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Research Article

Iterative Learning Control for Linear Discrete-Time Systems with Randomly Variable Input Trail Length

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For linear discrete-time systems with randomly variable input trail length, a proportional- (P-) type iterative learning control (ILC) law is proposed. To tackle the randomly variable input trail length, a modified control input at the desirable trail length is introduced in the proposed ILC law. Under the assumption that the initial state fluctuates around the desired initial state with zero mean, the designed ILC scheme can drive the ILC tracking errors to zero at the desirable trail length in expectation sense. The designed ILC algorithm allows the trail length of control input which is different from system state and output at a specific iteration. In addition, the identical initial condition widely used in conventional ILC design is also mitigated. An example manifests the validity of the proposed ILC algorithm.

1. Introduction

In practice, it is hard to obtain the precise mathematical model of robot system [1–4], rapid thermal processing [5], flexible system [6–8], etc. With simple recursive mode and model-free characteristic, by using the tracking error and control input of the previous iterations, iterative learning control (ILC) is widely used to the dynamical systems with repetitive operations in a fixed time interval [9–11].

Hitherto, in order to track the desired trajectory, most existing ILC works require that the trail length is fixed and uniform at each iteration [12–14]. Nevertheless, in many engineering applications of ILC, the requirement of fixed and uniform trail length might not be fulfilled. The trail length of system output, state, and control input would randomly vary from iteration to iteration due to the complex factors or randomly occurring events. Recently, there are some studies investigating the ILC issues with iteratively variable trail lengths [15–22]. By introducing the maximum pass length and adopting the lifted-system framework, Seel et al. [15] proposed the necessary and sufficient conditions of monotonic convergence for linear discrete-time single-input single-output (SISO) systems with varying trail lengths. For linear discrete-time multiple-input multiple-output (MIMO) systems, iteration-average operator and stochastic variable satisfying Bernoulli distribution are involved in ILC design to cope with the varying trail lengths issue [16]. It was proved that the system tracking errors can be driven to zero in mathematical expectation sense. Based on the Bernoulli stochastic variable, three varying trail lengths-based ILC schemes were proposed for linear discrete-time systems with vector relative degree [17]. In [18], an iteratively moving average operator, which contains the few most recent cycles, and Bernoulli stochastic variable are introduced into ILC scheme for nonlinear continuous-time SISO systems with iteratively varying trail lengths. Other iteratively moving average operator based ILC algorithms for dynamical systems with iteratively varying pass lengths could also be found in [19–21]. Recently, in [22], the tracking of ILC for discrete-time systems with varying trail lengths can be guaranteed in deterministic convergence way by a modified P-type ILC scheme. Among existing varying trail lengths-based ILC studies, it is commonly assumed that the trail lengths of state, control input, and output are identical at a specific iteration.

Clearly, more efforts should be made in the varying pass lengths-based ILC algorithms for dynamical systems.

As far as the issue of varying trail lengths is concerned, in most ILC algorithms, it is commonly assumed that the lengths of state, control input, and output are identical at a specific iteration. However, in many practical applications, it is hoped that the controlled system could achieve the control objective with less control efforts. For example, in the speed control of vehicle or robot, when the speed is controlled in a neighborhood of the desired one, the system can operate freely without any control efforts. It implied that the control inputs in a terminal time interval can be removed at one repetitive operation process. This can be represented by a repetitive system with randomly variable control input lengths. Motivated by the above observation, this paper investigates the convergence of varying input lengths-based ILC for linear discrete-time MIMO systems. Based on the assumption that the initial states randomly fluctuate around the desired initial states with zero mean, by applying the proposed P-type ILC law, the ILC tracking errors can be driven to zero in mathematical expectation at the desirable trail length as the iteration number increases. The requirements on identical initial state and trail lengths in the conventional ILC schemes are mitigated in this paper.

The rest of this paper is organized as follows. The ILC issue with randomly variable input trail length is formulated in Section 2. Section 3 presents the P-type ILC law with convergence analysis. An illustrative example is given in Section 4. Section 5 concludes this paper.

