Robust Stability of Optimal Iterative Learning Control and Application to Injection Molding Machine[1)]

SHAO Cheng[1] GAO Fu-Rong[2] YANG Yi[2]

[1] (Research Center of Information and Control, Dalian University of Technology, Dalian 116023)

[2] (Department of Chemical Engineering, Hong Kong University of Science and Technology, Hong Kong)

(E-mail: cshao@dlut.edu.cn)

Abstract A design of robust iterative learning controller is presented. A sufficient and necessary condition to ensure robust BIBO (bounded-input bounded-output) stability is derived for the optimal iterative learning controllers when tracking arbitrary bounded output. A practical scheme of selecting weighting matrices is proposed for the process with uncertain initial resetting and disturbances to ensure improvement of system performance from batch to batch. An application to the injection molding control is given to demonstrate the effectiveness of the proposed results.

Key words Batch control, learning control, robust stability, injection molding machine

1 Introduction

Since disturbances and uncertain initialization have to be faced by many batch processes, the robust stability analysis and design for iterative learning control of these processes are important issues. Some progresses and efforts have been made in this area[1~8], with several applications of iterative learning control to chemical reactor, injection molding machine and robots[9~13]. Optimal design criteria have also been applied to iterative learning control for improved performance. Steepest-descent-optimization method of iterative learning control was employed in continuous-time systems to minimize the L_2 norm of the tracking error, and the convergence could be guaranteed by properly choosing the step length for each trial[14]. For deterministic discrete time systems, Amann *et al.*[15] by means of minimization of one-step-ahead tracking errors and excessive input changes, have recently proposed an optimal iterative learning control algorithm with guaranteed exponential convergence under rather crucial condition requiring exact initial states resetting. However, robust stability with respect to uncertain initials and disturbances for optimal type of iterative learning controller have not been discussed.

This paper is to extend the optimal iterative learning control algorithm of Amann *et al.*[15] to a general batch process where exact initial resetting cannot be made and uncertain disturbances exist. A sufficient and necessary condition to ensure robust bounded-input bounded-output (BIBO) stability is established. Analysis on the selection of weighting matrices for the cost function is made. The application to control injection molding velocity using the introduced optimal iterative learning control is also demonstrated.

2 Problem statement

2.1 Problem formulation

The plant of interest is the following sampled-time linear system with disturbances

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$$\begin{aligned} \mathbf{x}_k(t+1) &= A\mathbf{x}_k(t) + B\mathbf{u}_k(t) + \mathbf{v}_k(t), \qquad 0 \leqslant t \leqslant N, \quad k = 0,1,2,\cdots \\ \mathbf{y}_k(t) &= C\mathbf{x}_k(t) + \boldsymbol{\omega}_k(t) \end{aligned} \tag{1}$$

where $\mathbf{x}_k(t) \in R^n, \mathbf{u}_k(t) \in R^m, \mathbf{y}_k(t) \in R^p$, $\mathbf{y}_k(t)$ is the system output at time t, $0 \leqslant t \leqslant N$, at the kth iteration, or the kth trial. $\mathbf{v}_k(t)$ and $\boldsymbol{\omega}_k(t)$ denote the bounded external disturbances. Note that the exact state initialization for equation (1) is not required in this work. The robustness to initial state variation and external disturbances will be discussed in this paper. The state-space matrices A, B, C are assumed to be time-invariant for simplicity. It is possible, without any technical difficulties, to extend all results of this paper to time-varying systems. Based on the linear system theory, the following solution to (1) can be deduced

$$\mathbf{y}_k(t) = \sum_{l=0}^{t-1} CA^{t-1-l}B\mathbf{u}_k(l) + \boldsymbol{\eta}_k(t) \tag{2}$$

$$\boldsymbol{\eta}_k(t) = CA^t\mathbf{x}_k(0) + \sum_{l=0}^{t-1} CA^{t-1-l}\mathbf{v}_k(l) + \boldsymbol{\omega}_k(t) \tag{3}$$

