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Iterative Feedback Tuning-based Model-Free Adaptive Iterative Learning Control of Pneumatic Artificial Muscle

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***Abstract*—Iterative feedback tuning (IFT) method is a data-driven control method, which can tune the parameters of the system controller without knowing the system model. Pneumatic artificial muscles (PAMs) are flexible actuators that are widely used in the field of rehabilitation robots because of their flexibility and light weight. However, its nonlinearity, difficult modeling and time-varying parameters make it difficult to control. In this paper, a model-free adaptive iterative learning control (MFAILC) method based on IFT is proposed for a strong nonlinear system such as PAM. The method obtains the dynamic linearization model of PAM behavior according to the dynamic linearization theorem, then designs the controller structure, and finally uses the IFT method to optimize the controller parameters. The method proposed in this paper was compared with the MFAILC method. The simulation results show that the proposed method has a faster convergence speed and smaller tracking errors in the desired trajectory tracking control, and its effectiveness is also verified.**

I. Introduction

Compared with traditional manual rehabilitation, robot-assisted rehabilitation has many advantages, such as high control accuracy, good repeatability and many training modes. It has been used to help the elderly and the patients with motor disabilities to train [1]. Pneumatic artificial muscles (PAM) is a kind of flexible driver, which is generally composed of a rubber tube with an approximate cylinder inside and a rigid fiber braided net outside. When the PMA is inflated, it will expand and produce contractile movement. When deflated, the PMA will gradually return to their original size and length. Because of its advantages of imitating human muscles, it has been widely used in the field of rehabilitation robots [2]. However, due to its nonlinear characteristics and time-varying parameters, it is very difficult to control it accurately. Because the establishment of mathematical models of PAM is difficult, it is difficult to achieve better control effects by using traditional model-based control methods. Therefore, it is important to find a control method that does not require modeling and can achieve higher control precision to control nonlinear systems such as PAM.

Model-Free Adaptive Control (MFAC) is a new data-driven control method proposed by Hou [3]. Its controller design and analysis do not require the use of model information, only the measurement of I/O data. The basis of MFAC is the dynamic linearization method. By introducing the concept of Pseudo-partial derivative (PPD), the equivalent dynamic linearization model is established at each working point of the original nonlinear system to replace the original system. The PPD of the model is estimated online by using the I/O data of the system. On this basis, the adaptive control law is designed [4]. Chi combined MFAC with iterative learning control in his doctoral dissertation in 2006. Based on a new iteration related nonparametric dynamic linearization scheme, the model-free adaptive iterative learning control (MFAILC) method was proposed. The design and analysis of the controller only depend on the I/O data of the system, and it is a model-free method [5]. Mei et al. applied the MFAILC method to the equalization control simulation experiment of the urban expressway main and auxiliary road system, which improved the efficiency of the fast road system [6]. In 2016, Zhao applied a model-free adaptive iterative learning control algorithm based on partial format dynamic linearization to noncircular turning tool feed system [7]. In 2018, the model-free adaptive iterative learning control algorithm based on full-format dynamic linearization is applied to the noncircular turning system [8], which improves the position error of the system. A distributed model-free adaptive iterative learning control method is proposed for a class of unknown nonlinear multiagent systems, which ensures that all agents can track the required trajectories [9].

Iterative feedback tuning (IFT) method is a model-free method driven by system I/O data, presented by the Swedish scholar H. Hjalmarsson in 1994 [10] and is now a well-established design methodology [11, 12]. The specific idea of this method is: given the structure of the controller beforehand, a LQG-type optimal performance index is proposed for the controlled system, and the experiment is completed iteratively on the closed-loop system. The gradient of the performance index function to the controller parameters is calculated with the obtained data, and then the Gauss-Newton iteration algorithm is used to search the controller parameters which minimize the index function, and finally the controller parameter vector converges to the local minimum point. The advantage is that it can learn and optimize controller parameters from repetitive scenarios without knowing the actual system, resulting in better controller performance [13, 14]. In 2017, a robust iterative feedback tuning technique was proposed for repetitive training control of compliant parallel

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ankle rehabilitation robots [15]. In 2016, Marcel develop an IFT approach with robustness constraints [16]. Instead of exploring the conventional model-based approaches, a multiple degree-of-freedom constrained iterative feedback tuning (CIFT) method is proposed [17]. Wang introduces the iterative feedback tuning into a Youla parameterization scheme for fault-tolerant control [18]. A model-free robust control method in form of iterative feedback tuning is proposed to tune the robot controller parameters [19].

