Journal of Process Control 36 (2015) 64–78

Contents lists available at ScienceDirect

Journal of Process Control

journal homepage: www.elsevier.com/locate/jprocont

Stochastic iterative learning control for discrete linear time-invariant system with batch-varying reference trajectories

Se-Kyu Oh, Jong Min Lee*

School of Chemical and Biological Engineering, Institute of Chemical Processes, Seoul National University, 1 Gwanak-ro, Gwanak-gu, Seoul 08826, Republic of Korea

ARTICLE INFO

Article history:
Received 2 March 2015
Received in revised form 3 June 2015
Accepted 30 September 2015
Available online 10 November 2015

Keywords:
Iterative learning control
Stochastic process
Kalman filter
Batch-varying reference trajectories
Iterative learning identification

ABSTRACT

In this paper, we present adaptive iterative learning control (ILC) schemes for discrete linear time-invariant (LTI) stochastic system with batch-varying reference trajectories (BVRT). If reference trajectories change every batch, ILC shows a different convergence property from that of the identical reference trajectory. First, we derive the convergence property and propose deterministic adaptive ILC combined with iterative learning identification for LTI system with BVRT. If the state noise and measurement noise exist, convergence rate and tracking performance are degraded because the controller considers the difference arising from the noise as tracking error. To deal with such a problem, we propose two approaches. The first is based on a batch-domain Kalman filter, which uses the difference between the current output trajectory and the next reference trajectory as a state vector, while the second is based on a time-domain Kalman filter. In the second approach, the system is identified at the end of each batch in an iterative fashion using the observer/Kalman filter identification (OKID). Then, the stochastic problem is handled using Kalman filter with a steady-state Kalman gain obtained from the identification. Therefore, the second approach can track the reference trajectories of discrete LTI stochastic system using only the input–output information. Simulation examples are provided to show the effectiveness of the proposed schemes.

1. Introduction

Iterative learning control (ILC) is an effective control scheme in handling a system repeating the same task on a finite interval. Iterative learning controller controls a system in batch or iteration domain, while general controller, PID, LQR or MPC, controls a system in time domain. In the ILC, the input values for the entire time of the next batch operation are computed using input and output values of the current batch. ILC was first introduced for robot manipulators; in addition, it has been implemented in many industrial processes such as semiconductor manufacturing and chemical processes [1–6]. Most of the ILC schemes focus on tracking batch-invariant reference trajectory. Recently, several ILC schemes have been studied for tracking batch-varying references [7–9], and they use a recursive least squares algorithm to update the parameters iteratively along the batch index. Our previous work [10] also handles a system with batch-varying references using lifted system framework and iterative learning identification. However, these studies present methods for deterministic system only.

In this paper, we present adaptive ILC schemes for discrete linear time-invariant (LTI) stochastic system with batch-varying reference trajectories (BVRT). In batch processes (polymerization reactor or rapid thermal process), reference trajectory can be changed in case feed conditions, start up speed or shut down speed needs to be varied. New reference trajectory can be calculated from off-line optimization. In addition, products with various specifications can be produced from the same system. For example, one etching system in semiconductor manufacturing can produce wafers with various critical dimensions if the system can track BVRT. If the system has BVRT, convergence property of ILC differs from traditional ILC which aims at tracking an identical reference trajectory [10]. In this case, we should identify precise Markov parameters of system dynamics. Hence, we introduce iterative learning identification to satisfy convergence condition. In case of stochastic system, the presence of noises decreases the convergence rate and performance. This is because the controller considers

* Corresponding author. Tel.: +82 2 880 1878; fax: +82 2 888 1604.
E-mail address: jongmin@snu.ac.kr (J.M. Lee).

http://dx.doi.org/10.1016/j.jprocont.2015.09.008

noise as tracking error. To handle these issues, we propose two Kalman filter-based approaches. In case of batch-to-batch control problem, Kalman filter can be used in either time-domain or batch-domain. We apply Kalman filter in both the domains, and then compare the rate and tracking performance of the two approaches. In the first approach, we use Kalman filter in the batch-domain. Ahn et al. [11] proposed Kalman filter-augmented iterative learning control. This method can be applied only if a system has an identical reference trajectory and a fixed learning gain matrix. Hence, we extend the method to handle BVRT and batch-varying learning gain matrix. In the second approach, system Markov parameters are identified using the observer/Kalman filter identification (OKID) [12] in an iterative learning manner. The OKID algorithm is numerically efficient and robust with respect to measurement noise if the output residual error is zero-mean and Gaussian noise [13]. It also provides steady-state Kalman gain and system Markov parameters. With the steady-state Kalman gain, we can use the general Kalman filter in the time-domain for handling stochastic issue without covariance information of state and measurement noises. Therefore, the second approach uses only input–output information. The comparative results of the two approaches are provided in Section 4.