It can be observed that uncertainty terms of initial actions of each trial and external disturbances appear in the plant, extending Amann *et al.*[15] s' results to the general case. Since finite time intervals of each trial are considered, equation (2) can be made in a vector form by building supervecotors $\mathbf{y}_k$, $\mathbf{u}_k$ and $\boldsymbol{\eta}_k$ from $\mathbf{y}_k(t)$, $\mathbf{u}_k(t)$ and $\boldsymbol{\eta}_k(t)$ as follows:

$$\mathbf{y}_k = G\mathbf{u}_k + \boldsymbol{\eta}_k \tag{4}$$

where

$$\mathbf{y}_k = \begin{bmatrix} \mathbf{y}_k(1) \\ \mathbf{y}_k(2) \\ \vdots \\ \mathbf{y}_k(N) \end{bmatrix}, \quad \mathbf{u}_k = \begin{bmatrix} \mathbf{u}_k(0) \\ \mathbf{u}_k(1) \\ \vdots \\ \mathbf{u}_k(N-1) \end{bmatrix}, \quad \boldsymbol{\eta}_k = \begin{bmatrix} \boldsymbol{\eta}_k(1) \\ \boldsymbol{\eta}_k(2) \\ \vdots \\ \boldsymbol{\eta}_k(N) \end{bmatrix}$$

$$G = \begin{bmatrix} CB & 0 & \cdots & 0 \\ CAB & CB & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ CA^{N-1}B & CA^{N-2}B & \cdots & CB \end{bmatrix}$$

The supervectors are represented with omission of the argument time t. In the implementation of iterative learning control, a memory of $\mathbf{y}_k$ and $\mathbf{u}_k$ of previous trials is needed for computing $\mathbf{u}_{k+1}(t)$ of the current trial. The matrix G, a lower-triangular block matrix known as a Toeplitz matrix, can be determined from its first column. If plant (1) has relative degree of one, *i. e.* $CB \neq 0$, then matrix G is invertible in the SISO case. Otherwise, a regularizing procedure like the one of Amann *et al.* can be done[15] so that $G^{\mathrm{T}}G$ (or GG^{T}) has at least one positive eigenvalue. Based on this postulation a convergence proof different from the one of Amann *et al.*[15] will be given.

The control object considered here, a tracking problem, is that for a reference trajectory or desired output denoted by $\mathbf{r}(t)$, given $1 \leqslant t \leqslant N$, an iterative learning controller is derived such that when applied to system (1) the closed-loop tracking error is reduced iteratively from trial to trial, even with the existence of initial errors and uncertain disturbances.

Definition 1. An iterative learning control algorithm is causal if and only if the value of the input at time t on the $(k+1)$th trial/experiment is computed only from data that is available from the $(k+1)$th trial in the time interval$[0, t]$ and from previous trials on the whole time interval$[0, N]$.

2.2 Optimal iterative learning controller

Consider the following nominal system composed of the coefficient matrices A, B and C of (1)

$$\begin{aligned} \hat{\boldsymbol{x}}_k(t+1) &= A\hat{\boldsymbol{x}}_k(t) + B\boldsymbol{u}_k(t), \quad 0 \leqslant t \leqslant N, \quad k = 0,1,2,\cdots \\ \hat{\boldsymbol{y}}_k(t) &= C\hat{\boldsymbol{x}}_k(t) \end{aligned} \tag{5}$$

where $\hat{\boldsymbol{x}}_k(t) \in R^n, \boldsymbol{u}_k(t) \in R^m, \hat{\boldsymbol{y}}_k(t) \in R^p$, the variables with superscript ' $\hat{}$ ' denote the nominal outputs, and they are initialized by zeros, that is, they would be the outputs of (1) in the absence of any disturbances and initial errors. For the reference trajectory or desired output $\boldsymbol{r}(t)$, given $1 \leqslant t \leqslant N$, on the $(k+1)$th trial, the nominal optimal iterative learning control law is obtained by minimizing the following quadratic performance index with respect to $\boldsymbol{u}_{k+1}(t)$

$$J_{k+1} = \sum_{t=1}^{N} [\boldsymbol{r}(t) - \hat{\boldsymbol{y}}_{k+1}(t)]^{\mathrm{T}} Q(t) [\boldsymbol{r}(t) - \hat{\boldsymbol{y}}_{k+1}(t)] + \sum_{t=0}^{N-1} [\Delta \boldsymbol{u}_{k+1}(t)]^{\mathrm{T}} R(t) [\Delta \boldsymbol{u}_{k+1}(t)] \tag{6}$$

where $\Delta \boldsymbol{u}_{k+1}(t) = \boldsymbol{u}_{k+1}(t) - \boldsymbol{u}_k(t)$, and the weighting matrices $Q(t)$ and $R(t)$ are arbitrary symmetric positive definitive for all t. The index function (6) can be rewritten in matrix form as:

$$J_{k+1} = [\boldsymbol{r} - \hat{\boldsymbol{y}}_{k+1}]^{\mathrm{T}} Q [\boldsymbol{r} - \hat{\boldsymbol{y}}_{k+1}] + \Delta \boldsymbol{u}_{k+1}^{\mathrm{T}} R \Delta \boldsymbol{u}_{k+1} \tag{7}$$

