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Sliding mode iterative learning intermittent control for robot manipulators under nonidentical trial lengths and alignment condition

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Abstract: This paper is dedicated to the iterative learning control of robot manipulators under nonidentical trial lengths and the alignment condition with intermittent input. A sliding mode iterative learning control scheme is proposed to improve tracking performance against non-repetitive disturbances and the intermittent protocol is constructed by the norm of the sliding mode function. A modified reference trajectory is utilized to accommodate the alignment condition under nonidentical trial lengths. The composite energy function is built for the convergence analysis and a simulation example with comparison is provided to illustrate the effectiveness of the proposed sliding mode iterative learning intermittent control method.

Key Words: Iterative learning control, sliding mode control, intermittent control, nonidentical trial lengths, alignment condition.

1 Introduction

Iterative learning control (ILC) offers an effective solution for achieving precise control objectives by utilizing system repetitions to adjust control strategies [1]. It has gained widespread popularity in various applications, such as aerial vehicles, hard disk drives, high-speed trains, robot manipulators, etc. [2–5]. Meanwhile, some interesting theoretical works have been explored in [6–10], just mentioned a few. An ILC framework is put forward in [6] to perform trajectory tracking for underactuated compliant arms. An event-triggered model-free adaptive ILC is built in [7] by means of an equivalent linearization transformation. [8] puts forward an adaptive ILC (AILC) to treat perturbed robot manipulators with iteration-varying disturbances and dead-zone input.

Note that most of the above ILC studies commonly require identical initial conditions which is restrictive in practical scenarios, such as resetting the initial velocity of manipulator joints [11]. To ease this limitation, an alignment condition is pioneered by [12] considering continuous operation without resetting. Driven by this idea, [13] discusses an ILC based automatic train operation with iteration-varying operation condition and speed constrains. It should be pointed that these results are based on identical iteration lengths. However, changing product specifications, transmission errors, and fault shutdown may incur nonidentical trial lengths [14]. To provide a viable solution, a Bernoulli distribution function is utilized in [15] to describe the varying iteration lengths. A searching mechanism is inserted into ILC algorithms by [16] to speed up convergence under randomly lengths. On the other hand, sliding mode control (SMC) is favored by control community due to its quick response, robustness, and straightforward implementation [17–19]. Consequently, the combination of SMC and ILC has become an effective control method and has attracted much attention. For instance, [20] establishes an iterative sliding surface to suppress nonrepeated disturbances. A switched ILC is supplied in [21] to match the fast reaching and the slow sliding phases of SMC. Iterative action is separated from the design of SMC by updating iteration process with integral sliding mode function [22].

Additionally, in practical engineering, how to save energy is a critical topic for many control process, such as the life time of sensor networks [23, 24]. Intermittent control has been deemed as one of effective solutions for energy conservation by periodically turning on or off [25, 26]. To be specific, time scale theory is employed in [25] to exploit intermittent containment control for a class of heterogeneous systems. A matrix-based convex combination is developed by [26] to construct an aperiodic intermittent control scheme. However, none of them has taken the intermittent control to ILC under nonidentical trial lengths and the alignment condition, especially integrating with sliding mode to attenuate non-repetitive disturbances.

Actuated by above observations, this paper is devoted to intermittent ILC of robot manipulators under nonidentical trial lengths and the alignment condition. The proposed algorithm incorporates SMC with ILC to suppress non-repetitive disturbances and improve system robustness. Input intermittent protocol is delivered by the norm of the sliding mode function in terms of a proportional and sliding interval integral function. A modified reference trajectory is built to account nonidentical trial lengths and the alignment condition. The convergence analysis is given in terms of CEF and a simulation example is provided to demonstrate the effectiveness of the proposed control strategy over the existing result.

The paper is structured as follows. The problem statement

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is provided in Section 2, and the preliminary works are presented in Section 3. Intermittent sliding mode ILC scheme is proposed along with the convergence analysis in Section 4. Section 5 gives illustrative examples to verify the theoretical result and Section 6 concludes this work briefly.

Notations: $\mathbf{Z}_+$ denotes the set of positive integer. $\mathbf{R}^i$ represents the space of all i-dimensional vectors. $\mathbf{R}^{i\times j}$ is a matrix of $i \times j$ dimension. If A is a matrix, $\|A\|$ denotes the induced matrix norm of A. If A is a vector, then $\|A\|$ denotes its Euclidean norm. $tr(\cdot)$ denotes the trace of the matrix. $proj(\cdot)$ represents the projection of a parameter.