2. Problem Formulation

Consider the linear discrete-time MIMO system with varying input length, which can be represented as the following two subsystems:

$$\begin{aligned} x_k(t+1) &= Ax_k(t) + Bu_k(t), \\ y_k(t) &= Cx_k(t), \\ & t \in \{0,1,\ldots,N_k\} \end{aligned} \tag{1}$$

and

$$\begin{aligned} x_k(t+1) &= Ax_k(t), \\ y_k(t) &= Cx_k(t), \\ & t \in \{N_k+1, N_k+2,\ldots,N\}. \end{aligned} \tag{2}$$

For systems (1) and (2), $k \in \{0,1,\cdots\}$ and t denote the iteration index and time instant, respectively. Meanwhile, $x_k(t) \in R^n$, $u_k(t) \in R^q$, and $y_k(t) \in R^m$ represent the state, control input, and output, respectively. $A \in R^{n\times n}$, $B \in R^{n\times q}$, and $C \in R^{m\times n}$. N_k ($\underline{N} \le N_k \le N$) is the actual trail length of the control input $u_k(t)$ at the k-th iteration. It is assumed that N_k is unknown and random variable with iteration, but its lower bound $\underline{N}$ is given. The desired output of the linear discrete-time MIMO system represented by (1) and (2) is $y_d(t) = Cx_d(t)$, $t \in \{0,1,\ldots,N\}$, where $x_d(t)$ is the desired state. Assume that, for any realizable output trajectory $y_d(t) \in R^m$, there exists a unique control input $u_d(t) \in R^q$ such that

$$\begin{aligned} x_d(t+1) &= Ax_d(t) + Bu_d(t), \\ y_d(t) &= Cx_d(t), \\ & t \in \{0,1,\ldots,N\}. \end{aligned} \tag{3}$$

The ILC tracking error of the linear discrete-time MIMO system is thus defined as $e_k(t) = y_d(t) - y_k(t)$, $t \in \{0,1,\ldots, N\}$.

Assumption 1. The iterative initial state $x_k(0)$ is randomly variable, but its expectation satisfies

$$E\{x_k(0)\} = x_d(0). \tag{4}$$

Remark 2. Different from the general ILC requirement on identical initial condition that the iterative initial state $x_k(0) = x_d(0)$, Assumption 1 is relaxed, where $x_k(0)$ can be randomly variable with a certain expectation $x_d(0)$.

In this paper, for system (1), the objective of ILC under iteratively varying input lengths and Assumption 1 is to look for an input sequence $\{u_k(t)\}$, $t \in \{0,1,\ldots,N_k\}$ such that the ILC tracking can be improved.

3. ILC Method and Its Convergence

In order to well address the ILC issue of the linear discrete-time MIMO system (1) and (2) with the iteration-varying input trail lengths, let us denote $\xi_k(t)$, ($t \in \{0,1,\ldots,N\}$) to be a stochastic variable satisfying Bernoulli distribution and taking binary values 0 and 1. And $\xi_k(t) = 1$ denotes the event that the control input of system (1) can continue to the time instant t at the k-th iteration, which occurs with a probability function of $p(t)$, ($0 < p(t) \le 1$). $\xi_k(t) = 0$ denotes the event that the control input of system (1) cannot continue to the time instant t at the k-th iteration which occurs with a probability function of $1 - p(t)$.

Obviously, the expectation of $\xi_k(t)$ is $E\{\xi_k(t)\} = 1\cdot p(t) + 0\cdot(1-p(t)) = p(t)$.

Define a modified control input as

$$\tilde{u}_k(t) = \begin{cases} u_k(t), & t \in \{0,1,\ldots,N_k\}, \\ 0, & t \in \{N_k+1,\ldots,N\}. \end{cases} \tag{5}$$

From the definition of Bernoulli stochastic variable $\xi_k(t)$, (5) can be rewritten as

$$\tilde{u}_k(t) = \xi_k(t)\,u_k(t), \quad t \in \{0,1,\ldots,N\}. \tag{6}$$

From (5) and (6), systems (1) and (2) are presented as the following concise modified system for $t \in \{0,1,\ldots,N\}$

$$\begin{aligned} x_k(t+1) &= Ax_k(t) + B\tilde{u}_k(t), \\ y_k(t) &= Cx_k(t). \end{aligned} \tag{7}$$

In the following, for the modified system (7) under Assumption 1, a P-type ILC law is used for convergence analysis.

For $t \in \{0,1,\dots,N\}$, choose a P-type ILC law as follows:

$$u_{k+1}(t) = \tilde{u}_k(t) + L \cdot e_k(t+1), \tag{8}$$

where $L \in R^{q\times m}$ is the control gain. The control input sequence $u_k(t)$ at $t \in \{0,1,\dots,N\}$ is computed for each iteration by (8), which is a popular form in varying trail length based ILC literatures [18, 22].