where

$$Q = \mathrm{diag}\{Q(1), Q(2), \cdots, Q(N)\}, \ R = \mathrm{diag}\{R(0), R(1), \cdots, R(N-1)\}$$

$$\hat{\boldsymbol{y}}_k = \begin{bmatrix} \hat{\boldsymbol{y}}_k(1) \\ \hat{\boldsymbol{y}}_k(2) \\ \vdots \\ \hat{\boldsymbol{y}}_k(N) \end{bmatrix}, \quad \boldsymbol{r} = \begin{bmatrix} \boldsymbol{r}(1) \\ \boldsymbol{r}(2) \\ \vdots \\ \boldsymbol{r}(N) \end{bmatrix}$$

Then finding the partial derivative of (7) with respect to $\boldsymbol{u}_{k+1}$ one obtains the nominal optimal control input

$$\hat{\boldsymbol{u}}_{k+1} = \hat{\boldsymbol{u}}_k + R^{-1} G^{\mathrm{T}} Q [\boldsymbol{r} - \hat{\boldsymbol{y}}_{k+1}] \tag{8}$$

However, it is observed that the algorithm (8) is not causal for computation of $\hat{\boldsymbol{u}}_{k+1}$, because by this control law, $\hat{\boldsymbol{u}}_{k+1}(t)$ would depend on values of $\hat{\boldsymbol{y}}_{k+1}(t')$ for $t \leqslant t' \leqslant N$. Following Amann *et al.*[15] an equivalent form of (8) can be given below:

$$S(t) = A^{\mathrm{T}} S(t+1) \{I - B[B^{\mathrm{T}} S(t+1) B + R(t+1)]^{-1} B^{\mathrm{T}} S(t+1)\} A + C^{\mathrm{T}} Q(t+1) C \tag{9}$$

$$t = 0, 1, \cdots, N-1, \ S(N) = 0$$

$$\boldsymbol{\phi}_{k+1}(t) = [I + S(t) B R^{-1}(t) B^{\mathrm{T}}]^{-1} [A^{\mathrm{T}} \times \boldsymbol{\phi}_{k+1}(t+1) + C^{\mathrm{T}} Q(t+1) \hat{\boldsymbol{e}}_k(t+1)] \tag{10}$$

$$t = 0, 1, \cdots, N-1, \ \boldsymbol{\phi}_{k+1}(N) = \boldsymbol{0}$$

where $\hat{\boldsymbol{e}}_k(t+1) = \boldsymbol{r}(t+1) - \hat{\boldsymbol{y}}_k(t+1)$. The nominal input update law thus becomes

$$\hat{\boldsymbol{u}}_{k+1}(t) = \hat{\boldsymbol{u}}_k(t) - [B^{\mathrm{T}} K(t) B + R(t)]^{-1} B^{\mathrm{T}} \times S(t) A [\hat{\boldsymbol{x}}_{k+1}(t) - \hat{\boldsymbol{x}}_k(t)] + R^{-1}(t) B^{\mathrm{T}} \boldsymbol{\phi}_{k+1}(t) \tag{11}$$

This means that an extra computation effort for nominal states $\hat{\boldsymbol{x}}_k$ and outputs $\hat{\boldsymbol{y}}_k$ would be added. For practical application of the algorithm, $\boldsymbol{u}_k$ will be calculated by using real measurements of $\boldsymbol{x}_k$ and $\boldsymbol{y}_k$ of (1) instead of the nominal $\hat{\boldsymbol{x}}_k$ and $\hat{\boldsymbol{y}}_k$ in (10), (11) and (12). Therefore, a causal iterative learning control algorithm of interest can be summarized as follows:

$$\boldsymbol{u}_{k+1} = \boldsymbol{u}_k + R^{-1} G^{\mathrm{T}} Q \boldsymbol{e}_{k+1} \tag{12}$$

$$\boldsymbol{\phi}_{k+1}(t) = [I + S(t) B R^{-1}(t) B^{\mathrm{T}}]^{-1} \times [A^{\mathrm{T}} \boldsymbol{\phi}_{k+1}(t+1) + C^{\mathrm{T}} Q(t+1) \boldsymbol{e}_k(t+1)] \tag{13}$$

