Robust Iterative Learning Control Design Via μ-Synthesis

A. Tayebi, S. Abdul and M.B. Zaremba

Abstract

This paper deals with the robust iterative learning control (ILC) design for uncertain single input-single output (SISO) linear time invariant (LTI) systems. The design procedure is based upon solving the robust performance condition using the Youla parameterization and the μ-synthesis approach to obtain a feedback controller. Thereafter, a convergent iterative rule is obtained in a straightforward manner by using the performance weighting function involved in the robust performance condition. Experimental results on the first three links of a 6-degrees of freedom (6-DOF) robot manipulator are presented to illustrate the effectiveness of the proposed design method.

I. Introduction

In recent years, there has been a growing interest in iterative learning control design among the automatic control community (See, for instance, survey papers [16] and [17]). This approach, which is particularly suitable for systems performing repetitive tasks, consists in finding an adequate iterative rule which allows the controller to learn from the tracking errors of the previous iterations in order to increase the tracking accuracy with every new learning iteration. Iterative learning control was initially developed as a feedforward action applied directly to the open-loop system ([2], [4], [5] and [12]). Several closed-loop ILC schemes were later developed in order to benefit from the feedback properties in the first iteration, e.g., [1], [6], [11], [15] and [26].

Most of the ILC approaches proposed in the literature focus on the determination of the convergence conditions, which is a crucial part of the design, but there is little work that deals with solving these conditions to obtain the ILC filters especially under model uncertainties. In [6] and [15], the $\mathcal{H}_\infty$ and μ-synthesis approaches were used to design the learning filters, assuming that the feedback controller is already available. In [1] a two-steps procedure based on the $\mathcal{H}_\infty$ optimization was proposed to design the feedback and learning controllers. However, as the authors pointed out in the previous paper, this technique cannot be used for unstable systems and the convergence condition can only be satisfied if there is no uncertainty.

The main advantage of designing the feedback and learning controllers in two separate steps is obviously the increased number of degrees of freedom, which permits to assign the desired performance at the first iteration through the feedback controller, and the performance of the iterative process through the learning filters. The main practical drawback of this technique, besides the increased design complexity, is that it leads generally to high order ILC filters. In fact, a feedback controller designed using robust control techniques, such as μ-synthesis, is generally of a high order; hence, robust ILC design based on the high order feedback controller will lead to higher order ILC filters if those filters exist. From a practical point of view, it is important to keep the order of the feedback and learning filters as low as possible. One potential solution is to design the feedback and learning filters simultaneously. In fact, in [22], [23] it is shown that if the feedback controller is designed to satisfy the robust performance condition, then the performance weighting function can be used as a learning filter guaranteeing the convergence of the iterative process. Hence, there is no need to design the learning filter if a feedback controller can be designed to satisfy the robust performance condition. A quite similar result has also been proposed in [10].

In this paper, using the Youla parameterization and the μ-synthesis approach, we provide a robust ILC design procedure that guarantees robust performance for the feedback system and the convergence of the iterative process, for both stable and unstable uncertain LTI systems. We believe that the proposed procedure would help the designer to solve robust ILC problems in a straightforward manner. Finally, our approach is validated experimentally on a CRS465 robot manipulator.

II. Preliminaries and problem formulation

Let us consider the ILC scheme shown in Figure 1, with the following iterative rule

$$V_{k+1}(s) = W_1(s)\left(V_k(s) + U_k(s)\right), \tag{1}$$

with $V_1(s) = 0$. The plant G is described in the following multiplicative uncertain form:

$$G = (1 + \Delta W_2)G_n, \tag{2}$$

This work was supported by the Natural Sciences and Engineering Research Council of Canada (NSERC), the Canada Foundation for Innovation (CFI) and the Ontario Innovation Trust (OIT)

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where G_n is the nominal plant model, W_2 is a known stable transfer function, and Δ is an unknown stable transfer function satisfying $\|\Delta\|_\infty \leq 1$. We assume that the reference signal $y_d(t)$ is bounded and $y_k(0) = y_d(0)$, and without any loss of generality, we consider that $y_k(0) = y_d(0) = 0$.
It is shown in [22] that if the controller $C(s)$ is designed such that the robust performance condition

$$\| |W_1 S| + |W_2 T| \|_\infty < 1, \tag{3}$$

is satisfied, where $S = \dfrac{1}{1 + CG_n}$ is the sensitivity function, and $T = 1 - S$ is the complementary sensitivity function, then the tracking error is bounded for all $k \in \mathbb{N}$, and is uniformly $\mathcal{L}_2$-convergent to

$$\begin{aligned} e_\infty(t) &= \lim_{k\to\infty} e_k(t) \\ &= \mathcal{L}^{-1}\left(\frac{1 - W_1}{1 - W_1 + CG_n(1 + \Delta W_2)} Y_d\right), \end{aligned} \tag{4}$$

which tends to zero if $W_1(s)$ tends to one.