Theorem 3. *Suppose that the dynamic system with varying input length, which is represented by system (1) and system (2), satisfies Assumption 1, and the desired trajectory $y_d(t)$ is realizable. Using the P-type ILC law (8), if the control gain $L \in R^{q\times m}$ is chosen to make*

$$\Theta \le \sigma < 1, \tag{9}$$

where

$$\Theta = \begin{bmatrix} (I-LCB)\,p(0) & 0 & \cdots & 0 \\ -LCABp(0) & (I-LCB)\,p(1) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ -LCA^{N}Bp(0) & -LCA^{N-1}Bp(1) & \cdots & (I-LCB)\,p(N) \end{bmatrix}, \tag{10}$$

then $\lim_{k\longrightarrow+\infty} E\{e_k(t)\} = 0$ *for* $t \in \{0,1,\dots,N\}$.

Proof. Let $\delta u_k(t) = u_d(t) - u_k(t)$, $\delta\tilde{u}_k(t) = u_d(t) - \tilde{u}_k(t)$, and $\delta x_k(t) = x_d(t) - x_k(t)$ be the control input error, modified input error, and the state error, respectively. Then, it is obtained from (3) and (7)

$$\begin{aligned} \delta x_k(t+1) &= A\delta x_k(t) + B\delta\tilde{u}_k(t), \\ e_k(t) &= C\delta x_k(t), \end{aligned} \tag{11}$$

where $e_k(t) = y_d(t) - y_k(t)$. Subtracting both sides of (8) with $u_d(t)$, there is

$$\delta u_{k+1}(t) = \delta\tilde{u}_k(t) - L\cdot e_k(t+1). \tag{12}$$

According to (11) and (12), it yields

$$\begin{aligned} \delta u_{k+1}(t) &= \delta\tilde{u}_k(t) - LC\cdot\delta x_k(t+1) \\ &= \delta\tilde{u}_k(t) - LCA\cdot\delta x_k(t) - LCB\cdot\delta\tilde{u}_k(t) \\ &= (I-LCB)\,\delta\tilde{u}_k(t) - LCA\cdot\delta x_k(t). \end{aligned} \tag{13}$$

Then applying the mathematical expectation operator $E\{\cdot\}$ on both sides of (13), we have

$$\begin{aligned} E\{\delta u_{k+1}(t)\} &= (I-LCB)\cdot E\{\delta\tilde{u}_k(t)\} - LCA \\ &\quad\cdot E\{\delta x_k(t)\} \\ &= (I-LCB)\cdot p(t)\,E\{\delta u_k(t)\} - LCA \\ &\quad\cdot E\{\delta x_k(t)\}. \end{aligned} \tag{14}$$

where $E\{\delta\tilde{u}_k(t)\} = E\{\xi_k(t)\delta u_k(t)\} = p(t)E\{\delta u_k(t)\}$ according to (6) and $E\{\xi_k(t)\} = p(t)$.

The solution of $\delta x_k(t+1) = A\cdot\delta x_k(t) + B\cdot\delta u_k(t)$ for $t \in \{0,1,\dots,N_k\}$ is

$$\delta x_k(t) = A^t\cdot\delta x_k(0) + \sum_{i=0}^{t-1} A^{t-i-1}B\cdot\delta u_k(i), \quad t \ge 1. \tag{15}$$

For $t \in \{N_k+1, N_k+2,\dots,N\}$, the solution of $\delta x_k(t+1) = A\cdot\delta x_k(t)$ is

$$\delta x_k(t) = A^t\cdot\delta x_k(0). \tag{16}$$

According to (5), (15) and (16) are combined as for $t \in \{0,1,\dots,N\}$

$$\delta x_k(t) = A^t\cdot\delta x_k(0) + \sum_{i=0}^{t-1} A^{t-i-1}B\cdot\delta\tilde{u}_k(i). \tag{17}$$

Taking the mathematical expectation operator $E\{\cdot\}$ on both sides of (17) and considering (4) of Assumption 1, it is obtained that

$$E\{\delta x_k(t)\} = \sum_{i=0}^{t-1} A^{t-i-1}B\cdot E\{\delta\tilde{u}_k(i)\}, \quad t \ge 1. \tag{18}$$

