Improved Observer-Based Digital Redesign Tracker for Nonlinear Sampled Data Systems

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Abstract In this paper, a novel observer-based digital redesign tracker is proposed to resolve the output tracking problem for nonlinear sampled data systems. Acquiring parameters via a hybrid design of EP-based iterative learning control (EP-ILC) and linear quadratic analog tracker (LQAT), the tracker possesses good tracking performance both in transient state response and in steady state response when an appropriate sampling time is given. Furthermore, the tracker improves the conventional digital redesign tracker on tracking performance at a large sampling time. An illustrative example is demonstrated to show the effectiveness of the proposed methodology.

Keyword Observer-based tracker, Digital redesign, Linear quadratic analog tracker, Iterative learning control, Evolutionary programming

1. INTRODUCTION

Digital redesign methodology, converting the well-designed analog controller into the equivalent digital one and maintaining the properties of the original control system in the state-matching sense, is an efficient approach for sampled-data system control design. Not only does the digital redesign controller preserve the perfect control performance of the analog one, but it also possesses many benefits of the digital control technique — higher efficiency, lower cost, more flexibility, and better reliability. Recently, Shieh and his collaborators has investigated and proposed various types of digital redesign methods focusing on the state-feedback control design [1][2][3]; the linear quadratic analog tracker and its digital redesign will be applied and improved in this paper.

Linear quadratic analog tracker (LQAT) with a high gain property can suppress the uncertain errors such as nonlinear perturbations and external disturbances; it can make the system output quickly and accurately trace the desire reference in a short time interval. However, its control input signal is saturated easily due to the physical limitation of a system. Therefore, applying the digital redesign method overcomes the previous disadvantage. The main idea of the digital redesign is applying the energy equivalent concept, which means that the high energy in a short time interval is equal to the relative low one in an appropriate long one, to resolve the control input saturation problem; it can be realized by a sampler and a zero order hold. Notice that if the sampling time is too short, the tracker design is similar to the previous scheme of the analog controller. Furthermore, the fast-rate sampler is more expensive than general one and could not be realized physically. On the contrary, the tracker may not keep the perfect performance as well as the analog one. Hence, it is a significant factor to decide an appropriate sampling time for the tracker. However, the long sampling time must be considered in some case such as artificial heart control. The original digital redesign tracker may not be suitable for use in above situation. Therefore, in this paper, an improved digital redesign tracker combines an iterative learning controller and a linear quadratic analog tracker is proposed.

Iterative learning control (ILC) was first proposed by Arimoto et al. [4], and its basic idea is described that the performance of a system can be improved by learning from the previous iterations when the system executes the same task multiple times. Furthermore, the controller can exhibit the perfect control performance according to a less priori knowledge of the system. Due to its advantages which are higher efficiency and more convenience, many researchers discuss ardently the subjects of ILC and usually apply the controller in several of physical systems such as industrial robot, computer numerical control (CNC) machine, and antilock braking system (ABS), etc [5].

In this paper, a novel observer-based digital redesign tracker that combined with EP-based ILC and LQAT is proposed. Not only does the tracker possess the good performance both in transient and steady state response at an appropriate small sampling time, but its tracking result is also better than a conventional digital redesign tracker at a relative long sampling time.

The paper is organized as follows. In Section 2, the observer based EP-ILC is presented. In Section 3, the novel observer-based digital redesign tracker is proposed. An illustrative example is given to present the effectiveness of the proposed method in Section 4. Finally, some conclusions are presented in Section 5.
II. OBSERVER-BASED ITERATIVE LEARNING CONTROL VIA EVOLUTIONARY PROGRAMMING