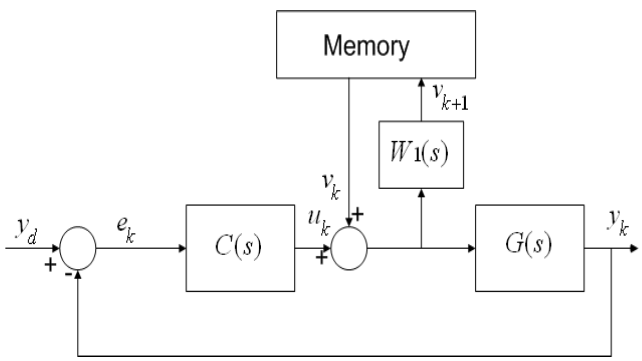

Fig. 1. ILC scheme

In the present paper, we propose a robust ILC design procedure, based on the Youla parameterization and the μ-synthesis approach, for both stable and unstable uncertain SISO-LTI systems. The effectiveness of this design procedure is shown through an experimental application to a 6-DOF robot manipulator.

III. Robust ILC design via μ-synthesis

In order to handle both stable and unstable systems, we use the Youla parameterization [27] for the feedback controller $C(s)$ as

$$C(s) = \frac{X(s) + N_2(s)Q(s)}{Y(s) - N_1(s)Q(s)}, \tag{5}$$

where $\dfrac{N_1(s)}{N_2(s)}$ is a coprime factorization of $G_n(s)$, with $N_1(s)$ and $N_2(s)$ being two stable rational transfer functions. The stable rational transfer functions $X(s)$ and $Y(s)$ are solutions of the Bezout identity

$$N_1(s)X(s) + N_2(s)Y(s) = 1, \tag{6}$$

As shown in [28], [7] and [19], transfer functions $N_1(s)$, $N_2(s)$, $X(s)$ and $Y(s)$ can be obtained using the following procedure:

- Step 1: Find a state space realization $\{A, B, C, D\}$ of $G_n(s)$, i.e.,
$$G_n(s) = D + C(sI - A)^{-1}B \triangleq \left[\begin{array}{c|c} A & B \\ \hline C & D \end{array}\right]$$
- Step 2: Find F such that $A + BF$ is stable. Transfer functions $N_1(s)$ and $N_2(s)$ are given by
$$N_1(s) \triangleq \left[\begin{array}{c|c} A+BF & B \\ \hline C+DF & D \end{array}\right], \; N_2(s) \triangleq \left[\begin{array}{c|c} A+BF & B \\ \hline F & 1 \end{array}\right]$$
- Step 3: Find H such that $A + HC$ is stable. Transfer functions $X(s)$ and $Y(s)$ are given by
$$X(s) \triangleq \left[\begin{array}{c|c} A+HC & H \\ \hline F & 0 \end{array}\right],$$
$$Y(s) \triangleq \left[\begin{array}{c|c} A+HC & -B-HD \\ \hline F & 1 \end{array}\right]$$

Note that for stable systems, one can take $N_1 = G_n$, $N_2 = 1$, $X = 0$, and $Y = 1$, which leads to the internal model parameterization [18], namely $C(s) = \dfrac{Q(s)}{1 - G_n(s)Q(s)}$, which is a special case of the Youla parameterization.

