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Feedforward and Feedback Model Free Adaptive Iterative Learning Control with Application to a Linear Motor System

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Abstract: In this paper, a discrete-time feedforward and feedback model-free adaptive iterative learning control (FFMFAILC) approach is applied to the position tracking of the linear motor gantry system LMG2A-CB6-CC8. Firstly, the feedforward controller is designed by utilizing the model-free adaptive iterative (MFAILC) approach. Then the FFMFAILC method is proposed by adding the feedback control law based on the original MFAILC to reject non-repetitive exogenous disturbance. Finally, the effectiveness and robustness of the FFMFAILC approach are verified through simulation and experiment on the linear motor gantry system compared with the MFAILC approach.

Key Words: feedforward and feedback control, model free adaptive iterative (MFAILC), linear motor, position tracking.

1 Introduction

A linear motor system is a transmission device that directly converts electrical energy into mechanical energy of linear motion [1]. Typical uses for this type of motor include wafer stage, microscale robotic decomposition, electronic assembly and manufacturing, and machine tools [2] for its high accuracy and high speed. The precision required by all of these applications is continuously increasing, which makes many existed control strategies facing challenges [3].

The linear motor system, performing repetitive tasks on a finite interval, is multivariable and time-varying nonlinear system due to the existence of many factors such as slot effect, end effect, the change of system parameters and nonlinear variation friction resistance. Many control methods, including PID control [4], adaptive control [5], robust control [6-7], neural network control [8] and sliding mode control [9], have been applied to the linear motor system. Traditional PID control is difficult to achieve given precision for such nonlinear systems. Other control methods can achieve better output performance than PID control, but cannot achieve an almost perfect tracking performance within a finite time interval.

Iterative learning control (ILC) approach [10-11], evolved over the past three decades, is most suitable for the linear motor system performing repetitive tasks. ILC can achieve complete tracking with a finite interval, and it can also deal with the repeated or periodic disturbance caused by factors such as slot effect, end effect, friction force and ripple thrust. Since the first introduction of ILC for robot application [12], ILC has been extensively applied in different fields of repetitive systems such as freeway traffic [13], robotics [14], inverted pendulums [15], and electromechanical benchmarking test facilities [16], etc. In most abovementioned applications, ILC approaches require to know the dynamic model of the controlled plant in controller design. These ILC approaches can be considered as model-based ILC. For model-based ILC approaches, the controller design may become very complicated when the plant is complex, which make the controller time-consuming and robustness-weak in practical applications.

Facing these challenges brought by the existing model-based ILC approaches, the data-driven or model-free ILC has attracted increasing attention in recent years. So far, there are many data-driven methods in literatures, such as model-free adaptive iterative learning control (MFAILC) [17], PID-type ILC [18], contraction mapping based ILC [19]. For PID-type ILC and contraction mapping based ILC approaches, they adopt iterative learning law with fixed learning gains. During the iterations, only the control input sequence is modified, while the mapping relationship and learning gains remain unchanged. Clearly, these ILC approaches require identical initial conditions. Although sufficient conditions have been given to ensure its convergence in sense of λ norm, the learning error may be very large if some non-repetitive exogenous disturbances exist for the fact that the controller structure of ILC is essentially open-loop [11]. For the linear motor system with the unknown disturbance made by variable factors, it is difficult to ensure the identical initial conditions. MFAILC approach is developed by using dynamic linearization technique in the iteration domain. The MFAILC just depends on the input-output (I/O) data of the controlled plant, and not includes any model information. It only can relax the identical initial conditions, in the sequel achieve an almost perfect tracking performance [17].

The FFMFAILC approach is proposed in this paper for the position tracking of the linear motor by adding a feedback

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controller based on the original MFAILC, which can reject exogenous disturbances (the exogenous factors that are not measurable) enhancing the robustness of the MFAILC controller.

The rest of this paper is organized as follows. In Section 2, the controller for the linear motor is designed by MFAILC approach and the FFMFAILC approach. Simulation and experiment for the linear motor are conducted to verify the effectiveness of the FFMFAILC in Section 3. Conclusions are presented in Section 4.

