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AN INNOVATIVE RECURRENT CEREBELLAR MODEL ARTICULATION CONTROLLER FOR PIEZO-DRIVEN MICRO-MOTION STAGE

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Abstract. *This paper proposes an innovative recurrent cerebellar model articulation control system (IRCMACS) for a micro-motion stage powered by linear piezoelectric motor (LPM). In this control system, the fast learning, generalization capability of the CMAC and good dynamic response of recurrent network are incorporated to handle nonlinear properties, disturbances of the LPM and noise to achieve high-precision positioning. According to getting rid of local minima problem, convergence speed of the system, the momentum and proportional elements are added into learning rules of the conventional CMAC to update parameters of the controller. The effects of disturbances and noise are vanished by an estimated bound compensator controller in the sense of the Lyapunov-Like Lema theory. The experimental results for the micro-motion stage system are shown to verify the effectiveness and applicability of the proposed control system for model-free nonlinear systems.*
Keywords: Recurrent cerebellar model articulation controller (RCMAC), Uncertain nonlinear systems, Lyapunov function, Linear piezoelectric motor (LPM), Micro-motion stage

1. **Introduction.** Along with development of nanotechnology, linear piezoelectric motors with their superior properties such as small dimension, high force at low speed, high-holding force, silence and nanometer displacement resolution have been more popular in many industrial applications and attracted much attention from researchers [1]. However, as dynamic equation of the LPM is too complex and highly nonlinear [2], the model-based controllers cannot achieve good performance for effects of different operation environments [3]. To deal with high nonlinear systems, many advanced controllers have been developed in recent years such as fuzzy PID [4], sliding mode controllers [5], neural adaptive sliding mode [6], neural network [7], robust adaptive controller [8], CMAC and wavelet cerebellar model articulation controller (WCMAC) [9-11]. Nevertheless, the local minima and dynamic response problems were not treated and discussed in these researches.

In this paper, the innovative recurrent cerebellar model articulation controller (IRCMAC) and the estimated bound compensator controller are comprised to control the

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Piezo-driven micro-motion stage in order to achieve high precision positioning. Therein, the IRCMAC is used to handle the nonlinearities, disturbances of the system to minimize error function, avoid local minima and adapt dynamic response. In addition, the estimated bound compensator controller is utilized to vanish the effects of uncertainties and noises for guaranteeing stability of the system.

The rest of this paper is organized as follows. Section 2 describes the dynamic system and proposed control system. Section 3 describes the structure of the IRCMAC, online learning rule and the estimated bound controller. Section 4 provides the experimental results and discussion, along with the conclusion and future work in Section 5.

2. **System Dynamic Description.** The micro-motion stage powered by LPM is represented in Figure 1 [12]. The system has some main parts such as XY stage base controlled by LPMs, driver AB5, ultrasonic distance sensors, 1711 PCI card and PC with MATLAB software.

