

Intelligent Controller Design for Precise Trajectory Control in Magnetic Levitation Systems

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ABSTRACT

As a form of soft computing technique, the application of fuzzy controllers for managing uncertain nonlinear systems has garnered significant attention from researchers. Although many fuzzy control methods have been proposed, most of them exhibit obvious limitations in weight learning and optimizing network structure. This paper aims to propose a design of a type-2 fuzzy cerebellar model articulation controller for uncertain nonlinear systems, which achieves high stability and accuracy for controlling magnetic levitation systems. The proposed controller is a combination of a type 2 fuzzy logic system and a cerebellar model articulation controller. A self-organizing algorithm is utilized to automatically construct the network structure. The adaptation laws based on the gradient descent method are derived to online update the network parameters. To ensure system stability, a Lyapunov stability function is employed. Finally, the numerical simulation results on trajectory tracking control of the magnetic levitation systems are given to illustrate the effectiveness and practicability of the proposed control method.

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1. Introduction

Nonlinearity and uncertainty are inherent characteristics of control systems, as practical systems often exhibit nonlinear behavior and the development of a precise mathematical model for a controlled system is challenging due to insufficient parameter information or external disturbances. To effectively handle these nonlinearities and uncertainties, a controller must respond appropriately. Robust control algorithms are widely recognized as the most popular type of control algorithm for this purpose [1]. The type-1 fuzzy logic system (T1FLS) was first introduced by Zadeh in 1965 [1]. This modern control system does not require knowledge of the mathematical model of the system but also can apply the knowledge and experiences of field experts in designing fuzzy rules. However, the number of membership functions in T1FLS is fixed and cannot cover good enough external and internal uncertainties or noises [2]. Thereby, Zadeh proposed the Type-2 fuzzy logic system (T2FLS) in 1975, which expectedly can handle uncertainty parts by fuzzy rules in its fuzzy sets [3]. The cerebellar model articulation controller (CMAC) is a type of neural network based on a model of the mammalian cerebellum. It was first introduced by Albus in 1975 [4]. In comparison with normal neural networks, CMAC has the advantages of fast learning, simple calculation, and good generalization ability [5]. This study combines T2FLS and CMAC in other to design a type-2 fuzzy cerebellar model articulation controller (T2FCMAC).

Moreover, a neural network with a fixed layer structure cannot achieve good performance in systems that have uncertainties or noises [6]. Therefore, many recent approaches apply the self-organizing Interval algorithm to get an appropriate neural network structure [7]-[12]. For instance, in 2017, Lin and Le proposed a PSO-self-organizing interval type-2 fuzzy neural network for antilock braking systems [10]. After that in 2018, Sabahi [11] presented a self-organizing neural network for impedance control.

Furthermore, in 2022, Zhao et al. introduced a self-organized method for a hierarchical fuzzy logic system based on a fuzzy autoencoder [12].

In recent times, magnetic levitation systems have drawn many researchers' attraction by their wide range of applications [13]. Floating systems operating under magnetic levitation are highly non-linear and unstable, especially under consideration of uncertainties and noises both internal and external [14]. In recent decades, various control techniques have been introduced to control these floating systems, such as PID controllers [15]-[17], sliding-mode controllers [18]-[20], fuzzy logic controllers [21]-[23], and robust controllers [24]-[26]. However, most of these methods are complicated and can be optimized more. Based on the above reviews, this paper proposes a type-2 fuzzy cerebellar model articulation controller T2FCMAC that can be employed to control the position of a ball in a magnetic levitation field. Therefore, the proposed T2FCMAC has the advantage as follows: (1) the ability to handle uncertainties of T2FLS; (2) The learning capacity of CMAC structure; (3) The ability to self-optimize network structure using the self-organizing algorithm.