Substituting (18) into (14), it yields from $E\{\delta\tilde{u}_k(t)\} = p(t)E\{\delta u_k(t)\}$

$$\begin{aligned} E\{\delta u_{k+1}(t)\} &= (I-LCB)\cdot E\{\delta\tilde{u}_k(t)\} - LCA \\ &\quad\cdot\sum_{i=0}^{t-1} A^{t-i-1}B\cdot E\{\delta\tilde{u}_k(i)\} \\ &= (I-LCB)\cdot p(t)\,E\{\delta u_k(t)\} - LCA \\ &\quad\cdot\sum_{i=0}^{t-1} A^{t-i-1}B\cdot p(t)\,E\{\delta u_k(i)\}, \\ &\qquad t \ge 1. \end{aligned} \tag{19}$$

As $t = 0$, it follows from (14) and (4) of Assumption 1

$$E\{\delta u_{k+1}(0)\} = (I-LCB)\cdot p(0)\,E\{\delta u_k(0)\}. \tag{20}$$

As $t = 1,2,\dots,N$, from (19) we have

$$\begin{aligned} E\{\delta u_{k+1}(1)\} &= (I-LCB)\cdot p(1)\,E\{\delta u_k(1)\} - LCAB \\ &\quad\cdot p(0)\,E\{\delta u_k(0)\} \\ E\{\delta u_{k+1}(2)\} &= (I-LCB)\cdot p(2)\,E\{\delta u_k(2)\} \\ &\quad - LCA^2B\cdot p(0)\,E\{\delta u_k(0)\} - LCAB \\ &\quad\cdot p(1)\,E\{\delta u_k(1)\} \\ &\cdots \\ E\{\delta u_{k+1}(N)\} &= (I-LCB)\cdot p(N)\,E\{\delta u_k(N)\} \\ &\quad - LCA^NB\cdot p(0)\,E\{\delta u_k(0)\} - LCA^{N-1}B \\ &\quad\cdot p(1)\,E\{\delta u_k(1)\} - \cdots - LCAB \\ &\quad\cdot p(N-1)\,E\{\delta u_k(N-1)\} \end{aligned} \tag{21}$$

Denote U_d and U_k as $U_d = \left[u_d^T(0) \ u_d^T(1) \ \cdots \ u_d^T(N)\right]^T \in R^{(N+1)q}$ and $U_k = \left[u_k^T(0) \ u_k^T(1) \ \cdots \ u_k^T(N)\right]^T \in R^{(N+1)q}$. And let $\delta U_k = U_d - U_k$; we can combine (20) and (21) as follows:

$$E\{\delta U_{k+1}\} = \Theta \cdot E\{\delta U_k\}, \quad (22)$$

where Θ is defined as in (10). Taking norm $\|\cdot\|$ on both sides of (22), and then applying the condition (9), we obtain

$$\left\|E\{\delta U_{k+1}\}\right\| \leq \sigma \cdot \left\|E\{\delta U_k\}\right\|. \quad (23)$$

Since $0 \leq \sigma < 1$, it yields from (23)

$$\lim_{k \longrightarrow +\infty} \left\|E\{\delta U_k\}\right\| = 0, \quad (24)$$

which implies for $t \in \{0, 1, \ldots, N\}$

$$\lim_{k \longrightarrow +\infty} E\{\delta u_k(t)\} = 0. \quad (25)$$

On the other hand, from (11), (18), and $E\{\delta\tilde{u}_k(t)\} = p(t)E\{\delta u_k(t)\}$, for $t \in \{1, 2, \ldots, N\}$, there is

$$\begin{aligned} E\{e_k(t)\} &= C \cdot E\{\delta x_k(t)\} \\ &= C \sum_{i=0}^{t-1} A^{t-i-1} B \cdot E\{\delta\tilde{u}_k(i)\} \\ &= C \sum_{i=0}^{t-1} A^{t-i-1} B \cdot p(i) \cdot E\{\delta u_k(i)\}. \end{aligned} \quad (26)$$

Since (25) holds, taking limitation to (26), we can prove that $\lim_{k \longrightarrow +\infty} E\{e_k(t)\} = 0$ for $t \in \{0, 1, \ldots, N\}$. □

Remark 4. Regarding the selection of the control gain in the ILC law (8), the convergent condition (9) with (10) in Theorem 3 provides us a theoretical guideline. It is noticed that the convergent conditions (9) is an inequality, and usually, ILC design does not require the accurate knowledge about the controlled systems. Therefore, based on the estimated values of A, B, C, and $p(t)$, we can decide the control gain L to satisfy inequality (9).

