SCIENCE CHINA
Information Sciences

• LETTER •

May 2019, Vol. 62 050215:1–050215:3
https://doi.org/10.1007/s11432-018-9769-8

Special Focus on Human-Robot Hybrid Intelligence

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

Xiuquan LIANG, Huan ZHAO*, Xiangfei LI & Han DING

State Key Laboratory of Digital Manufacturing Equipment and Technology, Huazhong University of Science and Technology, Wuhan 430074, China

Received 26 August 2018/Revised 2 November 2018/Accepted 17 December 2018/Published online 20 March 2019

Citation Liang X Q, Zhao H, Li X F, et al. Force tracking impedance control with unknown environment via an iterative learning algorithm. Sci China Inf Sci, 2019, 62(5): 050215, https://doi.org/10.1007/s11432-018-9769-8

Dear editor,

Force tracking control is important for constrained operations. In recent years, impedance control is garnering increasing attention in robot force control. 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 in [1, 2]. Further improvement was performed in [3]. However, the hypothesis of the null stiffness does not conform to the intuitive force tracking rules that humans always maintain stiffness when exerting the desired force on objects. Hence, a new variable target stiffness impedance control method was proposed [4]. Furthermore, a direct reference trajectory generation method based on force tracking error, and an indirect adaptive method by observing the environment stiffness and location to obtain reference trajectory were provided in [5]. Although an accurate reference trajectory has been calculated, robot position tracking error will primarily affect force tracking performance such as steady-state error, which is generally neglected. Using information from previous experiments repeatedly, iterative learning control is a highly simple and useful method to improve motion trajectory tracking accuracy to obtain the desired output [6]. In addition, some novel adaptive iterative algorithms to improve robotic trajectory tracking accuracy were reported in [7].

Within the impedance control framework, an adaptive force control scheme combined with an iterative learning algorithm is developed in this study. The primary purpose of this study is to estimate the environment stiffness and location in real time to induce observed force to converge to the desired ones. Consequently, an accurate reference trajectory will be acquired. Based on the force tracking error, the iterative learning algorithm is used to guarantee the trajectory tracking accuracy. The proposed method is robust to unknown environments, and simple to reduce steady-state errors caused by trajectory tracking error.

Position-based impedance control. Position-based impedance control consists of both inner position control loop and outer indirect force tracking loop. Owing to independent Cartesian variables, lower-case scalars x and f are used to represent any element of vectors X and F. The details are shown in [3]. The steady-state force tracking error can be expressed as

$$\Delta f_{\rm ss} = \frac{k}{k+k_e}[f_d - k_e(x_r - x_e)]. \tag{1}$$

From (1), 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 $\Delta f_{\rm ss}$ is always satisfied for any k_e; the other is to render the reference trajectory satisfying

$$x_r = x_e + \frac{f_d}{k_e}. \tag{2}$$

Null stiffness is unreasonable. One reason is that the impedance parameter k is closely related

* Corresponding author (email: huanzhao@hust.edu.cn)

to the natural frequency and damping ratio of the linear second-order system [8]. Additionally, the fact that humans exert force on an object through adapting arm stiffness cannot be ignored [4]. From (2), it is suitable to online estimate the environmental parameters x_e and k_e. Reference trajectory x_r can be computed indirectly. The reference trajectory generator can be devised with appealing simplicity and strong robustness.

Impedance control with iterative learning algorithm. First, the online estimation of environment stiffness and location helps to generate x_r. Subsequently, iterative learning contributes to $x \to x_r$. The x_r could be computed accurately if x_e and k_e are known exactly. However, owing to the complexity of contact environment, it is difficult to obtain accurate environment information in practice. One available approach is to calculate observation values $\hat{x}_e$ and $\hat{k}_e$ approximately; therefore, based on (2), x_r can be expressed as

$$x_r = \hat{x}_e + \frac{f_d}{\hat{k}_e}, \tag{3}$$

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 the robot manipulates, i.e., $x_c = x$; subsequently, the contact force can be written as

$$f = k_e(x_c - x_e) = k_e x_c - k_e x_e. \tag{4}$$

Consider the definition

$$\hat{f} = \hat{k}_e(x_c - \hat{x}_e) = \hat{k}_e x_c - \hat{k}_e \hat{x}_e, \tag{5}$$