2. CMAC self-organizing type-2 fuzzy logic controller

2.1. CMAC type-2 fuzzy logic controller

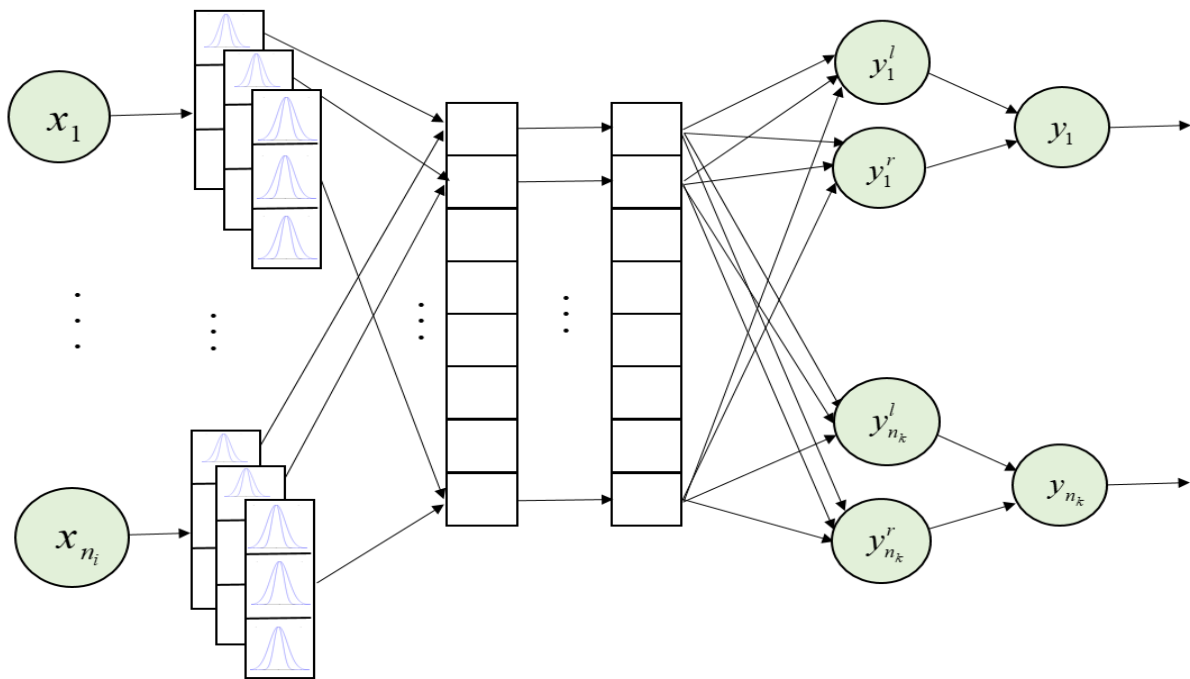


Figure 1. Structure of T2FCMAC controller.

The structure of a T2FCMAC combines the principles of fuzzy logic with the architecture of a cerebellar model articulation controller (CMAC). It seamlessly integrates fuzzy inference and adaptive learning mechanisms, enabling the controller to effectively govern systems characterized by uncertainty and nonlinearity, as presented in Figure 1.

The membership functions in a T2FCMAC are essential for capturing and simulating the inherent uncertainty present in the controlled system. They aid in the control decision-making processes and enable efficient fuzzy inference, as shown in Figure 2.

The structure of T2FCMAC is introduced in Figure 1 and consists of 5 spaces as follows:

- Input space: This space is for collecting input vector $X = [x_1, x_2, \dots, x_{n_i}]^T \in \mathcal{R}^{n_i}$ and forward directly to the next space.
- Membership function space: This space is divided into n_j layers. Every layer contains n_k block. Every block represents by a Type-2 Gaussian membership function (T2GMF) as in Figure 2.