2 Feedforward and Feedback Model Free Adaptive Iterative Leaning Control

2.1 Dynamic linearization

Consider a class of discrete-time systems with repetitive tasks on a finite interval

$$y_i(k+1) = f(y_i(k),\cdots,y_i(k-n_y),u_i(k),\cdots,u(k-n_u)) \tag{1}$$

where $u_i(k)$ and $y_i(k)$ are the control input and system output at time instant k of the *i*-th iteration; $k\in\{0,1\cdots,T\}$, T is the terminal time instant, $i=1,2,\cdots$. n_y and n_u are two unknown positive integers; $f(\cdots)$ is an unknown nonlinear function.

There are the two assumptions for the system (1).

Assumption 1: The partial derivative of $f(\cdots)$ with respect to system outputs $y_i(k),\cdots,y_i(k-n_y)$ and control input $u_i(k),\cdots,u_i(k-n_u)$ are continuous.

Assumption 2: Suppose that $\forall k\in\{0,1,\cdots,T\}$ and $\forall i=1,2,\cdots$, when $|\Delta\boldsymbol{H}_i(k)|\neq 0$, the system (1) satisfies generalized *Lipschitz* condition along the iteration axis, that is,

$$|\Delta y_i(k+1)|\le b|\Delta\boldsymbol{H}_i(k)|,$$

where

$\Delta\boldsymbol{H}_i(k)=[\Delta y_i(k),\cdots,\Delta y_i(k-n_y+1),\Delta u_i(k),\cdots,\Delta u_i(k-n_u+1)]^T$, $\Delta y_i(k+1)=y_i(k+1)-y_{i-1}(k+1)$, $\Delta u_i(k)=u_i(k)-u_{i-1}(k)$, $b>0$ is a finite positive constant.

Theorem 1 [17] Consider the nonlinear system (1) satisfying Assumption 1 and 2. If $|\Delta\boldsymbol{H}_i(k)|\neq 0$, then there exists a iteration-dependent time-varying parameter vector $\boldsymbol{\phi}_i(k)$ called pseudo gradient (PG), such that the system (1) can be transformed into the following full format dynamic linearization (FFDL) data model,

$$\Delta y_i(k+1)=\boldsymbol{\phi}_i^T(k)\Delta\boldsymbol{H}_i(k) \tag{2}$$

where $\boldsymbol{\phi}_i(k)$ is a bounded and unknown vector, $\boldsymbol{\phi}_i(k)=[\phi_1(k),\cdots,\phi_{L_y}(k),\phi_{L_u+1}(k),\cdots,\phi_{L_y+L_u}(k)]^T$, L_y and L_u are pseudo orders of (2), $0<L_y\le n_y$ and $0<L_u\le n_u$.

It is worthy to point out that equation (2) is a linear time-varying data model with simple incremental form, which is dynamically equivalent to the nonlinear system (1) and can be equivalent at any point of work.

2.2 MFAILC

For the system (1), the existed MFAILC is as follows [17].

$$\hat{\boldsymbol{\phi}}_i(k)=\hat{\boldsymbol{\phi}}_{i-1}(k)+\frac{\eta\Delta\boldsymbol{H}_{i-1}(k)}{\mu+\|\Delta\boldsymbol{H}_{i-1}(k)\|^2}\times(\Delta y_{i-1}(k+1)-\hat{\boldsymbol{\phi}}_{i-1}^T(k)\Delta\boldsymbol{H}_{i-1}(k)) \tag{3}$$

$$\hat{\boldsymbol{\phi}}_i(k)=\hat{\boldsymbol{\phi}}_1(k)\quad if\ \|\hat{\boldsymbol{\phi}}_i(k)\|\le\varepsilon\ or\ \|\Delta\boldsymbol{H}_{i-1}(k)\|\le\varepsilon\ or\ sign(\hat{\phi}_{i,L_y+1}(k))\neq sign(\hat{\phi}_{1,L_y+1}(k)) \tag{4}$$