The application of PAM-driven rehabilitation robots has become more widespread. In the recovery process of rehabilitation robots-assisted, fast tracking of desired trajectory means that time overhead can be reduced, which is very important for improving control performance. Fast tracking of desired trajectory means improving the convergence speed of MFAILC. However, the current research on the convergence of MFAILC method is limited. The convergence speed of the MFAILC method depends on the value of the controller parameters. When there is no suitable method to adjust the controller parameters, it can only be adjusted manually, which is a great burden. In this paper, a model-free adaptive iterative learning control method based on iterative feedback tuning is proposed, which combines MFAILC with IFT. This method can adjust the controller parameters to improve the convergence speed of the controller. The simulation results show the effectiveness of the method. The rest of this paper is arranged as follows: Section II introduces the design of the controller and the tuning method of its parameters. In Section III, simulation experiments are carried out. The conclusion is drawn in Section IV.

II. CONTROLLER DESIGN

A. Model-free Adaptive Iterative Learning Control

Consider a repeatable nonlinear discrete-time SISO system as follows:

$$\begin{aligned} y(k,t+1) = f\,(&y(k,t), y(k,t-1),\cdots, y(k,t-n_y), \\ &u(k,t), u(k,t-1),\cdots, u(k,t-n_u)), \end{aligned} \tag{1}$$

where $u(k,t)$ and $y(k,t)$ are the input and output of the system at time instant t of k-th iteration , respectively. $t = 0,1,\cdots, N-1$, $k \in Z_+$, N is a finite positive integer. n_u , n_y are two unknown positive integers representing the system order. $f(\cdot)$ representing an unknown nonlinear function. For system (1), the control objective is to find a suitable bounded control input signal to act on the system so that the system output is equal to the given desired trajectory.

Make the following assumptions for system (1):

Assumption 1: The system (1) is observable and controllable, i.e., there exists a bounded control input signal, which makes the output of the system equal to the given desired trajectory driven by the control input signal.

Assumption 2: The partial derivatives of $f(\cdot)$ with respect to control inputs $u(k,t)$ is continuous.

Assumption 3: System (1) is generalized Lipschitz, for all $t = 0,1,\cdots, N-1$ and $k \in Z_+$, when $\left|\Delta u(k,t)\right| \neq 0$, that is

$$\left|\Delta y(k,t+1)\right| \le b\left|\Delta u(k,t)\right|, \tag{2}$$

where $\Delta y(k,t+1) = y(k,t+1) - y(k-1,t+1)$, $\Delta u(k,t) = u(k,t) - u(k-1,t)$, b is a finite positive constant.

The above three assumptions are reasonable and acceptable. Assumption 1 is the basic assumption that a general nonlinear system should satisfy. Assumption 2 includes a large class of nonlinear systems. Assumption 3 gives the relationship between the input increment and the output increment of the system along the iteration axis at any time during any motion cycle. The existence of the constant b is a limitation on the output variation of the system, that is, a finite change in input energy can only bring about a finite change in output energy, which is clearly true for a large class of nonlinear systems.

Lemma 1: Consider nonlinear system (1) satisfying Assumption 1-3. For any $\Delta u(k,t) \neq 0$, there exists a parameter $\phi(k,t)$ so that:

$$\Delta y(k,t+1) = \phi(k,t)\Delta u(k,t), \tag{3}$$

where $\phi(k,t)$ is call pseudo-partial derivative (PPD) which satisfies $\left|\phi(k,t)\right| \le b$. For detailed certification process, please refer to the literature[5].

