Force tracking impedance control with unknown environment via an iterative learning algorithm

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A. INTORDUCTION

The applications of robot manipulators have evolved and broadened into many industrial fields, especially in some constrained tasks such as deburring, grinding, and finishing surface. Robot-constrained operations require manipulators that can interact with the environment compliantly even in an unknown environment. To improve the compliant performance of a robot-environment interaction, countless researchers have studied this problem over the past two decades. Two major force tracking methods to comply with a constrained environment have been proposed: hybrid position/force control [1] and impedance control [2].

Compared with hybrid position/force control, because impedance control provides a unified framework for both constrained and unconstrained spaces, it is garnering more attention. By regulating the virtual “mechanical impedance” of the end-effector, the impedance control scheme maintains the dynamic relationship between position and contact force to achieve an interaction force indirectly; this is advantageous for performing little task planning, overcoming uncertain disturbances, and transiting smoothly through an unconstrained operation to a constrained operation. Generally, for impedance control, the force tracking performance depends on the reference trajectory, environment stiffness and location, and robot position tracking accuracy.

Since the impedance control method was presented by Hogan [2], researchers have continually sought a remedy for the issue within the framework. To provide robustness and stability against disturbances and parameter uncertainties, a robust impedance control based on the sliding model [3], an iterative learning impedance control [4], a robust neural network [5], an adaptive optimal impedance control by minimizing a certain cost function [6], and a Q-learning method to achieve impedance parameter adaption [7] were proposed successively. In [8] and [9], a new two-phase impedance function through null stiffness in an original impedance equation to satisfy zero-force tracking error for any environment was presented, where an adaptive method was used by adjusting the damping parameter online to obtain robustness against the uncertainties of robot dynamics and environment parameters. Further improvement of the works mentioned in [8] and [9] was reported in [10]. However, the hypothesis of null stiffness did not conform to the intuitive force tracking rules, in that humans always maintain stiffness when exerting the desired force on objects. Hence, a new variable target stiffness impedance control method was proposed [11]. Furthermore, except using variable impedance parameters to realize adaptability, the other method is to generate the precise reference trajectory as an input to regulate the contact force online, thus demanding prior knowledge or estimation of environment parameters. Hence, a direct reference trajectory generation method based on the force tracking error, and an indirect adaptive method by observing the environment stiffness and location to obtain the reference trajectory were provided [12]. Recently, by minimizing a cost function including several interaction targets and a novel online reference trajectory adaptation algorithm, a new scheme to obtain a reference trajectory was proposed [13,14]. However, the accurate reference trajectory has been calculated, and the position tracking error will primarily affect the force tracking performance such as the steady-state error. Using information from previous experiments continually, iterative learning control is a highly simple and useful method to improve motion trajectory tracking accuracy to obtain the desired output [15]. In addition, some novel adaptive iterative algorithms to improve robotic trajectory tracking accuracy were presented in [16].

The objective of this study is to provide a simple and effective method to enhance impedance control. Within the impedance control framework, an adaptive control scheme is developed in this study for robust force tracking without any environment information, and an iterative learning method is employed to improve the tracking accuracy for a better force tracking performance. The primary idea of the study is to estimate the environment stiffness and location in real time to induce the observed force to converge to the desired ones. Consequently, the accurate reference trajectory will be acquired. Based on the force tracking error, an iterative learning algorithm is used to guarantee the trajectory tracking accuracy. The proposed method combines the adaptive reference trajectory generation technique with the iterative learning control (ILC) algorithm; it is robust to unknown environments, and simple to reduce steady-state errors caused by trajectory tracking errors. The simplicity and efficiency of the control methods are necessary for a real-time implementation.

B. ADAPTIVE FORCE TRACKING IMPEDANCE CONTROL

Subsection B.1 briefly reviews the typical compliant force control method: position-based impedance control. The adaptive scheme with environment information observation and ILC algorithm is presented in subsection B.2.