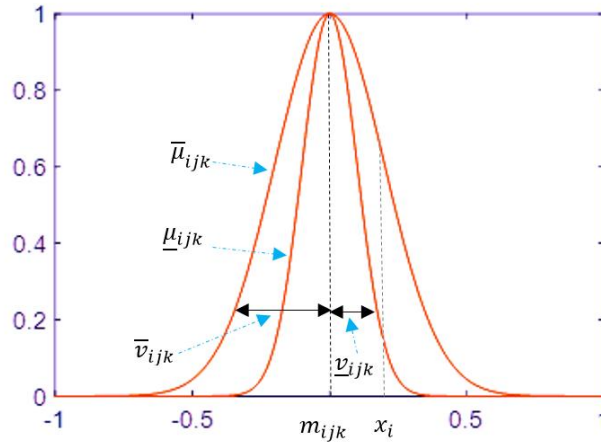


Figure 2. The type-2 fuzzy membership function.

$$\underline{\mu}_{ijk} = \exp \left\{ \frac{-(x_i - m_{ijk})^2}{2\bar{\sigma}_{ijk}^2} \right\} \quad (1)$$

$$\bar{\mu}_{ijk} = \exp \left\{ \frac{-(x_i - m_{ijk})^2}{2\underline{\sigma}_{ijk}^2} \right\} \quad (2)$$

Where, m_{ijk} is the average value of T2GMF; $\bar{\sigma}_{ijk}$ and $\underline{\sigma}_{ijk}$ is respectively upper variance and lower variance of T2GMF.

- Receptive-field space: In this space, the t-norm is applied to get fuzzy firing values.

$$\underline{f}_{jk} = \prod_{i=1}^{n_i} \underline{\mu}_{ijk} \quad (3)$$

$$\bar{f}_{jk} = \prod_{i=1}^{n_i} \bar{\mu}_{ijk} \quad (4)$$

- Connecting weight space: Every node in this space is used as weight connecting input space and output space.

$$\underline{w} = \begin{bmatrix} \underline{w}_1 \\ \vdots \\ \underline{w}_{n_j} \end{bmatrix} \begin{bmatrix} \underline{w}_{11} & \cdots & \underline{w}_{1n_k} \\ \vdots & \ddots & \vdots \\ \underline{w}_{n_j 1} & \cdots & \underline{w}_{n_j n_k} \end{bmatrix} \in \mathfrak{R}^{n_j n_k} \quad (5)$$

$$\bar{w} = \begin{bmatrix} \bar{w}_1 \\ \vdots \\ \bar{w}_{n_j} \end{bmatrix} \begin{bmatrix} \bar{w}_{11} & \cdots & \bar{w}_{1n_k} \\ \vdots & \ddots & \vdots \\ \bar{w}_{n_j 1} & \cdots & \bar{w}_{n_j n_k} \end{bmatrix} \in \mathfrak{R}^{n_j n_k} \quad (6)$$

- Output space: Every node in this space takes input space multiplied with connecting weight space as follows:

$$u_{T2FCMAC}^k = \frac{y_k^l + y_k^r}{2} = \frac{1}{2} \left[\sum_{j=1}^{n_j} \underline{f}_{jk} \underline{w}_{jk} + \sum_{j=1}^{n_j} \bar{f}_{jk} \bar{w}_{jk} \right] \quad (7)$$

where \bar{w}_{jk} and \underline{w}_{jk} are connection weights.

Firstly, a Lyapunov function is defined as $E = \frac{1}{2}(y_d(t) - y(t)) = \frac{1}{2}e(t)$. After that, apply the slope reduction method and series method, update rules for T2FCMAC will be:

$$\hat{w}_{jk}(t+1) = \hat{w}_{jk}(t) - \frac{1}{2} \hat{\eta}_w e(t) \underline{f}_{jk} \quad (8)$$

$$\hat{\bar{w}}_{jk}(t+1) = \hat{\bar{w}}_{jk}(t) - \frac{1}{2} \hat{\eta}_w e(t) \bar{f}_{jk} \quad (9)$$

$$\hat{m}_{ijk}(t+1) = \hat{m}_{ijk}^l(t) - \frac{1}{2} \hat{\eta}_m e(t) \left(\underline{w}_{jk} \underline{f}_{jk} \frac{(x_i - m_{ijk})}{(\underline{v}_{ijk})^2} + \bar{w}_{jk} \bar{f}_{jk} \frac{(x_i - m_{ijk})}{(\bar{v}_{ijk})^2} \right) \quad (10)$$