$$t = 0, 1, \cdots, N-1, \ \boldsymbol{\phi}_{k+1}(N) = \boldsymbol{0}$$

$$\boldsymbol{u}_{k+1}(t) = \boldsymbol{u}_k(t) - [B^{\mathrm{T}} K(t) B + R(t)]^{-1} B^{\mathrm{T}} \times S(t) A [\boldsymbol{x}_{k+1}(t) - \boldsymbol{x}_k(t)] + R^{-1}(t) B^{\mathrm{T}} \boldsymbol{\phi}_{k+1}(t) \tag{14}$$

where $S(t)$ is obtained by (9). Note that the proposed learning control law is optimal if $\boldsymbol{\eta}_k = \boldsymbol{0}$[15] in (4), however, this is carried out in the presence of uncertain initials and disturbances. It can be seen that the algorithm of (9), and (12)~(14) is causal and that $\boldsymbol{u}_{k+1}(t)$ is obtained in (14) by introducing feedback action and feed-forward action (the second and the third terms of (14), respectively) to $\boldsymbol{u}_k(t)$ of the last trial. Therefore the learning function of the iterative learning control algorithm is carried out by combing the current trial results with the previous trial.

3 Robustness and convergence analysis

Theorem 1 (Robust BIBO Stability). The application of the iterative learning control algorithm of (9), and (12)~(14) to plant (1) is robust BIBO stable if and only if $I+GR^{-1}G^{T}Q$ and $I+R^{-1}G^{T}QG$ have their all eigenvalues outside unit disc, or

$$\|I+R^{-1}G^{T}QG\|>1 \tag{15}$$

$$\|I+GR^{-1}G^{T}Q\|>1 \tag{16}$$

Proof. Premultiplying (12) by G and in view of (4) and $\boldsymbol{e}_k=\boldsymbol{r}-\boldsymbol{y}_k$ one obtains

$$\boldsymbol{e}_{k+1}=\boldsymbol{e}_k-GR^{-1}G^{T}Q\boldsymbol{e}_{k+1}-\Delta\boldsymbol{\eta}_{k+1} \tag{17}$$

where $\Delta\boldsymbol{\eta}_{k+1}=\boldsymbol{\eta}_{k+1}-\boldsymbol{\eta}_k$. Then using (4) and (12) gives

$$\boldsymbol{e}_{k+1}=(I+GR^{-1}G^{T}Q)^{-1}\boldsymbol{e}_k-(I+GR^{-1}G^{T}Q)^{-1}\Delta\boldsymbol{\eta}_{k+1} \tag{18}$$

$$\boldsymbol{u}_{k+1}=(I+R^{-1}G^{T}QG)^{-1}\boldsymbol{u}_k+(I+R^{-1}G^{T}QG)^{-1}R^{-1}G^{T}Q(\boldsymbol{r}-\boldsymbol{\eta}_{k+1}) \tag{19}$$

Therefore, by applying standard discrete time system theory the result follows. □

Compared with the one by Amann *et al.* [15] the proof given here is more straightforward. The convergence of the proposed algorithm is then given below.

Theorem 2 (Convergence). Apply the iterative learning control algorithm of (9), and (12)~(14) to plant (1), in which R and Q are chosen to satisfy (15) and (16). If all trials are repeated in the sense that all $\boldsymbol{x}_k(0)$, external disturbances $\boldsymbol{v}_k(t)$ and $\boldsymbol{\omega}_k(t)$ are the same for all trial index k, then the following convergence results hold.

$$\lim_{k\to\infty}\boldsymbol{u}_{k+1}=(G^{T}QG)^{-1}G^{T}Q(\boldsymbol{r}-\boldsymbol{\eta}^{*}) \tag{20}$$

$$\lim_{k\to\infty}\boldsymbol{e}_{k+1}=\boldsymbol{0} \tag{21}$$

where $\boldsymbol{\eta}^{*}$ is some constant vector.

Proof. If all trials are repeated, it follows from (3) that there exists some constant vector $\boldsymbol{\eta}^{*}$ such that $\boldsymbol{\eta}_k=\boldsymbol{\eta}^{*}$ for all trial index k. Iteratively using (18) and (19) one obtains

$$\boldsymbol{u}_{k+1}=(I+R^{-1}G^{T}QG)^{-k}\boldsymbol{u}_0+\sum_{l=1}^{k}(I+R^{-1}G^{T}QG)^{-l}R^{-1}G^{T}Q(\boldsymbol{r}-\boldsymbol{\eta}_{k+2-l}) \tag{22}$$

$$\boldsymbol{e}_{k+1}=(I+GR^{-1}G^{T}Q)^{-k}\boldsymbol{e}_0-\sum_{l=1}^{k}(I+GR^{-1}G^{T}Q)^{-l}\Delta\boldsymbol{\eta}_{k+2-l} \tag{23}$$

respectively. Therefore, with the assumptions and Theorem 1 the conclusions are derived readily. □

4 Choice of the weighting matrices and experimental results

Theorem 1 establishes the conditions for R and Q to ensure robust stability of the resulting closed loop system. Injection molding, a cyclic process with uncertain initialization and external disturbances, is a good candidate for applying the optimal iterative learning control method together with choosing R and Q. A brief introduction of injection molding will be given below.