B.1 Position-based Impedance Control

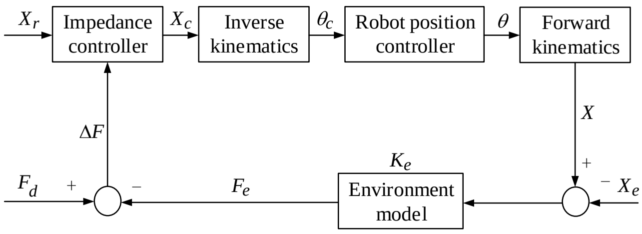

Fig. 1. Position-based impedance control algorithm

Through establishing a virtual mass-damping-stiffness model, impedance control regulates the dynamic relationship between the robot end-effector position and contact force. Position-based impedance control consists of both the inner position control loop and outer indirect force tracking loop. In Fig. 1, F_d and F_e are the desired force and actual contact force, respectively, and X_r, X_c, X_e, X represent the reference trajectory, commanded trajectory, environment location, and real robot end-effector position, respectively; K_e is the environment stiffness. For modeling the robot/environment interaction, the environment is simplified as a stiffness model such that $F_e = K_e(X - X_e)$ can be satisfied approximatively. If the position tracking error does not exist, $X = X_c$ can yield $F_e = K_e(X_c - X_e)$. By the force tracking error $\Delta F = F_d - F_e$. The outer impedance controller generates the trajectory modification to regulate the contact force indirectly. The inner position loop ensures the minimum position tracking error, because the residual position error contributes to the force error.

In general, the impedance equation can be expressed as

$$F_d - F_e = M\left(\ddot{X}_c - \ddot{X}_r\right) + B\left(\dot{X}_c - \dot{X}_r\right) + K\left(X_c - X_r\right), \quad (1)$$

where M, B, K are the diagonal mass, damping, and stiffness matrices, respectively. The commanded reference trajectory satisfies $X_c = X_r + E$, where E represents the position modification generated by the impedance controller. Further, (1) can be rewritten as

$$\Delta F = M\ddot{E} + B\dot{E} + KE\,, \quad (2)$$

Obviously, the impedance model can be regarded as a linear second-order system, and its transfer function is $K(s) = 1/(Ms^2 + Bs + K)$; therefore, $X_c = X_r + E = X_r + \Delta F K(s)$.

Owing to independent Cartesian variables, the lower-case scalars x and f were used to represent any element of vectors X and F. Subsequently, the force tracking error can be expressed as follows:

$$\Delta f = f_d - f_e = f_d - k_e\left(x_c - x_e\right). \quad (3)$$

Substituting $x_c = x_r + k(s)\Delta f$ and $k(s) = 1/(ms^2 + bs + k)$ into (3) yields

$$\Delta f\left(ms^2 + bs + k + k_e\right) = \left(ms^2 + bs + k\right)[f_d - k_e\left(x_r - x_e\right)]\,. (4)$$

From (4), the steady-state force tracking error can be expressed as

$$\Delta f_{ss} = \frac{k}{k + k_e}[f_d - k_e(x_r - x_e)]\,. \quad (5)$$

From (5), two methods can be used such that the force tracking error converges to zero. One is to set the impedance parameter $k = 0$ to guarantee that $\Delta f_{ss} = 0$ is always satisfied for any k_e; the other is to guarantee that the reference trajectory satisfies the following equation

$$x_r = x_e + \frac{f_d}{k_e}. \qquad (6)$$

It is unreasonable to use the null stiffness such that the steady-state force tracking error converges to zero. One reason is that the impedance parameter k is closely related to the natural frequency and the damping ratio of the linear second-order system [17]. Additionally, the fact that humans exert force on an object through adapting arm stiffness cannot be ignored [18]. From (6), the reference trajectory could be obtained accurately if the environment location and stiffness are both known exactly. Owing to the lack of exact environment information in practice, it is typically difficult to specify the accurate reference trajectory offline. However, through the online estimation of the environmental parameters x_e and k_e, the reference trajectory x_r can be computed indirectly. The reference trajectory generator can be devised with appealing simplicity and strong robustness.