We know that, the robust performance condition (3) is equivalent to the following condition [7]:

$$\left\| \frac{W_1 S}{1 + \Delta W_2 T} \right\|_\infty < 1 \text{ and } \|W_2 T\|_\infty < 1.$$

Therefore, since the sensitivity and the complementary sensitivity functions, with the Youla parameterization, are given respectively by $S = N_2(Y - N_1 Q)$ and $T = 1 - S = N_1(X + N_2 Q)$, one can conclude that if the following conditions:

$$\begin{aligned} &\left\| \frac{W_1 N_2 (Y - N_1 Q)}{1 + \Delta W_2 N_1 (X + N_2 Q)} \right\|_\infty < 1 \\ &\|W_2 N_1 (X + N_2 Q)\|_\infty < 1 \end{aligned} \tag{7}$$

are satisfied, then the ILC scheme in Figure 1 guarantees the boundedness of the tracking error, for all $k \in \mathbb{N}$, and its uniform $\mathcal{L}_2$-convergence to the value given in (4), when $k \to \infty$. Robust performance is also guaranteed for the feedback system.

Now, in order to design Q satisfying the robust performance condition (7), we introduce the following generalized matrix:

$$M_1 = \begin{pmatrix} -W_2 N_1 (X + N_2 Q) & W_2 N_1 (X + N_2 Q) \\ -W_1 N_2 (Y - N_1 Q) & W_1 N_2 (Y - N_1 Q) \end{pmatrix} \tag{8}$$

which has the following upper LFT:

$$\mathcal{F}_u(M_1, \Delta) = \frac{W_1 N_2 (Y - N_1 Q)}{1 + \Delta W_2 N_1 (X + N_2 Q)}, \tag{9}$$

which is well posed if $\|W_2 N_1(X + N_2 Q)\|_\infty < 1$. Now, one can state the following theorem:

Theorem 1: Consider the control scheme in Figure 1 with the controller C parameterized as in (5). If there exists Q satisfying $\sup_{\omega\in\Re} \mu_{\underline{\Delta}}(M_1(j\omega)) < 1$, then

(*i*) The tracking error is bounded for all $k \in \mathbb{N}$ and is uniformly $\mathcal{L}_2$-convergent to $e_\infty(t)$ given in (4), when k tends to infinity

(*ii*) Robust performance is guaranteed for the feedback system.

Proof: Straightforward from ([22], Theorem 1) and ([28], Theorem 11.8).

Now, for given W_1, W_2 and G_n, one can use the μ-synthesis procedure called D-K iteration [28], [3] to obtain $Q(s)$ satisfying $\sup_{\omega\in\Re} \mu_{\underline{\Delta}}(M_1(j\omega)) < 1$. To this end, we introduce the following matrix:

$$M_Q = \left(\begin{array}{cc|c} -W_2N_1X & W_2N_1X & W_2N_2 \\ -W_1N_2Y & W_1N_2Y & -W_1N_2 \\ \hline -N_1 & N_1 & 0 \end{array}\right), \qquad (10)$$

such that $M_1 = \mathcal{F}_l(M_Q, Q)$.

Now, some remarks should be made at this point.

Remarks:

1) It is also possible to choose M_1 and M_Q as follows:

$$M_1 = \begin{pmatrix} -W_2N_1(X+N_2Q) & -W_2N_2(X+N_2Q) \\ W_1N_1(Y-N_1Q) & W_1N_2(Y-N_1Q) \end{pmatrix} \qquad (11)$$

which has the following upper LFT:

$$\mathcal{F}_u(M_1, \Delta) = \frac{W_1N_2(Y-N_1Q)}{1+\Delta W_2N_1(X+N_2Q)}, \qquad (12)$$

and

$$M_Q = \left(\begin{array}{cc|c} -W_2N_1X & -W_2N_2X & W_2N_2 \\ W_1N_1Y & W_1N_2Y & W_1N_1 \\ \hline -N_1 & -N_2 & 0 \end{array}\right), \qquad (13)$$

such that $M_1 = \mathcal{F}_l(M_Q, Q)$.

2) In the ideal case, with $W_1 = 1$, it is obvious that the tracking error converges to zero when k tends to infinity. But the problem is not always solvable with $W_1 = 1$ as explained in [7], Chapter 6. One necessary condition for robust performance is $min\{|W_1(j\omega)|, |W_2(j\omega)|\} < 1$, $\forall\omega$. As an alternative solution, one can take W_1 close to one within the tracking bandwidth in order to minimize the tracking error.

