surface and the output of the fuzzy-neural system is the switching control gain value that mean the hitting control gain is modified by the fuzzy-neural system. The precision tracking based on the memorized system of the fuzzy-neural control law. The details is presented as following

Layer 1.

$$s_i(\mathrm{k}) = \mathrm{net}_i, \; i = 1, 2. \tag{2.11}$$

net_i is the input signal, and $s_i(\mathrm{k})$ is the output signal of the node k

Layer 2.

In this layer the input and output signal is represented as

$$s_j(\mathrm{k}) = s(\mathrm{net}_j) \tag{2.12}$$

$$s(\mathrm{net}_j) = \frac{1}{1 + e^{-\delta net_j}} \tag{2.13}$$

The input of hidden layer net_j contains the value are

$$\mathrm{net}_j = \sum_c x_c(\mathrm{k}) + \sum_l W_{ij} x_i(\mathrm{k}) \tag{2.14}$$

$\sum_c x_c(\mathrm{k})$ is the context layer output signal. W_{ij} is the connective weight between input signal and hidden layer of the neural network system.

Layer 3.

The signal go through this layer is represented as

$$x_c(\mathrm{k}) = x_j(\mathrm{k}-1) \tag{2.15}$$

where $x_j(\mathrm{k}-1)$ is the output signal of the hidden layer.

Layer 4. The output signal of the output layer is represented as

$$y_o(\mathrm{k}) = \mathrm{net}_o(\mathrm{k}) \tag{2.16}$$

$$\mathrm{net}_o(\mathrm{k}) = \sum W_{jo} \times x_j(\mathrm{k}) \tag{2.17}$$

The update function error is defined as

$$E(\mathrm{k}) = \frac{1}{2}(\mathrm{d}_m(\mathrm{k}) - \mathrm{d}(\mathrm{k}))^2 = \frac{1}{2} e^2(\mathrm{k}) \tag{2.18}$$

The update law is

$$W(\mathrm{k}+1) = \mathrm{W}(\mathrm{k}) + \Delta \mathrm{W}(\mathrm{k}) \tag{2.19}$$

This Fuzzy-Neural network function can train by function, the Back propagation is use to regulate the connective weight.

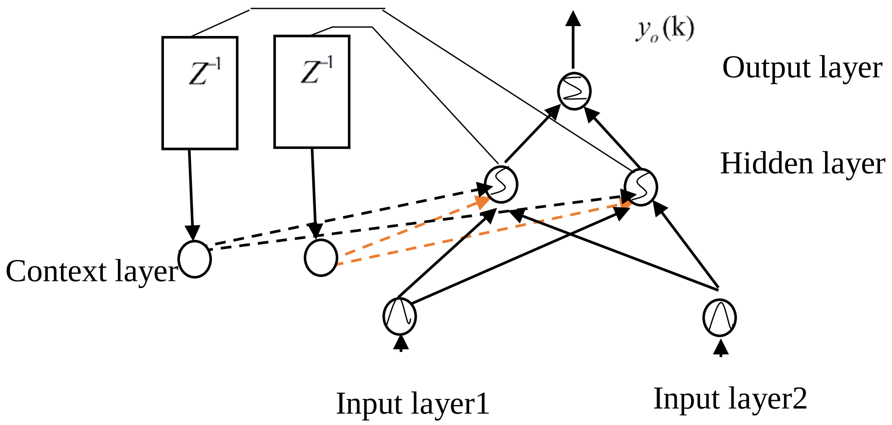


Figure 2.1 Elman Fuzzy Neural network system

The Elman Fuzzy neural network operation as following schedule.
Input signal is normalized by the input layer 1 and layer 2, the context layer was applied to memorize the hidden layer's output values of the previous time. Taking the advantage of the back propagation learning ability, this structure used the BP structure to store the data and training data.
The structure of the control design is as following.
(i) Inner and outer control loop was constructed.
(ii) Disturbance and uncertainty estimator structure was constructed.
(iii) The sliding mode surface is used as the fuzzy neural network input signal.
The control structure is represented as