B.2 Impedance Control with Iterative Learning Algorithm

An adaptive impedance control with iterative learning algorithm is proposed herein. The motivation is to regulate the reference trajectory adaptively, while reducing the influence of robot position tracking error on the force tracking performance. Consequently, the desired contact force and compliant interaction are achieved. First, the online estimation of the environment stiffness and location helps to generate x_r. Subsequently, iterative learning contributes to $x \rightarrow x_r$. The idea is also motivated by the fact that the online observation of the environment stiffness and location can provide appealing robustness properties. From subsection B.1 of Section B, the x_r can be computed accurately if the x_e and k_e are known exactly. However, owing to the complexity of the contact environment, it is difficult to obtain the accurate environment information in practice. One available approach is to approximately calculate the observation values $\hat{x}_e$ and $\hat{k}_e$; therefore, based on (6), x_r can be expressed as

$$x_r = \hat{x}_e + \frac{f_d}{\hat{k}_e}, \qquad (7)$$

where $\hat{x}_e$ and $\hat{k}_e$ are the calculated observation values of x_e and k_e, respectively. It is rational to regard a rigid environment as a stiffness model, as practiced by most researchers. Suppose that no position tracking error exists when a robot manipulates, i.e., $x_c = x$; subsequently, the contact force can be written as

$$f = k_e(x_c - x_e) = k_e x_c - k_e x_e. \qquad (8)$$

Considering the definition

$$\hat{f} = \hat{k}_e(x_c - \hat{x}_e) = \hat{k}_e x_c - \hat{k}_e \hat{x}_e, \qquad (9)$$

where $\hat{f}$ can be regarded as the observation value of the current actual contact force f based on the current observation values $\hat{x}_e$ and $\hat{k}_e$. From (8) and (9), the objective of the precise observation values $\hat{x}_e$ and $\hat{k}_e$ is to render $\hat{f} \rightarrow f$ when $t \rightarrow \infty$; therefore, the control scheme can be proposed according to the observation objective. Substituting (7) into (9) with $\hat{f} = f$, the following formulation holds

$$f = \hat{k}_e x_c - \hat{k}_e \hat{x}_e = -\hat{k}_e(x_r - x_c) + f_d. \qquad (10)$$

According to the target impedance equation, it can be shown that

$$f_d - f = m\ddot{e} + b\dot{e} + ke. \qquad (11)$$

Substituting (10) into (11), it becomes

$$m\ddot{e} + b\ddot{e} + \left(k + k_e\right)e = 0, \qquad (12)$$

Therefore, the convergence of (12) guarantees $\hat{f} \to f$; subsequently, $f \to f_d$ or $k = -\hat{k}_e$, and setting the estimation limits as $\hat{k}_e > 0$ can easily avoid the latter situation. To achieve the desired force tracking, it is necessary to develop an adaptive scheme such that $\hat{x}_e$ and $\hat{k}_e$ can be estimated such that $\hat{f}$ converges to *f*. The observation values $\hat{x}_e$ and $\hat{k}_e$ are defined as

$$\begin{aligned} \dot{\hat{k}}_e &= -(\lambda_1 x + \lambda_2)(\hat{f} - f) \\ \dot{\hat{x}}_e &= \frac{\hat{f} - f}{\hat{k}_e}\left[(\lambda_1 \hat{x}_e + \lambda_2)x + \lambda_2 \hat{x}_e + \lambda_3\right] \end{aligned}, \qquad (13)$$

where λ_1, λ_2, and λ_3 are positive constants for parameter estimation. The stability of the observation scheme is described in Section C by a Lyapunov-based approach. Through estimating x_e and k_e, the adaptive reference trajectory can be obtained; thus, $\hat{f} \to f$ is guaranteed. However, the position tracking error always exists, implying that the hypothesis $x_c = x$ is not satisfied generally. If we denote the steady-state position tracking error Δx as