4.1 Injection molding process

Injection molding is an important polymer processing technique. It transforms polymer granules into various shapes and types of products, ranging from simple cups to precision lens and compact discs. As a cyclic process, the injection molding comprises three stages: filling (injection), packing-holding and cooling. During filling, the injection screw moves forward and pushes the melt into the mold cavity. Once the mold is completely filled, the process switches to the packing-holding stage, during which additional polymer is added under a certain pressure to the mold to compensate for the shrinkage associated with the material cooling and solidification. The packing-holding stage continues until the nozzle, which is a narrow entrance to the mold cavity, freezes, isolating the material in the mold from that in the injection unit. During the cooling stage, the polymer inside the mold continues to cool down. At the same time, the material is melted and conveyed to the front of barrel by screw rotation. The process is then repeated.

It has been shown by many researches that precise control of some key variables of each stage is essential to the quality of the molded parts. Injection velocity is a key variable during injection phase. The dynamics of the injection velocity is found to be nonlinear and time-varying, and it is affected by many disturbances such as variations of material properties, injection molds and the surrounding conditions. A learning controller based on equations (9), (12) to (14) is thus designed and implemented to control the injection velocity. The experimental set-up is given below.

4.2 Experimental set-up

The machine used in this work was a Chen-Hsong reciprocating-screw injection molding machine, model JM88MKIII. The machine has a maximum clamping tonnage of 88 tons, and a maximum shot weight of 128 g. Fig. 1 shows a simplified diagram of the machine in the HKUST's advanced material lab. It consists of three main units: a clamping unit, an injection unit, a hydraulic unit and a control unit, which is not shown in this figure. The injection velocity is controlled by manipulating the servo-valve SV1, and is measured by a Temposonics series III displacement/velocity transducer, type RH-N-0200M. The sampling rate of the controller has been determined to be 5ms.