3) Throughout the numerous simulation tests we have performed, we have noticed that the results obtained with the generalized plant M_Q given in (10) are relatively better than those obtained with the M_Q in (13). However, whenever G_n and W_2 are strictly proper, the M_Q in (10) leads generally to a singular $\mathcal{H}_\infty$ problem which cannot be handled by the "dkit" command of the μ-synthesis toolbox [3]. To overcome this problem, we rolled-off the numerators of G_n and W_2 to obtain transfer functions with zero relative degree that approximate G_n and W_2 within a desired range of frequencies.

IV. Experimental results

Fig. 2. 6-DOF robot manipulator

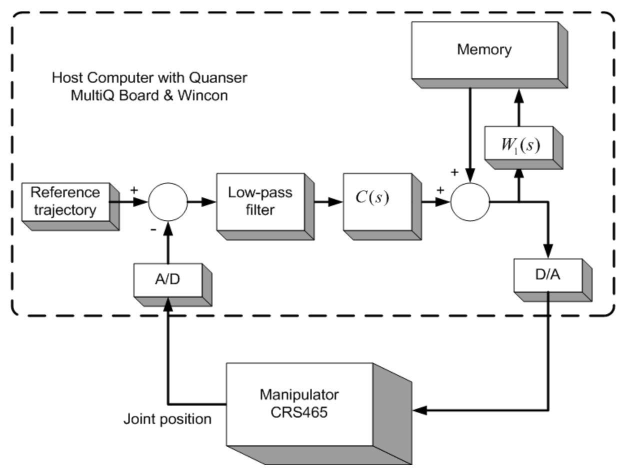

Fig. 3. Experimental setup for ILC implementation

Our Design procedure has been tested on a 6-DOF robot manipulator CRS465. The CRS465 is an open-chain articulated robot arm with 6 revolute joints powered by 6 DC motors. The motors are equipped with incremental encoders to measure the joint positions as well as automatic brakes to prevent the collapse of the manipulator configuration when the power supply to the motors is interrupted. The robot comes with the CRS C500 controller, which contains 6 independent PD-controllers, one for each joint. The ILC strategy proposed in this paper has been implemented using the Quanser open architecture (OA) mode. In the OA mode, all signals are routed to and from a Quanser-MultiQ data acquisition board as opposed to CRS controller. Quanser-MultiQ data acquisition board is used together with a Quanser WinCon software in order to generate real-time code from Simulink model. For the real-time implementation of the control algorithm using the Quanser open architecture mode, WinCon software is used together with MATLAB/Simulink/Realtime Workshop, Control System Toolbox as well as Visual C++ Professional. Our ILC scheme has been implemented, as shown in Figure 3, for the first three links of the robot manipulator. The transfer functions of the three links have been identified using the system identification toolbox of MATLAB [13], and the resulting higher order transfer functions were reduced using the balanced singular perturbation approximation (BSPA) technique [8]. The identified transfer functions for the three links are given, respectively, as follows:

$$G_1 = \frac{8.544\ 10^{-6}s^3 - 0.051186s^2 + 71.21s + 7889}{s^3 + 68.22s^2 + 487.4s + 113.4} \quad (14)$$

$$G_2 = \frac{0.004453s^2 - 0.3666s + 108.8}{s^2 + 6.909s + 0.1962} \quad (15)$$

$$G_3 = \frac{1.995\ 10^{-5}s^3 - 0.04025s^2 + 63.69s + 6937}{s^3 + 55.94s^2 + 293.7s + 38.44} \quad (16)$$

The filter W_1 is selected close to 1 in order to minimize the tracking error, while W_2 is selected from a rough approximation of the relative uncertainty at steady state, and the approximate frequency at which the relative uncertainty reaches 100% [21],

$$W_2(s) = \frac{\tau s + r_0}{(\tau/r_\infty)s + 1} \quad (17)$$

where $1/\tau$ gives the approximate frequency at which relative uncertainty reaches 100%, r_0 the relative uncertainty at steady state and r_∞ the magnitude of weight at high frequency, typically a value greater than 2.