$$\Delta x = x_c - x\,, \qquad (14)$$

it is easy to determine the force error Δf because the position tracking error is equal to $k_e \Delta x$. To improve the force tracking performance, the ILC algorithm is adopted in this study to reduce the position tracking error. The ILC algorithm can handle highly uncertain dynamic systems simply and does not depend on the exact mathematical model of the dynamic system; further, it does not require a large amount of prior knowledge and calculation. The ILC scheme is written as

$$u_{f,i}(t) = u_{f,i-1}(t) + k_0 \Delta f_{i-1}(t + t_f)\,, \qquad (15)$$

where $u_{f,i}(t)$, $u_{f,i-1}(t)$, and $\Delta f_{i-1}(t+t_f)$ are the force control inputs at time *t* in the *i*-th cycle, (*i*-1)-th cycle, and the force tracking error at time $t+t_f$ in (*i*-1)-th cycle, respectively. The parameters k_0 and t_f are positive constants, and t_f represents the leading phase. The convergence condition for this ILC scheme is as shown in (16), and its stability will be proven in Section C.

$$\left|1 - \frac{k_e k_0 G_c(j\omega) G_p(j\omega)}{1 + G_c(j\omega) G_p(j\omega)} e^{\Delta j\omega}\right| < 1\,, \qquad (16)$$

where G_c and G_p are the transfer functions of the position controller and robot, respectively. Figure 2 shows the structure of the adaptive position-based impedance control with the iterative learning scheme.

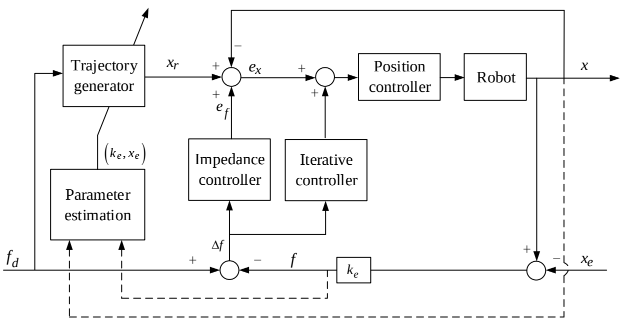

Fig. 2. Position-based impedance control scheme with iterative learning algorithm

C. Stability of Impedance Control with Iterative Learning Scheme

The form of the proposed method is given in (13) and (15). The convergence condition and stability analysis are presented below to prove that the force tracking error will converge to zero. The Lyapunov function and frequency domain method were used in this study.

First, the stability of the adaptive reference trajectory generator is given. Let $\phi_k = \hat{k}_e - k_e$, $\phi_x = \hat{k}_e \hat{x}_e - k_e x_e$, and $\phi = [\phi_k \quad \phi_x]^T$. Subsequently, substituting them into (8) and (9) yields

$$\hat{f} - f = [x_c \quad 1]\phi, \qquad (17)$$

To analyze the stability, we define the positive scalar Lyapunov function candidates as

$$V = \phi^T \Gamma \phi, \qquad (18)$$

where Γ is a 2 × 2 symmetric positive-definite constant matrix. Subsequently, we define the $\dot{\phi}$ as the following:

$$\dot{\phi} = -\Gamma^{-1}\begin{bmatrix} x_c \\ -1 \end{bmatrix}\left(\hat{f} - f\right). \qquad (19)$$

By substituting (17) and (19) into the derivative of (18), we have

$$\dot{V} = 2\phi^T \Gamma \dot{\phi} = -2\phi^T \begin{bmatrix} x_c \\ -1 \end{bmatrix}\left(\hat{f} - f\right) = -2\left(\hat{f} - f\right)^2, \qquad (20)$$

which is a negative semidefinite. (18) and (20) suggest that a suitable adjustment of ϕ according to (19) can render $\hat{f} \to f$ as $t \to \infty$. From (17), the simple scheme to adjust ϕ is to adapt $\hat{x}_e$ and $\hat{k}_e$. It is noteworthy that Γ is specified as

$$\Gamma = \begin{bmatrix} \lambda_1 & -\lambda_2 \\ -\lambda_2 & \lambda_3 \end{bmatrix} \qquad (21)$$

Subsequently, the observation values $\hat{x}_e$ and $\hat{k}_e$ can be formulated as (13).