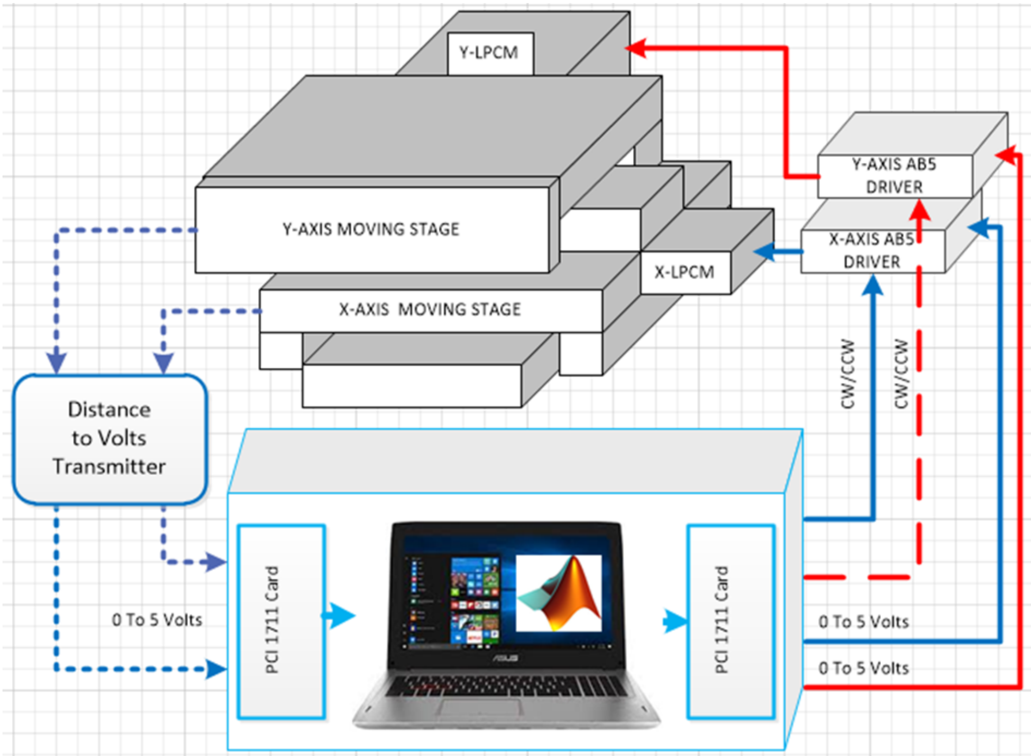


FIGURE 1. The structure of the micro-motion powered by the LPM

The dynamic equation of LPMs including hysteresis and stiffness behavior is described in detail in [5] and has following form.

$$\ddot{x}_a = -\frac{D_a}{M_a}\dot{x}_a + \frac{K_{Ea}}{M_a}u_a - \frac{F_{Ha} + F_{La}}{M_a} \tag{1}$$

where x_a stands for displacement of the x-axis, y-axis respectively; M_a is the effective mass of the moving stage; D_a is the friction coefficient; F_{La} is an external disturbance force; K_{Ea} is the voltage-to-force coefficient; u_a is the control volt of the LPMs; F_{Ha} is the hysteresis frictional force given as the following [5].

$$F_{Ha} = \alpha b + \beta \frac{db}{dt} + \gamma \dot{d}_a \tag{2}$$

In general, the parameters of the LPMs such as D_a, F_{La} and especially F_{Ha} cannot be obtained or measured exactly. Therefore, in this study, these parameters are considered as uncertainties, disturbances or noise and the proposed system must deal with these problems. The dynamic equation of the LPMs can be rewritten as state equation as below

$$\ddot{\mathbf{x}} = \mathbf{F}_0(\mathbf{x}) + \mathbf{G}_0(\mathbf{x})\mathbf{u} + \mathbf{ND}(\mathbf{x}) \tag{3}$$

where $\mathbf{F}_0(\mathbf{x}) = -\frac{D_{a0}}{M_{a0}}$, $\mathbf{G}_0(\mathbf{x}) = \frac{K_{Ea0}}{M_{a0}}$, $\mathbf{u}$ are nominal nonlinear vector, control gain and the control voltage of the LPMs, respectively. $\mathbf{ND}(\mathrm{x}) = -\frac{F_{Ha0}+F_{La0}}{M_{a0}} + f(D, F_{Ha}, F_{La}, N, t)$ denote nominal hysteresis frictional force, nominal external force, disturbances and noise, and $\mathbf{x} = [x, \dot{x}]^T$ is the state vector. To deal with the nonlinear parts, disturbances and noise, $\mathbf{ND}(\mathbf{x})$ a proposed IRCMAC system is depicted in Figure 2. This proposed controller comprises a main controller $\mathbf{u}_{\mathrm{IRCMAC}}$ and an estimated bound compensator controller, $\mathbf{u}_{\mathrm{CC}}$, where $\mathbf{u}_{\mathrm{IRCMAC}}$ is developed to handle nonlinearities, disturbances of the system for minimizing the error function, adapting dynamic response and escaping from stuck in local minima, and $\mathbf{u}_{\mathrm{CC}}$ is designed to dispel the effects of error due to uncertainties and noise during operation. The total proposed control system has the following form.

$$\mathbf{u} = \mathbf{u}_{\mathrm{ideal}} - \mathbf{u}_{\mathrm{IRCMAC}} + \mathbf{u}_{\mathrm{CC}} \tag{4}$$

