Design and Experiments of Anticipatory Learning Control: Frequency-Domain Approach

Danwei Wang, *Member, IEEE,* and Yongqiang Ye

***Abstract*—A frequency-domain design is presented for the anticipatory learning control. Convergence conditions are derived in terms of two design parameters, the lead-time and the learning gain. For minimum phase systems, the design of the anticipatory learning control in the frequency domain is decoupled into a two-step procedure. The design is robust against uncertainties in system modeling. The effectiveness of the anticipatory learning control is demonstrated by an example and experiments. Comparisons of the anticipatory learning control with the conventional P-type, D-type, and PD-type learning control highlight the differences between these close yet distinctive approaches.**

***Index Terms*—Anticipatory learning control, design, frequency-domain, iterative learning control (ILC).**

I. Introduction

THE FIRST academic paper to the idea of iterative learning control (ILC) is by Uchiyama [1] published in 1978. Because it was published in a Japanese journal, this paper did not arouse wide attentions. It was not until 1984 that a research area of ILC was formed. In 1984, Arimoto *et al.* [2], Casalino and Bartonili [3], and Craig [4] simultaneously and independently published papers about a method that could iteratively compensate for model errors and disturbances. One paper worth mention is [5], which is also a very early work. Since then, a large amount of research results have been published and many sophisticated ILC laws have been proposed. However, ILC is a relatively new area and it is yet to be fully understood. Recent papers [6], [7] reexamine the basic approaches and propose some new ILC laws that are simple in form but new in concept.

In [2], [8], the input update utilizes the derivative signals of the previous error signal and the learning law is termed D-type ILC. In D-type ILC, tracking error differentiation is needed, which may bring in noise. Another class of learning control, P-type ILC [9]–[12], requires only measurements of state variables, which are normally available and less noisy but have no anticipatory information of tracking error. Another, a scheme in between P-type and D-type is a fractional order ILC law in which the fractional order derivative (with transfer function s^{α}) of tracking error is employed—"D^{α}-type" where $\alpha \in (0,1]$ [6]. In [6], the necessity of phase lead to compromise or dilute the low pass characteristics of the plant is highlighted through convergence analysis on P-type, D-type, and D^{α}-type ILCs in the frequency-domain. It is pointed out that D-type ILC fulfills the argument of phase advancement (lead) whereas P-type does not.

Recently, an anticipatory learning scheme (A-type) was proposed in [7] based on the fact that an input $u(t)$ at time t to a dynamic system is causally paired with its output $y(t+\Delta)$ at time $t+\Delta$. Its discrete-time counterpart is the linear phase lead learning control [13]–[16]. It is a simple ILC that uses tracking error with a lead-time $\triangle$ as follows:

$$u_j(t) = u_{j-1}(t) + L(e_{j-1}(t+\triangle)). \tag{1}$$

A-type ILC has the anticipative nature and requires only position measurements that have low noise levels. In [7], tracking error convergence results are established in the time domain, with convergence proofs, under the presence of uncertainties, disturbances, and measurement noise. In this paper, we address the frequency-domain analysis and design of A-type ILC. Convergence conditions are derived in the frequency-domain and the design procedure is explicitly outlined. Applications to robotic manipulators are studied and experimental results are presented to support the theory and illustrate the effectiveness of the proposed scheme. Furthermore, P, D, PD, and A-type ILCs are compared in the frequency-domain designs and in the experimental results.

II. Convergence Analysis

Consider a system modeled by a Single-input Single-output continuous time invariant linear state space equation

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + w(t) \\ y(t) = Cx(t) + v(t) \end{cases} \tag{2}$$

where x is a n-dimensional state vector, u is scalar input, and y is scalar output; w and v represent deterministic state and output disturbances, respectively, that appear every repetition. This dynamics can represent a plant with or without feedback control. The Laplace transform of the output for the jth repetition is

$$\begin{aligned} Y_j(s) = G_p(s)U_j(s) + C(sI-A)^{-1}x(0) \\ + C(sI-A)^{-1}W(s) + V(s) \end{aligned} \tag{3}$$

where $G_p(s) = C(sI-A)^{-1}B$ is the input–output transfer function and $x(0)$ is the initial state position that is assumed to be the same for each repetition. The tracking error of the jth repetition is $E_j(s) = Y_d(s) - Y_j(s)$, where $Y_d(s)$ is the Laplace transform of a desired output $y_d(t)$ defined over a finite time interval $[0,T]$. Consider the A-type learning compensator in (1) chosen in a simple linear form

$$u_j(t) = u_{j-1}(t) + ke_{j-1}(t+\triangle) \tag{4}$$

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D. Wang is with the School of Electrical and Electronics Engineering, Nanyang Technological University, Singapore 639798 (e-mail: edwwang@ntu.edu.sg).

Y. Ye was with the School of Electrical and Electronics Engineering, Nanyang Technological University, Singapore 639798. He is now with the School of Information, Zhejiang University of Finance and Economics, Hangzhou 310012, China (e-mail: yongqiang_leaf@hotmail.com).