Next, the iterative learning control scheme will be proven in frequency domain. From Fig. 2, the following formulation holds

$$\begin{aligned} E_{x,i+1}(s) &= X_r(s) - X_{i+1}(s) \\ &= X_r(s) - (X_{x,i+1}(s) + U_{f,i+1}(s))G_c(s)G_p(s) \end{aligned}, \qquad (22)$$

where $E(s)$, $X(s)$, and $U(s)$ are the Laplace transforms of $e(t)$, $x(t)$, and $u(t)$. That is

$$E_{x,i+1}(s) = \frac{X_r}{1+G_cG_p} - \frac{U_{f,i+1}(s)G_cG_p}{1+G_cG_p}. \qquad (23)$$

Substituting Laplace transform of (15) into (23), it becomes

$$
\begin{aligned}
E_{x,i+1}(s) &= \frac{X_r}{1+G_cG_p} - \frac{(U_{f,i}(s)+k_0e^{\Delta s}\Delta F_i)G_cG_p}{1+G_cG_p} \\
&= E_{x,i}(s) - \frac{k_0G_cG_pe^{\Delta s}\Delta F}{1+G_cG_p}
\end{aligned}
\quad . \tag{24}
$$

The force tracking error caused by the position tracking error can be written as

$$
\Delta F_{i+1}(s) = k_eE_{x,i+1}(s)\,, \tag{25}
$$

where k_e is the environment stiffness. Substituting (24) into (25) yields

$$
\begin{aligned}
\Delta F_{i+1}(s) &= k_eE_{x,i}(s) - \frac{k_ek_0G_cG_pe^{\Delta s}\Delta F_i}{1+G_cG_p} \\
&= \Delta F_i(s) - \frac{k_ek_0G_cG_pe^{\Delta s}\Delta F_i}{1+G_cG_p}
\end{aligned}
\tag{26}
$$

Further,

$$
\Delta F_{i+1}(s) = (1 - \frac{k_ek_0G_cG_p}{1+G_cG_p}e^{\Delta s})\Delta F_i(s)\,, \tag{27}
$$

where ΔF is the Laplace transform of Δf . From (27), it is easy to obtain the convergence condition as (16). The proof is completed.

D. SIMULATION STUDIES AND EXPERIMENTAL RESULTS

D.1 Simulation

The proposed force tracking impedance control via the iterative learning algorithm is simulated based on the MATLAB/Simulink software. To discuss the adaptive reference trajectory generation scheme and the iterative learning control algorithm, some comparison simulations are performed. Both adaptive reference generation methods are shown in (7) and (13), and the iterative learning scheme shown in (15) was used. The block diagram of the simulation is illustrated in Fig. 3.

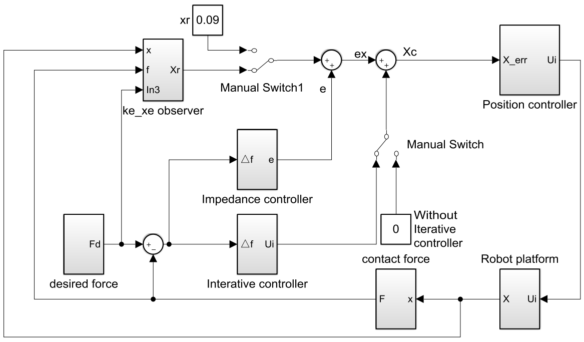

Fig. 3. Simulation block diagram.

