Feedback Feed-Forward Iterative Learning Control for Non-affine Nonlinear Discrete-Time Systems with Varying Trail Lengths

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Abstract. This paper introduces a feedback and feedforward iterative learning control (ILC) scheme for non-affine nonlinear systems featuring iteratively varying trail lengths. The random trail lengths lead to the loss of tracking information in the final iteration. To address this information loss, the deviation in tracking for the ongoing iteration is incorporated with the aid of the feedback control component. It is demonstrated that the convergence condition is contingent solely on the feedforward control gain, with the feedback control part contributing to an acceleration in convergent speed. By establishing the statistical expectation of the initial state as equal to the desired state, it is proven that the mathematical expectation of the error can be effectively controlled to zero. The efficacy of the proposed algorithm is illustrated through numerical simulation.

Keywords: Iterative learning control · iteratively varying trail lengths · non-affine nonlinear system · feedback control

1 Introduction

Iterative learning control (ILC) emerges as a robust methodology developed for dynamic mechanisms exhibiting repetitive operational patterns within a predetermined time interval. Drawing from previous control experiences, it leverages historical data to enhance the present conduct of the control mechanisms, progressively minimizing the tracking error within the iterative domain. Arimoto first introduced this concept in 1984 [1].

To attain optimal tracking capability within a specified time interval, a fundamental condition in design of ILC that is the regularity of the dynamical system. This involves ensuring that system set back to its identical starting point and comes to a halt at the same final destination in every iteration, as emphasized in [2, 3]. Nevertheless, in practical applications, the inherent uncertainty of the dynamical system may impede the fulfillment of the prerequisites for identical initial states and consistent trajectory lengths. When the industrial robots occurs an emergency case, the robots will stop their motion, resulting in shorter trial lengths and lost data packets. Furthermore, the initial point of the system might differ from one iteration to another due to the presence of resetting

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errors. Hence, Examining an ILC approach becomes crucial for non-affine nonlinear control systems that exhibit varying trial lengths iteratively.

Some studies have proposed ILC laws to address the issue of iteratively varying trial lengths. For instance, to address the varying iteration length problem for linear discrete-time systems, [4] proposed ILC algorithm incorporated an averaging operator during iterations. In situations involving linear discrete-time system characterized by iteratively changing trial lengths and unpredictable initial states, [5] suggested an ILC law with an integrated open closed loop structure, encompassing both feed-forward ILC and feedback control components. The feedback control component utilizes tracking data from the present iteration to offset the absence of certain information, this helps decrease the memory resource needed for tracking data. The teacher of Sheng Dong proposed the data loss problem about the non-affine nonlinear discrete time system in [6]. In [7–9], using the λ-norm technique to illustrate the convergence of tracking in nonlinear discrete-time systems. The Capability of the ILC technique in addressing the Changing trial durations and initial conditions is evident. Nevertheless, tackling the issue of non-affine nonlinear control systems with iteratively variable lengths is a formidable task that requires resolution.

This paper investigates the application of the ILC approach to non-affine nonlinear control systems featuring iteratively varying trial lengths. To address this, we present an iterative learning control algorithm incorporating both feed-forward and feedback control. The proposed approach includes a feed-forward component, ensuring the successive convergence of tracking deviation in mean value context. Additionally, the design of the feedback component aims to offset loss of tracking data caused by iteratively variable trial length. At last, It is worth noting that previous studies on ILC with iteration-varying trail length, such as those in [7–9], have widely employed the λ-norm and its variations to evaluate the tracking error. Nevertheless, there is a growing consensus in the literature that the λ-norm can not provide a contentment assessment of error. Hence, in this paper, we refrain from adopting the λ-norm to analyze the iteration-varying trial lengths within the context of the feed-forward and feedback ILC scheme.

This paper makes contributions in three key aspects relative to the existing literature:

(1) Differing from the current ILC laws in systems with varying trail lengths [7–10], [11] feedback component is employed in modified deviation formed on P-type ILC. This incorporation allows the utilization of tracking data from the current iteration to compensate for the loss of tracking data in previous iterations.
(2) The advanced feedback and feed-forward iterative learning control approach ensures the convergence of deviation in statistical expectation context and facilitates the speed of the convergence process.
(3) Non-affine nonlinear systems with iterative variable path lengths are considered.