B. Iterative Feedback Tuning

Assume that a nonlinear system can be described as[20]:

$$\begin{aligned} z(t) = f\,(&z(t-1), z(t-2),\cdots, z(t-n_z), \\ &u(t-1), u(t-2),\cdots, u(t-n_u)), \\ y(t) = x(t)&+v(t), \end{aligned} \tag{4}$$

Where the Where $f(\cdot)$ is an unknown nonlinear function, $z(t)$ is the ideal output of the controlled object, generally interfered by the $v(t)$, $y(t)$ is the actual output of the system, $u(t)$ is the control input, the integers n_z , n_u are the system order, and their values have no effect on the tuning of the controller parameters, do not have to be known.

In order to control the controlled object, select the controller as follows

$$u(t) = g(\rho, y(t),\cdots, y(t-n_y), r(t),\cdots, r(t-n_r)), \tag{5}$$

where $r(t)$ is the reference input and ρ are the controller parameters which we want to tune.

The purpose of the control is to adjust the parameter ρ to meet the control target, and the following performance indicators should be met:

$$J(\rho) = \frac{1}{2}E\left[(L_y(y(\rho)-y_d))^2\right] + \frac{\lambda}{2}E\left[L_u u(\rho)^2\right], \tag{6}$$

where L_y , L_u , are filters (L_y=L_u $=1$ is usually selected for convenience of calculation), λ is used to adjust the balance between control performance and control effect, and usually the performance indicator can also be without the control signal.

The approximate value obtained by minimizing the cost function (6) (for simplicity, $\lambda = 0$).

$$0 = \partial J / \partial \rho_i = E\left[\left(y(\rho_i) - y_d \right) y'(\rho_i) \right], \tag{7}$$

The approximate value of ρ can be obtained by the following formula

$$\rho_{i+1} = \rho_i - \gamma_i R_i^{-1} \frac{\partial J}{\partial \rho}(\rho_i), \tag{8}$$

where γ_i is a positive value, indicating the step size of the controller parameter optimization, and R_i is a matrix that searches for the controller parameter toward the optimization direction. Here, the Gauss-Newton optimization strategy is used, which is represented by the following formula.

$$R_i = \frac{1}{N} \sum_{i=1}^{N} \left[\frac{\partial \tilde{y}_i}{\partial \rho} \left(\frac{\partial \tilde{y}_i}{\partial \rho} \right)^T \right] + \lambda \left[\frac{\partial \tilde{u}_i}{\partial \rho} \left(\frac{\partial \tilde{u}_i}{\partial \rho} \right)^T \right], \tag{9}$$

According to (7), the difficulty in finding $J'(\rho)$ is how to obtain $y'(\rho)$. Because the system (1) is unknown, $y'(\rho)$ cannot usually be accurately calculated, so it must be obtained in other ways. The IFT method only needs the system's I/O data to get $y'(\rho)$. The following is a brief step, please refer to the literature [20] for details.

A reference signal is input to the system to complete the first experiment, thereby obtaining a set of trajectory sequences $\{y_0(t), u_0(t), r_0(t)\}$. At this time, the system can be described by Taylor expansion along the trajectory:

$$\begin{aligned} y(t) &= z_0(t) + \Delta z(t) + v(t), \\ \Delta z(t) &\approx \sum_{n=1}^{n_z} \frac{\partial f(\cdot)}{\partial z(t-n)} \Delta z(t-n) + \sum_{n=1}^{n_u} \frac{\partial f(\cdot)}{\partial u(t-n)} \Delta u(t-n), \end{aligned} \tag{10}$$

Similarly, the controller can also be described by the Taylor expansion along the first experimental trajectory.

$$\begin{aligned} u(t) \approx g\left(\{y_0(t), r_0(t)\}\right) &+ \sum_{n=1}^{n_y} \frac{\partial g(\cdot)}{\partial y(t-n)} \Delta y(t-n) \\ &+ \sum_{n=1}^{n_r} \frac{\partial g(\cdot)}{\partial r(t-n)} \Delta r(t-n), \end{aligned} \tag{11}$$

Since the controller is assumed to be used to stabilize the system, the nonlinear system can be described as a linear time-varying system when the reference signal we use is very close to the reference signal used in the first experiment, as shown in Fig. 1.