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where $\triangle > 0$ is the lead time and $k > 0$ is the learning gain. A Laplace transform of this linear A-type learning controller is

$$U_j(s) = U_{j-1}(s) + ke^{\triangle s}E_{j-1}(s). \tag{5}$$

Using (3) and (5), we get

$$\begin{aligned} Y_j(s) - Y_{j-1}(s) &= G_p(s)[U_j(s) - U_{j-1}(s)] \\ &= ke^{\triangle s}G_p(s)E_{j-1}(s). \end{aligned}$$

On the other hand

$$Y_j(s) - Y_{j-1}(s) = -[E_j(s) - E_{j-1}(s)].$$

Thus

$$E_j(s) = [1 - ke^{\triangle s}G_p(s)]E_{j-1}(s). \tag{6}$$

Similar to [6], [13], [17]–[19], the condition for the tracking error frequency components to converge is given by

$$|1 - ke^{j\triangle\omega}G_p(j\omega)| < 1. \tag{7}$$

The frequency-domain convergence condition is a sufficient condition for convergence though learning control is a finite time problem [20].

The frequency response can be expressed as $G_p(j\omega) = N_p(\omega)\exp(j\theta_p(\omega))$ with $N_p(\omega)$ and $\theta_p(\omega)$ being its magnitude characteristics and phase characteristics, respectively. The convergence condition (7) becomes

$$\left|1 - kN_p(\omega)e^{j(\theta_p(\omega)+\triangle\omega)}\right| < 1. \tag{8}$$

Or, equivalently

$$\begin{aligned} &|1 - kN_p(\omega)\cos(\theta_p(\omega) + \triangle\omega) \\ &\quad - jkN_p(\omega)\sin(\theta_p(\omega) + \triangle\omega)| < 1. \end{aligned}$$

Using the norm definition and taking the square on both sides, the above inequality is equivalent to

$$k^2N_p(\omega) < 2k\cos(\theta_p(\omega) + \triangle\omega). \tag{9}$$

We summarize the above development into the following theorem.

Theorem: Consider the ILC system with dynamics (2) and an A-type learning controller (4). A sufficient condition for tracking error convergence is that the lead time $\triangle > 0$ and the learning gain $k > 0$ are chosen so that the following inequality holds, for all $\omega \in [0, +\infty)$,

$$kN_p(\omega) < 2\cos(\theta_p(\omega) + \triangle\omega). \tag{10}$$

Remark 1: For (10) to hold, it is necessary that, for all $\omega \in [0, +\infty)$,

$$|\theta_p(\omega) + \triangle\omega| < 90^\circ. \tag{11}$$

For most systems, these two conditions cannot be guaranteed for all frequencies $\omega \in [0, +\infty)$. The frequency range within which the convergence conditions hold is termed the *learnable band*. We cut off the frequencies outside the learnable band to prevent the bad learning transient [13]. Thus, the wider the learnable bandwidth, the more precise the tracking of the actual output to the desired output.

Remark 2: The convergence analysis for general ILC laws can be found in [19] and [21], etc., whereas in our paper, the analysis is on the specific A-type law and concrete design procedures are outlined and parameter selection criteria are given. The aim of our paper is to provide an engineering design procedure or a guideline for self-tuning for A-type ILCs.

III. Design of A-Type ILCs

Note that (11) involves only one design parameter $\triangle$ and (10) involves both parameters $\triangle$ and k. Thus the lead-time $\triangle$ will be chosen first based on (11) and the learning gain k can be chosen then based on (10). In the meantime, selections of these two parameters should secure the best learnable bandwidth ω_{lbw} as much as possible.

A. Lead-Time Selection

Rewrite the system model as, $n > m$

$$G_p(s) = \frac{b_ms^m + b_{m-1}s^{m-1} + \cdots + b_1s + b_0}{s^n + a_{n-1}s^{n-1} + \cdots + a_1s + a_0}.$$

If it is a minimum phase process, the phase characteristics $\theta_p(\omega)$ are bounded and approach $-(n-m) \times 90^\circ$ as $\omega \to \infty$. If $(n-m) \geq 2$ and as $\omega \to \infty$, condition (11) cannot be satisfied for all frequencies and will be violated after the frequency $\bar{\omega}$ at which $|\theta_p(\bar{\omega}) + \triangle\bar{\omega}| = 90^\circ$. This frequency $\bar{\omega}$ is a function of the lead-time $\triangle$. The lead-time $\triangle$ should be chosen to maximize the frequency $\bar{\omega}$ subject to $|\theta_p(\omega) + \triangle\omega| < 90^\circ$, i.e.,

$$\max_{\triangle}\{\bar{\omega} : |\theta_p(\omega) + \triangle\omega| < 90^\circ, \forall\omega < \bar{\omega}\}. \tag{12}$$

B. Gain Selection

With the selected lead-time $\triangle$, the learning gain k should be chosen to satisfy condition (10) and to maximize the learnable bandwidth ω_{lbw}. The right side, $2\cos(\theta_p(\omega) + \triangle\omega)$, of condition (10) is fixed with a chosen $\triangle$ and approaches zero as ω increases toward $\bar{\omega}$.

The left side, $kN_p(\omega)$, also approaches zero as $\omega \to \infty$. The learning gain k should be chosen such that the curve for $kN_p(\omega)$ is below the curve for $2\cos(\theta_p(\omega) + \triangle\omega)$ and the crossing of these two curves is close to the frequency $\bar{\omega}$ as much as possible.