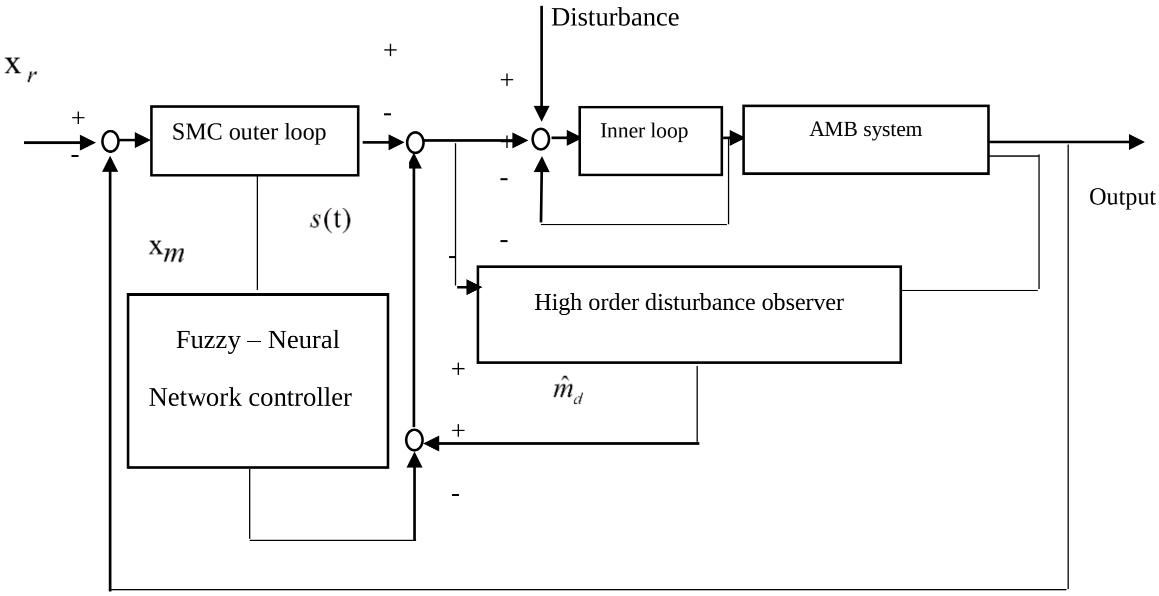
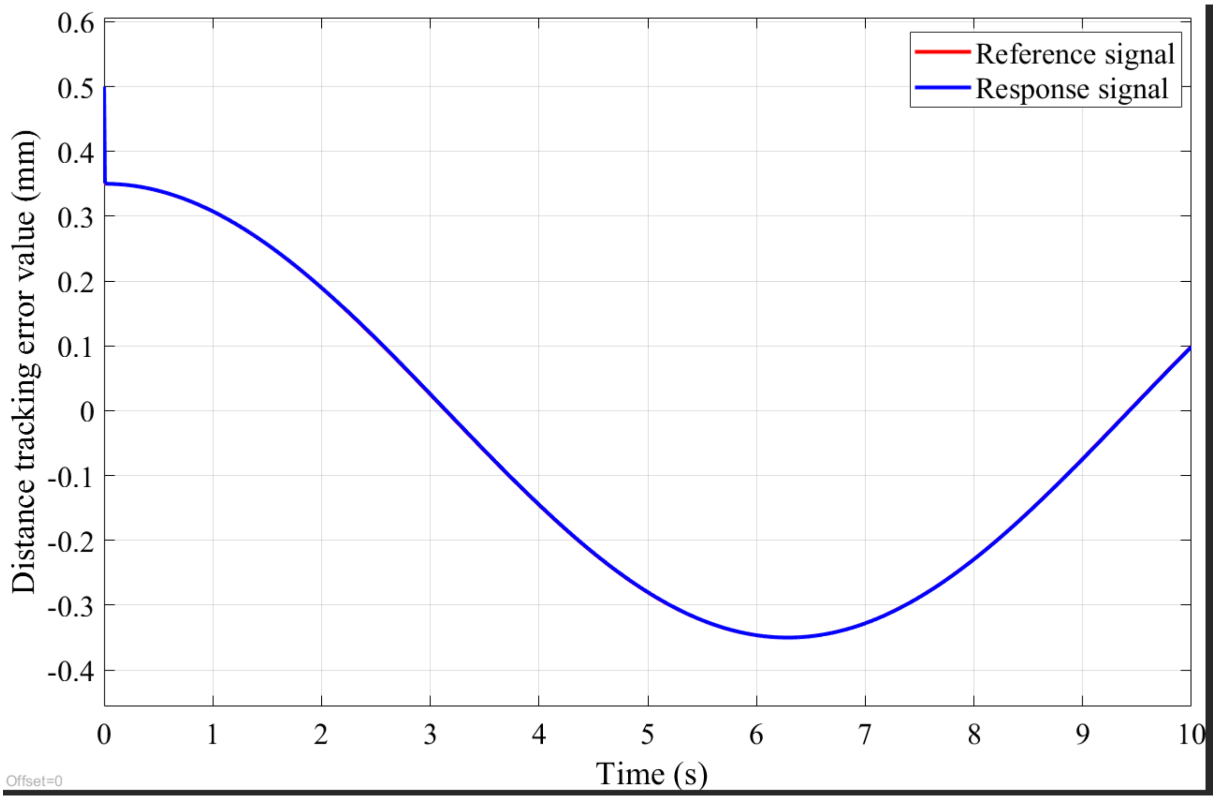