For convenience, the following definitions are introduced:

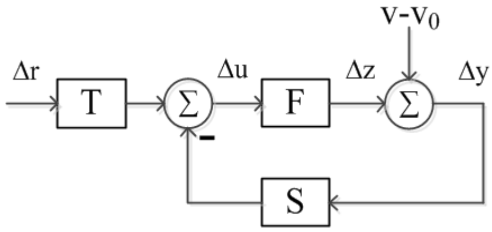

Figure 1. Linearization structure of a nonlinear system.

$$\begin{aligned} F &= F_2 / F_1, \\ F_1 &= 1 - f_{z1}(t) q^{-1} - \cdots - f_{zn_z}(t) q^{-n_z}, \\ F_2 &= f_{u1}(t) q^{-1} + \cdots + f_{un_u}(t) q^{-n_u}, \\ S &= -g_{y0}(t) - g_{y1}(t) q^{-1} - \cdots - g_{yn_y}(t) q^{-n_y}, \\ T &= g_{r0}(t) - g_{r1}(t) q^{-1} + \cdots + g_{rn_r}(t) q^{-n_r}, \end{aligned} \tag{12}$$

where

$$f_{zn}(t) = \left. \frac{\partial f(t)}{\partial z(t-n)} \right|_{\{z_0, u_0\}}, \tag{13}$$

and $f_{un}(t)$, $g_{yn}(t)$, $g_{rn}(t)$ and are defined analogically.

From Fig. 1, the system can be rewritten to:

$$\begin{aligned} \Delta z &= F \Delta u \\ \Delta y &= \Delta z + v - v_0, \end{aligned} \tag{14}$$

Introduce the linearized closed loop system

$$G_c = TF / (1 + FS), \tag{15}$$

In summary, $y'(\rho)$ can be obtained by

$$y' = \Delta y' = \frac{1}{1+FS} F \frac{T}{T} g\left(\{y_0, r_0\}\right)' = G_c \frac{1}{T} g\left(\{y_0, r_0\}\right)', \tag{16}$$

We can summarize the calculation steps of the controller parameter ρ as follows:

1. Complete the first experiment with r_0 to get the trajectory $\{y_0, u_0, r_0\}$.

2. Calculate $g\left(\{y_0, r_0\}\right)'$ and filter the result by $1/T$.

3. Complete a series of experiments with $r_\eta = r_0 + \kappa_\eta g\left(\{y_0, r_0\}\right)' / T$, $\eta = 1 \cdots \dim \rho$ to obtain y_η . The constant κ_η should be chosen so that r_η is "close" to r_0 .

4. Calculate $y'_\eta = (y_\eta - y_0) / \kappa_\eta$.

5. Update the controller parameter ρ by (8).

From this, the controller parameter ρ optimized by IFT can be obtained.

C. Controller Design and Parameter Tuning

The purpose of the controller design is to find a suitable control input, which is that the output of the system equals the expected output. Consider the following criteria function:

$$J(u(k,t)) = |y_d(t+1) - y(k,t+1)|^2 + \lambda |u(k,t) - u(k-1,t)|^2, \tag{17}$$

where λ is a weighting coefficient. Substituting (3) into the criterion function and using the optimal condition $\partial J(u(k,t))/\partial u(k,t)=0$, we have

$$u(k,t) = u(k-1,t) + \frac{\rho_{k,t}\phi(k,t)}{\lambda + |\phi(k,t)|^2}\left[y_d(t+1) - y(k-1,t+1)\right], \tag{18}$$

where $\rho_{k,t}$ is the step factor, and (18) is the learning law of model-free adaptive iterative learning control. Since $\phi(k,t)$ is unknown, it needs to be estimated online. Correspondingly, the learning control law (18) is rewritten as

$$u(k,t) = u(k-1,t) + \frac{\rho_{k,t}\hat{\phi}(k,t)}{\lambda + |\hat{\phi}(k,t)|^2}\left[y_d(t+1) - y(k-1,t+1)\right], \tag{19}$$