2 Problem Formulation

Consider a rigid manipulator modeled by the Lagrangian formulation as [27]

$$M(q_i)\ddot{q}_i + C(q_i,\dot{q}_i)\dot{q}_i + G(q_i) = \tau_i + d_i \tag{1}$$

where i represents the iteration index. $q_i \in \mathbf{R}^n$, $\dot{q}_i \in \mathbf{R}^n$ and $\ddot{q}_i \in \mathbf{R}^n$ are the joint position, velocity and acceleration vectors, respectively. $M(q_i) \in \mathbf{R}^{n\times n}$ is the inertia matrix, $C(q_i,\dot{q}_i) \in \mathbf{R}^{n\times n}$ is the centripetal-Coriolis matrix and $G(q_i) \in \mathbf{R}^n$ is the gravity vector. $\tau_i \in \mathbf{R}^n$ is the torque input and $d_i \in \mathbf{R}^n$ represents disturbances. From this point onwards, to simplify presentation, $M(q_i)$, $C(q_i,\dot{q}_i)$ and $G(q_i)$ are abbreviated as M, C and G, respectively.

According to [27], the system (1) has the following properties expressed as

Property 1. *The inertia matrix M is symmetric, positive definite and bounded.*

Property 2. $\|C\| \leqslant \upsilon_c\|\dot{q}_i\|$ *and* $\|G\| \leqslant \upsilon_g$, $\forall i \in \mathbf{Z}_+$, *where υ_c and υ_g are known positive parameters.*

The control objective is to make the joint position q_i track the desired trajectory q_d on time interval $[0,T]$ under the following proposed intermittent sliding mode ILC where the actual operation length is T_i satisfying $0 < T_i \leqslant T$.

3 Preliminary works

To proceed, the following assumptions are imposed.

Assumption 1. *[8] [27] The reference trajectory and its first and second time-derivatives, namely q_d, $\dot{q}_d$ and $\ddot{q}_d$, as well as the disturbance d_i and the robot velocity $\dot{q}_i$ are bounded by known bounds.*

Assumption 2. *[28] In each iteration, the system's initial states satisfy the alignment condition, namely $q_i(0) = q_{i-1}(T_i)$ and $\dot{q}_i(0) = \dot{q}_{i-1}(T_i)$.*

Remark 1. *The first assumption is originated from the mechanical limitations [30], and is commonly used for robot manipulators as in [8]. The second one is consistent with continuous running robots as in [28].*

To implement the alignment condition, as [29], the modified reference trajectory $q_{m,i}$ is

$$q_{m,i} = q_d - \chi_1\left(q_d - q_d\left(T_{i-1}\right)\right) - \chi_2\left(\dot{q}_d - \dot{q}_d\left(T_{i-1}\right)\right) \tag{2}$$

where χ_1 is a second order differentiable function such that

- $\chi_1(0) = 1, \chi_1(T_a) = 0$, and $\chi_1 = 0$ for $t \in [T_a, T]$;
- $\dot{\chi}_1, \ddot{\chi}_1$ are bounded over $[0,T]$;
- $\dot{\chi}_1(0) = 0, \dot{\chi}_1(T_a) = 0$, and $\dot{\chi}_1 = 0$ for $t \in [T_a, T]$;
- $\ddot{\chi}_1(T_a) = 0$, and $\ddot{\chi}_1 = 0$ for $t \in [T_a, T]$,

and where χ_2 is a second order differentiable function such that

- $\chi_2(0) = 0, \chi_2(T_a) = 0$, and $\chi_2 = 0$ for $t \in [T_a, T]$;
- $\dot{\chi}_2, \ddot{\chi}_2$ are bounded over $[0,T]$;
- $\dot{\chi}_2(0) = 1, \dot{\chi}_2(T_a) = 0$, and $\dot{\chi}_2 = 0$ for $t \in [T_a, T]$;
- $\ddot{\chi}_2(T_a) = 0$, and $\ddot{\chi}_2 = 0$ for $t \in [T_a, T]$.

where T_a selected by the designer can be arbitrarily small and satisfies $0 < T_a \leqslant T_i$. By setting $\tilde{q}_i = q_{m,i} - q_i$, from (2), one has $\tilde{q}_i(0) = \tilde{q}_i(T_i)$ and $\dot{\tilde{q}}_i(0) = \dot{\tilde{q}}_i(T_i)$.

To implement the control objective, the torque input τ_i is designed as a combination of SMC and ILC as below

$$\tau_i = \tau_{S,i} + \tau_{I,i}. \tag{3}$$

where $\tau_{I,i}$ is the ILC part to be designed and the SMC part $\tau_{S,i}$ is given as

$$\tau_{S,i} = k_1 sign(S_i) + k_2 sign(\dot{S}_i) + k_3 S_i + k_4 \dot{S}_i, \tag{4}$$

where k_1, k_2, k_3 and k_4 are positive constants selected by the designer and the sliding mode function S_i is given as

$$S_i = \begin{cases} k_P\tilde{q}_i + k_I\int_0^t \tilde{q}_i d\iota, t \in [0, T_s] \\ k_P\tilde{q}_i + k_I\int_{t-T_s}^t \tilde{q}_i d\iota, t \in (T_s, T_i] \end{cases} \tag{5}$$

where the integral interval length T_s is determined by the designer. k_P and k_I are positive coefficients representing the weight of the proportion and integration, respectively. On the basis of this sliding mode function (5), the input is turned off once $\|S_i\|_2 \leqslant P_C$ and restarted once $\|S_i\|_2 \geqslant P_O$, where P_C and P_O are selected positive constants. To describe the time interval between on and off, $[0, T_i]$ is divided into $[T^{l_i}, T^{l_i+1})$, $l_i \in \mathbf{N}_+$, and then the working time interval is recorded as $[T^{2l_i}, T^{2l_i+1})$.