$$u_i^f(k)=u_{i-1}^f(k)+\frac{\rho_{L_y+1}\hat{\phi}_{i,L_y+1}(k)(y_d(k+1)-y_{i-1}(k+1))}{\lambda+|\hat{\phi}_{i,L_y+1}(k)|^2}-\frac{\hat{\phi}_{i,L_y+1}(k)\sum_{m=1}^{L_y}\rho_m\hat{\phi}_{i,m}(k)\Delta y_i(k-m+1)}{\lambda+|\hat{\phi}_{i,L_y+1}(k)|^2}-\frac{\hat{\phi}_{i,L_y+1}(k)\sum_{m=L_y+2}^{L_y+L_u}\rho_m\hat{\phi}_{i,m}(k)\Delta u_i^f(k+L_y-m+1)}{\lambda+|\hat{\phi}_{i,L_y+1}(k)|^2} \tag{5}$$

where $\lambda>0$, $\mu>0$, $\eta\in(0,1]$, $\rho\in(0,1]$, ε is a tiny positive constant, y_d is desired trajectory; $\hat{\boldsymbol{\phi}}_i(k)$ is an estimation of $\boldsymbol{\phi}_i(k)$; $\hat{\boldsymbol{\phi}}_1(k)$ is the initial values of $\hat{\boldsymbol{\phi}}_i(k)$.

The MFAILC is designed only using I/O data of the controlled plant. Therefore, it is a data-driven control approach. It is worth pointing out that the PG estimation $\hat{\boldsymbol{\phi}}_i(k)$ affects the learning gains in MFAILC approach and can be iteratively calculated by iterative updating algorithm (3) and resetting mechanism (4) together, which is quite different from traditional ILC, where its the learning gain is fixed and cannot be tuned automatically.

2.3 FFMFAILC

Due to the feedforward characteristic of the MFAILC controller structure, the learning error may be very large if some non-repetitive exogenous disturbances exist. In order to deal with this problem, the FFMFAILC is proposed by adding a feedback control law to reject the exogenous disturbances [20, 21].

The designed FFMFAILC is as follows.

$$u_i(k)=u_i^b(k)+u_i^f(k) \tag{6}$$

$$u_i^b(k)=\alpha e_i(k) \tag{7}$$

$$u_i^f(k)=u_{i-1}^f(k)+\frac{\rho_{L_y+1}\hat{\phi}_{i,L_y+1}(k)(y_d(k+1)-y_{i-1}(k+1))}{\lambda+|\hat{\phi}_{i,L_y+1}(k)|^2}-\frac{\hat{\phi}_{i,L_y+1}(k)\sum_{m=1}^{L_y}\rho_m\hat{\phi}_{i,m}(k)\Delta y_i(k-m+1)}{\lambda+|\hat{\phi}_{i,L_y+1}(k)|^2}-\frac{\hat{\phi}_{i,L_y+1}(k)\sum_{m=L_y+2}^{L_y+L_u}\rho_m\hat{\phi}_{i,m}(k)\Delta u_i^f(k+L_y-m+1)}{\lambda+|\hat{\phi}_{i,L_y+1}(k)|^2} \tag{8}$$

$$\hat{\boldsymbol{\phi}}_i(k)=\hat{\boldsymbol{\phi}}_{i\text{-}1}(k)+\frac{\eta\Delta\boldsymbol{H}_{i\text{-}1}(k)}{\mu+\left\|\Delta\boldsymbol{H}_{i\text{-}1}(k)\right\|^2}\times(\Delta y_{i\text{-}1}(k+1) \\ -\hat{\boldsymbol{\phi}}_{i\text{-}1}^T(k)\Delta\boldsymbol{H}_{i\text{-}1}(k)) \tag{9}$$

$$\hat{\boldsymbol{\phi}}_i(k)=\hat{\boldsymbol{\phi}}_1(k) \quad if\left\|\hat{\boldsymbol{\phi}}_i(k)\right\|\le\varepsilon\ or\ \left\|\Delta\boldsymbol{H}_{i\text{-}1}(k)\right\|\le\varepsilon \\ or\ sign(\hat{\phi}_{i,L_y+1}(k))\ne sign(\hat{\phi}_{1,L_y+1}(k)) \tag{10}$$

where u_i^b is a feedback control law, u_i^f is a feedforward control law, $\alpha>0$ is the proportional gain.

