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A synthetic approach for robust constrained iterative learning control of piecewise affine batch processes☆

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ABSTRACT

For industrial nonlinear batch processes that can be practically divided into a series of piecewise affine operating regions, a two-dimensional (2D) closed-loop iterative learning control (ILC) method is proposed for robust tracking of the set-point profile against cycle-to-cycle process uncertainties and load disturbances. Both state feedback and output feedback are considered for the control design, together with the process input and output constraints for implementation. Based on a 2D system description for the batch operation, a few synthetic performance and robust control objectives are proposed for developing the 2D ILC schemes, in combination with the 2D Lyapunov–Krasovskii functions that can guarantee monotonic state energy (or output error) decrease in both the time (during a cycle) and batch (from cycle to cycle) directions. Both the polyhedral and norm-bounded descriptions of process uncertainties are considered to derive the corresponding linear matrix inequality (LMI) conditions for the closed-loop ILC system robust stability. An important merit of these LMI conditions is that there are adjustable convergence indices prescribed for both the time and batch directions, and an adjustable robust control performance level for the closed-loop system. By specifying/optimizing these adjustable parameters to solve these LMI conditions, the 2D ILC controller can be explicitly derived for implementation. The application to a highly nonlinear continuous stirred tank reactor (CSTR) is shown to illustrate the effectiveness and merits of the proposed ILC method.

1. Introduction

Industrial and chemical batch processes with a wide range of operating conditions are generally nonlinear and therefore have been widely concerned for advanced control design to obtain the desired system performance such as perfect tracking of the set-point profile to guarantee good product quality and consistency. To avoid the difficulties in model identification for control system design or to overcome the deficiencies of existing model-based control methods that cannot eliminate unexpected dynamic output response errors from cycle to cycle, iterative learning control (ILC) methods have been increasingly developed in recent years to realize perfect tracking and control optimization (Wang, Gao, & Doyle, 2009). This methodology is in principle based on using repetitive operation information of a batch process from historical cycles to progressively improve tracking performance from cycle to cycle. As surveyed in the recent literature (Ahn, Chen, & Moore, 2007; Bonvin, Srinivasan, & Hunkeler, 2006; Wang et al., 2009), most reported studies have been devoted to ILC methods for time-invariant linear or nonlinear batch processes. In fact, many batch processes, e.g., the membrane filtration process and pharmaceutical crystallization, are slowly time-varying from cycle to cycle, while repeating fundamental dynamic response characteristics or subject to repetitive and/or non-repetitive load disturbance (Busch, Cruse, & Marquardt, 2007; Nagy, Chew, Fujiwara, & Braatz, 2008). ILC methods based on using time-invariant process information cannot maintain robust stability for such batch processes (Rogers, Galkowski, & Owens, 2007). As far as we know, only a few papers have reported robust ILC methods for nonlinear batch processes with time-varying uncertainties. For uncertain nonlinear systems with specific structural properties or uncertainty types, adaptive ILC schemes have been developed to ensure the boundedness or asymptotic convergence of the

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set-point tracking error (Chien & Yao, 2004; Qu & Xu, 2002). A Lyapunov-based adaptive ILC scheme was proposed by Tayebi and Chien (2007) for the cycling operation with time-varying uncertainties. Xu and Tan (2002) suggested a composite energy function (CEF) to analyze the ILC system stability for a class of nonlinear systems with time-varying parametric uncertainties. For highly nonlinear batch processes, robust ILC schemes based on specific nonlinear model structures were proposed to guarantee batch-to-batch stability while complying with the process input constraints (Hermanto, Braatz, & Chiu, 2011; Nagy, Mahn, Franke, & Allgöwer, 2007), and a comparison between several nonlinear model structures for the ILC design was made by Nagy and Braatz (2007).

It has been widely recognized that many industrial nonlinear processes including batch processes can be decomposed into a series of linearized operating regions for system operation. Accordingly, piecewise affine control strategies, called linear parameter varying (LPV) control or gain-scheduling control (using multiple linear models), have been explored for robust control of such nonlinear processes (Forni & Galeani, 2010; Lu & Arkun, 2002; Özkan, Kothare, & Georgakis, 2003; Park & Jeong, 2004; Rugh & Shamma, 2000; Wan & Kothare, 2003, 2004, 2008). Due to the fact that the control system robust stability for batch process operation is required for both the time (during a cycle) and batch (from cycle to cycle) directions (Galkowski, Rogers, Xu, Lam, & Owens, 2002; Owens, Amann, Rogers, & French, 2000), the above control methods cannot be extended to nonlinear batch processes. It should be noted that for linear batch processes with uncertainties, two-dimensional (2D) robust ILC methods have been developed in recent years to address the control system robust stability in both the time and batch directions. However, these ILC methods have been mainly focused on robust tracking for linear batch processes subject to time-invariant or slowly varying (but cycle-to-cycle invariant) uncertainties and load disturbance (Wang et al., 2009). To cope with cycle-to-cycle varying process uncertainties, recent papers (Liu & Gao, 2010; Shi, Gao, & Wu, 2005, 2006) developed robust 2D ILC methods based on the output feedback and the norm-bounded description of process uncertainties. To enhance system performance against non-repetitive load disturbance, alternative on-line adaptive ILC schemes have been presented for practical implementation and performance improvement (Chen & Kong, 2009; Chin, Qin, Lee, & Cho, 2004; Zhang, 2008).