A. Problem description

Consider the nonlinear system as follows:

\[
\dot{x}_i(t) = f(x_i(t), u_i(t)), \quad \text{(1.a)}
\]

\[
y_i(t) = Cx_i(t), \quad \text{(1.b)}
\]

where \( x_i(t) \in \mathbb{R}^n \), \( u_i(t) \in \mathbb{R}^m \), and \( y_i(t) \in \mathbb{R}^m \) are the state vector, the control input, and the system output, respectively. Furthermore, the subscript \( i \) represents the iteration number of learning, and \( f(\cdot) \) and \( B(\cdot) \) are nonlinear functions. Now, the control problem can be formulated as follows: Suppose that the desired trajectory \( r(t) \) over the time interval \([0, T]\) is differentiable. The main objective is to design an iterative updating rule of input such that the output \( y_i(t) \) converges to the desired trajectory \( r(t) \) for \( t \in [0, T] \) when learning epoch \( i \) approaches to infinity. For the design of the ILC-based tracker, the following assumptions are considered.

A1. There exits an upper limit \( u_{\text{max}} \) which is the physical limitation of a system, and the control input \( u_i(t) \) satisfies the rule \( \|u_i(t)\| \leq u_{\text{max}} \).

A2. There exits a bounded control rule \( \|u_i(t)\| \leq u_{\text{max}} \) over the time interval \([0, T]\) such that the output \( y_i(t) \) converges to the desired trajectory \( r(t) \) for \( t \in [0, T] \) when learning epoch \( i \) approaches to infinity.

A3. The matrix \( B \) is \( B_0 \leq B_n \) and satisfies the Lipschitz condition \( \|B(x_1) - B(x_2)\| \leq K_B \|x_1 - x_2\| \) with respect to \( x_1 \in \mathbb{R}^n \) and \( x_2 \in \mathbb{R}^n \) over the time interval \([0, T]\), where \( B_n \) and \( K_B \) are positive constants. Furthermore, the function \( f(\cdot) \) satisfies the condition too.

A4. \( \text{rank}(CB(\cdot)) = m \).

A5. The resetting initial condition \( x_i(0) = x_d(0) \) is satisfied at each iteration, where \( x_d(0) \) is the initial state corresponding to the desired trajectory.

In this paper, some norms are used as follows:

\[
\|M\| = \max_{1 \leq i \leq p} \left\{ \sum_{k = 1}^{n} m_{ik} \right\}
\]

for a given matrix

\[
M = [m_{ik}] \in \mathbb{R}^{p \times n}
\]

\[
\|V\| = \max_{1 \leq i \leq p} \left\| v_i \right\|
\]

for a given vector

\[
V = [v_1, ..., v_p]^T
\]

the sup-norm denoted by

\[
\left\| (t) \right\|_{\infty} = \sup_{t \in [0, T]} \left\| (t) \right\|
\]

and the \( \lambda \)-norm denoted by

\[
\left\| (t) \right\|_{\lambda} = \sup_{t \in [0, T]} \left| e^{-\lambda t} \right| \left\| (t) \right\|
\]

Moreover, the time argument \( t \) of the following equations are omitted in order to present a concise form.

B. Observer-based iterative learning control

In many practical problems, some states of system (1) can not be measured due to technical or economic reasons. However, according to [6], designing the control input may needs unmeasured system states. Hence, the observer-based iterative learning control (OBILC) is proposed and depicted in Fig. 1.

Consider the state observer as follows:

\[
\hat{x}_i = A(\hat{x}_i)x_i + B(\hat{x}_i)u_i + \phi(\hat{x}_i) + L_c(\hat{x}_i)(y_i - \hat{y}_i), \quad \text{(2.a)}
\]

\[
\hat{y}_i = Cx_i, \quad \text{(2.b)}
\]

where \( \phi(\hat{x}_i) \triangleq f(\hat{x}_i) - A(\hat{x}_i)x_i \) and \( L_c(\hat{x}_i) \) is the observer gain. Furthermore, \( A(\hat{x}_i)x_i \) is derived from \( f(\hat{x}_i) \) by optimal linearization algorithm [3], and \( A(x_k)x_k = f(x_k) \) at any operating state \( x_k \). Then, observer gain \( L_c(\hat{x}_i) \) can be obtained as follows:

\[
L_c(\hat{x}_i) = P_o C^T R_n^{-1},
\]

\[
A(\hat{x}_i)P_o + P_o A^T(\hat{x}_i) - P_o C^T R_n^{-1}CP_o + Q_o = 0,
\]

where \( Q_o \in \mathbb{R}^{m \times m}, R_n \in \mathbb{R}^{m \times m}, \) and \( P_o \) is the symmetric and positive definite solution of Riccati equation (4). Note that if the high ratio between \( Q_o = q_o I_s \) and \( R_n = r_n I_s \), \( q_o >> r_o \) where \( q_o \) and \( r_o \) are scalars, holds, the estimated state error \( \hat{x}_i - \hat{x}_i \) is bounded and converges asymptotically to zero.

Now, consider the following iterative learning controller

\[
u_{i+1} = u + G(\hat{x}_i)(\hat{r} - \hat{y}_i),
\]

\[
= u + G(\hat{x}_i)(\hat{r} - CA(\hat{x}_i)x_i - CB(\hat{x}_i)u_i - CP(\hat{x}_i) - CL(\hat{x}_i)C_1),
\]

\[
u_{i+1} = \text{sat}(\nu_{i+1}),
\]

where \( \hat{r} \) and \( \hat{y}_i \) are the time derivatives of \( r \) and \( y_i \), respectively, \( \hat{x}_i \) is the estimated state by the observer (2), and \( G(\hat{x}_i) \) is the learning gain. The initial control input is such that \( \|\nu_0\| \leq u_{\text{max}} \). For a vector

\[
U = [u_1, ..., u_m]^T \in \mathbb{R}^m,
\]

the saturation function is defined as

\[
\text{sat}(U) = \left[ \text{sat}(u_1), ..., \text{sat}(u_m) \right]^T
\]

where

\[
\text{sat}(u_k) = \begin{cases} u_k, & \text{if } u_k \leq u_{\text{max}}, \\ u_{\text{max}}, & \text{if } u_k > u_{\text{max}}, \text{ for } k \in \{1, ..., m\}, \\ -u_{\text{max}}, & \text{if } u_k < -u_{\text{max}} \end{cases}
\]

and the up subscript \( k \) means the the \( k \)-th element of the vector \( U \).

C. Improved ILC tracker via evolutionary programming

According to the convergence analysis of [6], if the

\[ \text{Fig. 1. Observer-based ILC for a class of nonlinear system.} \]
converging condition,
\[ \|r - G(\hat{x}_i)CB(\hat{x}_i)\|_\infty < 1, \tag{8} \]
where \(G(\hat{x})\) is the learning gain of the ILC tracker and equals to \((CB(\hat{x}))^{-1}\) for simplicity and convenience, is satisfied, the tracking error will approach to zero when \(i \to \infty\). However, the performance about the converging rate might be not desirable in some systems. In order to increase the speed of the converging rate, the learning gain must be considered preferentially in the ILC scheme. Hence, an optimal searching algorithm called Evolutionary Programming (EP) will be applied to construct the EP-based ILC (EP-ILC) tracker.