The structure is outlined in the following manner: Sect. 2 presents the problem formulation and details updating algorithms. In Sect. 3, a rigorous analysis of the algorithms' convergence is provided. Section 4 includes a simulation example to illustrate the methodology. Last, Sect. 5 presents the conclusions drawn from this study.

Notations: In this article R signifies the actual values and R^n represents space of n-dimensional vectors. $\|X\|$ denote norm applicable to both vectors and matrices. $E\{\cdot\}$ is used to denote the statistical expectation.

2 Problem Formulation

Examine the subsequent nonlinear non-affine discrete-time system with iteratively variable trail lengths

$$\begin{cases} x_k(t+1) = f(x_k(t), u_k(t), t) \\ y_k(t) = C(t)x_k(t) \end{cases} \tag{1}$$

here, $k = \{1, 2, ...\}$ denote the indicator of iteration and $t \in \{0, 1, ..., N_k\}$ represent the index of time. $u_k(t) \in R^n$, $x_k(t) \in R^n$ and $y_k(t) \in R^q$ depict control input, system condition and system output, Individually. $f(\cdot, \cdot, \cdot) \in R^n$, $C(t) \in R^{q\times n}$. For the system described by Eq. (1), the actual trail length N_k $\left(\underline{N} \le N_k \le \overline{N}\right)$ is both iteration-variant and unknown. However, its lower bound is $\underline{N}$ and upper bound is $\overline{N}$. The desired trail $y_d = C(t)x_d(t)$, $t \in \{0, 1, .., N+1\}$, the $x_d(t)$ represent the reference state and N is the desired lengths. The error in the ILC context is outlined as $e_k(t) = y_d(t) - y_k(t)$, $t \in \{0, 1, ..., \min\{N_k + 1, N + 1\}\}$.

Considering the desired signal $y_d(t)$, assume the existence of a only control input $u_d(t) \in R^n$ $t \in \{0, 1, ..., N\}$, there is

$$\begin{cases} x_d(t+1) = f(x_d(t), u_d(t), t) \\ y_d(t) = C(t)x_d(t) \end{cases} \tag{2}$$

here, $\forall t$, assume that $f(t, \cdot, \cdot)$ is continuously differentiable in relation to both its variables x and u. To provide great precision, denote $D_{2,k}(t) \triangleq \frac{\delta f}{\partial u}\Big|_{u_k^*(t)}$, $D_{1,k}(t) \triangleq \frac{\delta f}{\partial x}\Big|_{x_k^*(t)}$, where represent $u_k^*(t)$ lying between $u_d(t)$ as well as $u_k(t)$, $x_k^*(t)$ represents vector resets between $x_d(t)$ and $x_k(t)$.

The technical analysis relies on the subsequent assumptions.

Assumption 1: The system's start state is configured to be $x_d(0)$ at the commencement of per iteration.

$$x_k(0) = x_d(0), \ \forall k \ge 1 \tag{3}$$

Assumption 2: For all t, the nonlinear function $f(\cdot, \cdot, \cdot)$ in Eq. (1) is presumed to be differentiable to t and adheres the overall Lipschitz condition. To clarify, for all t, x_1,$x_2 \in R^n$ and u_1, $u_2 \in R^n$, there exists two constant $k_f > 0$ and $k_b > 0$, such that.

$$\|f(x_1, u_1, t) - f(x_2, u_2, t)\| \le k_f\|x_1 - x_2\| + k_b\|u_1 - u_2\| \tag{4}$$

under normal conditions, considering $D_{1,k}(t)$ and $D_{2,k}(t)$ are non singular, Furthermore, $\left\|D_{2,k}(t)\right\| \le k_b$, $\left\|D_{1,k}(t)\right\| \le k_f$ $\forall k, t$

Lemma 1: Given a difference inequality.

$$h(t+1) \le g(t) + sh(t) \tag{5}$$

Here, $h(t)$ and $g(t)$ are scalar functions of $t \ge 0$, and s is a constant, then, for $t \ge 1$

$$h(t) \le \sum_{i=0}^{t-1} s^{t-i-1} g(i) + s^t h(0) \tag{6}$$

Due to the controlled system with varying trail lengths, the stochastic variables $\lambda_k(t)$ introducing a variable that follows Bernoulli distribution. $\lambda_k(t) = 1$ indicate that system (1) is unable to persist beyond time point t at the k th iteration, taking place with a likelihood function $\overline{\lambda}(t)$,$\left(0 \le \overline{\lambda}(t) \le 1\right)$. $\lambda_k(t) = 0$ indicate that system (1) is unable to persist beyond time point t at k th iteration, taking place with a likelihood function of $1 - \overline{\lambda}(t)$. Clearly, the average of $\lambda_k(t)$ is

$$E\{\lambda_k(t)\} = 1 \cdot \overline{\lambda}(t) + 0 \cdot \left(1 - \overline{\lambda}(t)\right) = \overline{\lambda}(t) \tag{7}$$