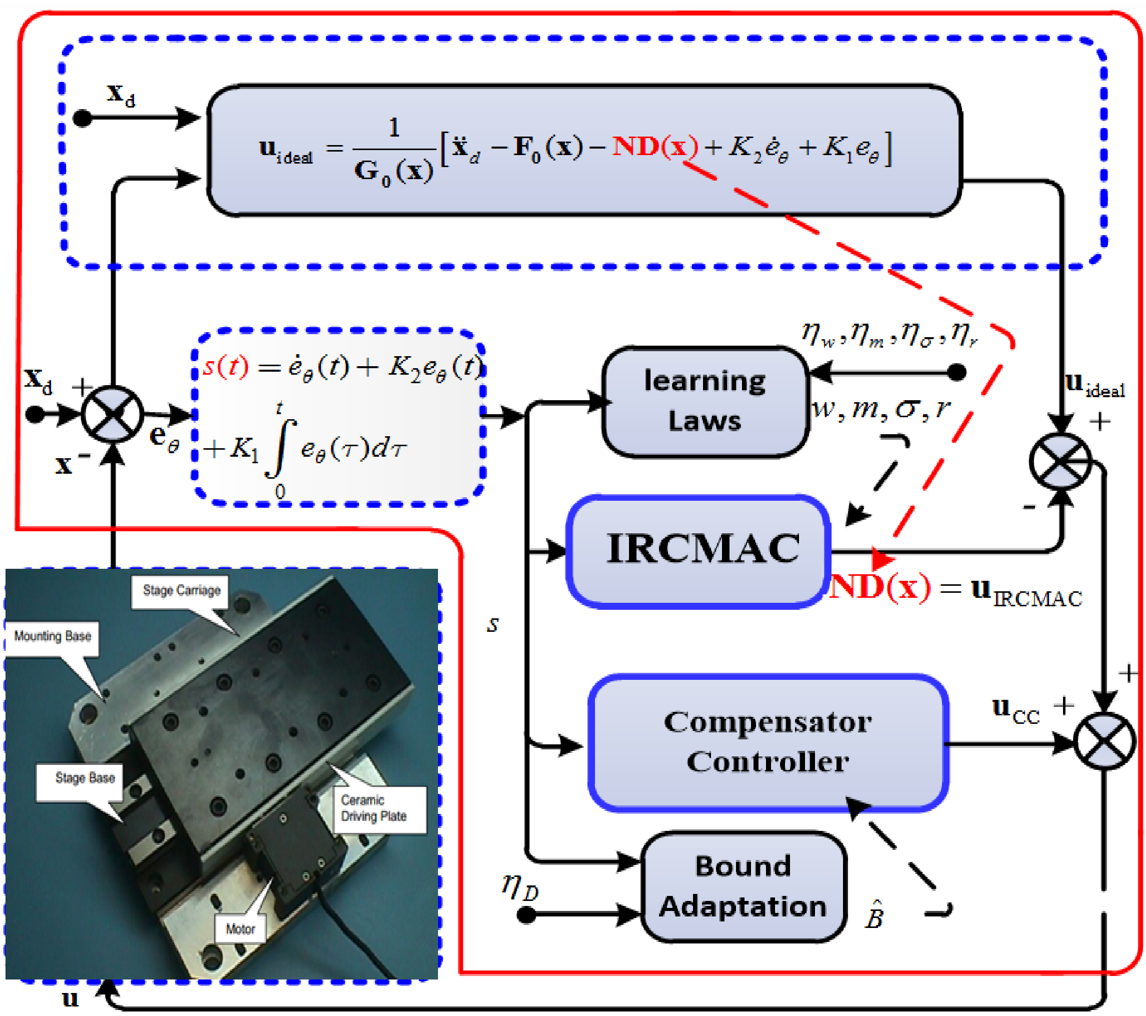


FIGURE 2. The proposed IRCMAC system

3. The Innovative Recurrent Cerebellar Model Articulation Controller System (IRCMACS).

3.1. The structure of the IRCMAC. The CMAC with its fast learning, good generalization capability places an important role in learning uncertainties $\mathbf{ND}(\mathbf{x})$ to minimize the error sliding surface [9]. However, the activation function of this controller only depends on direct inputs, so it is suitable for static problems [6]. In this investigation, recurrent technique is incoporated into the CMAC to form the IRCMAC to adapt the dynamic problems [13,14]. The structure of the IRCMAC is depicted in Figure 3 including input space S, association memory space A, receptive field space R, weight memory space W and output spaces O. The signal propagation in the IRCMAC is the same as the CMAC excepting association memory space A.