Now, in order to apply the EP algorithm to search for an optimal learning gain \(G_{EP}(\hat{x}_i)\), let converging condition (8) be equal to \(\xi\) which is a tuning matrix and \(\xi \in \mathbb{R}^{m \times m}\) such as
\[ \xi = I_m - G_{EP}(\hat{x}_i)CB(\hat{x}_i), \text{ if } (CB(\hat{x}_i))^{-1} \text{ exists.} \tag{9} \]
From (8) and (9), it implies
\[ \lim_{i \to \infty} \|r - G_{EP}(\hat{x}_i)CB(\hat{x}_i)\|_\infty < 1. \tag{10} \]
According to (9) and (10), the learning gain \(G_{EP}(\hat{x}_i)\) can be derived easily as
\[ G_{EP}(\hat{x}_i) = (I_m - \xi)(CB(\hat{x}_i))^{-1} = (I_m - \xi)G(\hat{x}_i), \tag{11} \]
where \(G(\hat{x}_i) = (CB(\hat{x}_i))^{-1}\). Then, applying evolutionary algorithm in [7], the object function is modified as
\[ OF(\theta) = O_k \triangleq \xi_{final}, \tag{12} \]
where \(i_{\text{final}}\) is the final iteration epoch of the EP-ILC tracker when the sup-norm of the tracker error, \(\sup_{[\hat{x}_{i_{\text{final}}} - r]}\), satisfies the tolerant error bound \(\varepsilon_{\text{ILC}}\). After that, applying evolutionary programming searches for the best learning gain based on (12). The observer based EP-ILC tracker with the tuning matrix \(\xi\) is proposed and depicted in Fig. 2.

Step 1: Construct the optimal linear model.

Apply the optimal linearization algorithm to obtain the optimal linear model of the nonlinear system (1) at each sampling time \(t = kT_s\) as
\[ \dot{x}_i = f(x_i) + B(x_i)u_i = A_i x_i + B_i u_i, \tag{13} \]
where \(A_i = A(x_i(kT_s))\) is derived from [3] with the operation state \(x_i(kT_s)\) and \(B_i = B(x_i(kT_s))\).

Step 2: Design the EP-based iterative learning control with an observer.

According to (2) and (13), the state observer of ILC with LQR is given by
\[ \dot{\hat{x}}_i = \hat{A}_{i,k} \hat{x}_i + \hat{B}_{i,k} u_i + f(\hat{x}_i) - \hat{A}_{i,k} \hat{x}_i + L_{c,k}(y_i - \hat{y}_i), \tag{14.a} \]
\[ \hat{y}_i = C_i \hat{x}_i, \tag{14.b} \]
where \(\hat{x}_i\) is the estimated state of \(x_i\), \(\hat{A}_{i,k} = A(\hat{x}_i(kT_s))\), \(\hat{B}_{i,k} = B(\hat{x}_i(kT_s))\), and \(L_{c,k} \in \mathbb{R}_{q > p}\) is the observer gain at the fast sampling time \(t = kT_f\). Furthermore, from (3), the observer gain \(L_{c,k}\) is designed as follows:
\[ L_{c,k} = P_o k_{\text{opt}} R_o^{-1}, \tag{15} \]
\[ \hat{A}_{i,k} P_o k_{\text{opt}} + P_o k_{\text{opt}} \hat{A}_{i,k} - P_o k_{\text{opt}} C_i R_o^{-1} C_i P_o k_{\text{opt}} + Q_o = 0, \tag{16} \]
where \(Q_o \in \mathbb{R}_{q > p}\), \(R_o \in \mathbb{R}_{p \times p}\), and \(P_o\) is the symmetric and positive definite solution of Riccati equation (16). Note that if the high ratio between \(Q_o = q_o I_o\) and \(R_o = \gamma_o I_o\), \(q_o \gg \gamma_o\), where \(q_o\) and \(\gamma_o\) are scalars, holds, the estimated state \(\hat{x}_i\) will be close to the system state \(x_i\).