Taking into account the random lengths in the ILC error of system (1), the modified error is indicated by.

$$\overline{e}_k(t) = \lambda_k(t) e_k(t), \ \ 0 \le t \le N+1 \tag{8}$$

Based on description of $\lambda_k(t)$, (8) expressed for $N_k < N$,

$$\overline{e}_k(t) = \begin{cases} e_k(t), & 0 \le t \le N_k + 1 \\ 0, & N_k + 1 < t \le N + 1 \end{cases} \tag{9}$$

For $N_k \ge N$,

$$\overline{e}_k(t) = e_k(t), \ \ 0 \le t \le N+1 \tag{10}$$

For the system (1) under Assumption 1, The convergence analysis of a feedback and feed-forward algorithm for $t \in \{0, 1, \cdots, N\}$ the adjusted deviation is outlined bellow.

$$u_{k+1}(t) = u_{k+1}^f(t) + u_{k+1}^b(t) \tag{11}$$

$$u_{k+1}^f(t) = u_k(t) + P\overline{e}_k(t+1) \tag{12}$$

$$u_{k+1}^b(t) = L\overline{e}_k(t) \tag{13}$$

here, $u_{k+1}^f(t)$ represents open loop component incorporating the open loop control parameter $P \in R^{q \times m}$. While $u_{k+1}^b(t)$ represents the close loop control component incorporating the close loop control gain $L \in R^{q \times m}$.

3 Convergence Analysis of Feedback Feed-Forward ILC

In this section, we delve into the algorithm design and convergence investigation according to lemmas and assumptions provided in Sect. 2.

Theorem 1: Assuming Assumption 1 hold, consider the non-affine nonlinear discrete-time system (1) within varying trail lengths and a desired trail $y_d(t)$, Employ feedback and feed-forward algorithm (11), (12), (13). If the parameter $P \in R^{q\times m}$ satisfy.

$$\left\| I - \overline{\lambda}(t+1)PC(t+1)D_{2,k}(t) \right\| = \Phi(t) < 1 \tag{14}$$

then $\lim\limits_{k\to\infty} E\{\|y_d(t) - y_k(t)\|\} = 0, t = 0, 1, \ldots, N+1$.

Proof: Denote $\delta u_k^f(t) = u_d(t) - u_k^f(t)$, $\delta u_k(t) = u_d(t) - u_k(t)$. Deducting both side of (12) from $u_d(t)$, we have.

$$\delta u_{k+1}^f(t) = \delta u_k(t) - P\overline{e}_k(t+1) \tag{15}$$

From the Eq. (11) and (13), there is

$$\delta u_k(t) = \delta u_k^f(t) - L\overline{e}_k(t) \tag{16}$$

Substituting (16) into (15) results in

$$\delta u_{k+1}^f(t) = \delta u_k^f(t) - L\overline{e}_k(t) - P\overline{e}_k(t+1) \tag{17}$$

Then $\delta x_k(t) = x_d(t) - x_k(t)$ given (1), (2), (8) and (17) transforms into

$$\begin{aligned}\delta u_{k+1}^f(t) &= \delta u_k^f(t) - L\lambda_k(t)e_k(t) - P\lambda_k(t+1)e_k(t+1)\\ &= \left[1 - P\lambda_k(t+1)C(t+1)D_{2,k}(t)\right]\delta u_k^f(t)\\ &-\left[1 - P\lambda_k(t+1)C(t+1)D_{2,k}(t)\right]L\lambda_k(t)e_k(t)\\ &-P\lambda_k(t+1)C(t+1)D_{1,k}(t)\delta x_k(t)\end{aligned} \tag{18}$$