It can be seen from (7), the feedback control law is P-type. In order to attenuate the sum errors in the on-line control, a PI-type control law is added in (7) to further strengthen the control performance of the applied FFMFAILC, which forms a new type FFMFAILC. The details are as follows.

$$u_i(k)=u_i^b(k)+u_i^f(k) \tag{11}$$

$$u_i^b(k)=\alpha e_i(k)+\beta\sum_{j=1}^{k}e_i(j) \tag{12}$$

$$u_i^f(k)=u_{i\text{-}1}^f(k)+\frac{\rho_{L_y+1}\hat{\phi}_{i,L_y+1}(k)(y_d(k+1)-y_{i\text{-}1}(k+1))}{\lambda+\left|\hat{\phi}_{i,L_y+1}(k)\right|^2} \\ -\frac{\hat{\phi}_{i,L_y+1}(k)\sum_{m=1}^{L_y}\rho_m\hat{\phi}_{i,m}(k)\Delta y_i(k-m+1)}{\lambda+\left|\hat{\phi}_{i,L_y+1}(k)\right|^2} \\ -\frac{\hat{\phi}_{i,L_y+1}(k)\sum_{m=L_y+2}^{L_y+L_u}\rho_m\hat{\phi}_{i,m}(k)\Delta u_i^f(k+L_y-m+1)}{\lambda+\left|\hat{\phi}_{i,L_y+1}(k)\right|^2} \tag{13}$$

$$\hat{\boldsymbol{\phi}}_i(k)=\hat{\boldsymbol{\phi}}_{i\text{-}1}(k)+\frac{\eta\Delta\boldsymbol{H}_{i\text{-}1}(k)}{\mu+\left\|\Delta\boldsymbol{H}_{i\text{-}1}(k)\right\|^2}\times(\Delta y_{i\text{-}1}(k+1) \\ -\hat{\boldsymbol{\phi}}_{i\text{-}1}^T(k)\Delta\boldsymbol{H}_{i\text{-}1}(k)) \tag{14}$$

$$\hat{\boldsymbol{\phi}}_i(k)=\hat{\boldsymbol{\phi}}_1(k) \quad if\left\|\hat{\boldsymbol{\phi}}_i(k)\right\|\le\varepsilon\ or\ \left\|\Delta\boldsymbol{H}_{i\text{-}1}(k)\right\|\le\varepsilon \\ or\ sign(\hat{\phi}_{i,L_y+1}(k))\ne sign(\hat{\phi}_{1,L_y+1}(k)) \tag{15}$$

(12) is the added PI-type control law, where $\beta>0$ is the integral gain. FFMFAILC can constitute a closed-loop system improving the stability of the system by adding a feedback control law based on the original designed MFAILC.

3 Simulation and Experiment

In this Section, the simulation and experiment on the linear motor gantry system using the MFAILC and FFMFAILC approach are shown, which verify the effectiveness and robustness of the FFMFAILC.

3.1 Simulation

The simulation is given to verify the effectiveness and robustness of the presented FFMFAILC, the controlled plant is discretized using zero-order holder [22]

$$s(k+1)=(1+e^{-\frac{Bt_s}{M}})s(k)+e^{-\frac{Bt_s}{M}}s(k\text{-}1)+\frac{(1+e^{-\frac{Bt_s}{M}})}{B}u(k)+\zeta(k) \tag{16}$$

where s is the motor position (m), v is the motor velocity (m/s), u is the control input voltage (V), M is the moving thrust block mass ($V/m/s^2$), B is the viscous friction parameter ($V/m/s$), ξ denotes the non-repetitive exogenous random disturbance to simulate a stochastic environment, t_s is the sampling period, k is the time index (i.e. sample number).

Based on the data generated by the abovementioned discretized model (16), the simulation comparisons of control performance between the MFAILC and the applied FFMFAILC are given. In this simulation, the sampling period t_s is adopted as 0.001s, the simulation time is 13s, the iteration times $iter$ is 30, and the desired trajectory s_d is $0.1\sin(0.5t_sk)$, the random disturbance $\xi\in[-0.00005,0.00005]$. the control input at the first iteration is given as $\boldsymbol{u}_i(k)=0$ for all $k\in\{0,1,2,\cdots\}$. $M=0.000882$, $B=15.2$. The controller parameters of the FFMFAILC are $\eta=1$, $\mu=1$, $\boldsymbol{\phi}=[5,5]$, $\boldsymbol{\rho}=[0.5,0.5]$, $\lambda=0.1$, $\alpha=1$, $\beta=0.1$.