4 Main Results

Following the aforementioned preparations, like [27], one has

$$\dot{\tilde{q}}_i^T[M\ddot{q}_{m,i} + C\dot{q}_i + G - d_i] \leqslant \tilde{q}_i^T\Psi\delta_i, \tag{6}$$

where $\Psi = [\dot{\tilde{q}}_i\ sign(\dot{\tilde{q}}_i)]$, and δ_i is an unknown time-varying vector. Thus, Combining Properties 1 and 2, Assumption 1 and (5) via (6) yields

$$\dot{S}_i^T[M\ddot{q}_{m,i} + C\dot{q}_i + G - d_i] \leqslant k_P\tilde{q}_i^T\Psi\delta_i + \beta, \tag{7}$$

where β is known and bounded by $\beta \geqslant k_I\int_{t-T_s}^t \tilde{q}_i d\iota[M\ddot{q}_{m,i} + C\dot{q}_i + G - d_i]$. Now, it is the position to supply ILC input $\tau_{I,i}$ as $\tau_{I,i} = \Psi\hat{\delta}_i$ where $\hat{\delta}_i$ (the estimation of δ_i) is constructed by

$$\hat{\delta}_i = \begin{cases} \hat{\delta}_{i-1} + k_5\Psi^T\dot{\tilde{q}}_i, t \in [T^{2l_i}, T^{2l_i+1}) \\ \hat{\delta}_{i-1}, t \in [T^{2l_i+1}, T^{2l_i+2}) \\ \hat{\delta}_{i-1}, t \in [T_i, T] \end{cases} \tag{8}$$

where k_5 is a positive constant selected by the designer.

Theorem 1. *Consider the system (1) with Properties 1 and 2 under Assumptions 1 and 2, the bounded convergence of S_i and $\dot{S}_i$ are guaranteed for $t \in [0, T_i]$ as $i \longrightarrow \infty$ under the control law (3).*

Proof. Select the candidate CEF as

$$V_i = V_{1,i} + V_{2,i} + V_{3,i} + V_{4,i}, \tag{9}$$

where

$$V_{1,i} = \begin{cases} \frac{1}{2k_P} e^{-st} \dot{S}_i^T M \dot{S}_i, t \in [T^{2l_i}, T^{2l_i+1}) \\ V_{1,i}(T^{2l_i+1}), t \in [T^{2l_i+1}, T^{2l_i+2}) \\ V_{1,i}(T_i), t \in [T_i, T] \end{cases},$$

$$V_{2,i} = \begin{cases} \frac{k_3}{2} e^{-st} S_i^T S_i, t \in [T^{2l_i}, T^{2l_i+1}) \\ V_{2,i}(T^{2l_i+1}), t \in [T^{2l_i+1}, T^{2l_i+2}) \\ V_{2,i}(T_i), t \in (T_i, T] \end{cases}, \tag{10}$$

$$V_{3,i} = \begin{cases} k_1 e^{-st} \|S_i\|_1, t \in [T^{2l_i}, T^{2l_i+1}) \\ V_{3,i}(T^{2l_i+1}), t \in [T^{2l_i+1}, T^{2l_i+2}) \\ V_{3,i}(T_i), t \in (T_i, T] \end{cases},$$

$$V_{4,i} = \frac{k_P}{2} \int_0^t e^{-s\iota} \tilde{\delta}_i^T \tilde{\delta}_i d\iota,$$

where $s > \frac{\lambda_{max}(\dot{M})}{\lambda_{min}(M)}$ and $\tilde{\delta}_i = \delta_i - \hat{\delta}_i$.