C. Robustness in Design

In general, the system model $G_p(s)$ contains uncertainties and these uncertainties will introduce an uncertainty in the frequency at which the plant phase crosses the -90° bound. The design parameters Δ and k have to be chosen under this consideration. One simple solution is to modify condition (11) as

$$|\theta_p(\omega) + \triangle\omega| \leq 90^\circ - \epsilon \tag{13}$$

for a positive constant $\epsilon > 0$. The value of ϵ reflects the modeling uncertainties. The other effects of this remedy are a smaller $\bar{\omega}$ and a larger k.

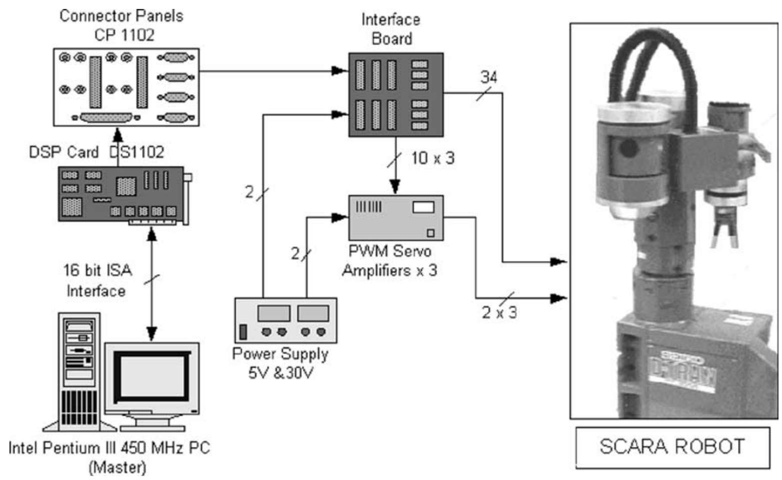

Fig. 1. Robot control system.

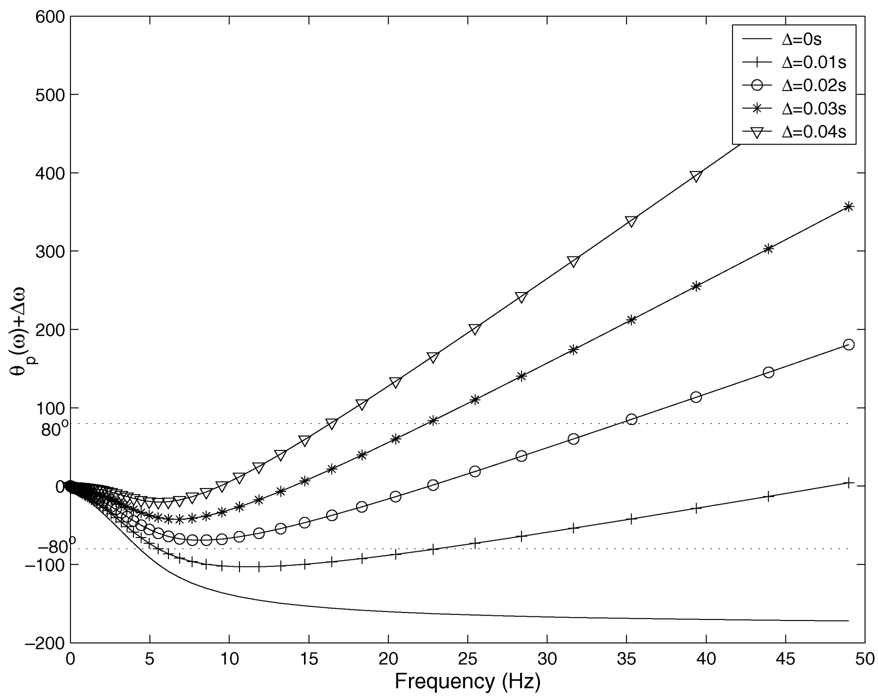

Fig. 2. Lead-time selection for joint 3.

For these two design parameters, [14] and [16] develop self-tuning laws to tune them empirically for convergence or better convergence. The contribution of our design procedure is that it decouples the design of the lead time and the learning gain. Robustness is also explicitly considered. Moreover, the design results can serve as a guideline for self-tuning.

IV. Application to Robot Manipulators

Joints 2 and 3 of an industrial robot, Seiko TT3000 (a selective compliant assembly robot arm [SCARA] type) as in Fig. 1, control two links moving in a horizontal plane. Joints 2 and 3 are first stabilized by decentralized feedback P controllers with $k_{p2} = k_{p3} = 0.1$. Learning control is applied to the closed-loop systems independently. The closed-loop transfer functions of joints 2 and 3 can be approximated as

$$\begin{cases} G_{p2}(s) = \frac{416}{s^2+17.6s+416} & \text{Joint 2} \\ G_{p3}(s) = \frac{948}{s^2+42s+948} & \text{Joint 3.} \end{cases} \tag{14}$$

A. Learning Control Design

For conciseness, we only describe the design procedure for joint 3. The design procedure for joint 2 is similar and is thus omitted.