The simulation using MFAILC approach is shown in Fig. 1 and Fig. 2. Fig. 1 shows the position tracking performance of the linear motor at the 1-st iteration, the 2-nd iteration, the 10-th iteration, the 30-th iteration, which can be seen that MFAILC based on the linear motor is sensitive to the non-repetitive exogenous disturbances. Meanwhile, it can be seen from Fig. 2 that the exogenous disturbances have an influence on the control input.

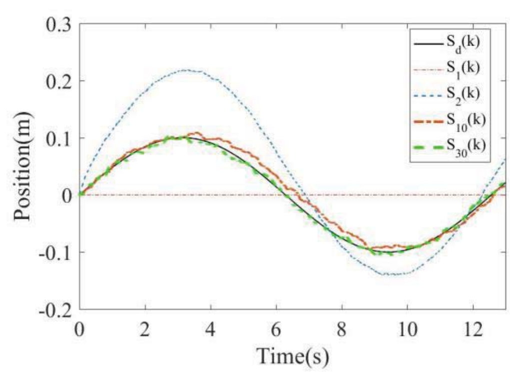

Fig. 1: The position tracking performance with the MFAILC

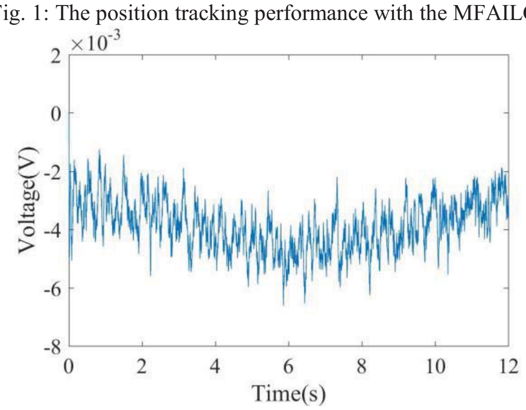

Fig. 2: The control input at 30-th iterations with the MFAILC

The simulation results using the applied FFMFAILC approach are shown in Fig. 3 -- Fig. 6. For clarification, the (6) -- (10) is called FFMFAILC1, and the (11) -- (15) is called FFMFAILC2.

It can be seen that a better control performance can be achieved by FFMFAILC in comparison with Fig. 3, Fig. 5 and Fig. 1, which illustrates that the FFMFAILC can reject the non-repetitive exogenous disturbance to some extent. Fig. 4 and Fig. 6 show the control input at 30-th iterations.