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 (4) and (5), the objective of precise observation values $\hat{x}_e$ and $\hat{k}_e$ is to generate $\hat{f} \to f$ when $t \to \infty$; therefore, a control scheme can be proposed according to the observation objective. Substituting (3) into (5) with $\hat{f} = f$, the following formulation holds:

$$f = \hat{k}_e x_c - \hat{k}_e \hat{x}_e = -\hat{k}_e(x_r - x_c) + f_d. \tag{6}$$

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

$$f_d - f = m\ddot{e} + b\dot{e} + ke, \tag{7}$$

where $e = x_c - x_r$. Substituting (6) into (7), it becomes

$$m\ddot{e} + b\dot{e} + (k + \hat{k}_e)e = 0. \tag{8}$$

Therefore, the convergence of (8) guarantees $\hat{f} \to f$; subsequently, $f \to f_d$ or $k = -k_e$. 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

$$\begin{aligned} \dot{\hat{k}}_e &= -(\lambda_1 x + \lambda_2)(\hat{f} - f), \\ \dot{\hat{x}}_e &= \frac{\hat{f} - f}{\hat{k}_e}[(\lambda_1 \hat{x}_e + \lambda_2)x + \lambda_2 \hat{x}_e + \lambda_3], \end{aligned} \tag{9}$$

where λ_1, λ_2, and λ_3 are positive constants for parameter estimation. Through estimating x_e and k_e, the adaptive reference trajectory will be obtained; thus, $\hat{f} \to f$ can be obtained. However, a position tracking error always exists, implying that the hypothesis $x_c = x$ is not satisfied generally. If we define the steady-state position tracking error Δx as $\Delta x = x_c - x$, it is easy to determine that the force error $\Delta f = k_e \Delta x$. To improve the force tracking performance, the iterative learning control (ILC) algorithm is adopted to reduce the position tracking error. The ILC algorithm can handle highly uncertain dynamic systems simply, does not depend on the exact mathematical model of the dynamic system, and does not require a large amount of prior knowledge and calculation. The ILC scheme is written as follows:

$$u_{f,i}(t) = u_{f,i-1}(t) + k_0 \Delta f_{i-1}(t + t_f), \tag{10}$$

where $u_{f,i}(t)$, $u_{f,i-1}(t)$, and $\Delta f_{i-1}(t + t_f)$ are the force control input at time t in the i-th cycle, $(i-1)$-th cycle, and the force tracking error at time $t + t_f$ in the $(i-1)$-th cycle, respectively. t_f denotes the leading phase. The parameters k_0 and t_f are positive constants. The convergence condition for this ILC scheme is as shown in

$$\left| 1 - \frac{k_e k_0 G_c(\mathrm{j}\omega) G_p(\mathrm{j}\omega)}{1 + G_c(\mathrm{j}\omega) G_p(\mathrm{j}\omega)} \mathrm{e}^{\Delta \mathrm{j}\omega} \right| < 1, \tag{11}$$

where G_c and G_p are the transfer functions of the position controller and robot, respectively.

Stability of impedance control with iterative learning scheme. The form of the proposed method is given in (9) and (10). The convergence condition and stability analysis are given below to prove that the force tracking error will converge to zero. The Lyapunov function and frequency domain method are 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 $\phi = [\phi_k \ \phi_x]^{\mathrm{T}}$. Subsequently, substituting them into (4) and (5), it can be obtained that

$$\hat{f} - f = [x_c \ -1]\phi. \tag{12}$$

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

$$V = \phi^{\mathrm{T}}\Gamma\phi, \tag{13}$$

where Γ is a 2×2 symmetric positive-definite constant matrix. Subsequently, $\dot{\phi}$ can be specified as

$$\dot{\phi} = -\Gamma^{-1}\begin{bmatrix} x_c \\ -1 \end{bmatrix}(\hat{f}-f). \tag{14}$$

By substituting (12) and (14) into the derivative of (13), we have

$$\dot{V} = 2\phi^{\mathrm{T}}\Gamma\dot{\phi} = -2\phi^{\mathrm{T}}\begin{bmatrix} x_c \\ -1 \end{bmatrix}(\hat{f}-f) = -2(\hat{f}-f)^2, \tag{15}$$

which is a negative semidefinite. Eqs. (13) and (15) suggest that the suitable adjustment of ϕ according to (14) can render $\hat{f}\to f$ as $t\to\infty$. From (12) and (14), the simple scheme to adjust ϕ is to adapt $\hat{x}_e$ and $\hat{k}_e$. It is noteworthy that Γ is specified as $\Gamma = [\begin{smallmatrix} \lambda_1 & -\lambda_2 \\ -\lambda_2 & \lambda_3 \end{smallmatrix}]$. Subsequently, the observation values $\hat{x}_e$ and $\hat{k}_e$ can be formulated as (9).