$$\hat{v}_{ijk}(t+1) = \hat{v}_{ijk}(t) - \frac{1}{2} \hat{\eta}_v e(t) \left(\frac{\underline{w}_{jk} - \hat{y}_k^l}{\sum_{j=1}^{n_j} \underline{f}_{jk}} \right) \frac{(x_i - m_{ijk})^2}{(\underline{v}_{ijk})^3} \quad (11)$$

$$\hat{\bar{v}}_{ijk}(t+1) = \hat{\bar{v}}_{ijk}(t) - \frac{1}{2} \hat{\eta}_v e(t) \left(\frac{\bar{w}_{jk} - \hat{y}_k^r}{\sum_{j=1}^{n_j} \bar{f}_{jk}} \right) \frac{(x_i - m_{ijk})^2}{(\bar{v}_{ijk})^3} \quad (12)$$

2.2. Self-organizing algorithm

This section presents a self-organizing algorithm designed to automate the construction of the suggested neural network, including the addition of new layers and the removal of unnecessary ones. A new layer is added if

$$A_{\max}^i < A_t \quad (13)$$

where A_t is creation threshold; A_{\max}^i is the maximum value of i^{th} input member function, as given:

$$A_{\max}^i = \max \left[\mu_{i11}, \dots, \mu_{i1n_k}, \mu_{i21}, \dots, \mu_{i2n_k}, \dots, \mu_{in_1}, \dots, \mu_{in_n_k} \right] \quad (14)$$

where μ_{ijk} is the average membership function, as given:

$$\mu_{ijk} = \frac{\underline{\mu}_{ijk} + \bar{\mu}_{ijk}}{2} \quad (15)$$

An unneeded layer is removed if all the requirements are met:

$$D_{\min}^i < D_t \quad (16)$$

where D_t is removing threshold; D_{\min}^i is the minimum value of i^{th} input membership function, as given:

$$D_{\min}^i = \min \left[\mu_{i11}, \dots, \mu_{i1n_k}, \mu_{i21}, \dots, \mu_{i2n_k}, \dots, \mu_{in_1}, \dots, \mu_{in_n_k} \right] \quad (17)$$

2.3. Stability analysis of the T2FCMAC Controller

Given the consideration of the Lyapunov function,

$$V(t) = E(t) = \frac{1}{2} (e(t))^2 \quad (18)$$

Then, the derivation of (18) can be deduced as follows:

$$\Delta V(t) = V(t+1) - V(t) = \frac{1}{2} \left[(e(t+1))^2 - (e(t))^2 \right] = \Delta e(t) \left[\frac{1}{2} \Delta e(t) + e(t) \right] \quad (19)$$

Through the utilization of the Taylor expansion linearization methodology, the nonlinear function can be reconfigured into a partially linear structure [27]. Consequently,

$$e(t+1) = e(t) + \Delta e(t) \cong e(t) + \left[\frac{\partial e(t)}{\partial \varepsilon} \right]^T \Delta \varepsilon \quad (20)$$

Here ε is substituted with \hat{w}_{jk} , \underline{w}_{jk} , \hat{m}_{ijk} , \hat{v}_{ijk} , \underline{v}_{ijk} ; Δe and $\Delta \varepsilon$ represent variations in e and ε , respectively.

From (8)-(12), obtain

$$\Delta \varepsilon = -\eta_\varepsilon \frac{\partial E(t)}{\partial \varepsilon} = -\eta_\varepsilon \frac{\partial E(t)}{\partial e(t)} \frac{\partial e(t)}{\partial k(t)} \frac{\partial k(t)}{\partial \hat{u}_{T2FCMAC}^k} \frac{\partial u_{T2FCMAC}^k}{\partial \varepsilon} = \eta_\varepsilon e(t) \Theta_\varepsilon(t) \quad (21)$$