Calculate the difference of $V_i(T)$ at the ith iteration as

$$\Delta V_i(T) = \sum_{l=1}^{4} \Delta V_{l,i}(T). \tag{11}$$

Firstly, according to (3)-(5) and (9), $\Delta V_{1,i}(T)$ in (11) is given as

$$\begin{aligned} \Delta V_{1,i}(T) &= V_{1,i}(T_i) - V_{1,i-1}(T_{i-1}) \\ &= V_{1,i}(0) + \int_0^{T_i} \dot{V}_{1,i} d\iota - V_{1,i-1}(T_{i-1}) \\ &= \int_0^{T_i} \left\{ \frac{1}{k_P} e^{-s\iota} \dot{S}_i^T M \ddot{S}_i + \frac{1}{2k_P} e^{-s\iota} \dot{S}_i^T \dot{M} \dot{S}_i \right. \\ &\quad \left. - \frac{s}{2k_P} e^{-s\iota} \dot{S}_i^T M \dot{S}_i \right\} d\iota \\ &\leqslant \int_0^{T_i} \left\{ e^{-s\iota} \dot{S}_i^T \{[M\ddot{q}_{m,i} + C\dot{q}_i + G - d_i] - \tau_i\} \right. \\ &\quad \left. + \frac{k_I}{k_P} e^{-s\iota} \dot{S}_i^T M[\dot{\tilde{q}}_i(\iota) - \dot{\tilde{q}}_i(\iota - T_s)] \right\} d\iota \\ &\leqslant \int_0^{T_i} \left\{ e^{-s\iota}[-k_1 \dot{S}_i^T sign(S_i) - k_2 \dot{S}_i^T sign(\dot{S}_i) \right. \\ &\quad - k_3 \dot{S}_i^T S_i - k_4 \dot{S}_i^T \dot{S}_i] + k_P e^{-s\iota} \dot{\tilde{q}}_i^T \Psi \tilde{\delta}_i + e^{-s\iota} \beta \\ &\quad \left. + \frac{k_I}{k_P} e^{-s\iota} \dot{S}_i^T M[\dot{\tilde{q}}_i(\iota) - \dot{\tilde{q}}_i(\iota - T_s)] \right\} d\iota. \end{aligned} \tag{12}$$

Secondly, $\Delta V_{2,i}(T)$ in (10) is

$$\begin{aligned} \Delta V_{2,i}(T) &= V_{2,i}(T_i) - V_{2,i-1}(T_{i-1}) \\ &= V_{2,i}(0) + \int_0^{T_i} \dot{V}_{2,i} d\iota - V_{2,i-1}(T_{i-1}) \\ &\leqslant \int_0^{T_i} \left\{ e^{-s\iota} k_3 \dot{S}_i^T S_i - \frac{s}{2} e^{-s\iota} k_3 S_i^T S_i \right\} d\iota. \end{aligned} \tag{13}$$

Thirdly, $\Delta V_{3,i}(T)$ in (10) is

$$\begin{aligned} \Delta V_{3,i}(T) &= V_{3,i}(T_i) - V_{3,i-1}(T_{i-1}) \\ &= V_{3,i}(0) + \int_0^{T_i} \dot{V}_{3,i} d\iota - V_{3,i-1}(T_{i-1}) \\ &\leqslant \int_0^{T_i} \left\{ e^{-s\iota} k_1 \dot{S}_i^T sign(S_i) - \frac{s}{2} e^{-s\iota} k_1 \|S_i\|_1 \right\} d\iota. \end{aligned} \tag{14}$$

Fourthly, $\Delta V_{4,i}(T)$ in (10) is

$$\begin{aligned} \Delta V_{4,i}(T) &= V_{4,i}(T) - V_{4,i-1}(T) \\ &= \frac{k_P}{2} \int_0^{T_i} \left\{ e^{-s\iota} (\tilde{\delta}_i^T \tilde{\delta}_i - \tilde{\delta}_{i-1}^T \tilde{\delta}_{i-1}) \right\} d\iota \\ &= \frac{k_P}{2} \int_0^{T_i} \left\{ e^{-s\iota} (\tilde{\delta}_i - \tilde{\delta}_{i-1})^T (\tilde{\delta}_i + \tilde{\delta}_{i-1}) \right\} d\iota \\ &= \frac{k_P}{2} \int_0^{T_i} \left\{ e^{-s\iota} (\tilde{\delta}_i - \tilde{\delta}_{i-1})^T (\tilde{\delta}_{i-1} - \tilde{\delta}_i + 2\tilde{\delta}_i) \right\} d\iota \\ &= \int_0^{T_i} \left\{ - k_P e^{-s\iota} \dot{\tilde{q}}_i^T \Psi \tilde{\delta}_i \right\} d\iota. \end{aligned} \tag{15}$$

Combining (11)-(15) renders

$$\begin{aligned} \Delta V_i(T) &\leqslant \int_0^{T_i} \left\{ e^{-s\iota}[\beta - \frac{s}{2} k_1 \|S_i\|_1 - \frac{s}{2} k_3 S_i^T S_i \right. \\ &\quad - k_2 \dot{S}_i^T sign(\dot{S}_i) - k_4 \dot{S}_i^T \dot{S}_i] \\ &\quad \left. + e^{-s\iota} \dot{S}_i^T M[\dot{\tilde{q}}_i(\iota) - \dot{\tilde{q}}_i(\iota - T_s)] \right\} d\iota \\ &\leqslant \int_0^{T_i} \left\{ e^{-s\iota}[\beta - \frac{s}{2} k_1 \|S_i\|_1 - k_2 \|\dot{S}_i\|_1 \right. \\ &\quad \left. - \frac{s}{2} k_3 \|S_i\|_2^2 - k_4 \|\dot{S}_i\|_2^2] + \frac{k_I}{k_P} e^{-s\iota} \|\dot{S}_i(\iota)\|_p \gamma \right\} d\iota, \end{aligned} \tag{16}$$

