NEURAL NETWORK-BASED ROBUST TRACKING CONTROL FOR MAGNETIC LEVITATION SYSTEM

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ABSTRACT

This paper proposes a robust tracking controller with bound estimation based on neural network for the magnetic levitation system. The neural network is to approximate an unknown uncertain nonlinear dynamic function in the model of the magnetic levitation system. And the robust control is proposed to compensate for approximation error from the neural network. The weights of the neural network are tuned on-line and the bound of the approximation error is estimated by the adaptive law. The stability of the proposed controller is proven by Lyapunop theory. The robustness effect of the proposed controller is verified by the simulation and experimental results for the magnetic levitation system.

1. INTRODUCTION

Magnetic levitation (Maglev) systems are widely used in many engineering systems such as frictionless bearings, vibration isolation of sensitive machinery, high-speed maglev passenger trains. Highly nonlinear and open-loop unstable make Maglev have difficulties in control.

The performance of the PID controller will be deteriorated when system parameters such as resistance and inductance vary with electromagnet heating. Controllers for magnetic levitation systems are proposed based on the feedback linearization technique [1]. Sliding mode control has been used to design the robust nonlinear controllers [2]. However, to design the controller, all the model parameters need to be available. In practical applications these conditions are not always satisfied.

In recent years, neural networks (NN) based control methodology has become an alternative to adaptive control since NNs are considered as universal approximation, learning and adaptation abilities to handle unknown knowledge about real plants. The robust nonlinear controller based on NN for Maglev system is carried out in [3], modeling and control for Maglev system based on NN with minimal structure is designed [4].

In this paper, a NN-based robust tracking controller for Maglev system is proposed. The controller can guarantee robustness to dynamic uncertainties and also estimates the bound of the NN approximation error. The stability of the proposed controller is proven by the Lyapunop theory.

The rest of this paper is organized as follows. Section 2 presents the nonlinear model for the magnetic levitated system. Section 3 deals with a NN-based robust tracking control scheme with bound estimation for the magnetic levitated system. The simulation results of the proposed controller are presented and discussed in Section 4. Finally, the conclusion is given in Section 5.

2. MODEL OF THE MAGNETIC LEVITATION SYSTEM

Figure 1 shows the experiment model for the Maglev system that has been carried out in a project at National key lab for Digital Control & System Engineering, Vietnam.

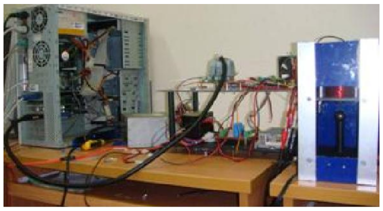


Fig.1 Experiment model

The Maglev system in the model contains two feedback sensors. One is a small current sense resistor in series with the coil. The other is a phototransitor embedded in the chamber pedestal and providing the ball position signal. After amplifying, both current sensor and phototransitor are wired to analog inputs of card PCI-1711. The control signal from the computer is sent to the controllable voltage source through the analog output of card PCI-1711.

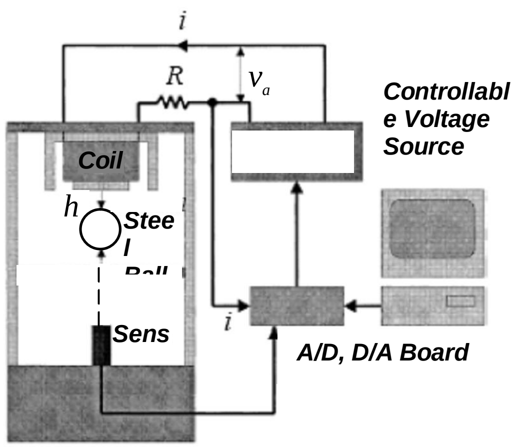


Fig.2. Diagram of magnetic levitation

To develop the mathematical model, the schematic diagram in Figure 2 is considered. Where R is the coil's resistance; h is the position of the ball; L is the coil's inductance; i is the current in the coil of electromagnet. The applied voltage v_a is defined using Kirchhoff's voltage law:

$$v_a = Ri + \frac{d\left(L(h)i\right)}{dt} \qquad (1)$$

The force due to gravity applied on the levitation ball is defined as

$$F_g = mg \qquad (2)$$

where g is the gravitational constant; m is the mass of the ball.

The velocity of the ball is define as

$$\dot{h} = \frac{dh}{dt} \qquad (3)$$

Applying Newton's second law of the motion ball:

$$m\frac{d^2h}{dt^2} = F_g - K_m\left(\frac{i}{h}\right)^2 \qquad (4)$$

where K_m is the magnetic force constant.

The inductance L is a nonlinear function of the position of the ball h and it can be approximated by [2]:

$$L(h) = L_p + \frac{2K_m}{h} \qquad (5)$$

where L_p is a parameter of the system.