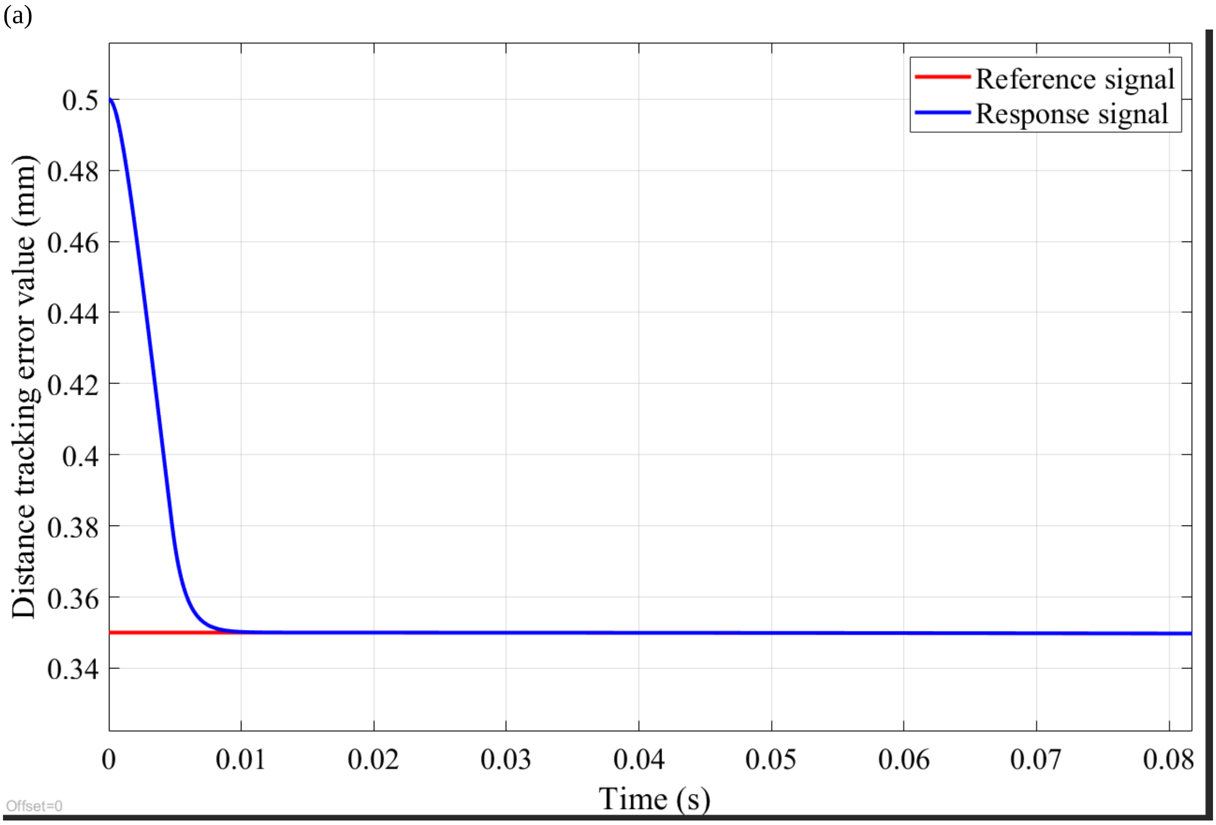