The signal propagation in the IRCMAC is presented as follows [9-11]

$$s_{ri}(k) = s_i(k) + r_{ik}\mu_{ik}(k-1) \tag{5}$$

$$\mu_{ik}(s_{ri}) = \exp\left[-\frac{(s_{ri} - m_{ik})^2}{\sigma_{ik}^2}\right] \tag{6}$$

$$b_{ik} = \prod_{i=1}^{n} \mu_{ik}(s_{ri}) \tag{7}$$

$$\mathrm{O}_j = \sum_{j=1}^{nj}\sum_{k=1}^{nk} w_{jk} \prod_{i=1}^{n} \mu_{ik}(s_{ri}) \tag{8}$$

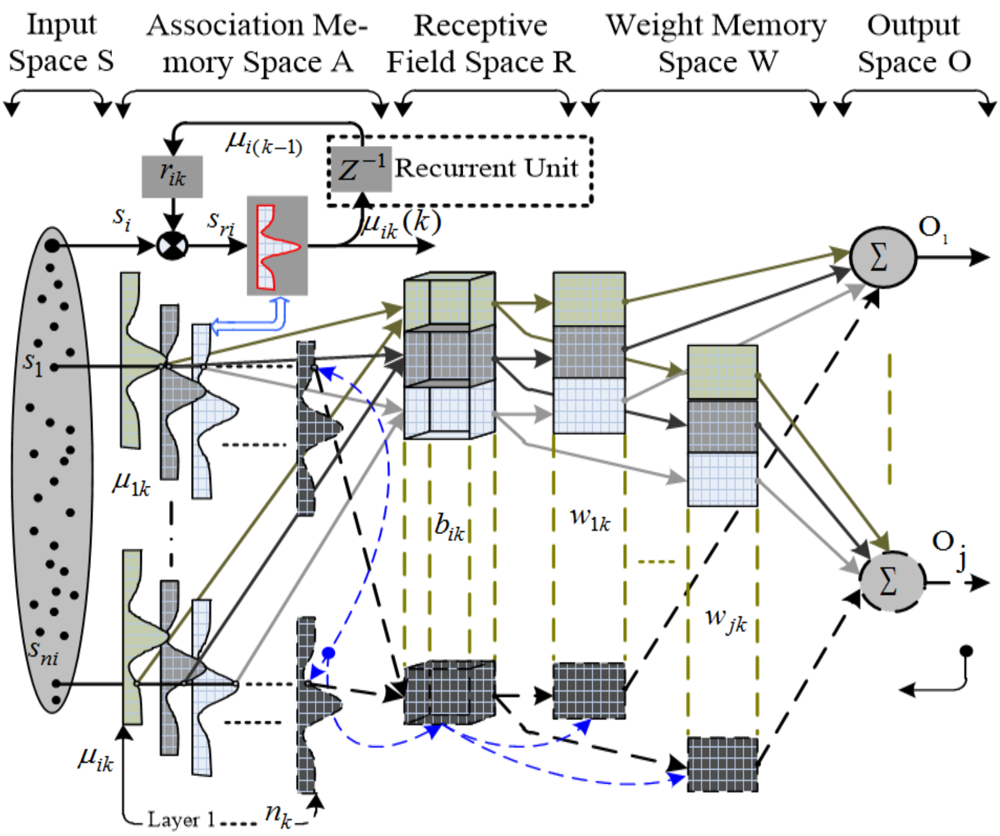


FIGURE 3. The structure of the IRCMAC

3.2. **The online learning rules.** The unknown lumped uncertainties and disturbances, $\mathbf{ND}(\mathbf{x})$, are learned by the IRCMAC $\mathbf{u}_{\text{IRCMAC}}$ with approximation error ε as follows.

$$\mathbf{ND}(\mathbf{x}) = \mathrm{O}_j = \frac{1}{\mathbf{G}_0(\mathbf{x})}\mathbf{u}_{\text{IRCMAC}}(s_{ri}, w_{kj}, m_{ik}, \sigma_{ik}) + \varepsilon = \sum_{j=1}^{nj}\sum_{k=1}^{nk} w_{jk}\prod_{i=1}^{n}\mu_{ik}(s_{ri}) \tag{9}$$

The error function is chosen as (10) and the learning rules are calculated in (11)-(14) as the following [9,11].