We choose the robustness threshold $\epsilon = 10^\circ$ in (13). Fig. 2 shows $\theta_p(\omega) + \triangle\omega$ for various values of the lead time, $\triangle = 0 \sim 0.04$ s. When $\triangle = 0$ s (corresponding to P-type ILC), $\theta_p(\omega)$ is negative, crosses the lower limit -80° at the frequency

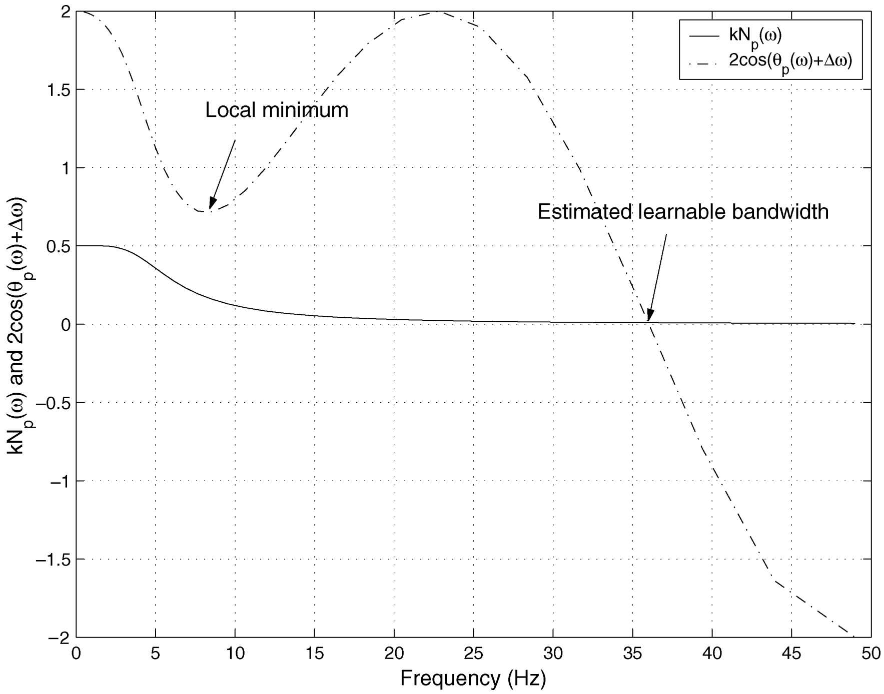

Fig. 3. Learning gain selection for joint 3.

4.2 Hz, and approaches -180° at high frequency. When the lead-time $\triangle > 0, \theta_p(\omega) + \triangle\omega$ first decreases and is negative and then increases due to the increasing compensation effect of $\triangle\omega$ as ω increases. The curve corresponding to $\triangle = 0.01$ s has a dip below the lower limit -80°, and thus (13) is violated at a low frequency around 5.5 Hz. For the cases $\triangle = 0.02$ s, 0.03 s, and 0.04 s, the dips are above the lower limit -80° and all curves cross the upper limit $+80^\circ$. But $\triangle = 0.02$ s offers the highest crossing frequency. Thus lead-time $\triangle = 0.02$ s is chosen because it offers the highest frequency $\bar{\omega}$ among the tested lead-time values.

Fig. 3 plots $2\cos(\theta_p(\omega) + \triangle\omega)$ with $\triangle = 0.02$ s. Note it has one local minimum at about $\omega_1 = 7$ Hz before the curve decreases to zero for the first time at about 19 Hz. The learning gain k is chosen as 0.5 such that $kN_p(\omega)$ is well below the local minimum. The learnable bandwidth frequency ω_{lbw} is the frequency at which $2\cos(\theta_p(\omega) + \triangle\omega)$ crosses $kN_p(\omega)$, and it is about 36 Hz. Similarly, $\triangle = 0.03$ s is selected for joint 2. Then the learning gain is set as $k = 0.5$ (Fig. 4).

B. Comparison of D-, P-, PD-, and A-Type ILCs

In this section, we will compare A-type with D-, P-, and PD-type laws and this may help to reveal other advanced ILC approaches based on these fundamental laws. D-type and P-type ILCs have been studied extensively in the literature and a comparison can be found in [7]. An A-type ILC is different from a P-type ILC because an A-type ILC has additional features offered by the lead-time $\triangle$. However, a P-type ILC can be viewed as a limiting case of an A-type ILC as $\triangle \to 0$

$$u_j(t) = u_{j-1}(t) + ke_{j-1}(t) \tag{15}$$

and its convergence condition is

$$|1 - kG_p(j\omega)| < 1. \tag{16}$$

A D-type ILC is known as

$$u_j(t) = u_{j-1}(t) + k\dot{e}_{j-1}(t) \tag{17}$$

and its convergence condition can be shown as

$$|1 - kj\omega G_p(j\omega)| < 1. \tag{18}$$

A PD-type ILC is

$$u_j(t) = u_{j-1}(t) + k_d\dot{e}_{j-1}(t) + k_pe_{j-1}(t). \tag{19}$$

Its convergence condition is

$$|1 - (k_dj\omega + k_p)G_p(j\omega)| < 1. \tag{20}$$

We have

$$e^{\triangle s} = 1 + \triangle s + \frac{\triangle^2 s^2}{2!} + \cdots. \tag{21}$$

If ignoring higher order terms starting from $\triangle^2 s^2/2!$, an A-type ILC is similar to a PD-type ILC at low frequency. But an A-type ILC needs no error differentiation.