Finally, using (10) with $N_1 = G_n$, $N_2 = 1$, $X = 0$, $Y = 1$ and

$$W_1(s) = \frac{1}{0.09s + 1}, \qquad W_2(s) = \frac{0.01s + 0.5}{0.005s + 1},$$

for link 1 and link 2, and

$$W_1(s) = \frac{1}{0.09s + 1}, \qquad W_2(s) = \frac{0.01s + 0.5}{0.0025s + 1},$$

for link 3, and using the μ-synthesis toolbox [3], we obtain, after model reduction, the following controllers for link 1, link 2 and link 3, respectively

$$C = \frac{1.985s^3 + 1.857\ 10^6 s^2 + 9.81\ 10^8 s + 1.587\ 10^8}{s^3 + 6456s^2 + 1.202\ 10^7 s + 4.005\ 10^9}$$

$$C = \frac{0.9074s^3 + 5673s^2 + 4.597\ 10^6 s + 8.83\ 10^4}{s^3 + 668.6s^2 + 7.578\ 10^4 s + 1.739\ 10^7}$$

$$C = \frac{0.5408s^4 + 7.29\ 10^5 s^3 + 3.384\ 10^8 s^2 + 7.38\ 10^9 s + 7.267\ 10^8}{s^4 + 2380s^3 + 4.074\ 10^6 s^2 + 9.797\ 10^8 s + 4.197\ 10^{10}}$$

satisfying the robust performance condition (3).

The reference trajectory considered here for the end-effector is a circle of radius $40mm$ in the x-y plane and the desired angular velocity is $0.3142 rad/sec$. The joint reference trajectories have been generated through the inverse kinematics procedure. To reduce the measurement noise, we used low pass filters with a cut-off frequency of $0.6 rad/sec$. The experiment was conducted with a sampling time of $1ms$. We performed 15 iterations with a time-interval of 20 seconds for each iteration. The tracking errors for the three links are shown in Figures 7,8 and 9. In fact, after 15 iterations, the RMS error has been, roughly, reduced by a factor of 6 for the first link, a factor of 34 for the second link and a factor of 24 for the third link. On the other hand, as predicted by the theory, the convergence to zero is not guaranteed if $W_1 \neq 0$ and finding a causal controller C satisfying the robust performance condition with $W_1 = 1$ was difficult to get in this particular case. In order to minimize the tracking error, we took W_1 as close as possible to 1 within the tracking bandwidth. This choice resulted in a poor performance at the first iteration as shown in Figures 4,5 and 6.

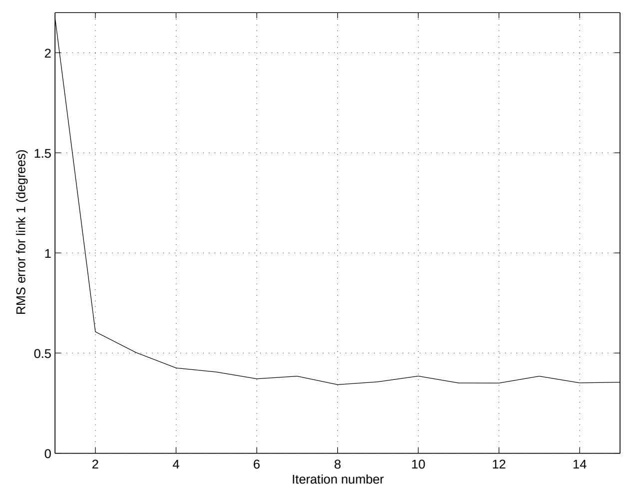

Fig. 4. RMS norm of the tracking error (in degrees) versus iteration number (link1)

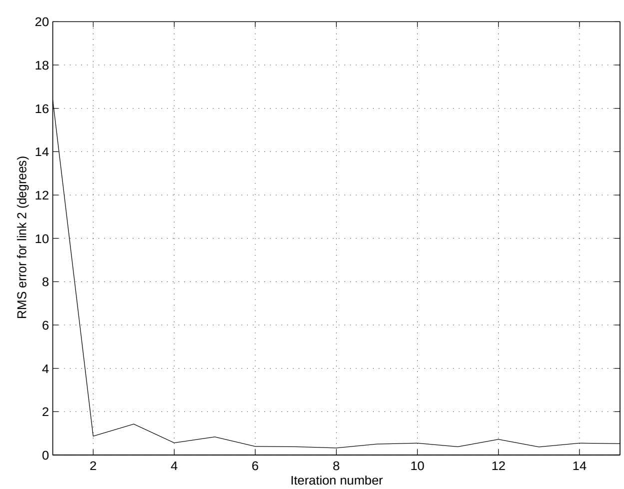

Fig. 5. RMS norm of the tracking error (in degrees) versus iteration number (link2)