$$\begin{aligned}\mathbf{s}^{\mathrm{T}}\dot{\mathbf{s}} = &-\mathbf{s}^{\mathrm{T}}\mathbf{F}_0(\mathbf{x}) - \mathbf{s}^{\mathrm{T}}\mathbf{G}_0(\mathbf{x})(\mathbf{u}_{\text{ideal}} - \mathbf{u}_{\text{IRCMAC}} + \mathbf{u}_{\text{CC}})\\ &+ \mathbf{s}^{\mathrm{T}}\left(\ddot{\mathbf{x}}_d - \mathbf{ND}(\mathbf{x}) + K_1\dot{e}_\theta + K_2 e_\theta\right)\end{aligned} \tag{10}$$

$$\Delta w_{kj} = -\eta_w\frac{\partial \mathbf{s}^{\mathrm{T}}\dot{\mathbf{s}}}{\partial w_{kj}} = -\eta_w\frac{\partial \mathbf{s}^{\mathrm{T}}\dot{\mathbf{s}}}{\partial \mathbf{u}_{\text{IRCMAC}}}\frac{\partial \mathbf{u}_{\text{IRCMAC}}}{\partial w_{kj}} = \eta_w\mathbf{s}^{\mathrm{T}}\mathbf{G}_0(\mathbf{x})\left(\prod_{i=1}^{n}\mu_{ik}(s_{ri})\right) \tag{11}$$

$$\Delta m_{ik} = -\eta_m\frac{\partial \mathbf{s}^{\mathrm{T}}\dot{\mathbf{s}}}{\partial m_{ik}} = -\eta_m\frac{\partial \mathbf{s}^{\mathrm{T}}\dot{\mathbf{s}}}{\partial \mathbf{u}_{\text{IRCMAC}}}\frac{\partial \mathbf{u}_{\text{IRCMAC}}}{\partial \mu_{ik}}\frac{\partial \mu_{ik}}{\partial m_{ik}} = \eta_m\mathbf{s}^{\mathrm{T}}\mathbf{G}_0(\mathbf{x})w_{kj}2\frac{(s_{ri} - m_{ik})}{\sigma_{ik}^2} \tag{12}$$

$$\Delta \sigma_{ik} = -\eta_\sigma\frac{\partial \mathbf{s}^{\mathrm{T}}\dot{\mathbf{s}}}{\partial \sigma_{ik}} = -\eta_\sigma\frac{\partial \mathbf{s}^{\mathrm{T}}\dot{\mathbf{s}}}{\partial \mathbf{u}_{\text{IRCMAC}}}\frac{\partial \mathbf{u}_{\text{IRCMAC}}}{\partial \mu_{ik}}\frac{\partial \mu_{ik}}{\partial \sigma_{ik}} = \eta_\sigma\mathbf{s}^{\mathrm{T}}\mathbf{G}_0(\mathbf{x})w_{kj}2\frac{(s_{ri} - m_{ik})^2}{\sigma_{ik}^3} \tag{13}$$

$$\begin{aligned}\Delta r_{ik} = &-\eta_r\frac{\partial \mathbf{s}^{\mathrm{T}}\dot{\mathbf{s}}}{\partial r_{ik}} = -\eta_\sigma\frac{\partial \mathbf{s}^{\mathrm{T}}\dot{\mathbf{s}}}{\partial \mathbf{u}_{\text{IRCMAC}}}\frac{\partial \mathbf{u}_{\text{IRCMAC}}}{\partial \mu_{ik}}\frac{\partial \mu_{ik}}{\partial s_{ri}}\frac{\partial s_{ri}}{\partial r_{ik}}\\ &= \eta_\sigma\mathbf{s}^{\mathrm{T}}\mathbf{G}_0(\mathbf{x})w_{kj}2\frac{(s_{ri} - m_{ik})}{\sigma_{ik}^2}\mu_{i(k-1)}\end{aligned} \tag{14}$$

According to local minima problem of learning algorithm [15], factors of momentum term and proportional term, ρ, υ are added into learning rules of the conventional CMAC to update the parameters of the controller [16]. The momentum term places an important role in preventing the network trapping of local minima and the proportional term speeds up the convergence as the activation having flat slope. The new parameters calculating the IRCMAC are given as follows.