From (1) and (5) the applied voltage v_a is rewritten as

$$v_a = Ri - 2K_m\left(\frac{i}{h^2}\right)\left(\frac{dh}{dt}\right) + L\left(\frac{di}{dt}\right) \qquad (6)$$

Let choose the state vector $x = [x_1 \quad x_2 \quad x_3]$ such that $x_1 = h, x_2 = \dot{h}, x_3 = i$ and the control input $u = v_a$ then the state-space model of Maglev system can be defined as

$$\begin{aligned}
\dot{x}_1 &= x_2 \\
\dot{x}_2 &= g - \frac{K_m}{m}\left(\frac{x_3}{x_1}\right)^2 \\
\dot{x}_3 &= -\frac{R}{L}x_3 + \frac{2K_m}{L}\left(\frac{x_2 x_3}{x_1^2}\right) + \frac{1}{L}u
\end{aligned} \tag{7}$$

Given the desired state vector $x_d = [x_{1d} \quad x_{2d} \quad x_{3d}]$, the control objective is to make the state vector x be driven to x_d.

Remark 1: From (3) and (4) that the desired state vector to drive the ball to a constant position is $x_d = \left[x_{1d} \quad 0 \quad \sqrt{\frac{2mg}{K_m}}x_{1d} \right]$

The new states are defined as

$$\begin{aligned}
z_1 &= x_1 - x_{1d} \\
z_2 &= x_2 \\
z_3 &= g - \frac{K_m}{m}\left(\frac{x_3}{x_1}\right)^2
\end{aligned} \tag{8}$$

Remark 2: When $t \to \infty$ the state vector x will converge to x_d as long as the new state vector $z = [z_1, z_2, z_3]$ is driven to zero.

The dynamic model of the Maglev system with the new states can be rewritten as

$$\begin{aligned}
\dot{z}_1 &= z_2 \\
\dot{z}_2 &= z_3 \\
\dot{z}_3 &= f(z) + g(z)u
\end{aligned} \tag{9}$$

where

$$f(z) = 2(g - z_3)\left(\left(1 - \frac{2K_m}{L(z_1 + x_{1d})}\right) \times \frac{z_2}{(z_1 + x_{1d})} + \frac{R}{L}\right) \tag{10}$$

$$g(z) = -\frac{2}{L(z_1 + x_{1d})}\sqrt{\frac{K_m}{m}(g - z_3)}$$

3. DESIGN OF A NEURAL NETWORK – BASED ROBUST CONTROL WITH BOUND ESTIMATION

A design of dynamic sliding mode control for the magnetic levitation system is proposed in [2] with the nonlinear model dynamic $f(z)$ in Eq. (10) is assumed to be available. But in practice applications, the uncertainty such as R changes over time and is difficult to compute. Motivated by this work, a NN–based robust controller is now designed for the Maglev system where the $f(z)$ is assumed unknown.

Let the output of the system as

$$y = z_1 \tag{11}$$

Then, define a filtered tracking error as

$$r = \lambda_1 z_1 + \lambda_2 z_2 + z_3 \tag{12}$$

where λ_1, λ_2 are real positive constants chosen such that the state vector $z(t)$ exponentially goes to 0 as $r(t)$ tends to 0, i.e., the polynomial $s^2 + \lambda_2 s + \lambda_1$ is a Hurwitz polynomial. Then the time derivative r can be written as

$$\dot{r} = f(z) + g(z)u + \lambda_1 z_2 + \lambda_2 z_3 \tag{13}$$

If we knew the exact form of the nonlinear function $f(z)$, then the ideal control law

$$u = -\frac{1}{g(z)}\left(f(z) + Kr + \lambda_1 z_2 + \lambda_2 z_3\right) \tag{14}$$

would bring $r(t)$ to zero exponentially for any $K > 0$. Based on NN, an unknown smooth function $f(z)$ can be presented as

$$f(z) = W^T \sigma(V^T z) + \varepsilon \tag{15}$$

where the NN approximation error ε is assumed to be bounded by $\|\varepsilon\| \le E$; $\sigma(.)$ is a continuous sigmoid activation function. The first layer weights V are selected randomly and will not be tuned while the second weights W are tunable. The ideal weights W for the best approximate the given function $f(z)$ are difficult to reach. So the approximation value of $f(z)$ can be estimated as

$$\hat f(z) = \hat W^T \sigma(V^T z) \qquad (16)$$

Propose the robust adaptive control law as

$$\hat u = -\frac{1}{g(z)}\left(\hat f(z) + Kr + \lambda_1 z_2 + \lambda_2 z_3 + v\right) \qquad (17)$$

where v is the robust controller that is added in the system to compensate the NN approximation error ε.