The rest of this paper is organized as follows: In Section 2, the deterministic ILC scheme for BVRT and convergence property are presented. In Section 3, the two Kalman filter-based approaches are proposed for handling stochastic issue. Then, numerical illustrations are provided in Section 4. Section 5 provides concluding remarks.

2. ILC for batch-varying reference trajectories

2.1. Convergence property for ILC with batch-varying reference trajectories

First, we consider the following linear discrete time-invariant system which operates on an interval $t \in [0, N]$:

$$\begin{aligned} x_k(t+1) &= Ax_k(t) + Bu_k(t) \\ y_k(t) &= Cx_k(t) \end{aligned} \tag{1}$$

where $x_k(t) \in \mathbb{R}^n$ is the state vector; $u_k(t) \in \mathbb{R}^m$ is the input vector; $y_k(t) \in \mathbb{R}^q$ is the output vector; t is the time index; k is the batch index; and the matrices A, B, and C are real matrices of appropriate dimensions and assumed to be time-invariant. Because finite time intervals $[0, N]$ are considered in ILC, this system can be rewritten as a lifted system:

$$\mathbf{y}_k = \mathbf{G}_p \mathbf{u}_k \tag{2}$$

with $x_k(0) = 0$ and the plant matrix $\mathbf{G}_p = \mathbb{R}^{(qN)\times(mN)}$ defined as

$$\mathbf{G}_p = \begin{bmatrix} CB & 0 & \cdots & 0 \\ CAB & CB & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ CA^{N-1}B & CA^{N-2}B & \cdots & CB \end{bmatrix} \tag{3}$$

and the vectors $\mathbf{y}_k \in \mathbb{R}^{qN}$, and $\mathbf{u}_k \in \mathbb{R}^{mN}$ are defined as

$$\mathbf{y}_k = \begin{bmatrix} y_k^T(1) & y_k^T(2) & \cdots & y_k^T(N) \end{bmatrix}^T \tag{4}$$

$$\mathbf{u}_k = \begin{bmatrix} u_k^T(0) & u_k^T(1) & \cdots & u_k^T(N-1) \end{bmatrix}^T \tag{5}$$

The system matrix $\mathbf{G}_p$ is a Markov matrix with a lower triangular Toeplitz structure.

The most general input update law of the conventional ILC with batch-invariant reference trajectory is represented by $\mathbf{u}_{k+1} = \mathbf{u}_k + \mathbf{H}(\mathbf{r} - \mathbf{y}_k) = \mathbf{u}_k + \mathbf{H}\mathbf{e}_k$ where $\mathbf{H}$ is a learning gain matrix, and $\mathbf{r}$ is a reference trajectory. It is assumed that input trajectory for next batch is calculated when the current batch operation is finished. Thus, $\mathbf{u}_{k+1}$ is calculated using available information $\mathbf{u}_k$ and $\mathbf{y}_k$. In this case, it is well known that $\mathbf{e}_k \to 0$ as $k \to \infty$ if $\|\mathbf{I} - \mathbf{G}_p\mathbf{H}\|_\infty < 1$ where $\mathbf{I}$ is the identity matrix [14]. In the conventional ILC formulation, $\mathbf{y}_k$ converges to the same reference $\mathbf{r}$ for all batches. Hence, it is possible to make the output converge as long as we know the values of the error and the model satisfying the convergence condition. If the reference trajectories are varied in batches, we should know not only the values of the error but also the input variation necessary to move the output from the current reference $\mathbf{r}_k$ to the next reference $\mathbf{r}_{k+1}$. The desired input of $(k+1)$-th batch can be expressed as the following form:

$$\mathbf{u}_{k+1}^d = \mathbf{u}_k + (\mathbf{u}_{k+1}^d - \mathbf{u}_k) \tag{6}$$

where $\mathbf{u}_{k+1}^d$ is the desired input for next reference $\mathbf{r}_{k+1}$. With the plant description of $\mathbf{y}_k = \mathbf{G}_p\mathbf{u}_k$ and $\mathbf{r}_{k+1} = \mathbf{G}_p\mathbf{u}_{k+1}^d$, Eq. (6) can be rewritten as:

$$\mathbf{u}_{k+1}^d = \mathbf{u}_k + \mathbf{G}_p^{-1}(\mathbf{r}_{k+1} - \mathbf{y}_k) \tag{7}$$

In the ILC problem, it is assumed that the plant matrix $\mathbf{G}_p$ is unknown or not invertible. Hence, we introduce batch-varying learning gain matrix to obtain input update law of the ILC for BVRT:

$$\mathbf{u}_{k+1} = \mathbf{u}_k + \mathbf{H}_k(\mathbf{r}_{k+1} - \mathbf{y}_k) \tag{8}$$

Theorem 1. *Consider the linear system (1) and the ILC controller (8). The system is convergent if* $\mathbf{H}_k$ *is chosen such that* $\mathbf{G}_p\mathbf{H}_k = \mathbf{I}$.