Then, the learning update rule of input \(u_i\) is defined as
\[ v_{i+1} = u_i + G_{i,k}(\hat{r} - \hat{y}), \tag{17.a} \]
\[ u_{i+1} = \text{sat}(v_{i+1}), \tag{17.b} \]
where \(\hat{r}\) is the time derivative of desired reference input \(r\), \(\hat{y}_i = f(\hat{x}_i) - \hat{A}_{i,k} \hat{x}_i\), \(\hat{C}_i = \hat{C}_i \hat{x}_i\), \(\hat{G}_{i,k} = G(\hat{x}_i(kT_s))\) is the learning gain of ILC. In order to possess the perfect performance of ILC tracker, some sufficient conditions, Assumptions A1-A5 and the convergence condition (8), must be satisfied. Furthermore, according to (8), let \(G_{i,k}\) be equal to \((CB_{i,k})^{-1}\) for convenience and simplicity. The observer-based iterative learning control can be constructed according to the above procedure. However, the learning convergence rate of the tracker is not desirable in some case. In order to resolve the problem, the evolutionary programming is applied to improve the observer-based iterative learning controller. Firstly, apply the convergence condition (8) to equal the tuning matrix \(\xi\). Then, the new learning gain \(G_{EP,k}\) can be obtained from
\[ G_{EP,k} = (I_m - \xi)(CB_{i,k})^{-1}, \text{ if } (CB_{i,k})^{-1} \text{ exists.} \tag{18} \]

Then, according to the procedure of the evolutionary programming in [7], the observer-based EP-ILC is

![Fig. 2. Observer-based EP-ILC tracker with tuning matrix \(\xi\) for a class of nonlinear systems.](image-url)
developed and depicted as Fig. 3.

**Step 3:** Construct the observer-based linear quadratic analog tracker (LQAT).

Before constructing LQAT, the optimal linear model is obtained from Step 1 at the fast sampling time $t = kT_f$ . Then, based on the optimal control theorem [3], the control input of LQAT is given as

$$u_c = -K_{c,k} x_k + E_{c,k} r,$$  

(19)

$$K_{c,k} = R_{c,k}^{-1} B_{c,k}^T P_{c,k},$$  

(20)

$$E_{c,k} = -R_{c,k}^{-1} B_{c,k}^T \left( A_k - B_k x_k \right)^{-1} C^T Q,$$  

(21)

$$A_k P_{c,k} + P_{c,k} A_k - P_{c,k} B_k R_{c,k}^{-1} B_{c,k}^T P_{c,k} + C^T Q C = 0,$$  

(22)

where the analog feedback gain $K_{c,k} \in \mathbb{R}^{m \times p}$, the forward gain $E_{c,k} \in \mathbb{R}^{m \times p}$, $A_k = A(x_k(t))$, $B_k = B(x_k(t))$, and $P_{c,k}$ is the positive definite and symmetric solution of the Riccati equation (22), $Q_k = q_k I_p \geq 0$, $R_k = r \gamma_k > 0$, $q_k, r > \gamma_k$, and $\gamma_k$ are scalars. When the system state $x_k$ is not measurable, the state observer for a nonlinear system is presented as follows:

$$\dot{\hat{x}}_k = \hat{A}_k \hat{x}_k + \hat{B}_k u_c + \phi(\hat{x}_k) + L_{c,k}(y_k - \hat{y}_k),$$  

(23a)

$$\hat{y}_k = C \hat{x}_k,$$  

(23b)

where $\hat{A}_k = A(\hat{x}_k(t))$, $\hat{B}_k = B(\hat{x}_k(t))$, $\phi(\hat{x}_k) = f(\hat{x}_k) - \hat{A}_k \hat{x}_k$, and the observer gain $L_{c,k} \in \mathbb{R}^{m \times p}$ is given by

$$L_{c,k} = P_{c,k} C^T R_{c,k}^{-1}.$$

(24)

In (24), $P_{c,k}$ is the positive definite and symmetric solution of the following Riccati equation:

$$A_k P_{c,k} + P_{c,k} A_k - P_{c,k} B_k R_{c,k}^{-1} B_{c,k}^T P_{c,k} + Q_o = 0,$$  

(25)

where $Q_o \geq 0$ and $R_o > 0$ with appropriate dimensions. The observer-based linear quadratic analog tracker is depicted as Fig. 4.