Figure. 2.2 Nonlinear disturbance observer for AMB system

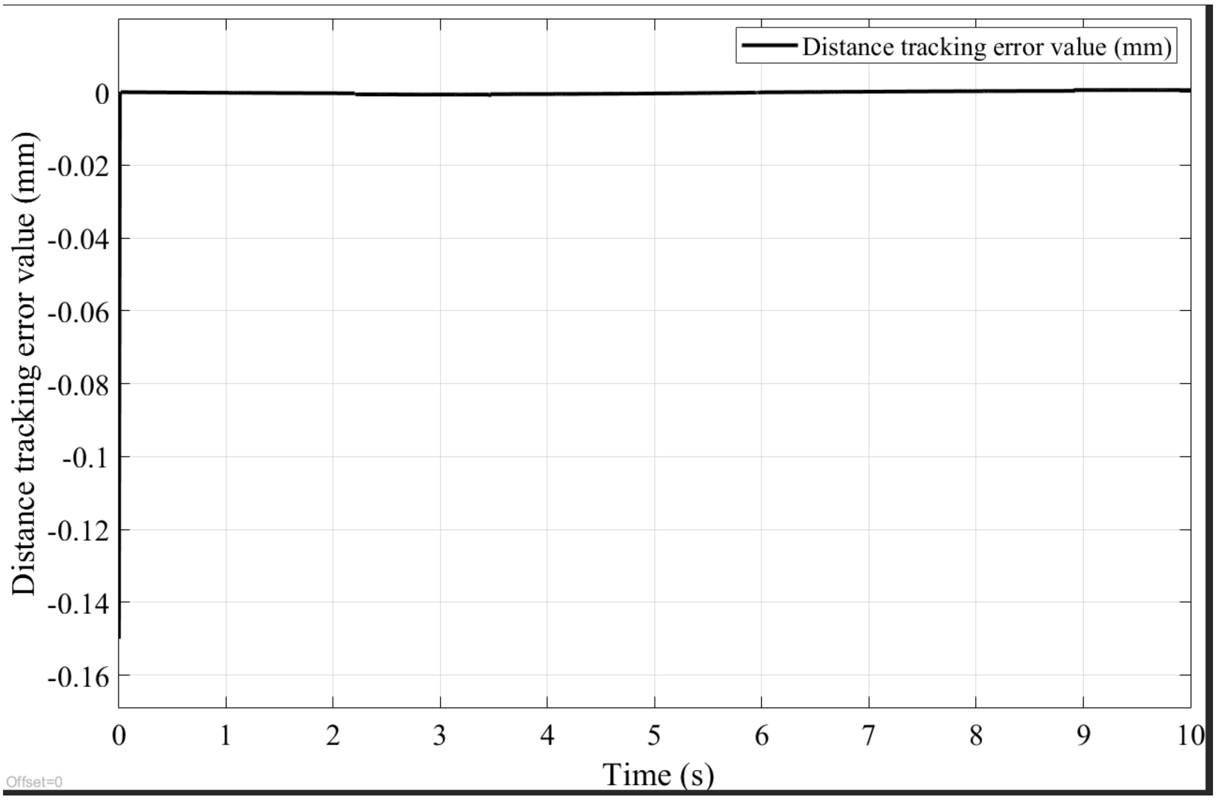
This section presented the control system for active magnetic bearing system based on inner and outer loops, the disturbance and uncertainty value was estimated and rejected by the disturbance observer. The chattering value was softened by a fuzzy neural network structure. The performance of the proposed controller are as following figures.