The criterion function for the estimated value $\hat{\phi}(k,t)$ of $\phi(k,t)$ is:

$$J(\hat{\phi}(k,t)) = \left|\Delta y(k-1,t+1) - \hat{\phi}(k,t)\Delta u(k-1,t)\right|^2 + \mu\left|\hat{\phi}(k,t) - \hat{\phi}(k-1,t)\right|^2, \tag{20}$$

where $\mu > 0$ is positive weighting factor. Using the optimal condition $\partial J(\hat{\phi}(k,t))/\partial\hat{\phi}(k,t)=0$, we have

$$\hat{\phi}_k(k,t)=\hat{\phi}(k-1,t) + \frac{\eta_{k,t}\Delta u(k-1,t)}{\mu + |\Delta u(k-1,t)|^2}\begin{pmatrix}\Delta y(k-1,t+1) \\ -\hat{\phi}(k-1,t)\Delta u(k-1,t)\end{pmatrix}, \tag{21}$$

where $\eta_{k,t}$ is the step factor. In order to ensure that the dynamic linearization model along the iterative axis is always true and has better tracking ability for time-varying parameters, the following reset algorithm needs to be introduced:

$$\hat{\phi}(k,t)=\hat{\phi}_0(t), \text{ if } \hat{\phi}(k,t) \le \varepsilon \text{ or } |\Delta u(k,t)| \le \varepsilon, \tag{22}$$

where ε is a small positive constant. For the stability and convergence analysis of the controller, please refer to the literature [5].

By (18) we have:

$$u(k,t) = u(k-1,t) + \rho\left[y_d(t+1) - y(k-1,t+1)\right], \tag{23}$$

where $\rho = \rho_{k,t}\phi(k,t)/(\lambda + |\phi(k,t)|^2)$.

From (23), the design of the nonlinear controller $u(k,t)$ has only one controller parameter ρ to be optimized, and we can use the IFT method. The tuning steps for the controller parameter ρ are as follows:

1. Complete the first experiment with the reference input signal $r_{k0}(t)$ to obtain the trajectory $\{y_{k0}(t), u_{k0}(t), r_{k0}(t)\}$.

2. Calculate $g\left(\{y_{k0}, r_{k0}\}\right)'\Big|_{\rho} = y_d(t+1) - y(k-1,t+1)$ we have $r_{k1}(t+1) = r_{k0}(t+1) + \kappa_1(y_d(t+1) - y(k-1,t+1))/T$, let the filter $T = 1$.

3. Complete the experiment with $r_{k1}(t+1)$ and we get $y_{k1}(t+1)$.

4. Calculate by $y'_{k1} = (y_{k1} - y_{k0})/\kappa_1$ to get $y'(\rho)$.

5. Substitute (7) and get $\partial J/\partial\rho_i$.

6. Select matrix R by (9).

7. Update the controller parameter ρ by (8).

III. SIMULATION RESULTS AND ANALYSIS

In order to verify the control effect of the proposed method, simulation experiments were conducted in which we introduce the following system as the control object:

$$y(k,t+1) = \begin{cases} \dfrac{y(k,t)(u(k,t)+\xi(t))}{1+y(k,t)^2} \\ +[u(k,t)+\xi(t)+a(t)\sin(y(k,t))]^3, & t < 250 \\ \dfrac{y(k,t)(u(k,t)+\xi(t))^3}{1+y(k,t)^2} \\ +(u(k,t)+\xi(t))^3, & 250 \le t \le 500 \end{cases}$$

where $a(t) = 0.1 \times round(t/100)$ is the system time-varying parameter and $\zeta(t) = \sin(t/\pi)$ is the repetitive interference. Obviously, the system is a nonlinear discrete-time system, and both the parameters and the structure are time-varying.