The contact environment in the simulation is an elastic plane, and the environment location x_e= 0.1 mm, and the fixed reference trajectory x_r = 0.09 mm indicates that the robot end-effector is not in contact with the environment at the initial time. The constant parameters in (15) are set to $k_0 = 7 \times 10^6$ and t_f = 1; the impedance parameters m = 50, b = 1500, k = 500, f_d = 20 N; the parameters in (13) are $\lambda_1 = 1$, $\lambda_2 = 15$, $\lambda_3 = 1$. Abrupt changes in the environment stiffness are considered to test the robustness of the proposed control scheme. The variable environment stiffness is shown as follows:

$$k_e = \begin{cases} 1500(N/mm), 0 < t \le 15 \\ 2500(N/mm), 15 < t \le 30 \\ 4000(N/mm), 30 < t \le 45 \end{cases}, \qquad (28)$$

With the fixed reference trajectory x_r = 0.09 mm, Fig. 4 shows the position tracking result and contact force response on a plane. The lower subfigure shows that the robot end-effector moves from a free space to be in contact with the environment surface at 1.96 s, and that a large steady-state error exists. After analyzing the different positions in the upper subfigure, a conclusion can be drawn in that the fixed x_r is unsuitable because x_r cannot be calculated when it lacks accurate environment information. The conclusion coincides with the fact that, only when impedance parameter k = 0 or the accurate x_r is given can the steady-state zero force tracking error be achieved, as shown in (5). The result motives us to devise a useful reference trajectory generator to achieve an accurate force tracking.

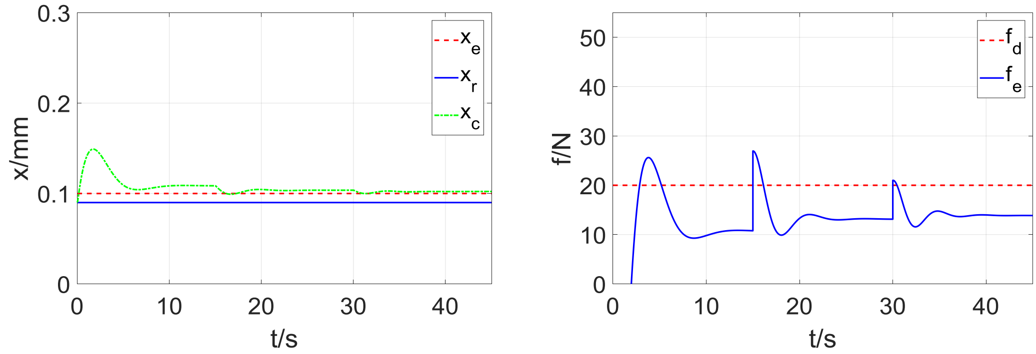

Fig. 4. Position tracking (upper) and contact force tracking (lower): constant impedance control with fixed x_r = 0.09 mm, without ILC algorithm, and m = 50, b = 1500, k = 500, f_d = 20 N.

Figure 5 shows position and contact force tracking results on a plane with variable x_r generated by the developed adaptive reference trajectory generator. Compared with the fixed x_r, by estimating the stiffness and position of the environment shown in (7) and (13), the proposed adaptive reference trajectory generation scheme produces a more accurate x_r and realizes better force tracking result as shown in Fig. 5. Additionally, the adaptive scheme provides effective robustness to the abruptly changing environment stiffness. From the lower subfigure, although the adaptive scheme renders the force tracking error to be close to zero, the steady-state force tracking error still exists. As shown in the upper subfigure, the primary cause of the residual force error is the position tracking error, which has been studied in subsection B.2.

To reduce the steady-state force tracking error caused by the position tracking error, an iterative learning control is combined with the former adaptive generator. The simulation results are shown in Fig. 6, and all the experimental conditions are the same as before but the iterative learning scheme is added. The constant parameter k_0 is set to 7×10^6 and t_f is set to 1. The simulation result is obvious. It is observed that the steady-state force tracking error is smaller than 0.01 N after adding the ILC algorithm. The lower subfigure shows that an overshoot appears during the transient process, and the overshoot appears to be slightly large. This is because, in this study, only to the force tracking control is emphasized when the robot is in contact with the environment; the overshoot during the transition between the free motion and constrained motion is not treated.