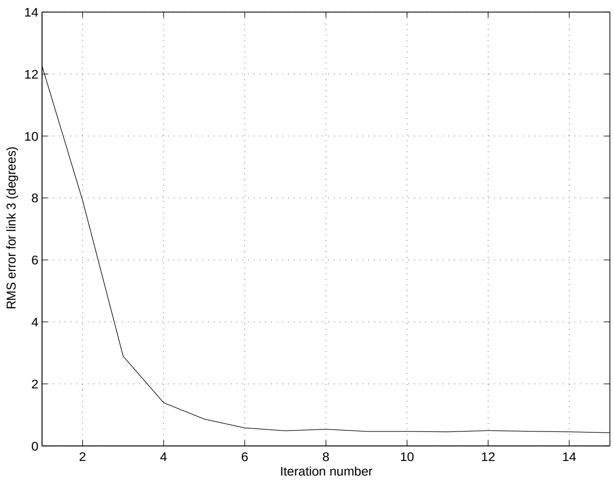

Fig. 6. RMS norm of the tracking error (in degrees) versus iteration number (link3)

V. Conclusions

In this paper, we proposed a robust ILC design procedure, based on the Youla parameterization and the μ-synthesis approach, for both stable and unstable uncertain LTI systems. The stable case has been dealt with in our previous work [23], where the feedback controller has been parameterized as $C(s) = \dfrac{Q(s)}{1 - G_n(s)Q(s)}$. Owing to the fact that the convergence of the proposed ILC scheme is guaranteed under the robust performance condition, we show that it is possible to design a single filter $Q(s)$ that ensures simultaneously robust performance for the feedback system and the convergence of the iterative process.

Since the best ILC performance one can achieve is obtained with $W_1 = 1$, one can take W_1 as close as possible to one within the tracking bandwidth and solve the robust performance condition, using the wide range of tools from robust control theory, to obtain $Q(s)$. One of the possible tools is the μ-synthesis approach, which is used in this paper.

It is worth noting that our approach involves a certain trade-off between the performance of the feedback system at the first iteration and the performance of the iterative process. In fact, the controller $C(s)$ obtained with W_1 close to one leads to the best ILC performance, but does not necessarily lead to the best feedback performance at the first iteration.

In this paper, we dealt with continuous-time systems, but the proposed design procedure is the same for discrete-time systems except that the unit circle should be used rather than the imaginary axis for norm computation (Matlab μ-Analysis and synthesis toolbox deals with both continuous-time and discrete-time systems).

Our procedure has been successfully applied to a CRS465 robot manipulator. The obtained experimental results—although satisfactory and conform to the theory— do not outperform the results that one can find in the literature for robot manipulators, simply because the proposed method is not, probably, the best one for this kind of systems (see for instance, [9], [14], [20], [24], [25]). In fact, our primary objective is not the control of robot manipulators which are nonlinear coupled MIMO systems, but to provide efficient and systematic tools, based on robust control theory, to solve ILC problems for uncertain SISO-LTI systems. The experiments were used to validate the proposed procedure experimentally, and to show that the proposed control scheme—although designed for SISO-LTI systems— could handle, to a certain extent, coupled MIMO nonlinear systems such as robot manipulators.

VI. Acknowledgments

The authors would like to thank Dr. Jacob Apkarian and Matthew Hodjera from Quanser consulting Inc. for their precious help in acquiring the robot manipulator.

References

[1] N. Amman, D.H. Owens, E. Rogers and A. Wahl, "An $\mathcal{H}_\infty$ approach to linear iterative learning control design," Int. Journal of Adaptive Control and Signal Processing, 10, pp. 767-781, 1996.

[2] S. Arimoto, S. Kawamura and F. Miyazaki, "Bettering operation of robots by learning," Journal Robot. Syst., 1, pp. 123-140, 1984.

[3] G.J. Balas , J.C. Doyle, K. Glover, A. Packard and R. Smith, μ-Analysis and synthesis toolbox, The Mathworks Inc., 1998.

[4] Y. Chen, C. Wen, Z. Gong and M. Sun, "An iterative learning controller with initial state learning," IEEE Trans. on Automatic Control, 44(2), pp. 371-376, 1999.

[5] T.W.S. Chow and Y. Fang, "An iterative learning control method for continuous-time systems based on 2-D system theory," IEEE Trans. on Circuit and Systems-1: Fundamental theory and applications, 45(4), pp.683-689, 1998.