**Step 4:** Organize a hybrid design of EP-ILC and LQAT to generate the ideal system state $x_d(t)$.

The hybrid design which is the combination of EP-ILC and LQAT is depicted as Fig. 5. In this figure, let LQAT perform the tracking task firstly. Then, the input signal of LQAT is applied to set the initial control input $u_{ilc}(t)$ of EP-ILC. Thereafter, the system state $x_{ilc}(t)$ of EP-ILC is obtained to construct the optimal linear model for LQAT. This procedure is executed repeatedly until the tracking error satisfies a specific error tolerant bound. Once the above process achieves the tracking purpose, the ideal system state by using the optimal linearization methodology will be applied to design a digital redesign tracker.

**Step 5:** Design the observer-based digital redesign tracker via the hybrid design for nonlinear sampled-data system.

Use the generated ideal system state $x_{ilc}(t)$ which is sampled at the slowing sampling time $t = kT_s$ to construct the optimal linear model by Step 1 and to design the digital redesign tracker for the nonlinear sampled-data system at each sampling instant $t = kT_s$. From [3], the discrete-time state-feedback controller is given as

$$u_d(kT_s) = -K_{d,k} x_d(kT_s) + E_{d,k} r^*(kT_s),$$  

(26)

where

$$K_{d,k} = \left( I_m + K_{c,k} H_{k_f} \right)^{-1} K_{c,k} G_{k_f},$$  

(27)

$$E_{d,k} = \left( I_m + K_{c,k} H_{k_f} \right)^{-1} E_{c,k} G_{k_f},$$  

(28)

$$r^*(kT_s) = r(kT_s + T_s),$$  

(29)

$$G_{k_f} = \exp(A_{k_f} T_s),$$  

(30)

$$H_{k_f} = (G_{k_f} - I_m) A_{k_f}^T B_{k_f},$$  

(31)

$K_{d,k} \in \mathbb{R}^{m \times m}$ is a digital state-feedback gain, $E_{d,k} \in \mathbb{R}^{m \times p}$ is a digital feed-forward gain, and $r^*(kT_s)$ is a reference vector due to the controller design feature. Noted that $A_{k_f} = A(x_f(kT_s))$, $B_{k_f} = B(x_f(kT_s))$, and $x_f(kT_s)$ are the ideal system state of observer-based EP-ILC at each sampling instant $t = kT_s$ in last learning epoch $i_f$. According to the previous design description, the digital controller for the sampled-data system is presented as

$$x_d(0) = x_0,$$  

(32)

$$y_d(kT_s) = C x_d(kT_s),$$  

(33)

Moreover, the discrete-time observer is obtained as
\[
\dot{x}_d(kT_s) = \dot{\hat{x}}_d(kT_s - T_s) + H_d(kT_s - T_s) \dot{u}_d(kT_s - T_s) + L_d(kT_s - T_s) y_d(kT_s),
\]
and
\[
\hat{y}_d(kT_s) = C \hat{x}_d(kT_s),
\]
where
\[
L_{d,k-1} = (\hat{G}_{d,k-1} - I_k) \hat{C}_{d,k-1}(I_n + C(\hat{G}_{d,k-1} - I_k) \hat{C}_{d,k-1})^{-1},
\]
\[
\hat{G}_{d,k-1} = \hat{G}_{d,k-1} - L_{d,k-1} C \hat{G}_{d,k-1},
\]
\[
\hat{H}_{d,k-1} = (I_n - L_{d,k-1} C) \hat{H}_{k-1},
\]
\[
\hat{G}_{k-1} = \exp(\hat{A}_k T_s),
\]
\[
\hat{H}_{k-1} = (\hat{G}_{k-1} - I_k) \hat{A}_{k-1} \hat{B}_{k-1},
\]
\[
\hat{A}_{k-1} = A(\hat{x}_d(kT_s - T_s))_1, \quad \text{and} \quad \hat{B}_{k-1} = B(\hat{x}_d(kT_s - T_s))_2.
\]
In (34), the currently estimated state \( \hat{x}_d(kT_s) \) can be obtained from the currently output \( y_d(kT_s) \). The observer-based digital tracker for the nonlinear sampled-data system is depicted in Fig. 6.