where γ is greater than a known bound $\|M[\dot{\tilde{q}}_i(\iota) - \dot{\tilde{q}}_i(\iota - T_s)]\|_p$ from Property 1 and Assumption 1. Taking $p = 1$ and selecting $k_2 \geqslant \frac{k_I \gamma}{k_P}$ for (17) provides

$$\begin{aligned} &\Delta V_i(T) \\ &\leqslant \int_0^{T_i} \left\{ e^{-s\iota}[-\frac{s}{2} k_1 \|S_i\|_1 - \frac{s}{2} k_3 \|S_i\|_2^2 - k_4 \|\dot{S}_i\|_2^2 + \beta] \right\} d\iota. \end{aligned} \tag{17}$$

Hence, once $\|S_i\|_1 > \frac{2}{sk_1}\beta$, $\|S_i\|_2 > \sqrt{\frac{2\beta}{sk_3}}$ or $\|\dot{S}_i\|_2 > \sqrt{\frac{\beta}{k_4}}$, $\Delta V_i(T) < 0$ holds. Since the convergence of V_i is determined by the boundedness of V_1, therefore, calculate $\dot{V}_1(t)$ as

$$\begin{aligned} \dot{V}_1 &= \dot{V}_{1,1} + \dot{V}_{2,1} + \dot{V}_{3,1} + \dot{V}_{4,1} \\ &\leqslant e^{-st}[-\frac{s}{2} k_1 \|S_i\|_1 - \frac{s}{2} k_3 \|S_i\|_2^2 - k_4 \|\dot{S}_i\|_2^2 + \beta^*] \end{aligned} \tag{18}$$

where $\beta^* = \beta + \frac{k_P}{2} \tilde{\delta}_0^T \tilde{\delta}_0$. It is seen that $\dot{V}_1 < 0$ holds if $\|S_i\|_1 > \frac{2}{sk_1}\beta^*$, $\|S_i\|_2 > \sqrt{\frac{2\beta^*}{sk_3}}$ or $\|\dot{S}_i\|_2 > \sqrt{\frac{\beta^*}{k_4}}$, which enables the boundedness of $V_1(t)$. Combining the positiveness of $V_i(t)$ and the boundedness of $V_1(t)$, the bounded convergence of S_i and $\dot{S}_i$ are expressed by $\|S_i\|_1 \leqslant \frac{2}{sk_1}\beta$, $\|S_i\|_2 \leqslant \sqrt{\frac{2\beta}{sk_3}}$ and $\|\dot{S}_i\|_2 \leqslant \sqrt{\frac{\beta}{k_4}}$ as $i \longrightarrow \infty$. □

Remark 2. *Since the intermittent protocol is established on the sliding mode function, there is no need to carry out the intermittent effect on convergence as [31].*

Remark 3. *From the above derivation, the sliding mode integral part incurs negative effect on the convergence, such as $[\dot{\tilde{q}}_i(\iota) - \dot{\tilde{q}}_i(\iota - T_s)]$ which contains historical information that is not conducive to transient performance. However, this historical information could be adopted to automatically adjust the on and off time and avoid frequent switching actions. Moreover, The sliding integral interval further avoids the failure to trigger the closing threshold due to excessive accumulation.*