$$\Delta w_{kj}(t) = \Delta w_{kj}(t) + \rho\Delta w_{kj}(t-1) + \upsilon(d - d_d) \tag{15}$$

$$\Delta m_{kj}(t) = \Delta m_{kj}(t) + \rho\Delta m_{kj}(t-1) + \upsilon(d - d_d) \tag{16}$$

$$\Delta \sigma_{kj}(t) = \Delta \sigma_{kj}(t) + \rho\Delta \sigma_{kj}(t-1) + \upsilon(d - d_d) \tag{17}$$

$$\Delta r_{kj}(t) = \Delta r_{kj}(t) + \rho\Delta r_{kj}(t-1) + \upsilon(d - d_d) \tag{18}$$

The parameter updating laws of the controller are as below

$$w_{kj}(t+1) = w_{kj}(t) + \Delta w_{kj} \tag{19}$$

$$m_{ik}(t+1) = m_{ik}(t) + \Delta m_{ik} \tag{20}$$

$$\sigma_{ik}(t+1) = \sigma_{ik}(t) + \Delta \sigma_{ik} \tag{21}$$

$$r_{ik}(t+1) = r_{ik}(t) + \Delta r_{ik} \tag{22}$$

3.3. **The estimated bound compensator controller.** The most superior property of the IRCMAC is compensating the nonlinear functions, disturbances through fast learning capability. According to the IRCMAC in (9) with learning rules in (11)-(22), the approximation error ε is assumed to be bounded by a positive constant, B, and then the compensator controller is designed following the sliding mode theory to vanish the effects of disturbances and noise so as to achieve the stability of the system. The estimated compensator controller is designed as follows [17].

$$\mathbf{u}_{CC} = -\mathbf{G}_0^{-1}(\mathbf{x})\hat{B}\mathrm{sgn}(s) \tag{23}$$

where $\hat{B}$ is estimated value of B, and s is error sliding surface. The selection of parameter B exactly is unobtainable and trade off between convergence error and chattering phenomenon at output control signal. Therefore, an error bound estimation technique is developed to estimate error bound and given by estimation law as below [11].

$$\dot{\hat{B}} = \eta_B \|s\|_1 \tag{24}$$

In conclusion, the proposed IRCMAC is represented in (9), and the parameters $\hat{w}$, $\hat{m}$, $\hat{\sigma}$ and $\hat{r}$ are adjusted and updated online (11)-(22). Besides that, the estimated bound compensator controller $\mathbf{u}_{CC}$ is proposed as (23) with error bound estimation law as (24). The IRCMAC control system can be guaranteed stability in the Lyapunov-Like Lemma sense [18].

4. Experimental Results and Discussion.

4.1. **Setting experiments and practical results.** An image of the experimental equipment of the micro-motion stage system is shown in Figure 4 [12]. To illustrate the superiority of the IRCMAC, the experimental results of the CMAC and IRCMAC are provided to further demonstrate the effectiveness of the proposed control system.

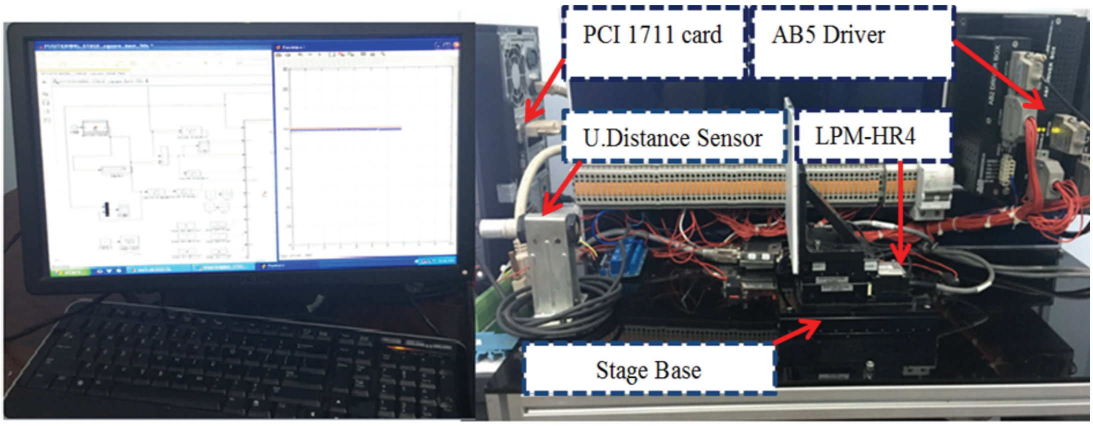


FIGURE 4. Image of practical control system

The parameters of the nominal model and controller are given as:

$$M_{a0} = 5\text{kg},\ D_{a0} = 66[\text{N.sec/m}],\ K_{Ea0} = 3[\text{N/Volt}],\ \eta_w = \eta_m = \eta_\sigma = \eta_r = \eta_D = 0.001$$

$$\eta_k = 7,\ K_1 = 0.02,\ K_2 = 0.04,\ \upsilon = 0.04,\ \rho = 0.97$$

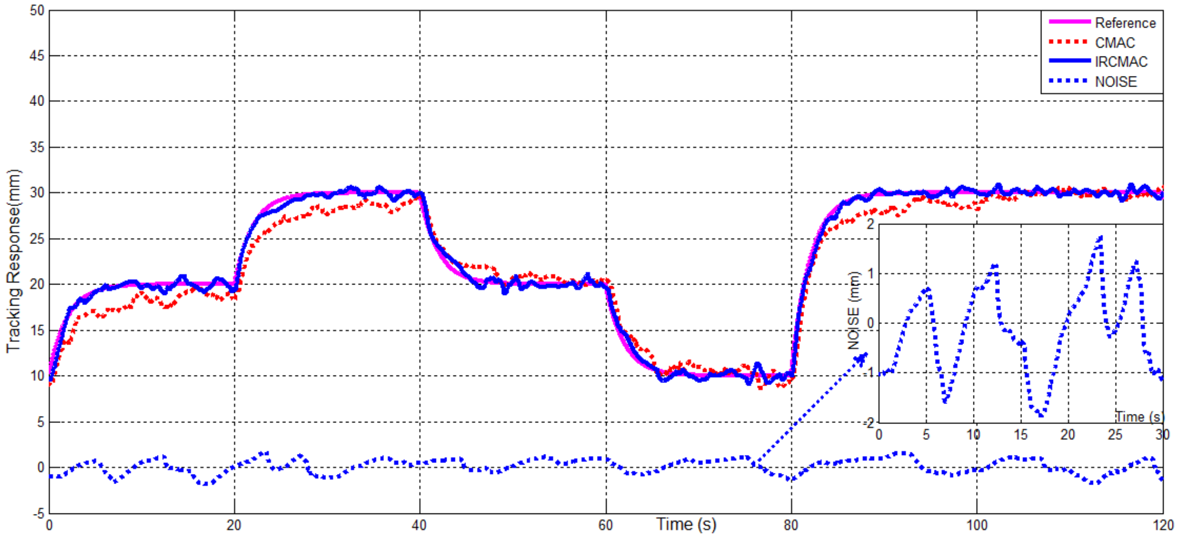
$$w = [-0.2\ \ -0.2\ \ -0.3\ \ -0.2\ \ 0.22\ \ 0.36\ \ 0.39]$$

$$m = [-0.54\ \ -0.3\ \ -0.16\ \ -0.12\ \ 0.32\ \ 0.45\ \ 0.64]$$

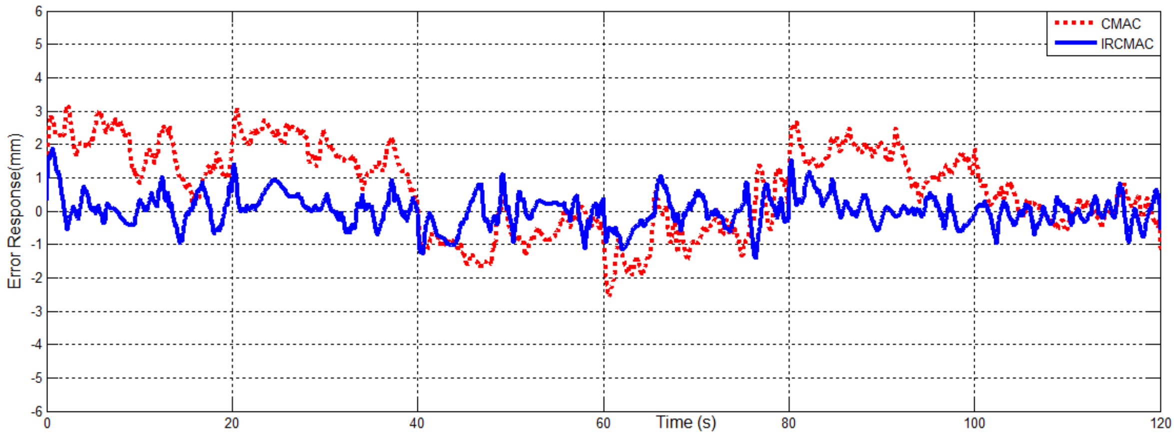
$$\sigma = [0.32\ \ 0.31\ \ 0.26\ \ 0.27\ \ 0.29\ \ 0.36\ \ 0.36]\quad r = [0.1\ \ 0.12\ \ 0.12\ \ 0.05\ \ 0.07\ \ 0.09\ \ 0.12]$$