Reference signal
Response signal
Distance tracking error value (mm)
Time (s)
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
0
1
2
3
4
5
6
7
8
9
10
Offset=0

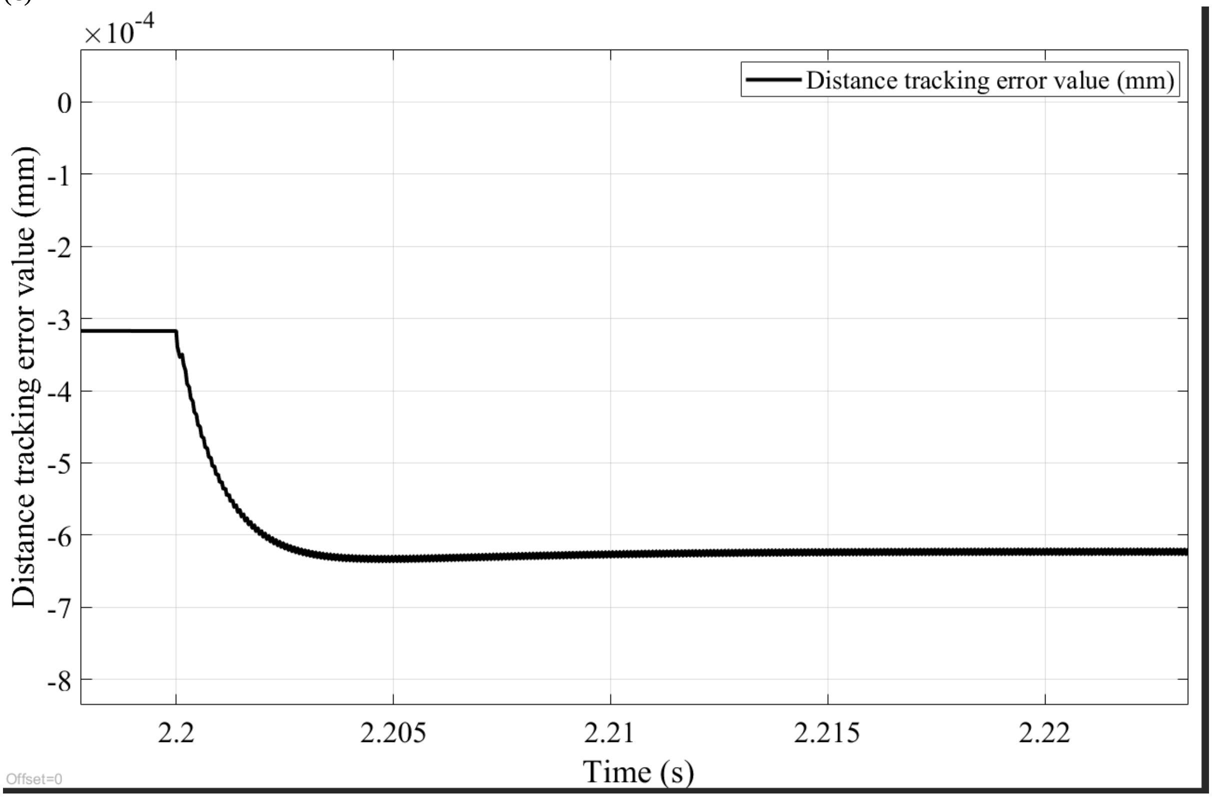
(a)


Reference signal
Response signal
Distance tracking error value (mm)
Time (s)
0.5
0.48
0.46
0.44
0.42
0.4
0.38
0.36
0.34
0
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
Offset=0