**IV. AN ILLUSTRATIVE EXAMPLE**

Consider the chaotic system
\[
\begin{align*}
\dot{x}_1 &= 35(x_2 - x_1) + 0.05, \\ x_1 &= -7x_1 - 4.5\sin(x_1) + 0.18, \\ x_2 &= x_1 - 3x_2 + 0.05, \\ u_1 &= 0.6, \\ u_2 &= 0.7.
\end{align*}
\]
and
\[
\begin{align*}
\hat{x}_1 &= \begin{bmatrix} 0.18 & 0.6 & 0 & x_1 \\ 0.05 & 0.7 & x_2 & x_3 \end{bmatrix},
\end{align*}
\]
The related parameters of the observer-based ILC tracker are
\[
\begin{align*}
\begin{bmatrix} 35 & 0 \\ 0 & 4.5 \end{bmatrix} + 205.5\sin(12t) \quad & \text{for} \ t \in [0, 1], \quad \varepsilon_{ILC} = 0.01, \\
I_{ILC} = 80, \quad Q_o = 10^4 I_2, \quad \text{and} \quad R_o = I_2. \end{align*}
\]
Moreover, applying the proposed initial input decision to the EP-ILC significantly improves its convergence learning rate.

**Fig. 6. The observer-based digital redesign tracker via the hybrid design scheme for nonlinear sampled-data system.**

After the previous simulation for the chaotic system, these ideal states of the system with fast sampling and hold period \( T_i = 1ms \) are obtained from the hybrid design scheme, which is an extended version of observer-based EP-ILC with initial input decision. According the optimal linearization algorithm, two types of linear models can be derived by these ideal states with the sampling and hold periods \( T_i = 10ms \) and \( T_i = 70ms \), respectively. In addition, the parameters of a digital redesign tracker are given as \( Q_o = 10^4 I_2, \quad R_o = I_2, \quad Q_o = 10^4 I_2, \quad \text{and} \quad R_o = I_2. \) The simulation result of the tracker for the small sampling time \( T_i = 10ms \) is depicted in Fig. 8. From Fig. 8, the tracker exhibits the good control performance both in transient and steady state response. Fig. 9 shows the case of the large sampling time \( T_i = 70ms \). From Fig. 9, it is obviously that the proposed methodology can improve the original digital redesign tracker at the relative large sampling time.
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Fig. 8. Output response of observer-based digital redesign tracker with the hybrid design scheme for sampling time $T_s = 10\text{ms}$.  

Fig. 9. (a) Output response of original observer-based digital redesign tracker for sampling time $T_s = 70\text{ms}$. (b) Output response of the proposed observer-based digital redesign tracker with the hybrid design scheme for sampling time $T_s = 70\text{ms}$.  

V. CONCLUSIONS

In this paper, the observer-based digital redesign tracker via a hybrid design that combines EP-ILC with LQAT are proposed. At first, in order to increase the learning convergence speed of ILC as far as possible, evolutionary programming is applied to search for the optimal learning gain of ILC in specific search domain. The result shows that the number of learning iterations for observer-based EP-ILC is extremely less than that of the original OBILC. Then, the hybrid design which combines EP-ILC with LQAT is constructed and generates the ideal system state for digital redesign tracker. Based on the prediction-based digital redesign technique, the observer-based digital redesign tracker with the previous ideal state is proposed. The tracker with high gain property can suppress the uncertainty, modeling conversion error, and make the system output approach the desire target quickly. Simulation result shows that the tracker exhibits the perfect tracking performance at the appropriate small sampling time; the tracking result shows that the original digital redesign tracker is improved by the hybrid design at the large sampling time.

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