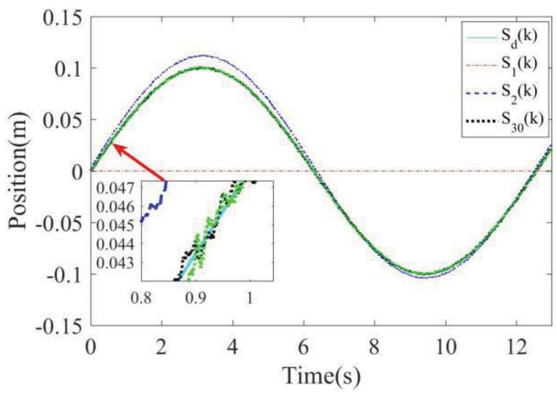

Fig. 3: The position tracking performance with FFMFAILC1

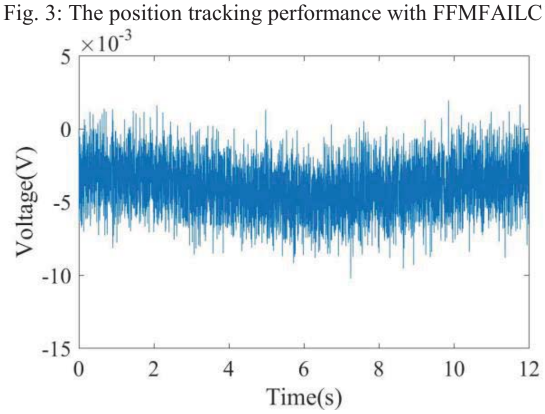

Fig. 4: The control input at 30-th iterations with the FFMFAILC1

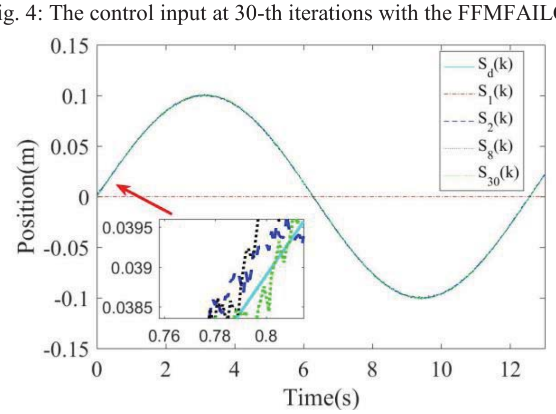

Fig. 5: The position tracking performance with FFMFAILC2

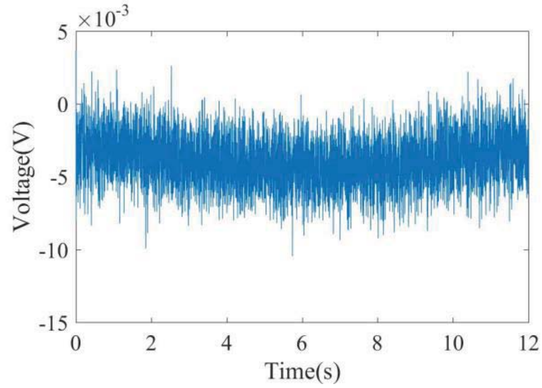

Fig. 6: The control input at 30-th iterations with the FFMFAILC2

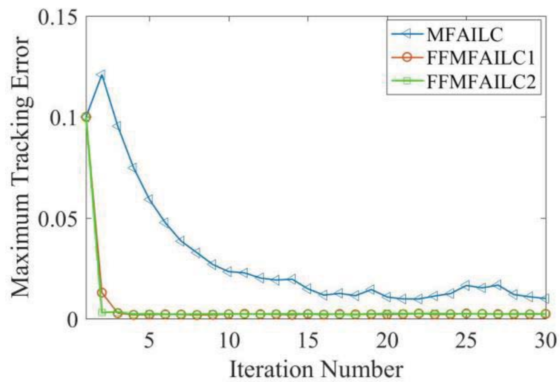

Fig. 7: The learning convergence of the tracking error with MFAILC, FFMFAILC1 and FFMFAILC2

Besides, the maximum tracking errors $E=[e_1, e_2, \cdots e_{iter}]$ of the MFAILC, FFMFAILC1 and FFMFAILC2 are shown in Fig. 7, $e_i = max\,|\,s_d(k)-s_i(k)\,|$ and e_i is maximum tracking error at i-th iteration. It can be seen from Fig. 7 that the learning ability of the FFMFAILC approach is superior than the MFAILC method and the FFMFAILC2 is the best.

3.2 Experiment

In order to further demonstrate the effectiveness of the FFMFAILC, it is applied to the practical HIWIN linear motor gantry system LMG2A-CB6-CC8, which is the LMG2A-C series produced by the Delta Tau company. The gantry system is a multi-axis linkage structure and high precision positioning type linear motor. The hardware components and experimental setup of the whole linear motor gantry system are shown in Fig. 8 and Fig. 9, respectively.

As shown in Fig. 8, the servo control process of HIMIN linear motor gantry system is as follows. Firstly, the desired trajectory is generated on the host computer, Meanwhile the encoder measures the position information of the linear motor. Secondly, the measured information is transmitted back to the host computer by the linear motor electric box, fixed terminal block and the link-RT simulation platform. Then the control input voltage is calculated by FFMFAILC approach utilizing desired trajectory and position information. Finally, the linear motor is driven by the control input voltage can move according to the desired trajectory.