Then, the Eq.(13) can be rewritten as

$$\dot r = \tilde W^T \sigma(V^T z) - Kr - v + \varepsilon \qquad (18)$$

where $\tilde W = W - \hat W$ is the NN weights error.

Theorem: Given the magnetic levitation system (9), propose the robust adaptive control law (17), and the weights adaptation law of NN as

$$\dot{\hat W} = -\dot{\tilde W} = \alpha_1 r \sigma(V^T z) \qquad (19)$$

where $\alpha_1 > 0$ is the learning rate of NN

The robust controller is proposed as

$$v = \hat E \, sgn(r) \qquad (20)$$

where the estimate of bound E is $\hat E$, $sgn(.)$ is a standard sign function. The bound adaptation law is chosen as

$$\dot{\hat E} = -\dot{\tilde E} = \alpha_2 r \, sgn(r) \qquad (21)$$

where $\tilde E = E - \hat E$ is the bounded estimation error; $\alpha_2 > 0$ is a positive constant.

Then, the closed loop system (9) and (18) is asymptotically stable, the filtered error r, the NN weights error $\tilde W$ and the bounded estimation error $\tilde E$ are all bounded.

Proof: Choose Lyapunop function candidate as

$$V = \frac{1}{2}r^2 + \frac{1}{2\alpha_1}\tilde W^T \tilde W + \frac{1}{2\alpha_2}\tilde E^T \tilde E \qquad (22)$$

Differentiating yields

$$\dot V = r\dot r + \frac{1}{\alpha_1}\tilde W^T \dot{\tilde W} + \frac{1}{\alpha_2}\tilde E^T \dot{\tilde E} \qquad (23)$$

Substitute (18), (19) and (21) into (23) and perform a simple manipulation to obtain

$$\begin{aligned}\dot V &= r\left(\tilde W^T \sigma(V^T z) - v + \varepsilon - Kr\right) \\ &\quad - r\tilde W^T \sigma(V^T z) - r\tilde E^T sgn(r) \\ &= -Kr^2 + r\varepsilon - r\hat E^T sgn(r) - r\tilde E^T sgn(r) \quad (24) \\ &\le r\varepsilon - rE\, sgn(r) \\ &\le -\|r\|\left(E - \|\varepsilon\|\right) \le 0\end{aligned}$$

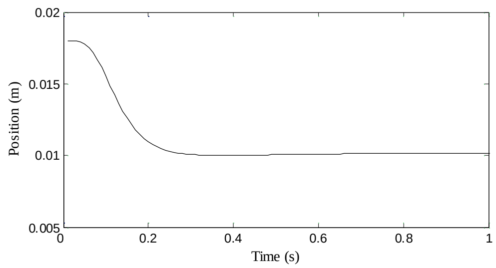
Since $\dot V \le 0$, it can be seen that $r, \tilde W$ and $\tilde E$ are all bounded. Let function $\Phi(t) = -\dot V$ and integrate function $\Phi(t)$ with respect to time

$$\int_0^t \Phi(\tau)d\tau \le V\left(r(0), \tilde W, \tilde E(0)\right) - V\left(r(t), \tilde W, \tilde E(t)\right) \qquad (25)$$

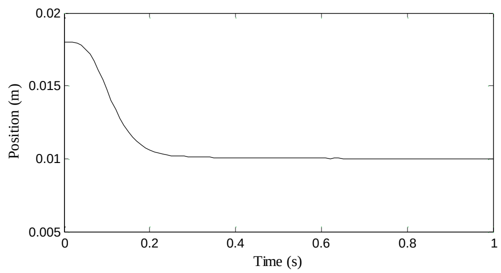
Since $V\left(r(0), \tilde W, \tilde E(0)\right)$ is bounded and $V\left(r(t), \tilde W, \tilde E(t)\right)$ is nonincreasing and bounded, we get

$$\lim_{t\to\infty} \int_0^t \Phi(\tau)d\tau \le 0 \qquad (26)$$

Remark 3: $\dot\Phi(t)$ is bounded.



(a)



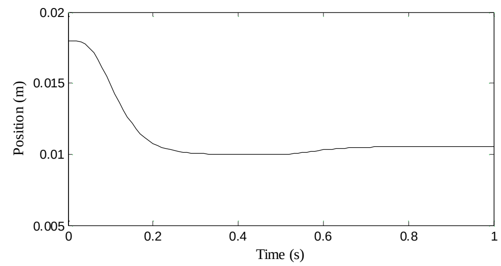
(b)

Fig.3 The position versus time when $m = 11.87(g)$, $R = 18.7(\Omega)$ and $m = 11.87(g) + 125\%$ after 0.5 seconds. (a) the dynamic sliding mode controller, (b) the proposed controller.