We will examine the convergence conditions of joint 3 for an A-type ILC [with $\triangle = 0.02$ s and $k = 0.5$ in (4)], P-type ILC [with $k = 0.5$ and $\triangle = 0$ s in (4)], D-type ILC [with $k = 0.5 \times 0.02 = 0.01$ in (17)] and PD-type ILC [with $k_d = 0.01$ and $k_p = 0.5$ in (19), noting that $e^{0.02s} \approx 1 + 0.02s$]. Fig. 5 shows the convergence conditions for joints 3, i.e., the curves of $|1 - ke^{j\triangle\omega}G_p(j\omega)|$ [for A-type ILC (7)], $|1 - kj\omega G_p(j\omega)|$ [for D-type ILC (18)], $|1 - kG_p(j\omega)|$ [for P-type ILC (7) with $\triangle = 0$] and $|1 - (k_dj\omega + k_p)G_p(j\omega)|$ [for PD-type ILC (20)], respectively. The convergence conditions are satisfied for the

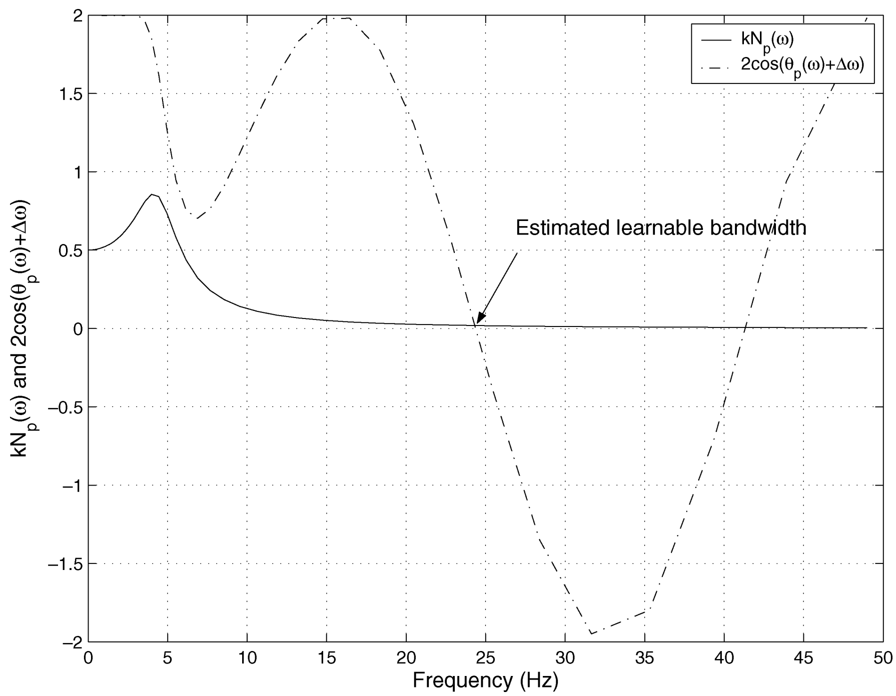

Fig. 4. A-type learning control design for joint 2.

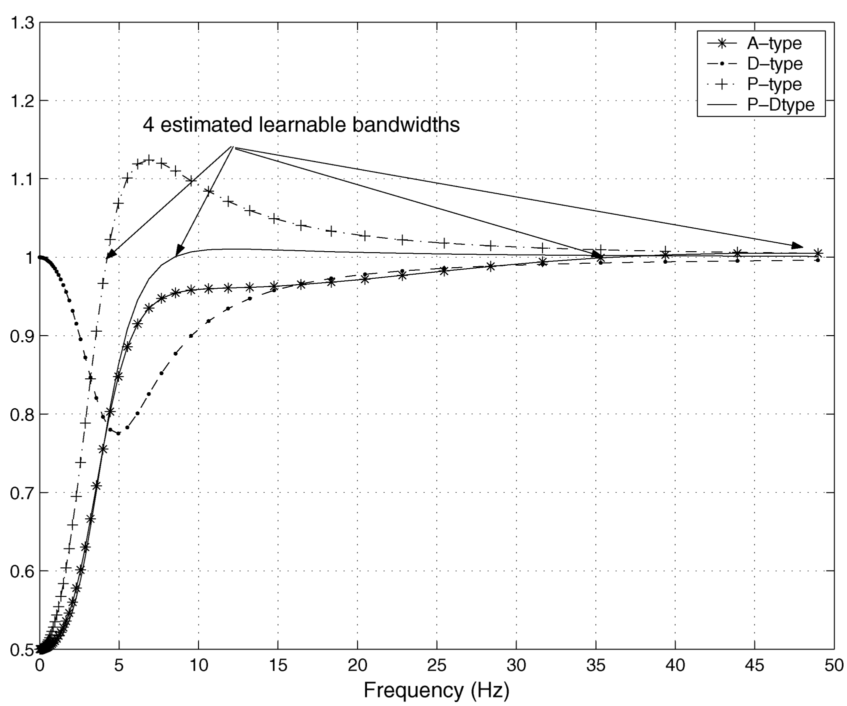

Fig. 5. Convergence conditions for A-, D-, P-, and PD-type ILCs, joint 3.

range in which the curves are between the limits of 0 and 1. It can be seen that the estimated learnable bands of A-type, D-type, P-type, and PD-type learning controllers are [0–36) Hz, (0–50) Hz, [0–4.2) Hz, and [0–8.4) Hz, respectively (the highest frequency being considered is 50 Hz). It seems that a D-type ILC can learn the whole frequency band. For a second-order plant, this may be true. But for a plant whose order is more than two, even if the learning gain of a D-type ILC is approaching 0, the highest learnable frequency cannot exceed the limit at which the phase characteristics of the plant are -180°. Also note that a D-type ILC cannot learn dc components and its convergence rate is poor at both low frequency and