$$\text{Sample time} = 0.01\text{s}$$

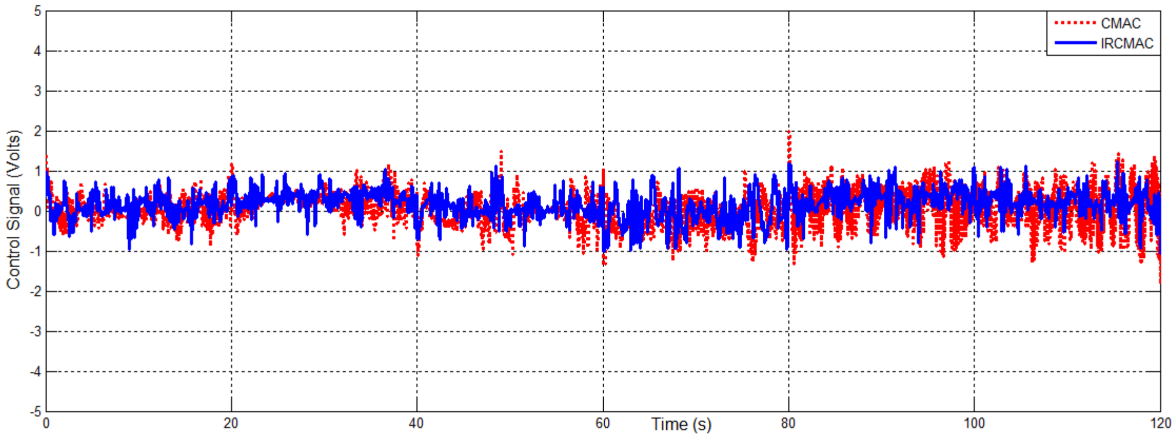
The experimental results of the CMAC and the IRCMAC due to periodic step commands are depicted in Figure 5.



(a)



(b)



(c)

Figure 5. Experimental results of the CMAC and the IRCMAC system due to periodic step command: (a) tracking response; (b) error response; (c) control signal

4.2. **Discussion.** The micro-motion stage powered by LPM is a high nonlinear system and disturbance due to the hysteresis frictional force, parameter changing. However, the proposed system can deal with these problems in the presence of noise during operation time. The experimental results show that the IRCMACS can achieve good performance during operation. Compared to CMAC, the IRCMAC has many better performances of response time, convergence error and control signal in real time. Table 1 shows MSE comparison between the CMAC (0.460) and the IRCMAC (0.071). These results once again confirm the effectiveness of the proposed system.

TABLE 1. Mean square error (MSE) comparison

Periodic step command	CMAC	RCMAC
MSE	0.460 mm	0.071 mm

5. **Conclusion and Future Work.** In this study, the IRCMAC system was proposed to control the micro-motion stage powered by the LPM successfully. The proposed control system comprised the IRCMAC and the estimated bound compensator controller. The parameters of the IRCMAC were tuned on line, the stability of the system was proven in the Lyapunov-Like Lemma sense. In addition, the effectiveness of the proposed control system was verified by the experimental results with the presence of noise. Furthermore, it is not necessary to know the elements of $\mathbf{F}_0(\mathbf{x})$ and $\mathbf{G}_0(\mathbf{x})$ exactly. If there are differences between nominal and practical parameters, they belong to uncertainties, $\mathbf{ND}(\mathbf{x})$. Consequently, the proposed control system is available for model-free nonlinear control designs. However, to enhance system performance, the robust controller should be investigated and incorporated to guarantee the robustness of the system under effects of different environment.

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