4. Illustrative Example

Consider the following discrete-time linear system with randomly variable input trail length, which can be represented as

$$\begin{aligned} x_k(t+1) &= \begin{bmatrix} 0.587 & 0.3 & -0.066 \\ 0.04 & -0.45 & 0.02 \\ 0.86 & 0.88 & 0.8 \end{bmatrix} x_k(t) \\ &\quad + \begin{bmatrix} 0 \\ 0 \\ 0.1 \end{bmatrix} u_k(t), \\ y_k(t) &= \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} x_k(t), \\ &\qquad t \in \{0, 1, \ldots, N_k\} \end{aligned} \quad (27)$$

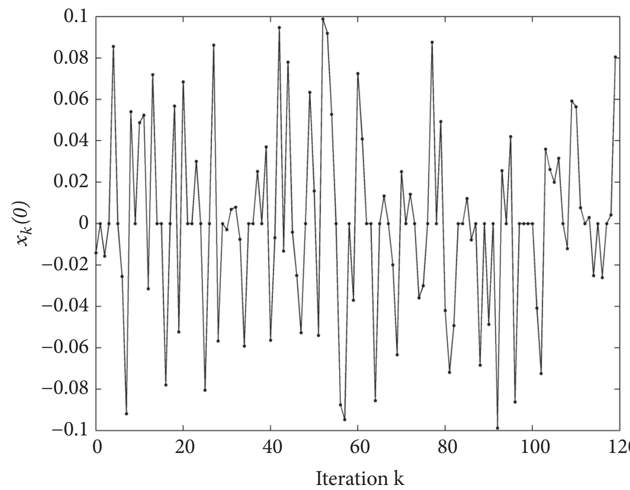

Figure 1: The variation profiles of $x_k(0)$ at different iterations.

and

$$\begin{aligned} x_k(t+1) &= \begin{bmatrix} 0.587 & 0.3 & -0.066 \\ 0.04 & -0.45 & 0.02 \\ 0.86 & 0.88 & 0.8 \end{bmatrix} x_k(t) \\ y_k(t) &= \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} x_k(t), \\ &\qquad t \in \{N_k + 1, \ldots, N\} \end{aligned} \quad (28)$$

where the state and output trail length $N = 100$ and the randomly control input length $N_k \in \{95, 96, \cdots 100\}$. The desired output $y_d(t)$ is described by

$$y_d(t) = 0.2t \sin\left(\frac{2\pi t}{N}\right), \quad t \in \{0, 1, \ldots, 100\}. \quad (29)$$

Without loss of generality, we set the initial imposing time length $N_0 = 100$ in system (27); the actual input of the initial iteration $u_0(t) = 0$, $t \in \{0, 1, \ldots, 100\}$. The corresponding modified control input of the initial iteration $\tilde{u}_0(t) = u_0(t) = 0$, $t \in \{0, 1, \ldots, 100\}$. For systems (27) and (28), the accuracy of iteratively varying input lengths-based ILC is evaluated by the sum of absolute error in mathematical expectation

$$JE_k = \sum_{t=0}^{100} \left|E\{y_d(t) - y_k(t)\}\right|. \quad (30)$$

The proposed P-type ILC law (8) is applied. According to the convergent conditions (9) and (10) provided in Theorem 3, the control gain for the ILC law is chosen as $L = 0.54$. The iterative initial states are randomly generated as shown in Figure 1, which satisfy $E\{x_k(0)\} = x_d(0)$. Figure 2 presents the performance index JE_k at different iterations. Figure 3 presents the actual tracking situation of the outputs in system (27) and system (28) to the desired trajectory (29) at iterations $k = 11$ and $k = 21$ with the P-type ILC law (8). The control inputs with randomly trail length at iterations $k = 11$ and $k = 21$ are depicted in Figure 4.

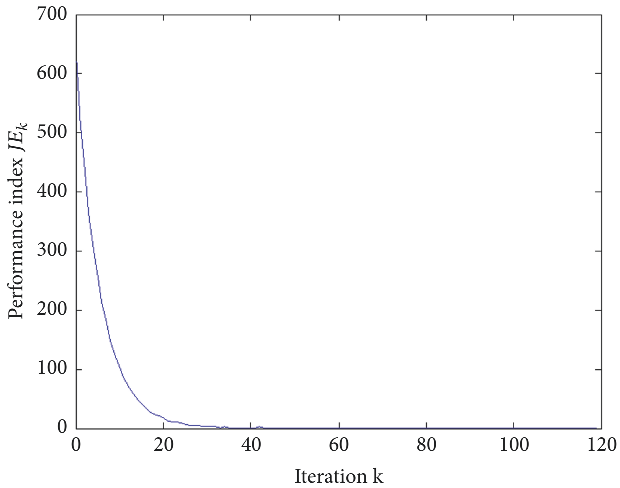

FIGURE 2: The performance index JE_k at different iterations by using the proposed P-type ILC law (8).