The desired trajectory is set to:

$$y_d(t+1) = \begin{cases} 0.5 \times (-1)^{round(t/100)}, t < 250 \\ 0.5 \times \sin(t\pi/100) \\ +0.3 \times \cos(t\pi/50), 250 \le t \le 500 \end{cases}$$

The original MFAILC method is used to control the system. The parameters of the MFAILC controller are selected as: $\lambda = 1$, $\rho_{k,t} = 1$, $\mu = 2$, $\eta_{k,t} = 0.6$, and the initial PPD is $\hat{\phi}_{ini} = 10$. The simulation results are shown in Fig. 2 and Fig. 3. In Fig. 2, the red solid line indicates the desired trajectory, and the dotted line indicates the actual output trajectory during different iterations. It can be seen from Fig. 2 and Fig. 3 that with continuous iteration, the maximum tracking error is

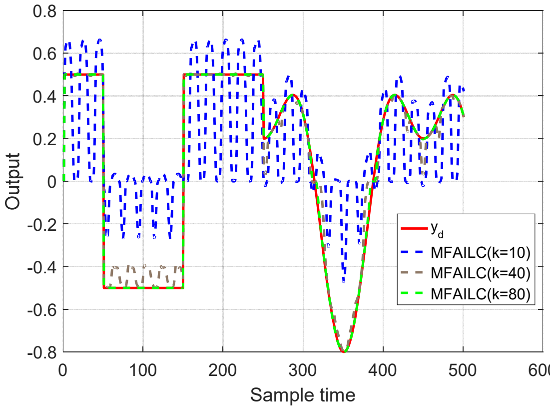

Figure 2. Trajectory tracking results using MFAILC.

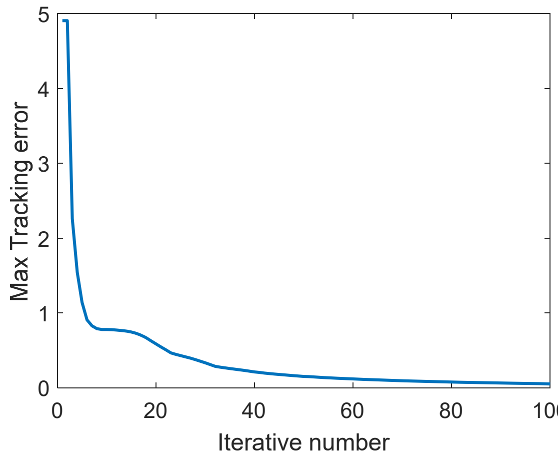

Figure 3. Convergence curve of maximum tracking error using MFAILC.

continuously reduced, and finally converges to the allowable range, the actual trajectory gradually tracks the desired trajectory, and the trajectory can completely track the desired trajectory within a finite time.

The system is controlled by the IFT-based MFAILC method proposed in this paper. The parameters required for iterative feedback tuning are set to $\lambda = 0.001$, $\gamma = 0.9$, $\kappa = 0.01$, and the initial value of the tuning parameters is set to $\rho_{ini} = 0.30$. The simulation results are shown in Fig. 4 and Fig. 5. After the simulation is over, the IFT-based MFAILC controller parameters is $\rho = 0.1745$. It can be seen from Fig. 4 and Fig. 5 that the method proposed in this paper can also realize the progressive tracking of the actual trajectory to the desired trajectory, and achieve the full tracking of the desired trajectory in a limited time. Comparing Fig. 2 with Fig. 4, the proposed method has faster convergence speed and better tracking effect than the original MFAILC method, and the IFT-based MFAILC needs to set the initial value less than the MFAILC. When iterating 40 times, the proposed method can track the expected trajectory well, and the tracking result of the original MFAILC method has a large error.