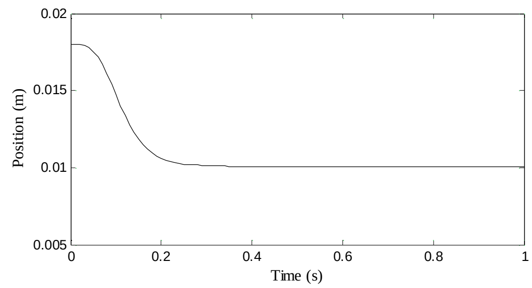
By Barbalat's Lemma, it can be seen that $\lim_{t \to \infty} \Phi(t) \le 0$. Thus $r(t) \to 0$ when $t \to \infty$. As result, the closed loop system (9) and (18) is asymptotically stable.

4. SIMULATION AND EXPERIMENTAL RESULTS

Simulations are performed to verify the proposed controller. The parameters of the Maglev system are chosen as follows. The coil's nominal resistance $R = 18.7(\Omega)$, the inductance $L_h = 0.65(H)$, the gravitation constant $g = 9.81(m/s^2)$, the magnetic force constant $K_m = 1.410^{-4}$ and the nominal mass value of the ball $m = 11.87(g)$.



(a)



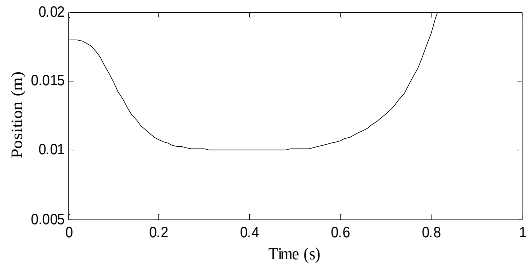
(b)

Fig.4 The position versus time when $m = 11.87(g)$, $R = 18.7(\Omega)$ and $R = 58.7(\Omega)$ after 0.5 seconds. (a) the dynamic sliding mode controller, (b) the proposed controller.

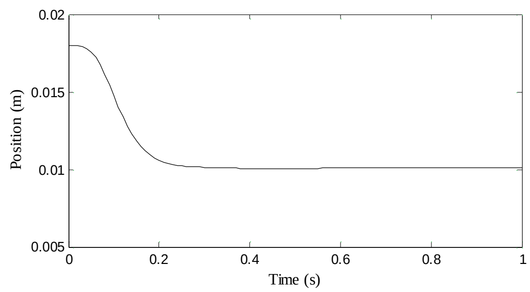
The initial values of neural network weights W are chosen randomly in $[0,1]$ and the bound estimation is $\hat{E}(0) = 0$. $\lambda_1 = 400$, $\lambda_2 = 20$, $K = 250$.

To design the dynamic sliding mode law [2], nominal values of mass of the ball and the coil's resistance are used to substitute into the function $f(z)$ in Eq. (10). The simulation result of the controller is shown in Figure 3.a. After 0.5 seconds the mass value of the ball is changes to 125%. In the same case but $f(z)$ is assumed unknown, the simulation result of the proposed controller is shown in Figure 3.b. The performance of two kind of controllers in the situation are almost the same.

In Figure 4.a, after 0.5 seconds the coil's resistance value is changed from $18.7(\Omega)$ to



(a)



(b)

Fig.5 The position versus time when $m = 11.87(g)$, $R = 18.7(\Omega)$ and $m = 11.87(g) + 125\%$, $R = 58.7(\Omega)$ after 0.5 seconds. (a) the dynamic sliding mode controller, (b) the proposed controller.

$58.7(\Omega)$ the dynamic sliding mode controller causes the a steady state error. In addition if the mass value is changed by 125% in Figure 5.a, the dynamic sliding mode controller becomes unstable. Under same conditions, Figures 4.b and 5.b show the results using the proposed controller. As it can be seen form the figures that the tracking performance of the magnetic levitation system is robust.

Experiments were carried out with respect to conditions above except the mass value of ball $m = 68(g)$. Figure 6 shows the effectiveness of the proposed controller when attracting the ball from the initial position $0.014(m)$ to $0.01(m)$ and keeping it at this position during 15 seconds afterward.

5. CONCLUSION

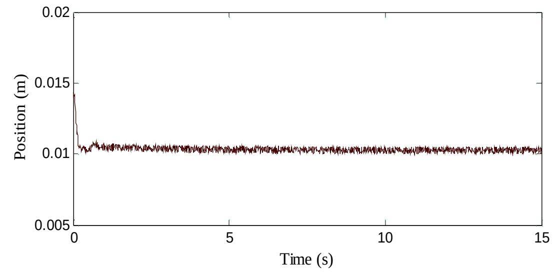


Fig.6 Experimental result of the proposed controller for the position versus time when $m = 68(g)$.

The robust tracking controller with bounded estimation based on NN is proposed for Maglev system. This controller is robust to system parameter variations such as the resistance due to electromagnet heating and the ball mass values. The stability is proven using Lyapunop theory.

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