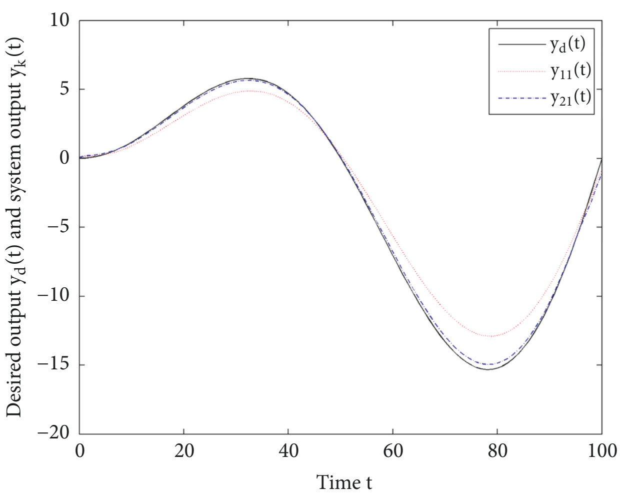

FIGURE 3: The output trajectories of the ILC system (27) and (28) for $t \in \{0, 1, \ldots, 100\}$ at iterations $k = 11$ and $k = 21$.

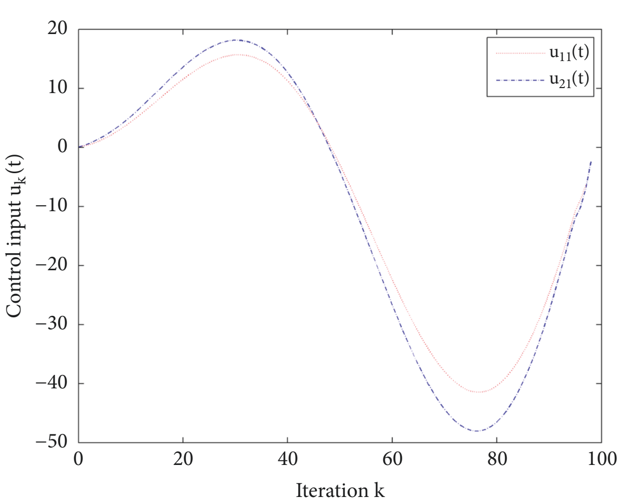

FIGURE 4: For $t \in \{0, 1, \ldots, N_k\}$, the control input trajectories of the ILC system (27) at iterations $k = 11$ and $k = 21$.

Figure 1 indicates that the initial condition $E\{x_k(0)\} = x_d(0)$ in Assumption 1 is quite different from the identical initial condition $x_k(0) = x_d(0)$ of the general ILC schemes. It implies that Assumption 1 is very relaxed, where $x_k(0)$ can randomly fluctuate around $x_d(0)$ with zero mean. From Figure 2, it is illustrated that the performance index JE_k can be certainly driven to zero as the iteration number k goes to infinity by the proposed P-type ILC law (8). Although the actual input length of system (27) is randomly variable with iteration number k as shown in Figure 4 and the initial states fluctuate randomly satisfying $E\{x_k(0)\} = x_d(0)$ as shown in Figure 1, a progressively improved tracking performance of the outputs in system (27) and system (28) to the desired trajectory $y_d(t)$ has been accomplished for $t \in \{0, 1, \ldots, 100\}$ as shown in Figure 3.

5. Conclusions

For linear discrete-time systems with randomly variable input trail length, where the initial states fluctuate around the desired initial states with zero mean, this paper presents a modified P-type ILC law. Modified control input at the desirable trail length is introduced in ILC designs in order to tackle the randomly variable input trail length. The designed ILC scheme can drive the ILC tracking errors to zero at the desirable trail length in mathematical expectation. The requirements on identical trail lengths at a specific iteration and identical initial condition in previous varying trail length based ILC schemes are mitigated. Future research will extend the varying input trail length based ILC results of this paper to the multiagent systems [23, 24] and other robot systems [25].

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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