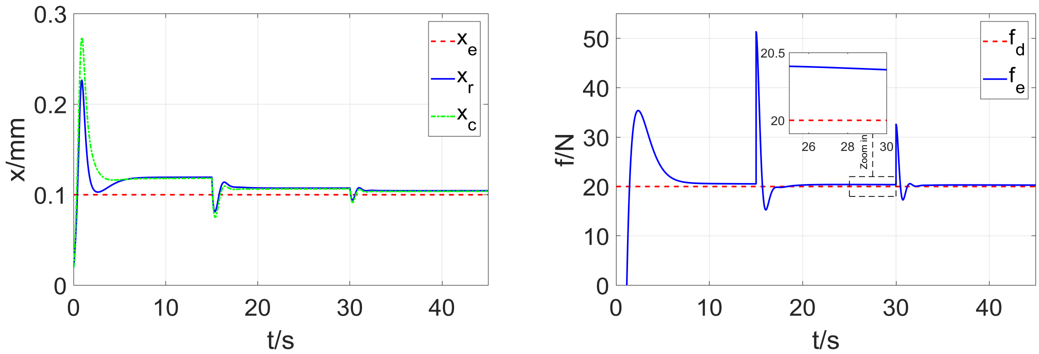

Fig. 5. Position tracking (upper) and contact force tracking (lower): constant impedance control with adaptive x_r, without ILC algorithm, and m = 50, b = 1500, k = 500, f_d = 20 N, λ_1 = 1, λ_2 = 15, λ_3 = 1

D.2 Experiment Results

Based on the impedance control, experiments were devised to demonstrate the performance of the adaptive reference trajectory generator and ILC algorithm. The experimental platform is a biaxial platform as shown in Fig. 7. An external PC was used to design the controllers in MATLAB/Simulink. The control system dSPACE DS1006 controller board runs programs in real time to generate a control command. An ATI Gama wrist force sensor (nominal capacity, F_z of 400 N, measurement uncertainty of 95% confidence level) collects the force information. The *Z*-axis moves to achieve a contact interaction in the position loop and the *X*-axis moves a plate at 2 mm/*s*, and both are driven by a Yasukawa ac servo motor with a 10 mm/*pitch* lead screw.

Two comparison tests were conducted in one experimental process. The experiment results are shown in Fig. 8, which are in accordance with the simulation studies. Only the force in the negative direction of the *Z*-axis was considered, and the impedance parameters were set to m = 50, b = 20, k = 60, the constant parameters λ_1= 0.5, λ_2= 0.1, λ_3= 0.6, the constant parameter of the iterative learning controller k_0 = 1.8 $\times 10^{-5}$, f_d =20 N, respectively.

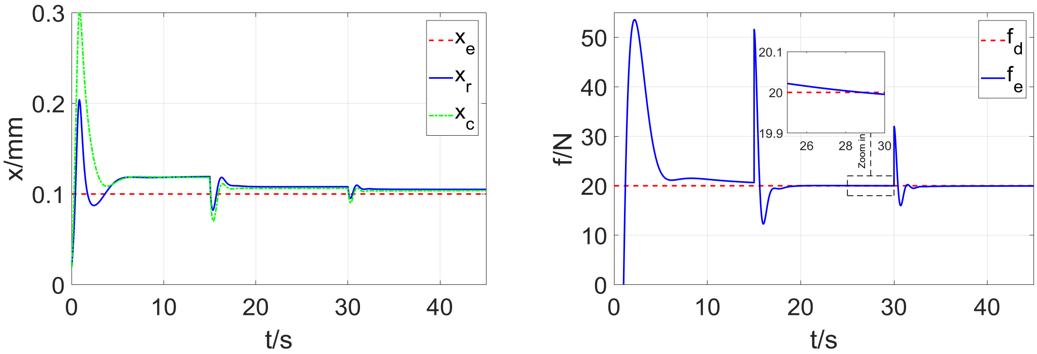

Fig. 6. Position tracking (upper) and contact force tracking (lower): constant impedance control with adaptive x_r and ILC algorithm, and m = 50, b = 1500, k = 500, f_d = 20 N, λ_1 = 1, λ_2 = 15, λ_3 = 1, k_0 = 7 × 106.