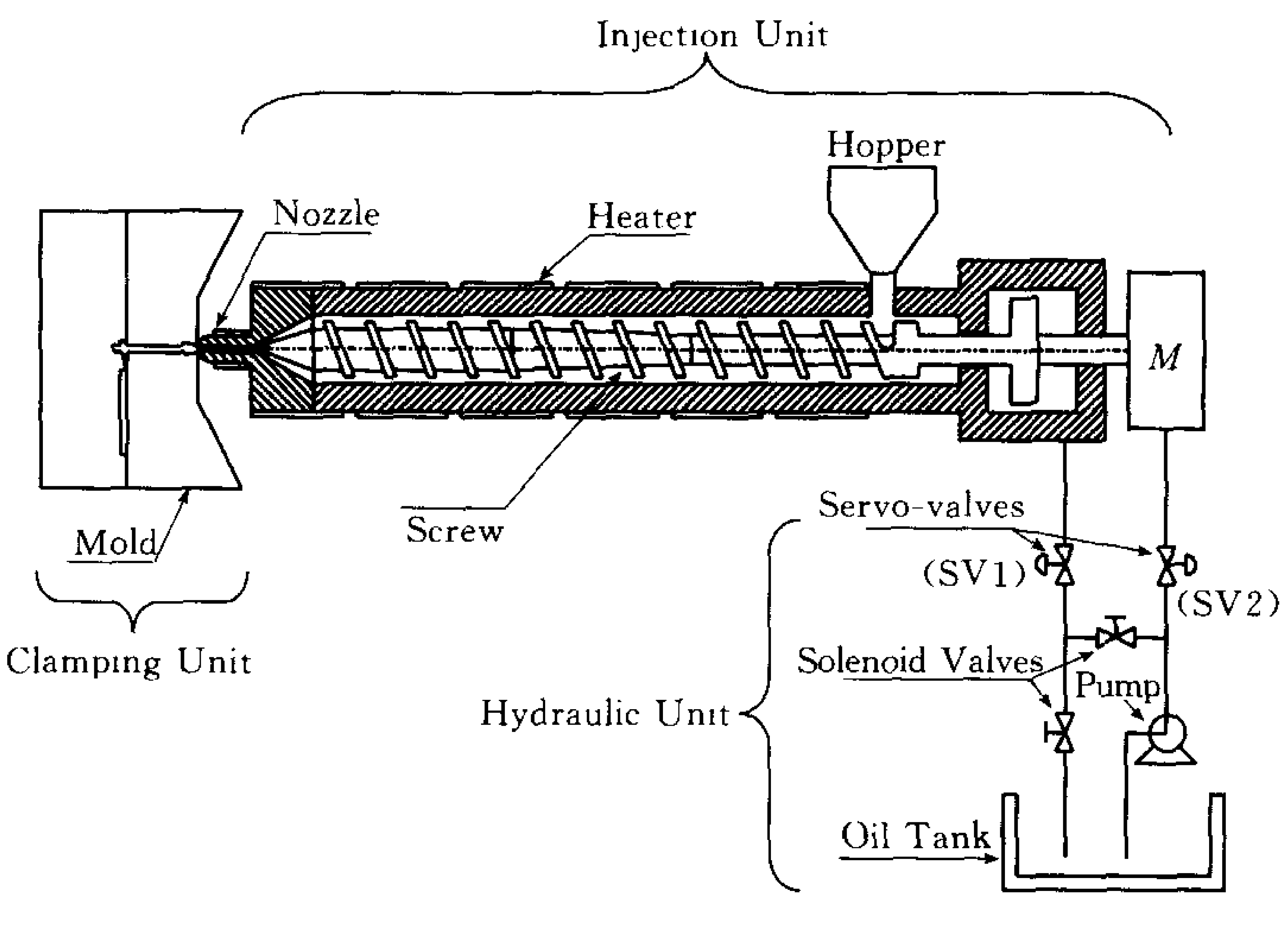

Fig. 1 Simplified schematic diagram of an injection mould machine

4.3 Results and discussion

For the sake of simplicity, let $R=\lambda I$, $Q=\mu I$, where λ and μ are some arbitrary positive constants chosen by the designer, and $\rho=\mu/\lambda$. λ and μ must satisfy (15) and (16) to ensure robust BIBO stability. This necessary condition can be met if λ and μ are positive and $G^{\mathrm{T}}G$ or GG^{T} has at least one positive eigenvalue. The following problem is to determine positive constants λ and μ such that the resulted control system can not only reject uncertain disturbances but also track the desired reference with the insurance of rapid convergence. It follows from (22) and (23) that

$$\boldsymbol{u}_{k+1} = (I+\rho G^{\mathrm{T}}G)^{-k}\boldsymbol{u}_0 + \sum_{l=1}^{k}\rho(I+\rho G^{\mathrm{T}}G)^{-l}G^{\mathrm{T}}(\boldsymbol{r}-\boldsymbol{\eta}_{k+2-l}) \tag{24}$$

$$e_{k+1} = (I+\rho GG^{T})^{-k}e_0 - \sum_{l=1}^{k}(I+\rho GG^{T})^{-l}\Delta\boldsymbol{\eta}_{k+2-l} \tag{25}$$

Therefore, a larger value of ρ (equivalently, a lager value of μ) will be helpful in reducing error of the first trial to reach the optimal state, i. e. a quickly convergent rate can be achieved trial by trial. On the other hand, from (13) and (14) one obtains

$$\begin{gathered}\boldsymbol{\phi}_{k+1}(t) = \lambda[\lambda I + S(t)BB^{T}]^{-1}\times[A^{T}\boldsymbol{\phi}_{k+1}(t+1)+\mu C^{T}\boldsymbol{e}_k(t+1)] \\ t=0,1,\cdots,N-1,\ \boldsymbol{\phi}_{k+1}(N)=\mathbf{0}\end{gathered} \tag{26}$$

$$\boldsymbol{u}_{k+1}(t) = \boldsymbol{u}_k(t) - [B^{T}K(t)B+\lambda I]^{-1}B^{T}\times S(t)A[\boldsymbol{x}_{k+1}(t)-\boldsymbol{x}_k(t)] + \lambda^{-1}B^{T}\boldsymbol{\phi}_{k+1}(t) \tag{27}$$

It can be seen that the larger value of ρ (larger value of μ) leads to the larger feedforward action on $\boldsymbol{u}_{k+1}(t)$ through $\boldsymbol{\phi}_{k+1}(t)$, making the control system less sensitive to the variation of the reference signal. In addition, a strong feedforward action tends to accumulate stochastic errors resulted from various uncertainties and external disturbances, resulting strong fluctuations in the control input. This can be demonstrated easily by application to injection molding control. The designed iterative learning controller is first tested with $\rho=1.0$, which is a critical value. The input signal, i. e. , the servo-valve opening is arbitrarily set to be 10%, as shown by the short dash line in Fig. 2(b). The control results are plotted in Fig. 2, where Fig. 2(a) shows the injection velocity (output) and Fig. 2(b) shows the corresponding servo-valve opening (input). It is observed that the control response becomes oscillatory with the increase of the cycle number k. This is caused by the strong feed-forward action. With the existence of disturbance and model mismatch, a large ρ leads to strong feedforward action and weak feedback action, weakening the error reducing capability of the learning controller.