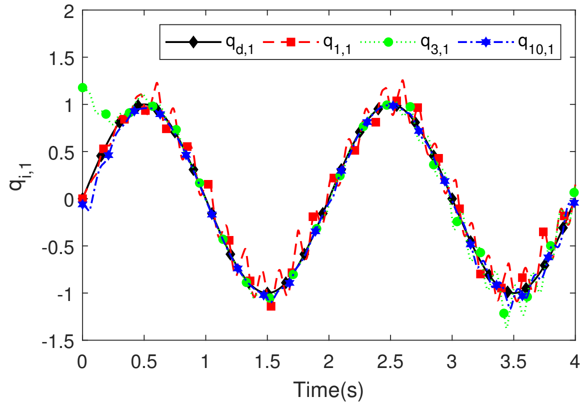
5 Illustrative Example

Consider a two-degrees-of-freedom planar manipulator from [27] with revolute joints described by (1). The elements of $M = [m_{ij}]_{2\times2}$ are given by $m_{11} = m_1 l_{c1}^2 + m_2(l_1^2 + l_{c2}^2 + 2l_1 l_{c2}\cos q_{i,2}) + I_1 + I_2$, $m_{12} = m_{21} = m_2(l_{c2}^2 + l_1 l_{c2}\cos q_{i,2})$ and $m_{22} = m_2 l_{c2}^2 + I_2$. The elements of $C = [c_{ij}]_{2\times2}$ are given by $c_{11} = h\dot{q}_{i,2}$, $c_{12} = h\dot{q}_{i,1} + h\dot{q}_{i,2}$, $c_{11} = -h\dot{q}_{i,1}$, and $c_{22} = 0$, where $h = -m_2 l_1 l_{c2}\sin q_{i,2}$. The vector $G = [G_1, G_2]^T$ is given by $G_1 = (m_1 l_{c1} + m_2 l_1)g\cos q_{i,1} + m_2 l_{c2} g\cos(q_{i,1} + q_{i,2})$, and $G_2 = m_2 l_{c2} g\cos(q_{i,1} + q_{i,2})$. $d_i = [d_{i,1}, d_{i,2}]^T$ is assumed to be $d_{i,1} = d_{i,2} = rand(i)\sin(t)$ which is a random function taking values between 0 and 0.1. The robot parameters are given by $m_1 = m_2 = 1\,Kg$, $l_1 = l_2 = 0.5\,m$, $l_{c1} = l_{c2} = 0.25\,m$, $I_1 = I_2 = 0.1\,Kg\cdot m^2$, $g = 9.81\,m/s^2$. $q_d = [sin(\pi t), cos(\pi t)]^T$, and the desired operation length $T = 4s$.

The proposed algorithm parameters are selected as $k_1 = 10$, $k_2 = 2$, $k_3 = 10$, $k_4 = 2$, $k_5 = 1$, $T_a = 0.5s$, $T_s = 1s$. $\chi_1 = cos^3(\frac{\pi}{2T_a}t)$ and $\chi_2 = t\cos^3(\frac{\pi}{2T_a}t)$ for $t \in [0, T_a)$.

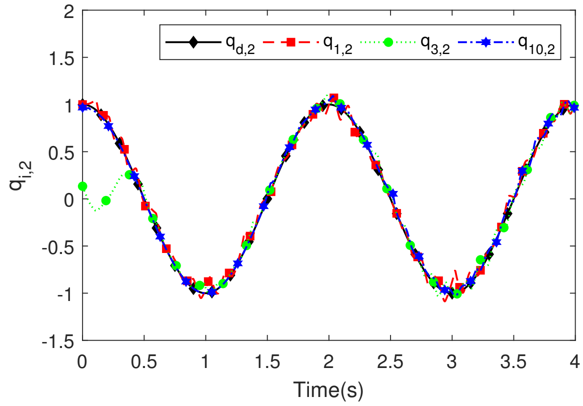
Next, to clarify the effectiveness of the proposed intermittent scheme, assume that the operation length obeys a uniform distribution over time interval $[3, 4]$ with a probability of $\mathbb{P}[T_i = T] = 0.5$. At the same time, take the input intermittent protocol into account with $P_C = 1$ and $P_O = 5$. q_i and τ_i at the 1st, the 3rd and the 10th iterations are presented in Figs. 1-4, respectively. In order to display the input on and off more clearly, record the running time as 1 and the stop time as 0, expressed by $P_i = \begin{cases} 1, t \in [T^{2l_i}, T^{2l_i+1}) \\ 0, t \in [T^{2l_i+1}, T^{2l_i+2}) \end{cases}$. P_i at the 1st, the 3rd and the 10th iterations are presented in Fig. 5. ϕ_e for the first 10 iterations is given in Fig. 6.

It is seen from Figs. 1-2 that tracking performance improves rapidly in several iterations, and this observation is more intuitively in Fig. 6. Figs. 3-4 show that the torque input amplitude decreases gradually with iteration, which is the benefit of ILC part. Fig. 5 shows that the proposed intermittent protocol works at the different iteration batches. In summary, the above simulation curves demonstrate the validity of the proposed intermittent sliding mode ILC scheme.