The first contrast test was set such that the end-effector was in contact with the plate, but the plate remained actionless during 0–72.5 *s*, and only the adaptive reference trajectory generator operated before 41 *s*. As shown, the steady-state force tracking error exists up to 0.95 N owing to the position tracking error $x_c \neq x$ in stage 1, as shown in Fig. 8. The result is consistent with the analysis in subsection B.2. The iterative learning algorithm was added during 41–72.5 s through a software switch and the plate was still motionless. Because the position tracking accuracy was compensated, the steady-state force tracking error was almost adjusted to 0 N in stage 2.

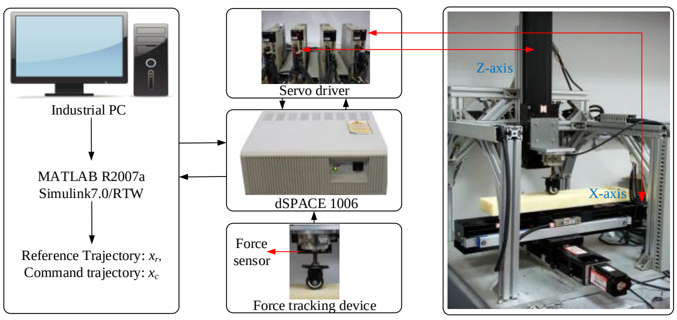

Fig. 7. Hardware architecture for plate-contact experiment

The second contrast test was to test the dynamic performance of the situations with or without the iterative learning algorithm. The plate continued moving during 72.5–132.5 s, as shown in Fig. 8. The adaptive reference trajectory generator and the iterative learning operated synergistically during 72.5–104.5 s, shown in stage 3, and the average of the tracking force is -20.0456 N. When the iterative learning algorithm was removed in 104.5 s with software switch, the average tracking force was -21.2558 N, as shown in stage 4. The comparative experimental results indicate that the iterative learning algorithm is effective in improving the force tracking accuracy.

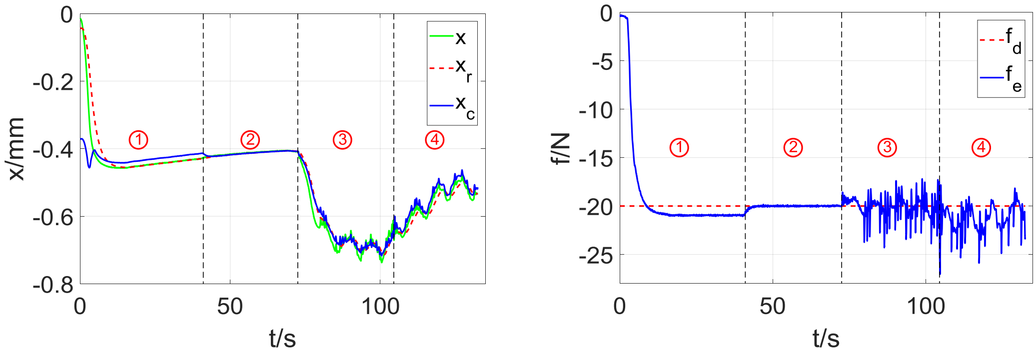

Fig. 8. Results of comparative experiments. Stage 1, fixed reference trajectory without ILC and the plate is actionless; stage 2, adaptive reference trajectory with ILC algorithm added and the plate is actionless; stage 3, adaptive reference trajectory with ILC algorithm added and the plate keeps moving; stage 4, adaptive reference trajectory is generated without ILC and the plate keeps moving.

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