[6] D. De Roover, "Synthesis of a robust iterative learning controller using an H_∞ approach," Proc. of the 35th Conference on Decision and Control, Kobe, Japan, pp. 3044-3049, 1996.

[7] J. Doyle, B. Francis and A. Tannenbaum, Feedback control theory, Macmillan Publishing Co, 1990.

[8] M. Green and D.J.N. Limebeer, Linear Robust Control Prentice-Hall, 1995.

[9] K. Hamamoto and T. Sugie, "Iterative Learning Control for Robot Manipulators Using the Finite Dimensional Input Subspace," IEEE Transactions on Robotics and Automation, Vol. 18, No. 4 pp. 632-635, 2002.

[10] Q. Hu, J.-X Xu and T. H. Lee, "Iterative learning control design for Smith predictor," Systems and Control Letters, Vol. 44, pp. 201-210, 2001.

[11] T.Y. Kuc, J.S. Lee and K. Nam, "An iterative learning control theory for a class of nonlinear dynamic systems," Automatica, 28(6), pp. 1215-1221, 1992.

[12] J.E. Kurek and M. Zaremba, "Iterative learning control synthesis based on 2-D system theory," IEEE Trans. on Automatic Control, 38(1), pp. 121-125, 1993.

[13] L. Ljung, System Identification Toolbox, The Mathworks Inc., 2001.

[14] R.W. Longman, "Iterative learning control and repetitive control for engineering practice," International Journal of Control, Vol. 73, No. 10, pp. 930-954, 2000.

[15] J. H. Moon , T.Y. Doh and M. J. Chung, "A robust approach to iterative learning control design for uncertain systems," Automatica, 34(8), pp. 1001-1004, 1998.

[16] K.L. Moore, M. Dahleh and S. P. Bhattacharyya, "Iterative learning control: A survey and new results," Journal of Robotic Systems, 9(5), pp. 563-594, 1992.

[17] K.L. Moore, "Iterative Learning Control: An Expository Overview," Applied and Computational Controls, Signal Processing, and Circuits, Vol. 1, pp. 151-214, 1999.
[18] M. Morari and E. Zafriou, Robust Process Control, Prentice Hall, 1989.
[19] C.N. Nett, C.A. Jacobson and M.J. Balas, "A connection between state space and doubly coprime fractional representations," IEEE Trans. on Aut. Control, 29(9), pp. 831-832, 1984.
[20] M. Norrlöf and S. Gunnarsson, "Experimental comparison of some classical iterative learning control algorithms," IEEE Transactions on Robotics and Automation, Vol. 18, pp. 636-641, 2002.
[21] S. Skogestad and I. Postlewaite, Multivariable Feedback Control, John Wiley & Sons Inc., 1996.
[22] A. Tayebi and M.B. Zaremba, "Robust Iterative Learning Control Design is Straightforward for Uncertain LTI Systems Satisfying the Robust Performance Condition," IEEE Transactions on Automatic Control, Vol. 48, No. 1, pp. 101-106, 2003.
[23] A. Tayebi and M.B. Zaremba, "Internal model-based robust iterative learning control for uncertain LTI systems," In Proc. of IEEE Conference on Decision and Control, Sydney, Australia, pp. 3439-3444, 2000.
[24] A. Tayebi, "Adaptive iterative learning control for robot manipulators," Automatica, Vol.40, no.7, pp. 1195-1203, 2004.
[25] A. Tayebi and S. Islam, "Experimental evaluation of an adaptive iterative learning control scheme on a 5-DOF robot manipulator," IEEE Conference on Control Applications, Taipei, Taiwan, pp. 1007-1011, 2004.
[26] J.X. Xu and B. Viswanathan, "Adaptive robust iterative learning control with dead zone scheme," Automatica, Vol. 36 No. 1, pp. 91-99, 2000.
[27] D. C. Youla, H. A. Jabr and J. J. Bongiorno, "Modern Wiener-Hopf design of optimal controllers–Part II: the multivariable case," IEEE Transactions on Automatic Control, Vol. 21, pp. 319-338, 1976.
[28] K. Zhou, J.C. Doyle and K. Glover, Robust and optimal control, Prentice Hall, Englewood Cliffs, NJ, 1996.