Then taking the $E\{\cdot\}$ on the both side of (18), there is

$$\begin{aligned}E\left\{\delta u_{k+1}^f(t)\right\} &= \left[1 - P\overline{\lambda}_k(t+1)C(t+1)D_{2,k}(t)\right]E\left\{\delta u_k^f(t)\right\}\\ &-\left[1 - P\overline{\lambda}_k(t+1)C(t+1)D_{2,k}(t)\right]L\overline{\lambda}_k(t)E\{e_k(t)\}\\ &-P\overline{\lambda}_k(t+1)C(t+1)D_{1,k}(t)E\{\delta x_k(t)\}\end{aligned} \tag{19}$$

Applying the norm $\|\cdot\|$ to both side of (19), we get

$$\left\| E\left\{\delta u_{k+1}^f(t)\right\} \right\| \le \left\| 1 - P\overline{\lambda}_k(t+1)C(t+1)D_{2,k}(t) \right\| \cdot \left\| E\left\{\delta u_k^f(t)\right\} \right\|$$

$$+\left\|\left[1-P\overline{\lambda}_k(t+1)C(t+1)D_{2,k}(t)\right]L\overline{\lambda}_k(t)\right\|\cdot\|E\{e_k(t)\}\|$$

$$+\left\|P\overline{\lambda}_k(t+1)C(t+1)D_{1,k}(t)\right\|\cdot\|E\{\delta x_k(t)\}\| \tag{20}$$

where $z_1 = \max\{||\{P\bar{\lambda}_k(t+1)C(t+1)D_{1,k}(t+1)||, ||[1-P\bar{\lambda}_k(t+1)C(t+1)D_{2,k}(t)]L\bar{\lambda}_k(t)||\}\}$, there is

$$\left\|E\left\{\delta u_{k+1}^f(t)\right\}\right\| \leq \left\|1-P\overline{\lambda}_k(t+1)C(t+1)D_{2,k}(t)\right\|\cdot\left\|E\left\{\delta u_k^f(t)\right\}\right\|$$

$$+z_1\cdot\{\|E\{\delta x_k(t)\}\|+\|E\{e_k(t)\}\|\} \tag{21}$$

On the contrary, based on (1), (2), and (18), we have

$$\|E\{\delta x_k(t)\}\| \leq \left\|D_{1,k}(t-1)\right\|\cdot\|E\{\delta x_k(t-1)\}\|+\left\|D_{2,k}(t-1)\right\|\cdot\|E\{\delta u_k(t-1)\}\|$$

$$\leq \left\|D_{1,k}(t-1)\right\|\cdot\|E\{\delta x_k(t-1)\}\|+\left\|D_{2,k}(t-1)\right\|\cdot\left\|E\left\{\delta u_k^f(t-1)\right\}\right\|$$

$$+\overline{\lambda}_k(t-1)\left\|D_{2,k}(t-1)\right\|\cdot\|L\|\cdot\|E\{e_k(t-1)\}\| \tag{22}$$

And

$$\|E\{e_k(t)\}\| \leq \|C(t)\|\cdot\|E\{\delta x_k(t)\}\|$$

$$\leq \|C(t)\|\cdot\left\|D_{1,k}(t-1)\right\|\cdot\|E\{\delta x_k(t-1)\}\|$$

$$+\overline{\lambda}_k(t-1)\cdot\left\|D_{2,k}(t-1)\right\|\cdot\|L\|\cdot\|C(t)\|\cdot\|E\{e_k(t-1)\}\|$$

$$+\|C(t)\|\cdot\left\|D_{2,k}(t-1)\right\|\cdot\left\|E\left\{\delta u_k^f(t-1)\right\}\right\| \tag{23}$$

Due to $E\{\delta x_k(0)\}=0$ and $E\{\delta e_k(0)\}=0$ from (3), it is feasible from (22) and (23), yield

$$\|E\{e_k(t)\}\|+\|E\{\delta x_k(t)\}\| \leq \left(\left\|D_{1,k}(t-1)\right\|+\|C(t)\|\cdot\left\|D_{1,k}(t-1)\right\|\right)\cdot\|E\{\delta x_k(t-1)\}\|$$

$$+\left(\left\|D_{2,k}(t-1)\right\|+\|C(t)\|\cdot\left\|D_{2,k}(t-1)\right\|\right)\cdot\left\|E\left\{\delta u_k^f(t-1)\right\}\right\|$$

$$+\overline{\lambda}_k(t-1)\cdot(1+\|C(t)\|)\cdot\left\|D_{2,k}(t-1)\right\|\cdot\|L\|\cdot\|E\{e_k(t-1)\}\|$$