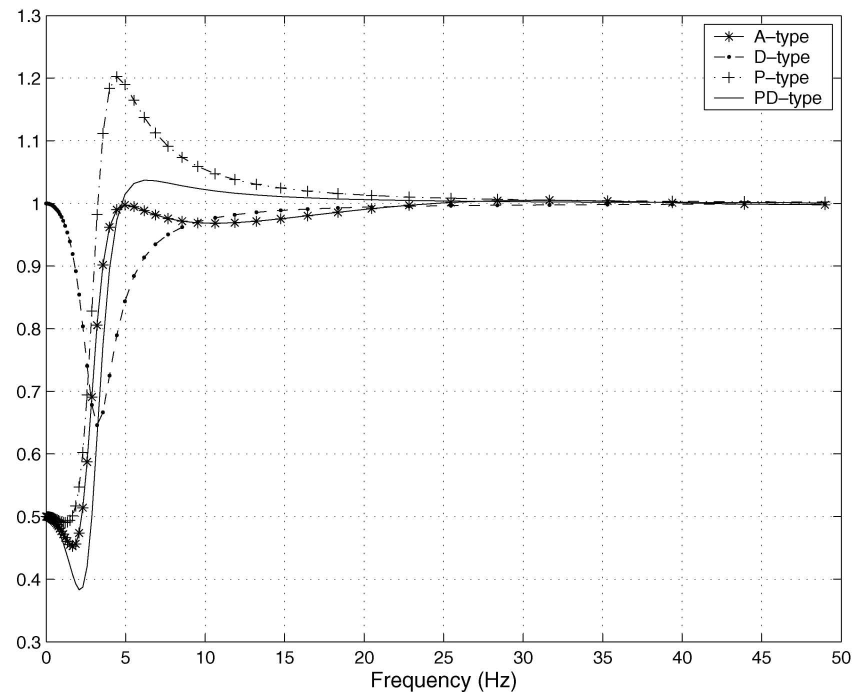

Fig. 6. Convergence conditions for A-, D-, P-, and PD-type ILCs, joint 2.

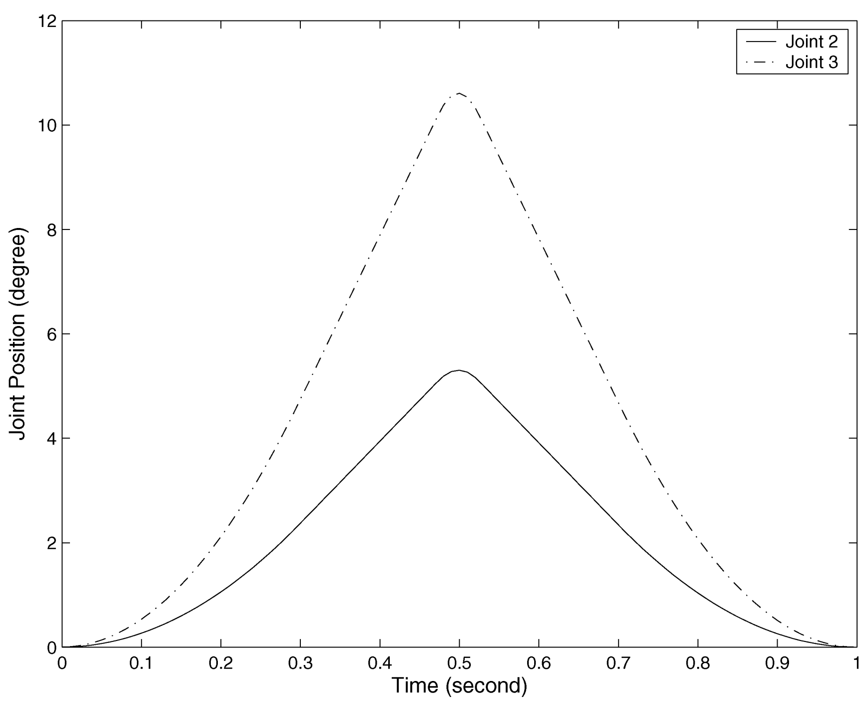

Fig. 7. Desired trajectories.

high frequency. Clearly, A-type offers a wide enough learning bandwidth. Fig. 6 shows the convergence conditions for joints 2 (A-type is with learning gain $k = 0.5$ and lead-time $\triangle = 0.03$ s. P-type is with learning gain $k = 0.5$. D-type is with learning gain $k = 0.015$. PD-type is with learning gains $k_p = 0.5$ and $k_d = 0.015$).