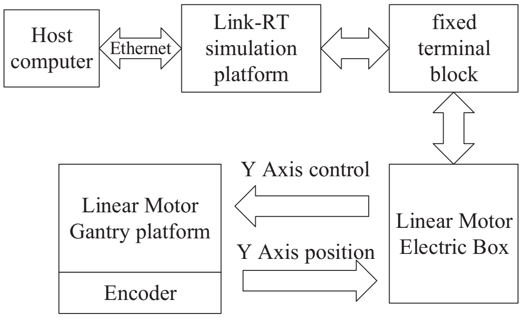

Fig. 8: Diagram of the experimental system

The experiment comparisons of control performance between the MFAILC and the FFMFAILC are given. The sampling period t_s is adopted as 0.001s, and the experiment time is 13s. the control input voltage at the first iteration is given as $\boldsymbol{u}_i(k)=0$ for all $k\in\{0,1,2,\cdots\}$ .The controller parameters of the FFMFAILC are. $\eta=1$, $\mu=1$, $\lambda=0.1$ $\boldsymbol{\phi}=[10,15]$, $\boldsymbol{\rho}=[1,1]$, $\alpha=30$, $\beta=10$.

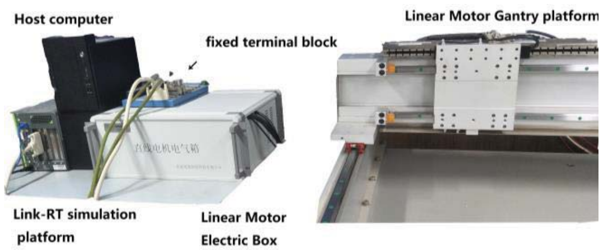

Fig. 9: Experimental Setup

The experiment results using MFAILC approach are shown in Fig. 10 and Fig. 11. Fig. 10 shows the position tracking performance at the 1-st iteration, the 2-nd iteration, the 3-th iteration, the 12-th iteration. It can be seen that the MFAILC can guarantee actual converge to desired trajectory from Fig. 10. Fig. 11 displays the control input at 12-th iteration.