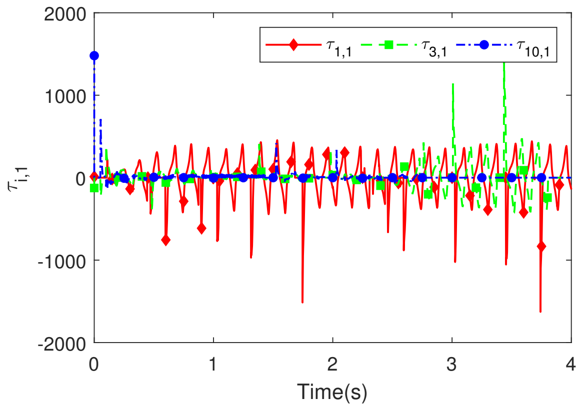
(a) The first joint

Fig. 1: $q_{i,1}$ at different iterations



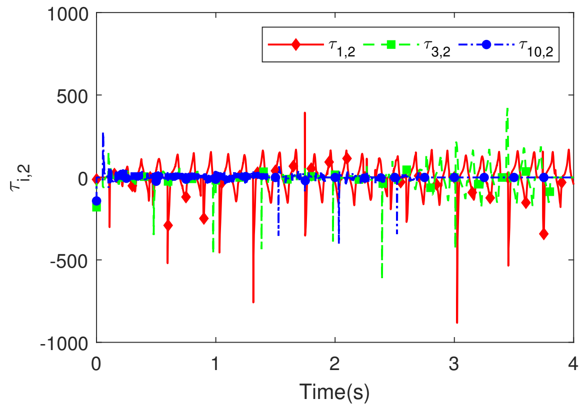
(a) The second joint

Fig. 2: $q_{i,2}$ at different iterations



(a) The first joint

Fig. 3: $\tau_{i,1}$ at different iterations



(a) The second joint

Fig. 4: $\tau_{i,2}$ at different iterations

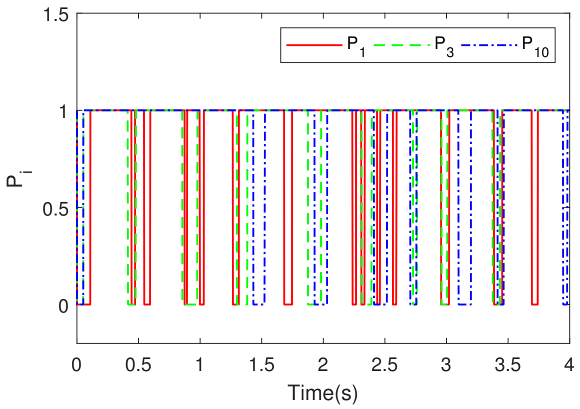


Fig. 5: P_i at different iterations

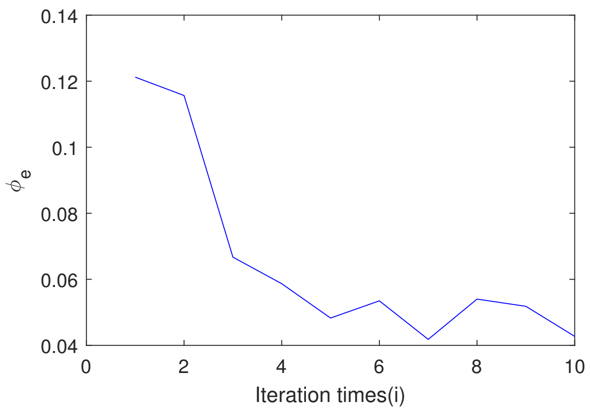


Fig. 6: ϕ_e for the first 10 iterations

6 Conclusion

This paper is concerned with ILC of robot manipulators with the alignment condition and nonidentical trial lengths. SMC is combined with ILC to enhance system robustness, suppress non-repetitive disturbances, and improve tracking accuracy. Meanwhile, the input intermittence protocol is established on the norm of the sliding mode function with a proportional and sliding interval integral structure. A modified reference trajectory is exploited to accommodate the alignment conditions against nonidentical trial lengths. The composite energy function is utilized for the convergence analysis and a simulation example with comparison is provided to illustrate the effectiveness of the proposed control strategy.

References

[1] R. Chi, H. Li, N. Lin, B. Huang. Data-driven indirect iterative learning control. *IEEE Transactions on Cybernetics*, vol. 54, pp. 1650-1660, 2024.

[2] W. He, T. Meng, X. He, C. Sun. Iterative learning control for a flapping wing micro aerial vehicle under distributed disturbances. *IEEE Transactions on Cybernetics*, vol. 49, pp. 1524-1525, 2019.

[3] D. Huang, V. Venkataramanan, J. Xu, T. C. T. Huynh. Contact-induced vibration in dual-stage hard disk drive servo systems and its compensator design. *IEEE Transactions on Industrial Electronics*, vol. 61, pp. 4052-4060, 2014.

[4] Y. Chen, D. Huang, Y. Li, X. Feng. A novel iterative learning approach for tracking control of high-speed trains subject to unknown time-varying delay. *IEEE Transactions on Automation Science and Engineering*, vol. 19, pp. 113-121, 2022.

[5] A. Tayebi, S. Abdul, M. B. Zaremba, Y. Ye. Robust iterative learning control design: Application to a robot manipulator. *IEEE/ASME Transactions on Mechatronics*, vol. 13, pp. 608-613, 2008.

[6] Michele Pierallini, Franco Angelini, Riccardo Mengacci, Alessandro Palleschi, Antonio Bicchi, Manolo Garabini. Iterative learning control for compliant underactuated Arms. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol.56, pp. 3810-3822, 2023.

[7] X. Bu, W. Yu, Q. Yu, Z. Hou, J. Yang. Event-triggered model-free adaptive iterative learning control for a class of nonlinear systems over fading channels. *IEEE Transactions on Cybernetics*, vol. 52, pp. 9597-9608, 2022.

[8] T. Bensidhoum, F. Bouakrif. Adaptive P-type iterative learning radial basis function control for robot manipulators with unknown varying disturbances and unknown input dead zone. *International Journal of Robust and Nonlinear Control*, vol. 30, pp. 4075-4094, 2020.