Considering (21), the value of $\Theta_\varepsilon(t) = \frac{\partial u_{T2FCMAC}^k}{\partial \varepsilon}$ can be characterized as

$$\Theta_{\hat{w}}(t) = \frac{\partial u_{T2FCMAC}^k}{\partial \hat{w}} = \left[\frac{\partial u_{T2FCMAC}^k}{\partial \hat{w}_{j11}}, \dots, \frac{\partial u_{T2FCMAC}^k}{\partial \hat{w}_{j1n_q}}, \frac{\partial u_{T2FCMAC}^k}{\partial \hat{w}_{j21}}, \dots, \frac{\partial u_{T2FCMAC}^k}{\partial \hat{w}_{j2n_q}}, \dots, \frac{\partial u_{T2FCMAC}^k}{\partial \hat{w}_{jn_k1}}, \dots, \frac{\partial u_{T2FCMAC}^k}{\partial \hat{w}_{jn_kn_q}} \right]^T \quad (22)$$

$$\Theta_{\underline{w}}(t) = \frac{\partial u_{T2FCMAC}^k}{\partial \underline{w}} = \left[\frac{\partial u_{T2FCMAC}^k}{\partial \underline{w}_{j11}}, \dots, \frac{\partial u_{T2FCMAC}^k}{\partial \underline{w}_{j1n_q}}, \frac{\partial u_{T2FCMAC}^k}{\partial \underline{w}_{j21}}, \dots, \frac{\partial u_{T2FCMAC}^k}{\partial \underline{w}_{j2n_q}}, \dots, \frac{\partial u_{T2FCMAC}^k}{\partial \underline{w}_{jn_k1}}, \dots, \frac{\partial u_{T2FCMAC}^k}{\partial \underline{w}_{jn_kn_q}} \right]^T \quad (23)$$

$$\Theta_{\hat{m}}(t) = \frac{\partial u_{T2FCMAC}^k}{\partial \hat{m}} = \left[\frac{\partial u_{T2FCMAC}^k}{\partial \hat{m}_{i11}}, \dots, \frac{\partial u_{T2FCMAC}^k}{\partial \hat{m}_{i1n_k}}, \frac{\partial u_{T2FCMAC}^k}{\partial \hat{m}_{i21}}, \dots, \frac{\partial u_{T2FCMAC}^k}{\partial \hat{m}_{i2n_k}}, \dots, \frac{\partial u_{T2FCMAC}^k}{\partial \hat{m}_{in_j1}}, \dots, \frac{\partial u_{T2FCMAC}^k}{\partial \hat{m}_{in_jn_k}} \right]^T \quad (24)$$

$$\Theta_{\hat{v}}(t) = \frac{\partial u_{T2FCMAC}^k}{\partial \hat{v}} = \left[\frac{\partial u_{T2FCMAC}^k}{\partial \hat{v}_{i11}}, \dots, \frac{\partial u_{T2FCMAC}^k}{\partial \hat{v}_{i1n_k}}, \frac{\partial u_{T2FCMAC}^k}{\partial \hat{v}_{i21}}, \dots, \frac{\partial u_{T2FCMAC}^k}{\partial \hat{v}_{i2n_k}}, \dots, \frac{\partial u_{T2FCMAC}^k}{\partial \hat{v}_{in_j1}}, \dots, \frac{\partial u_{T2FCMAC}^k}{\partial \hat{v}_{in_jn_k}} \right]^T \quad (25)$$

$$\Theta_{\underline{v}}(t) = \frac{\partial u_{T2FCMAC}^k}{\partial \underline{v}} = \left[\frac{\partial u_{T2FCMAC}^k}{\partial \underline{v}_{i11}}, \dots, \frac{\partial u_{T2FCMAC}^k}{\partial \underline{v}_{i1n_k}}, \frac{\partial u_{T2FCMAC}^k}{\partial \underline{v}_{i21}}, \dots, \frac{\partial u_{T2FCMAC}^k}{\partial \underline{v}_{i2n_k}}, \dots, \frac{\partial u_{T2FCMAC}^k}{\partial \underline{v}_{in_j1}}, \dots, \frac{\partial u_{T2FCMAC}^k}{\partial \underline{v}_{in_jn_k}} \right]^T \quad (26)$$