C. Experimental Results

The desired trajectories for the two joints are shown in Fig. 7. The desired trajectories both have sharp returns and contain more frequency components than a smooth curve. The sampling rate is 100 Hz. Cutoff is realized by discrete Fourier

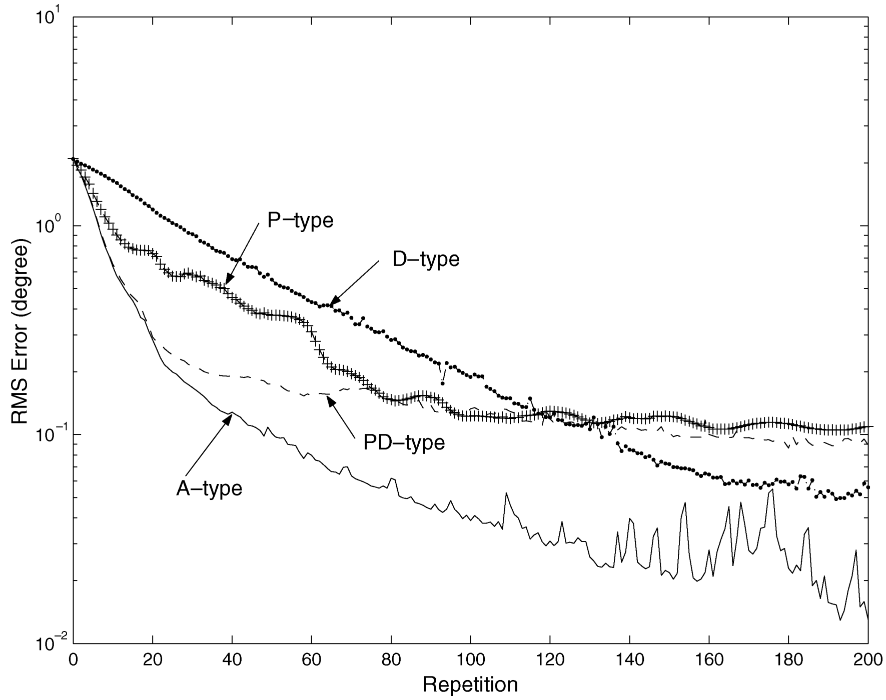

Fig. 8. RMS error histories of joint 2.

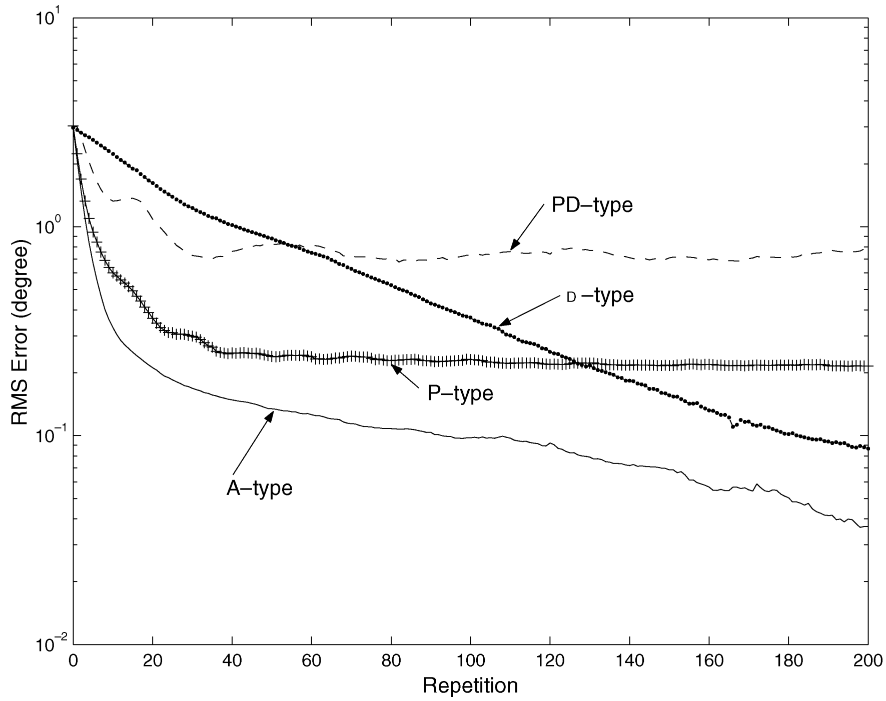

Fig. 9. RMS error histories of joint 3.

transform and inverse discrete Fourier transform (DFT/IDFT) with no end-extension.

A-type, D-type, P-type, and PD-type ILCs are performed on the two joints concurrently, using the learning gain and lead-time designs associated with Figs. 5 and 6. But the cutoff frequencies need to be tuned in the experiments until the behavior of first convergence followed by slow divergence never happens. For joint 2, the tuning results of cutoff frequency are 13 Hz for A-type, 11 Hz for D-type, 3 Hz for P-type, and 6 Hz for PD-type. For joint 3, the tuning results of cutoff frequency are 30 Hz for A-type, 11 Hz for D-type, 4 Hz for P-type, and 1 Hz for PD-type. Figs. 8 and 9 compare the root mean square error histories of 200 repetitions of A-type, D-type, P-type, and PD-type ILCs of two joints. A few different gains of other ILCs are used for