[9] F. Bouakrif, D. Boukhetala, F. Boudjema. Velocity observer-based iterative learning control for robot manipulators. *International Journal of Systems Science*, vol. 44, pp. 214-222, 2013.

[10] J. Qiao, H. Wu, X. Yu. High-precision attitude tracking control of space manipulator system under multiple disturbances. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 51, pp. 4274-4284, 2021.

[11] X. Jin. Iterative learning control for non-repetitive trajectory tracking of robot manipulators with joint position constraints and actuator faults. *International Journal of Adaptive Control and Signal Processing*, vol. 31, pp. 859-875, 2017.

[12] J. Xu, B. Viswanathan, Z. Qu. Robust learning control for robotic manipulators with an extension to a class of non-linear systems. *International Journal of Control*, vol. 73, pp. 858-870, 2000.

[13] Z. Li, Z. Hou, C. Yin. Iterative learning control for train trajectory tracking under speed constrains with iteration-varying parameter. *Transactions of the Institute of Measurement and Control*, vol. 37, pp. 485-493, 2014.

[14] L. Ma, X. Liu, F. Gao, K. Y. Lee. Event-based switching iterative learning model predictive control for batch processes with randomly varying trial lengths. *IEEE Transactions on Cybernetics*, vol.53, pp.7881-7894, 2023.

[15] S. Liu, J. Wang. Fractional order iterative learning control with randomly varying trial lengths. *Journal of the Franklin Institute*, vol. 354, pp. 967-992, 2017.

[16] X. Li, D. Shen. Two novel iterative learning control schemes for systems with randomly varying trial lengths. *Systems and Control Letters*, vol. 107, pp. 9-16, 2017.

[17] X. Su, Y. Wen, P. Shi, S. Wang, W. Assawinchaichote. Event-triggered fuzzy control for nonlinear systems via sliding mode approach. *IEEE Transactions on Fuzzy Systems*, vol. 29, pp. 336-344, 2021.

[18] W. Dou, S. Ding, X. Yu. Event-triggered second-order sliding-mode control of uncertain nonlinear systems. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 53, pp. 7269-7279, 2023.

[19] M. Fang, P. Shi, S. Dong. Sliding mode control for markov jump systems with delays via asynchronous approach. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 51, pp. 2916-2925, 2021.

[20] W. Wang, J. Ma, X. Li; Z. Cheng, H. Zhu, C. S. Teo, T. H. Lee. Iterative super-twisting sliding mode control for tray indexing system with unknown dynamics. *IEEE Transactions on Industrial Electronics*, vol. 68, pp. 9855-9865, 2021.

[21] A. A. Armstrong, A. J. W. Johnson, A. G. Alleyne. An improved approach to iterative learning control for uncertain systems. *IEEE Transactions on Control Systems Technology*, vol. 29, pp. 546-555, 2021.

[22] X. Zhang, R. W. Longman. Stability of sliding mode ILC design for a class of nonlinear systems with unknown control input delay. *IEEE Transactions on Neural Networks and Learning Systems*, vol. 33, pp. 4346-4360, 2022.

[23] M. Qiu, M. Chen, M. Liu, S. Liu, J. Li, X. Liu, Y. Zhu. Online energy-saving algorithm for sensor networks in dynamic changing environments. *Journal of Embedded Computing*, vol. 3, no. 4, pp. 289-298, 2009.

[24] D. Liu, D. Ye. Exponential stabilization of delayed inertial memristive neural networks via aperiodically intermittent control strategy. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 52, pp. 448-458, 2022.

[25] Q. Xiao, F. L. Lewis, Z. Zeng. Containment control for multiagent systems under two intermittent control schemes. *IEEE Transactions on Automatic Control*, vol. 64, pp. 1236-1243, 2019.

[26] P. Wan, Z. Zeng. Synchronization of delayed complex networks on time scales via aperiodically intermittent control using matrix-based convex combination method. *IEEE Transactions on Neural Networks and Learning Systems*, ?vol.34, pp.2938-2950, 2023.

[27] A. Tayebi. Adaptive iterative learning control for robot manipulators. *Automatica*, vol. 40, pp. 1195-1203, 2004.

[28] C. E. Boudjedir, M. Bouri, D. Boukhetala. Model-free iterative learning control with nonrepetitive trajectories for second-order MIMO nonlinear systems: Application to a Delta robot. *IEEE Transactions on Industrial Electronics*, vol. 68, pp. 7433-7443, 2021.

[29] M. Shen, X. Wu, J. H. Park, Y. Yi, Y. Sun. Iterative learning control of constrained systems with varying trial lengths under alignment condition. *IEEE Transactions on Neural Networks and Learning Systems*, vol.34, pp.6670-6676, 2023.

[30] X. Jin. Formation-based decentralized iterative learning cooperative impedance control for a team of robot manipulators. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 53, pp. 872-881, 2023.

[31] X. He, C. K. Ahn, P. Shi. Periodically intermittent stabilization of neural networks based on discrete-time observations. *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 67, pp. 3491-3501, 2020.