Next, the block diagram of our iterative learning control can be found in Appendix D. In our methods, the following formulation holds: $E_{x,i+1}(s) = X_r(s) - X_{i+1}(s) = X_r(s) - (X_{x,i+1}(s) + U_{f,i+1}(s))G_c(s)G_p(s)$, where $E(s)$, $X(s)$, and $U(s)$ are the Laplace transforms of $e(t)$, $x(t)$, and $u(t)$, respectively. That is,

$$E_{x,i+1}(s) = \frac{X_r}{1+G_cG_p} - \frac{U_{f,i+1}(s)G_cG_p}{1+G_cG_p}. \tag{16}$$

Substituting the Laplace transform of (10) into (16) yields

$$\begin{aligned} E_{x,i+1}(s) &= \frac{X_r}{1+G_cG_p} - \frac{(U_{f,i}(s)+k_0\mathrm{e}^{\Delta s}\Delta F_i)G_cG_p}{1+G_cG_p} \\ &= E_{x,i}(s) - \frac{k_0G_cG_p\mathrm{e}^{\Delta s}\Delta F_i}{1+G_cG_p}. \end{aligned} \tag{17}$$

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

$$\Delta F_{i+1}(s) = k_eE_{x,i+1}(s), \tag{18}$$

where k_e is the environment stiffness. Substituting (17) into (18) yields

$$\begin{aligned} \Delta F_{i+1}(s) &= k_eE_{x,i}(s) - \frac{k_ek_0G_cG_p\mathrm{e}^{\Delta s}\Delta F_i}{1+G_cG_p} \\ &= \Delta F_i(s) - \frac{k_ek_0G_cG_p\mathrm{e}^{\Delta s}\Delta F_i}{1+G_cG_p}, \end{aligned} \tag{19}$$

and then it becomes

$$\Delta F_{i+1}(s) = \left(1 - \frac{k_ek_0G_cG_p}{1+G_cG_p}\mathrm{e}^{\Delta s}\right)\Delta F_i(s), \tag{20}$$

where $\Delta F(s)$ is the Laplace transform of Δf. From (20), it is easy to gain the convergence condition as (11). The proof is completed.

Simulation studies and experimental results. Details are presented in Appendix D.

Conclusion. Within the impedance control framework, an adaptive scheme was developed to generate the reference trajectory and improve the force tracking performance by using an iterative learning algorithm. First, an adaptive scheme was used to estimate the environment stiffness and location such that an accurate reference trajectory could be obtained. Subsequently, based on the iterative learning algorithm, the force tracking performance was further improved by compensating the position tracking error. The proposed force tracking scheme is simple and useful, and can be applied in practical robot constrained operation where the environment parameters are generally unknown.

Acknowledgements This work was supported by National Key Research and Development Program of China (Grant No. 2017YFB1303401) and National Natural Science Foundation of China (Grant Nos. 91748114, 51535004, 51705175).

Supporting information Appendix A–D. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

References

1 Jung S, Hsia T C, Bonitz R G. Force tracking impedance control for robot manipulators with an unknown environment: theory, simulation, and experiment. Int J Robot Res, 2001, 20: 765–774
2 Jung S, Hsia T C, Bonitz R G. Force tracking impedance control of robot manipulators under unknown environment. IEEE Trans Control Syst Technol, 2004, 12: 474–483
3 Duan J J, Gan Y H, Chen M, et al. Adaptive variable impedance control for dynamic contact force tracking in uncertain environment. Robot Auton Syst, 2018, 102: 54–65
4 Lee K, Buss M. Force tracking impedance control with variable target stiffness. IFAC Proc Volumes, 2008, 41: 6751–6756
5 Seraji H, Colbaugh R. Force tracking in impedance control. Int J Robot Res, 1997, 16: 97–117
6 Arimoto S, Kawamura S, Miyazaki F. Bettering operation of robots by learning. J Robot Syst, 1984, 1: 123–140
7 Tayebi A. Adaptive iterative learning control for robot manipulators. Automatica, 2004, 40: 1195–1203
8 Mallapragada V, Erol D, Sarkar N. A new method of force control for unknown environments. Int J Adv Robot Syst, 2007, 4: 34