Using the chain rule in (20), we have

$$\frac{\partial e(t)}{\partial \theta} = \frac{\partial e(t)}{\partial u_{T2FCMAC}^k} \frac{\partial u_{T2FCMAC}^k}{\partial \varepsilon} = -\Theta_\varepsilon(t) \quad (27)$$

By reexpressing (19) with the aid of (21) and (27), we obtain

$$\begin{aligned} \Delta V(t) &= \Delta e(t) \left[\frac{1}{2} \Delta e(t) + e(t) \right] = \left(\left[\frac{\partial e(t)}{\partial \varepsilon} \right]^T \Delta \varepsilon \right) \left[\frac{1}{2} \left(\left[\frac{\partial e(t)}{\partial \varepsilon} \right]^T \Delta \varepsilon \right) + e(t) \right] \\ &= - \left[\Theta_\varepsilon(t) \right]^T \eta_\varepsilon e(t) \Theta_\varepsilon(t) \left[-\frac{1}{2} \left[\Theta_\varepsilon(t) \right]^T \eta_\varepsilon e(t) \Theta_\varepsilon(t) + e(t) \right] \\ &= \frac{1}{2} \eta_\varepsilon (e(t))^2 \left\| \Theta_\varepsilon(t) \right\|^2 \left[\eta_\varepsilon \left\| \Theta_\varepsilon(t) \right\|^2 - 2 \right] \end{aligned} \quad (28)$$

From (28), if η_ε is chosen to satisfy $0 < \eta_\varepsilon < \frac{2}{\left\| \Theta_\varepsilon(t) \right\|^2}$, then $\Delta V(t) < 0$. Consequently, the stability of the proposed control system can be guaranteed.

3. Simulation Results

Consider a magnetic levitation system in Figure 3 from [19]:

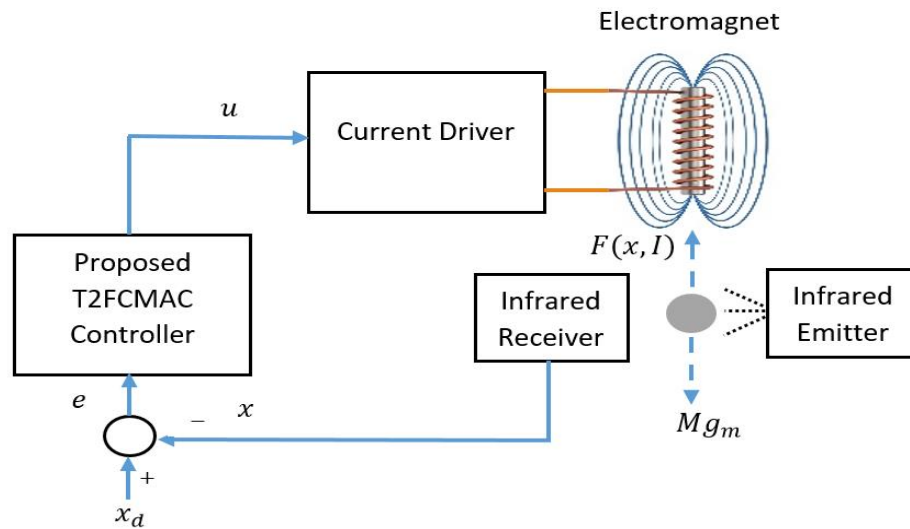


Figure 3. Magnetic levitation system diagram.