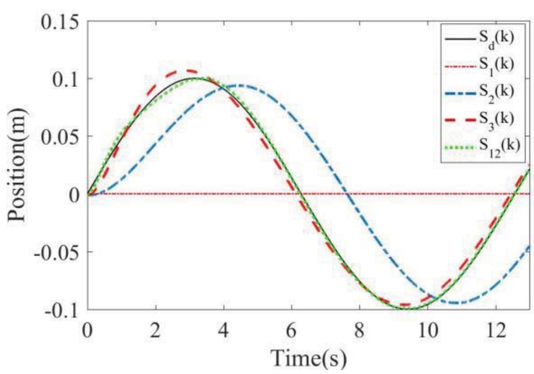

Fig. 10: The position tracking performance with the MFAILC

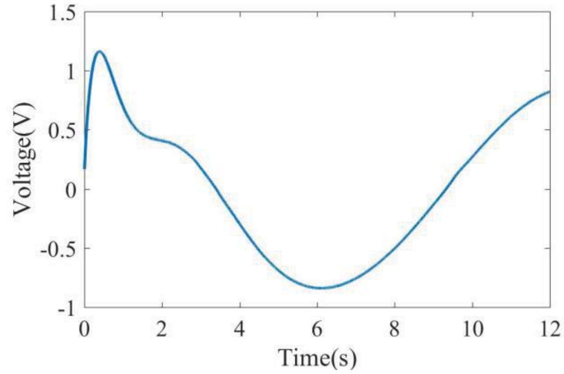

Fig. 11: The control input at 12-th iterations with the MFAILC

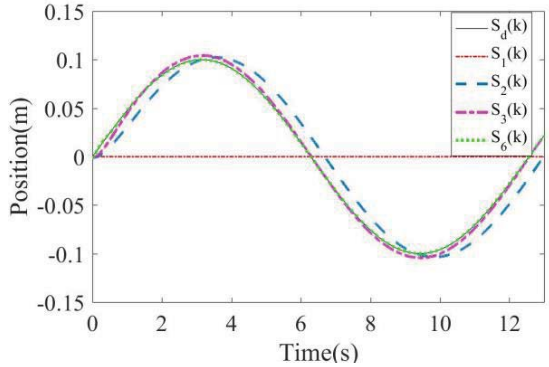

Fig. 12: The position tracking performance with the FFMFAILC1

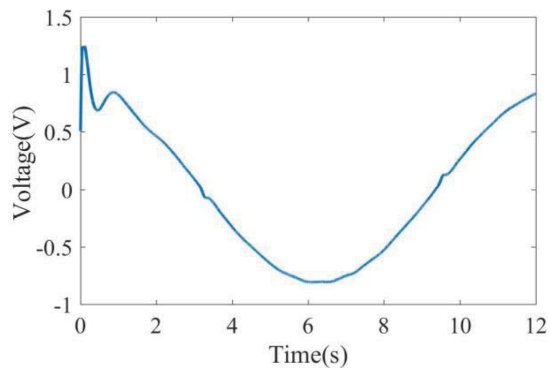

Fig. 13: The control input at 6-th iterations with the FFMFAILC1

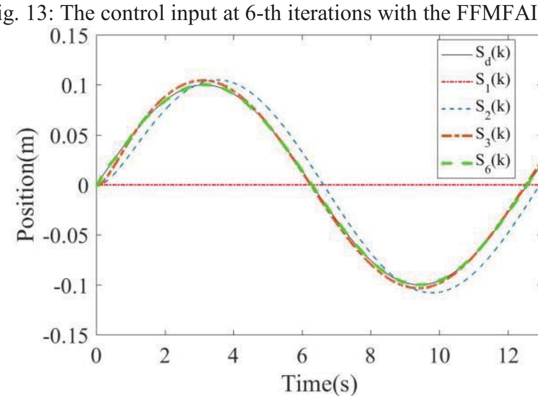

Fig. 14: The position tracking performance with the FFMFAILC2

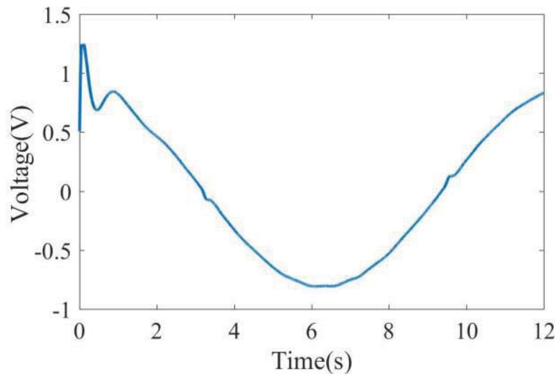

Fig. 15: The control input at 6-th iterations with the FFMFAILC2

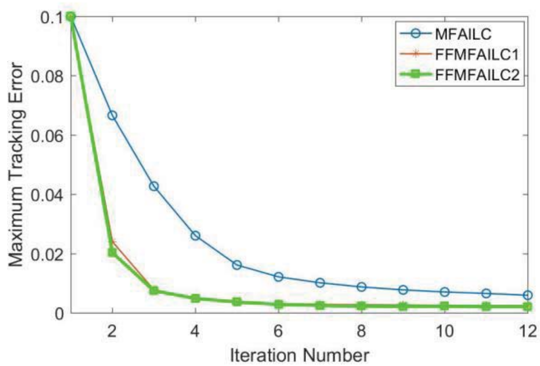

Fig. 16: The asymptotic convergence of the tracking error with MFAILC, FFMFAILC1 and FFMFAILC2

The experiment results using the applied FFMFAILC approach are shown in Fig. 12 -- Fig. 15. The results point out that the FFMFAILC can achieve a better position tracking after 6 iterations. Fig. 13 and Fig. 15 displays the control input at 6-th iteration.

Besides, the maximum tracking errors *E* of the MFAILC and FFMFAILC are shown in Fig. 16. It can be seen that the control performance of the FFMFAILC approach is superior to the MFAILC approach, and the FFMFAILC2 is the best.

4 Conclusion

The FFMFAILC is proposed for position tracking of the linear motor in this paper by adding a feedback controller based on the original MFAILC, which rejects the non-repetitive exogenous disturbances. Comparing with the MFAILC approach, the FFMFAILC can converge to the desired trajectory with stronger robustness. The simulation and experimental results demonstrate the effectiveness and robustness of the FFMFAILC approach.

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