The comparison of the maximum tracking error curve of the proposed method with the original MFAILC method is shown in Fig. 6. As can be seen in the figure, the maximum

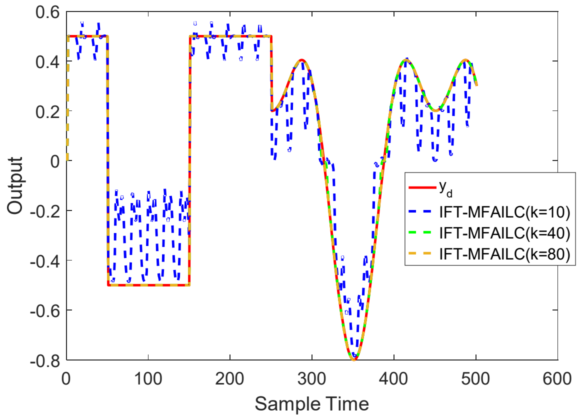

Figure 4. Trajectory tracking results using IFT-MFAILC.

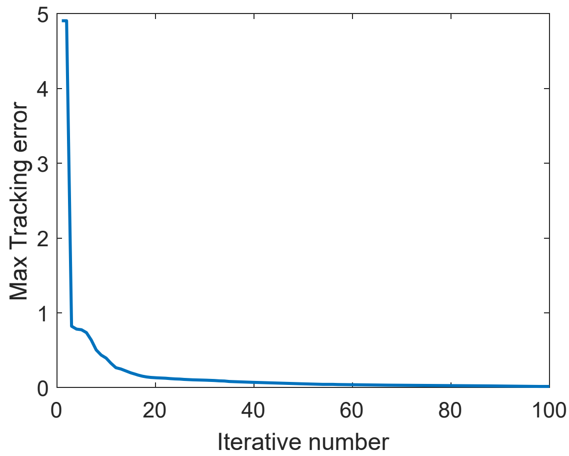

Figure 5. Convergence curve of maximum tracking error using IFT-MFAILC.

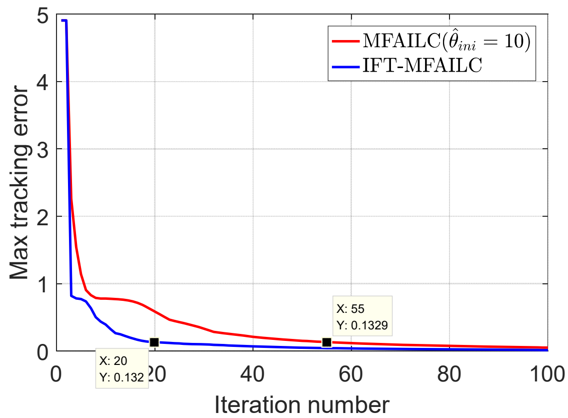

Figure 6. Comparison of maximum tracking error curves between MFAILC and IFT-MFAILC.

tracking error of the proposed method in the 20th iteration is almost the same as that of the MFAILC method in the 55th iteration. From the point of view of convergence speed, the proposed method is faster than the MFAILC method. From the perspective of maximum tracking error, the maximum tracking error of the proposed method is smaller than that of the MFAILC method. Therefore, the proposed method is better than the original MFAILC method. The results show that for the strong nonlinear systems such as PAM, the proposed method can track the desired trajectory well and ensure the control accuracy. This is important for precise control of the PAM.

IV. Conclusion

In this paper, a model-free adaptive iterative learning controller based on iterative feedback tuning algorithm and its parameter tuning method is proposed. Firstly, the non-parametric dynamic linearization principle is used to build a dynamic model. Based on this, the controller structure is designed. Then the IFT algorithm is used to tune the parameters of the controller, so that a performance index of the system can be optimized. Compared with the MFAILC method, the method proposed in this paper needs fewer parameters to set the initial value, and the tuning method is simple. It improves the convergence speed of the algorithm while reducing the tracking error. The simulation results show that the proposed method is effective and reasonable. In the future, the problem of PAM-driven rehabilitation robot tracking variable reference trajectory will be studied, so as to overcome the limitation of two basic assumptions of traditional iterative learning control, make the control conditions closer to reality, and improve the control performance and application scope of the robot.

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