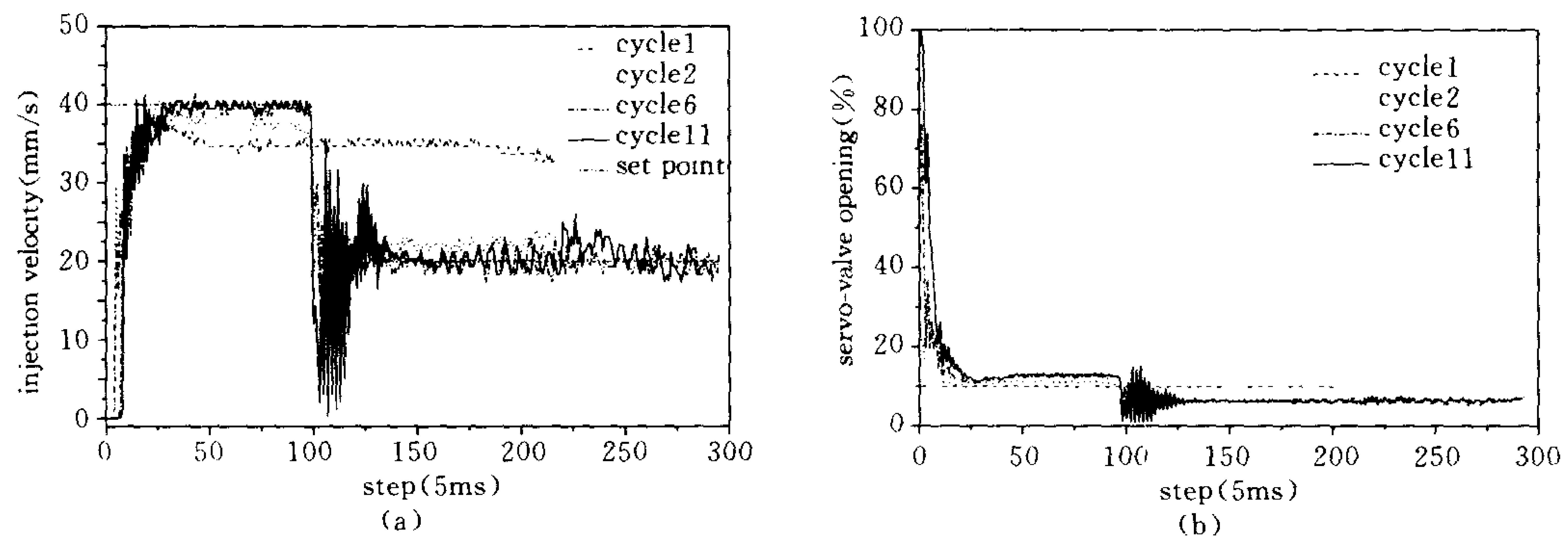

Fig. 2 Injection velocity control with $\rho=1$

The controller is thus modified with varying values of ρ. For the first cycle, the input is again set to be a constant value, 10%. The Riccati gain and the feedforward terms in (13) and (14) are then calculated with $\rho=1.0$ to make the control response converge rapidly. For the following cycles, ρ are set to decrease exponentially with the increase of the cycle number k, i. e. $\rho=0.6^{k-1}$. The results are demonstrated in Fig. 3(a) and Fig. 3(b). It is obvious that the control oscillation has been eliminated with the implementation of the proposed modification. The control response quickly converges, and the control system is stable with increase in the cycle number. The injection velocity follows a step set-point profile rapidly; this is an inherent advantage of the iterative learning controller.