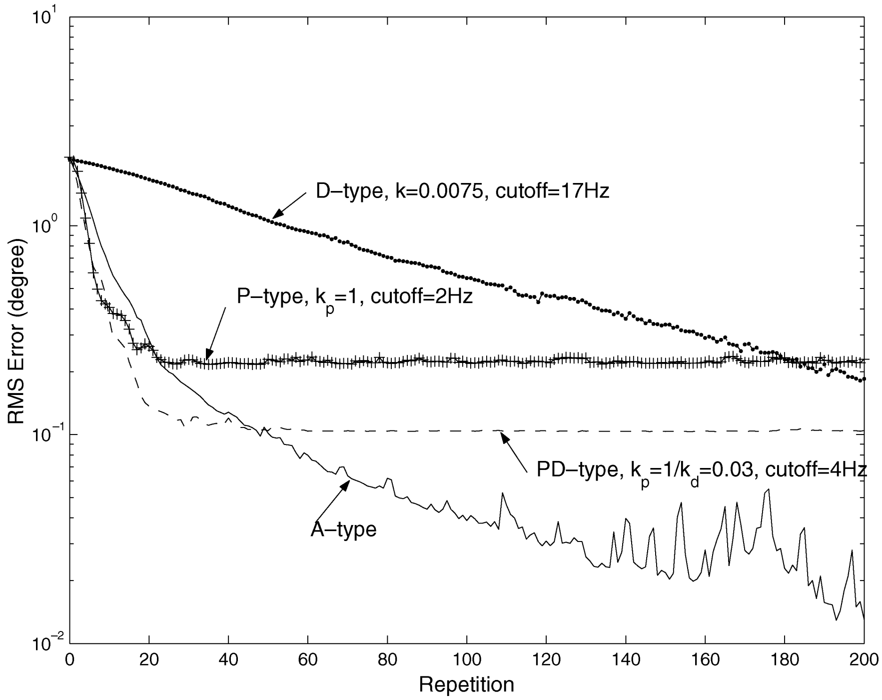

Fig. 10. RMS error histories of joint 2, other learning gains.

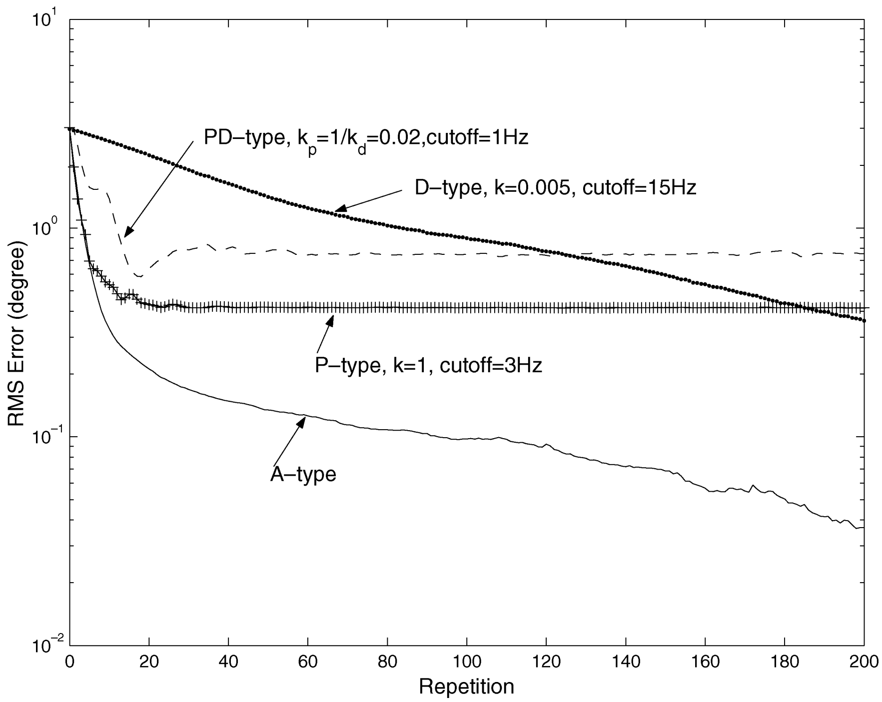

Fig. 11. RMS error histories of joint 3, other learning gains.

comparison with the above-designed A-type approach, Figs. 10 and 11, with the learning gains and cutoff frequencies indicated.

V. Conclusion

In the frequency domain, the anticipatory learning control features phase-lead characteristics and compensates phase-lag characteristics of a process. A decoupled two-step design procedure offers insight into the choice of the control parameters (the lead time, the learning gain, and the cutoff frequency) and facilitates the tuning of these parameters in experiments. Compared to a P-type, the lead time in an A-type ILC widens the learnable band substantially. Though a PD-type ILC has a similar phase-lead compensation effect as an A-type in low frequency range, an A-type ILC needs no error differentiation. A robotic example demonstrates the design procedure and the experimental results successfully verify the theory.

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Danwei Wang (M'90) received the B.E. degree from the South China University of Technology, Guangzhou, China, in 1982, and the M.S.E. and Ph.D. degrees from the University of Michigan, Ann Arbor, in 1985 and 1989, respectively.

Since 1989, he has been with the School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore, where he is currently an Associate Professor and Deputy Director of the Robotics Research Center. His research interests include robotics, control theory, and applications. He has authored more than 150 published technical articles in the areas of iterative learning control and applications, manipulator/mobile robot dynamics, path planning, robust control, adaptive control of such systems, and position/force control systems.

Yongqiang Ye was born in Zhejiang, China, in 1972. He received the B.E. and M.S. degrees in electrical engineering from Zhejiang University, China, in 1994 and 1997, respectively.

He was an Assistant Teacher from June 1997 to June 2000 and a Lecturer from July 2000 to September 2000 in the Department of Information, Zhejiang Institute of Finance and Economics, China. Since September 2000, he has studied at Nanyang Technological University, Singapore, for the Ph.D. degree in electrical engineering. His research has been concentrated on the areas of iterative learning control and repetitive control with applications to manipulator and power electronics. He has authored or coauthored over 20 journal and conference papers in the areas of iterative learning control, repetitive control, and applications.