From [19], the state equations of a metal ball are:

$$Ma = F(x, I) - Mg_m \quad (29)$$

where:

$$F(x, I) = \frac{\mu_0 N^4 I^2 S}{8} = \left((x+h) \ln \left| \frac{R_2 + \sqrt{R_2^2 + (x+h)^2}}{R_1 + \sqrt{R_1^2 + (x+h)^2}} \right| + x \ln \left| \frac{R_1 + \sqrt{R_1^2 + x^2}}{R_2 + \sqrt{R_2^2 + x^2}} \right| \right) \quad (30)$$

where M and x are respectively weight of the iron ball and distance from the ball to the magnet; a and g_m are respectively ball and gravitational acceleration; I and F are respectively current and controlled magnetic force; μ_0 and h are respectively vacuum permeability and magnetic wire length; N và S are respectively rotation speed (round per meter) and magnetic field cross-section area.; R_1 và R_2 are respectively the maximum and minimum radii of magnetic wire.

$$\ddot{x} = g(x)u(t) + d \quad (31)$$

where,

$$g(x) = \frac{\mu_0 N^4 S}{8M} = \left((x+h) \ln \left| \frac{R_2 + \sqrt{R_2^2 + (x+h)^2}}{R_1 + \sqrt{R_1^2 + (x+h)^2}} \right| + x \ln \left| \frac{R_1 + \sqrt{R_1^2 + x^2}}{R_2 + \sqrt{R_2^2 + x^2}} \right| \right) \quad (32)$$

And $u(t) = I^2$, $d = -g_m$.

Figure 4 shows the position of the iron ball in the magnetic levitation system. The ball is subjected to a sinusoidal command signal with an amplitude of 0.01m and a frequency of 0.14 Hz. The sampling time is set to 0.001 seconds. The simulation results demonstrate that the ball effectively tracks the reference position and exhibits rapid response.

The position control scheme of the magnetic levitation system using T2FCMAC is proposed in Figure 4. The reference signal is the red line and the position of the iron ball is the blue line. The controlling signal as in Figure 5 and the position error is in Figure 6. The simulation result shows that the T2FCMAC controller can quickly control the iron ball position following the reference signal. The root mean square error in this case is 0,00023.

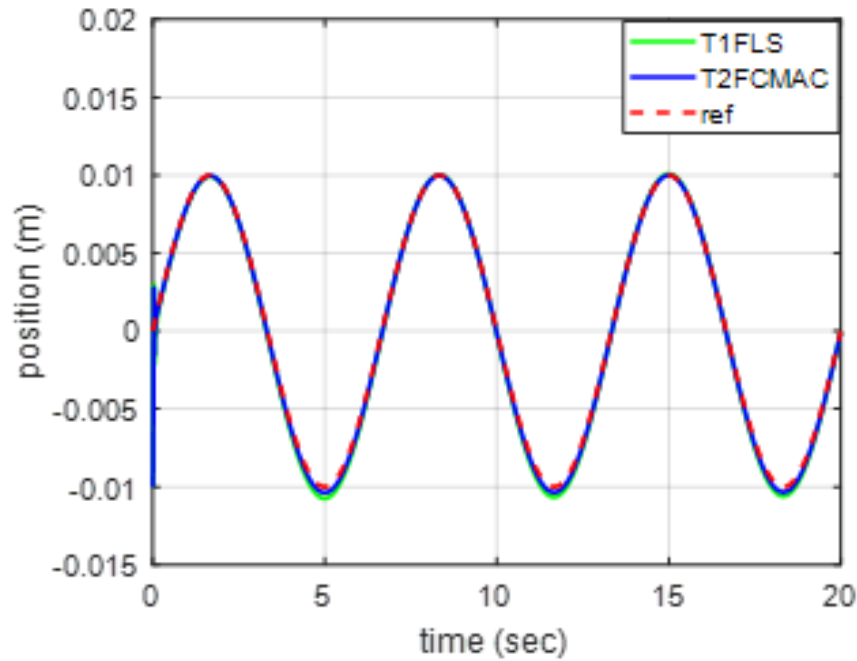


Figure 4. Position of the iron ball in the magnetic levitation system.