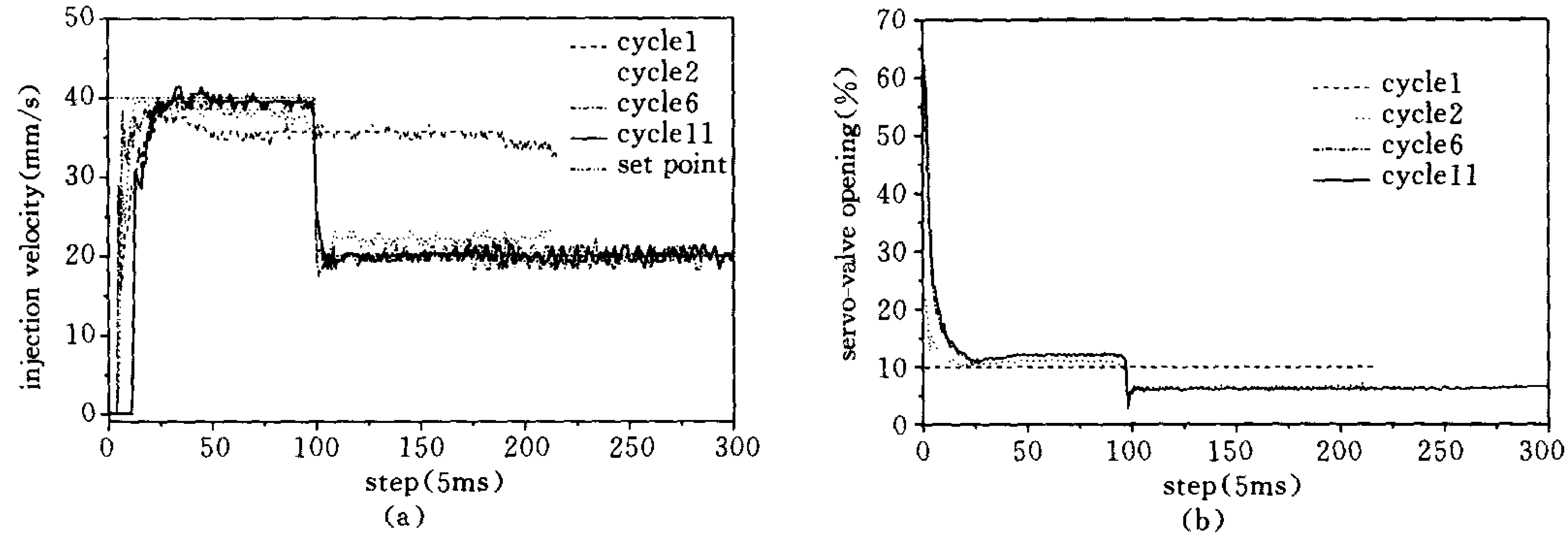

Fig. 3 Injection velocity control with $\rho=0.6^{k-1}$

5 Conclusions

The robustness and convergence issues of the optimal iterative learning control algorithm based on minimizing quadratic performance criteria have been considered in this paper for the processes with uncertain initializations and disturbances. A sufficient and necessary condition has been established to ensure robust BIBO stability of iterative learning control system when tracking arbitrary bounded desired output. Performance improvement is made by modifying weighting matrices of the quadratic cost function. The successful application of this algorithm to injection molding process makes us believe that the optimal iterative learning control can be applied to other industrial batch plants, especially processes with uncertain initials and disturbances, by appropriately adjusting the weighting matrices of the quadratic index.

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SHAO Cheng Professor of Research Center of Information and Control, Dalian University of Technology. His research interests include robust adaptive control, intelligent learning control, and optimizing control for chemical processes.

GAO Fu-Rong Professor of Department of Chemical Engineering, Hong Kong University of Science and Technology. His research interests include processes measurement, control and optimization.

YANG Yi Ph. D. candidate of Department of Chemical Engineering, Hong Kong University of Science and Technology. His research interests include adaptive control, predictive control, fuzzy control and advanced control for batch processes.

最优迭代学习控制的鲁棒稳定性及其在注塑机控制中的应有[1)]

邵 诚[1] 高福荣[2] 杨 毅[2]

[1](大连理工大学信息与控制研究中心 大连 116023)

[2](香港科技大学化学工程系 香港)

(E-mail: cshao@dlut.edu.cn)

摘 要 提出了一种鲁棒最优迭代控制器的设计方法.对于任意有界的参考输出和不确定的初始值,建立了由最优迭代学习控制器保证闭环系统有界输入有界输出(BIBO)鲁棒稳定性的充要条件.实际应用中可根据不确定初始设定值和干扰对加权矩阵进行调整,从而保证闭环系统性能随迭代过程的进行而得到改进.在注塑机控制中的应用验证了本文结论的有效性.

关键词 迭代学习控制,鲁棒性和稳定性,注塑机

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