$$\leq z_2\cdot\{\|E\{e_k(t-1)\}\|+\|E\{\delta x_k(t-1)\}\|\}+\overline{b}\cdot\left\|E\left\{\delta u_k^f(t-1)\right\}\right\|$$

$$\leq z_2\cdot\{\|E\{e_k(0)\}\|+\|E\{\delta x_k(0)\}\|\}+\sum_{s=0}^{t-1}z_2^{t-s-1}\overline{b}\left\|E\left\{\delta u_k^f(s)\right\}\right\|$$

$$\leq \sum_{s=0}^{t-1} z_2^{t-s-1}\overline{b}\left\|E\left\{\delta u_k^f(s)\right\}\right\| \tag{24}$$

where $.z_2 = \max\left\{\left\|D_{1,k}(t-1)\right\| + \|C(t)\| \cdot \left\|D_{1,k}(t-1)\right\|,\right.$ $\left.\bar{\lambda}_k(t-1)\cdot(1+\|C(t)\|)\cdot\left\|D_{2,k}(t-1)\right\|\cdot\|L\|\right\}$

$\overline{b} = \left\|D_{2,k}(t-1)\right\| + \|C(t)\| \cdot \left\|D_{2,k}(t-1)\right\|$, according to (14) and (24) substituting into (21), we obtain

$$\left\|E\left\{\delta u_{k+1}^f(t)\right\}\right\| \leq \|\Phi(t)\| \cdot \left\|E\left\{\delta u_k^f(t)\right\}\right\| + z_1 \cdot \sum_{s=0}^{t-1} z_2^{t-s-1}\overline{b}\left\|E\left\{\delta u_k^f(s)\right\}\right\| \tag{25}$$

Using mathematical induction to prove as follows:

As $t = 0$, considering the expression of (21) and (3), it is derived that

$$\left\|E\left\{\delta u_{k+1}^f(0)\right\}\right\| \leq \|\Phi(0)\| \cdot \left\|E\left\{\delta u_k^f(0)\right\}\right\| \tag{26}$$

Due to the $\|\Phi(t)\| < 1$ in Theorem 1, while iteration k goes to infinity, there is

$$\lim_{k\to\infty}\sup\left\|E\left\{\delta u_{k+1}^f(0)\right\}\right\| = 0 \tag{27}$$

As $t = 1$, this is implied by (25)

$$\left\|E\left\{\delta u_{k+1}^f(1)\right\}\right\| \leq \|\Phi(1)\| \cdot \left\|E\left\{\delta u_k^f(1)\right\}\right\| + z_1\overline{b}\left\|E\left\{\delta u_k^f(0)\right\}\right\| \tag{28}$$

According to the Theorem 1, we also know the $\delta u_k(0) = 0$, and consider the expression of (27), we can obtain

$$\lim_{k\to\infty}\sup\left\|E\left\{\delta u_{k+1}^f(1)\right\}\right\| = 0 \tag{29}$$

Suppose $t = 2, \ldots l-1$

$$\lim_{k\to\infty}\sup\left\|E\left\{\delta u_{k+1}^f(t)\right\}\right\| = 0 \tag{30}$$

As $t = l$, we can obtain from Eq. (29)

$$\left\|E\left\{\delta u_{k+1}^f(l)\right\}\right\| \leq \|\Phi(l)\| \cdot \left\|E\left\{\delta u_k^f(l)\right\}\right\| + z_1 \cdot \sum_{s=0}^{l-1} z_2^{l-s-1}\overline{b}\left\|E\left\{\delta u_k^f(s)\right\}\right\| \tag{31}$$

Noting that the expression of (30), we can know when the number of iterations k approaches infinity, the following is obtained

$$E\{\|\Delta u_{k+1}(l)\|\} = 0 \tag{32}$$

Hence, through the mathematical induction, we obtain.

$$\lim_{k\to\infty}\sup E\{\|\Delta u_k(t)\|\} = 0, 0 \leq t \leq N \tag{33}$$

From expression (33), we can obtain the $\|\Delta x_k(t)\| = 0$, then the errors $\lim_{k\to\infty}\sup E\{\|y_d(t) - y_k(t)\|\} = \lim_{k\to\infty}\sup E\{\|C(t)\Delta x_k(t)\|\} = 0$ for the $t = 0, 1 \ldots, N+1$. This demonstration is finished.