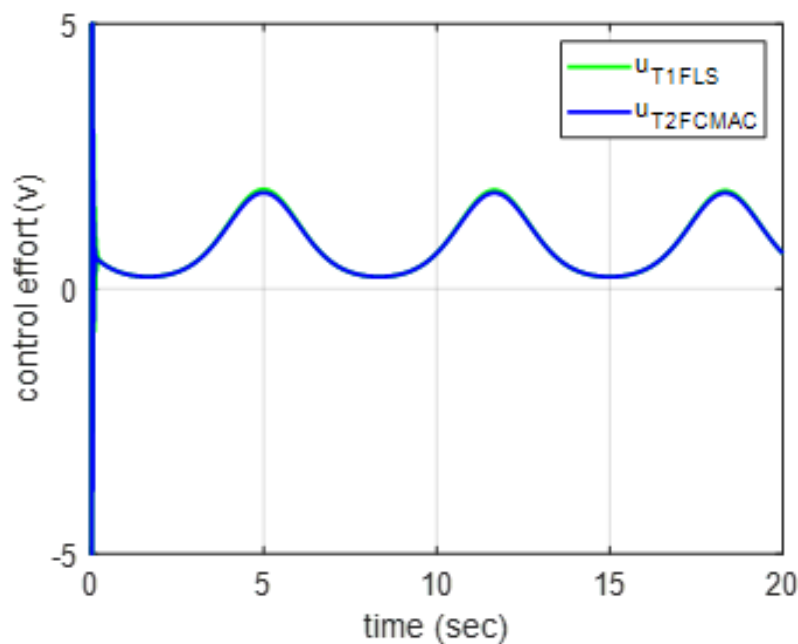


Figure 5. The control signal of T2FCMAC.

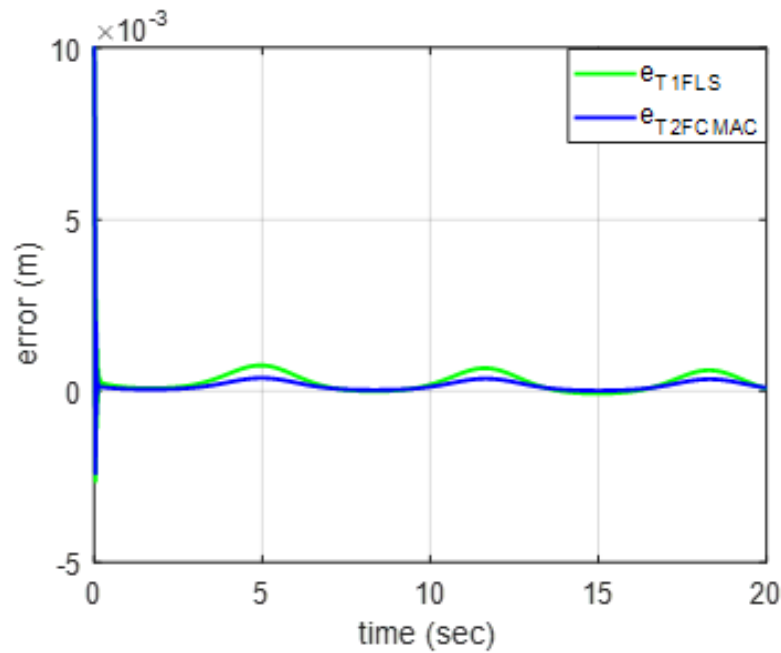


Figure 6. Position error of the iron ball.

The errors can be automatically adjusted to guarantee system stability, as illustrated in Figure 6.

4. Conclusions

In this study, a type-2 fuzzy cerebellar model articulation controller T2FCMAC for magnetic levitation system is proposed. A self-organizing algorithm that can automatically construct a neural network layer is proposed. Furthermore, an optimized law for updating network parameters is introduced based on the gradient descent method. The simulation results about the trajectory control of the magnetic levitation system can prove the effectiveness of the proposed method. In the future, the authors will be experimenting with verification the intelligent controller design aimed at achieving precise trajectory control in magnetic levitation systems.

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Table 1. List of Acronyms

T2FCMAC	Type-2 Fuzzy Cerebellar Model Articulation Controller
T2FLS	Type 2 Fuzzy Logic System
NPC	Cerebellar Model Articulation Controller
PID	Proportional Integral Derivative
PSO	Particle Swarm Optimization
T2GMF	Type-2 Gaussian membership function

Conflict of Interest

The authors declare no conflict of interest.

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