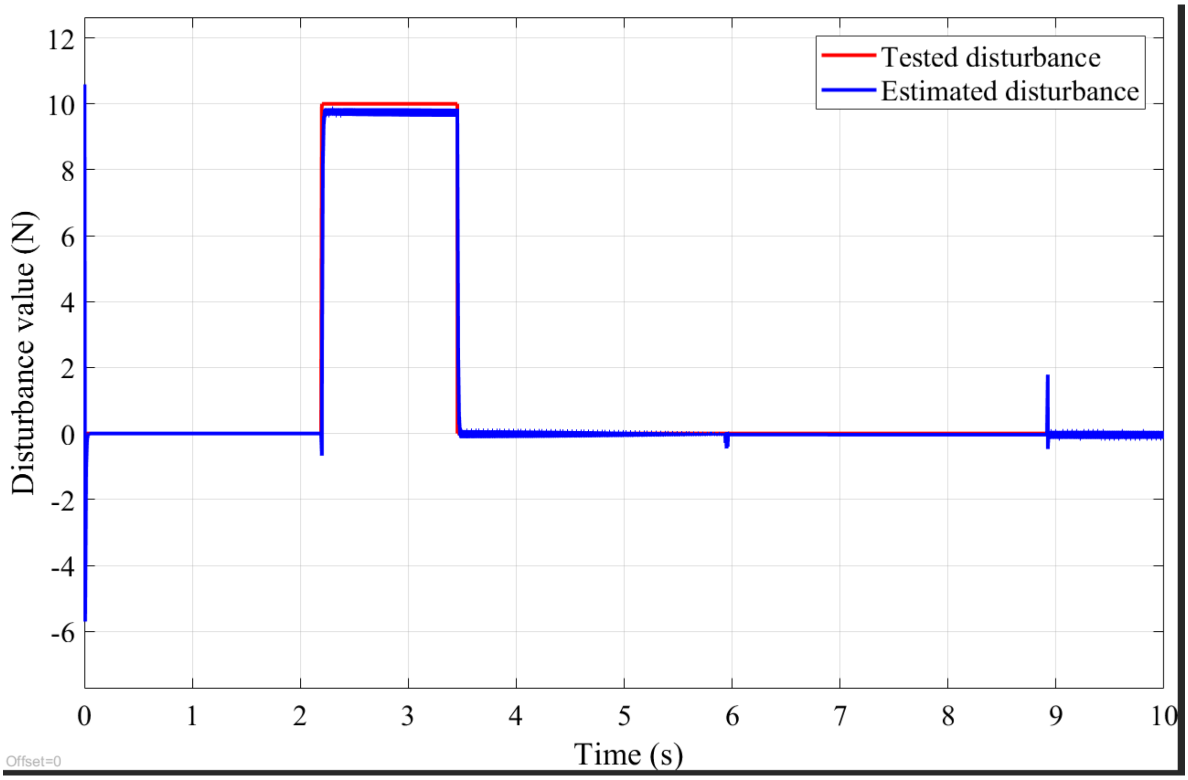
(b)


Distance tracking error value (mm)
Distance tracking error value (mm)
0
-0.02
-0.04
-0.06
-0.08
-0.1
-0.12
-0.14
-0.16
0
1
2
3
4
5
6
7
8
9
10
Time (s)
Offset=0

(c)


$\times 10^{-4}$
Distance tracking error value (mm)
Distance tracking error value (mm)
0
-1
-2
-3
-4
-5
-6
-7
-8
2.2
2.205
2.21
2.215
2.22
Time (s)
Offset=0

(d)



(e)

Figure. 2.3 The given output signal (a) The distance response signal in first 20s, (b) The distance response signal at first 0.1s, (c) The distance tracking error value, (d) The top value of the distance tracking error value, (e) The disturbance response signal.

The given output signals proved that the proposed controller with an observer is suitable to control the active magnetic bearing system. The settling time very small, it equal to $3ms,$ the top of the distance tracking error value is $20um,$ and the average of the distance tracking error value is $0.8um,$. In order to improve the performance of the proposed control method, this paper applied an uncertainty estimation by a sliding mode surface. A fuzzy is applied to guarantee the system distance tracking error value is force to zero.

Research		
This proposed method	$0.2mm,$	$3 \cdot 10^{-4} mm,$
Lin et al. [6]	$0.908.10^{-3} mm$	$5.666.10^{-3} mm$

III. Summary

A design methodology for active magnetic bearing system with many unexpected value is given out, the achieved results proved that the proposed method are very good at tracking flexible input signal. The chattering and the disturbance is reduced by an uncertainty estimator, the distance tracking error value is significantly reduced, and a top of the distance tracking value in two case very difference.

Table 3.1 The controller parameters

Parameter	Description	Value
λ	Sliding surface coefficient	500
κ	Hitting control gain	100
ε	Saturation function coefficient	0.0016
χ	Cascade inner output voltage parameter	800
δ	Cascade inner output voltage parameter	0.05
T_{out}	Low-pass filter parameter	0.01

T_{in}	Low-pass filter parameter	0.0952

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