4 Illustrative Simulation

To illustrate the capability of the algorithms (11), (12) and (13) in addressing random trial lengths, we introduce non-affine nonlinear system:

$$\begin{cases} x_k(t+1) = x_k(t) + \sin(2u_k(t)\cos(x_k(t))) \\ y_k(t) = x_k(t) + u_k(t) \end{cases} \tag{34}$$

where $t \in \{0, 1, \ldots N_k\}$ and $N_k \in \{47, 48, \ldots, 53\}$ represent the trajectory of system (34) depicted in Fig. 1. Suppose the desired trail $y_d(t)$ of the system (34) is denoted as

$$y_d(t) = 0.015t(1 + \cos(4\pi t/N - \pi)) \tag{35}$$

where $t \in \{0, 1, \ldots N+1\}$ and $N = 50$. Let $u_0(t) = 0, \forall t$. The iteratively varying initial state is set to $x_k(0) = 0$. To assess the ILC tracking precision, we examine the deviation indicator given by:

$$J_k = E\{\|y_d(t) - y_k(t)\|\} \tag{36}$$

Apply algorithms (11), (12), (13) and (14) into the system (34). In accordance with the convergence condition outlined in Theorem 1 and parameters for developed algorithms set as $P = 0.03$ and $L = 0.001$. The system output $y_k(t)$ at the 9th and 23th are depicted in Fig. 2, respectively. The proposed algorithms guarantee system output $y_k(t)$ approaches the reference trail as the number of iteration change larger, the ILC tracking error index of J_k is presented in Fig. 3. These figures showcase the effectiveness of the developed algorithms.

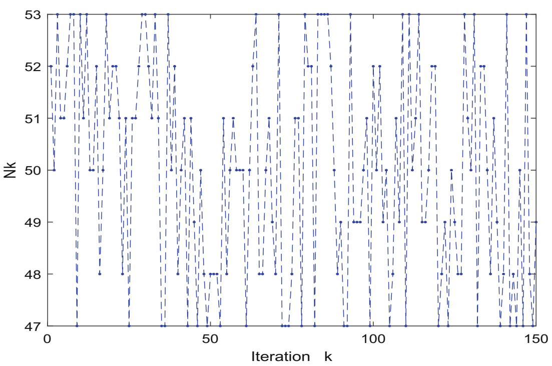

Fig. 1. The varying trial length N_k in system (34).

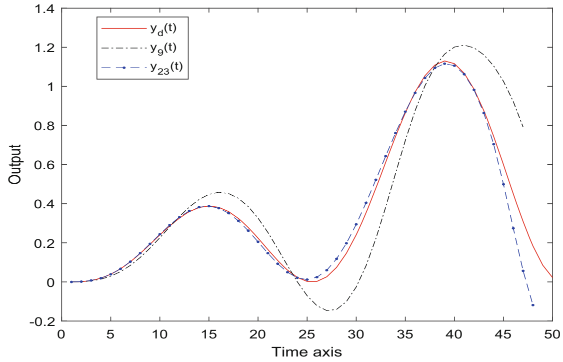

Fig. 2. The system outputs $y_k(t)$ at iterations 9 and 23 by adopting the feedback and feed-forward ILC law (11), (12) and (13).

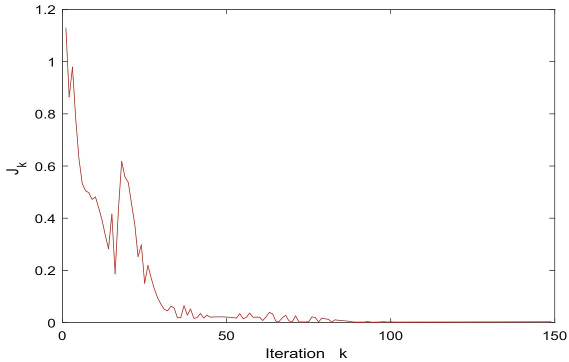

Fig. 3. The ILC tracking deviation profile with indicator J_k.

5 Conclusion

This article tackles the issue of ILC in non-affine system with iteratively changing trial length. The feedback and feed-forward algorithm is formulated. To account for the random lengths in the dynamic system, a adjusted error is incorporated into the developed algorithms. Notably, the convergence criterion of the proposed algorithm is subject to the open loop control parameter. The close loop part is aimed at hastening the convergence of iterative process by adjusting the feedback control gain value. Theoretical and simulation results demonstrate as the number of iterations approaches indefinitely, such that ILC deviation tends towards to zero in mathematical context.

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