In this paper, a synthetic robust 2D ILC method is proposed for nonlinear batch processes that can be practically divided into a series of piecewise affine operating regions. Based on a 2D system description of the process for operation, including the time response within a cycle (denoted by t) and the batch operation from cycle to cycle (denoted by k), both time-varying process uncertainties and non-repetitive load disturbance are considered in the control design, together with the process input and output constraints for implementation. By defining the convergence indices for both the time and batch directions, and introducing the desired performance objective or robust control objective in combination with the 2D Lyapunov–Krasovskii functions that can guarantee monotonic state energy (or output error) decrease in both the time and batch directions, linear matrix inequality (LMI) conditions are correspondingly established for the ILC controller design and performance optimization. In these LMI conditions, there are adjustable convergence indices for the time and batch directions, and an adjustable closed-loop robust control performance level. For the convenience of implementation, the control algorithms and stability conditions are detailed for the use of state feedback and output feedback, respectively. The effectiveness of the proposed ILC method is demonstrated through the application to a highly nonlinear continuous stirred tank reactor (CSTR) subject to cycle-to-cycle uncertainties and load disturbance. For clarity, the paper is organized as follows: Section 2 briefly presents a piecewise model description of a nonlinear batch process, together with the process input and output constraints. In Section 3, an equivalent 2D system representation of such a batch process is formulated for the ILC design, along with some definitions and lemmas for the analysis of control performance and robust stability. In Section 4, two 2D ILC schemes are presented for the use of state feedback and output feedback, respectively. With the polyhedral or norm-bounded description of process uncertainties, the corresponding robust stability theorems are given for the 2D ILC design. Section 5 discusses how the process input and output constraints can be considered in the control algorithms for system performance optimization or robust control. Section 6 shows the application to a piecewise affine batch process of CSTR with different disturbance tests. Finally, conclusions are drawn in Section 7.

Throughout this paper, the following notations are used: $\Re^{n\times m}$ denotes a $n \times m$ real matrix space. For any matrix $P \in \Re^{m\times m}$, $P > 0$ (or $P \geq 0$) means P is a positive (or semipositive) definite symmetric matrix, in which the symmetric elements are indicated as '$*$'. P^T denotes the transpose of P. For any vector, $x > 0$ (or $x \geq 0$) means all elements of x are positive (or nonnegative). All vector inequalities are interpreted in an element-wise sense. For any vector x and matrix $P > 0$, denote $V_P(x) = \|x\|_P^2 = x^T Px$. The identity vector/matrix and the zero vector/matrix with appropriate dimensions are denoted by $\boldsymbol{I}$ and $\mathbf{0}$, respectively. For a 2D signal, $z(t, k)$, if $\|z(t, k)\|_2 = \sqrt{\sum_{t=0}^{n}\sum_{k=0}^{m}\|z(t, k)\|^2} < \infty$ for any integers n and m, then $z(t, k)$ is said to be in the $L_2[0, \infty)$ space of all square integrable functions. Denote by Co a convex hull, an element belonging to Co$\{\cdot\}$ means that it is a convex combination of all the elements in $\{\cdot\}$ multiplied by nonnegative weighting coefficients of which the sum equals unity.

2. Piecewise linear model description of a nonlinear batch process

Consider a nonlinear batch process that can be practically divided into a series of piecewise affine operating regions,

$$\begin{cases} \dot{x}(t,k) = f[x(t,k), u(t,k)]; \\ y(t,k) = g[x(t,k)], \quad 0 \leq t \leq T_{\mathrm{p}}; \\ y(t,k) \in \Omega = \cup_{i=1}^{m} \Omega_i; \\ x(0,k) = \bar{x}(0), \quad k = 1, 2, \ldots. \end{cases} \tag{1}$$

where $x(t, k) \in \Re^{n_x}$, $y(t, k) \in \Re^{n_y}$, $u(t, k) \in \Re^{n_u}$, t and k denotes the time and cycle indices, respectively. $\Omega \subset \Re^{n_y}$ denotes the real space of the output response, which includes m piecewise affine operating regions denoted by Ω_i $(i = 1, 2, \ldots, m)$. T_{p} is the cycling time, and $\bar{x}(0)$ denotes the initial resetting condition of each cycle that may be reset to zero with respect to each affine operating region for the convenience of control design.

A typical scenario of linearizing the nonlinear batch process in (1) with respect to a number of equilibrium operating points $([y_{\mathrm{eq}}^{[i]}, x_{\mathrm{eq}}^{[i]}, u_{\mathrm{eq}}^{[i]}], i = 1, 2, \ldots, m)$ is

$$\begin{cases} \dot{x}^{[i]}(t,k) = f(x_{\mathrm{eq}}^{[i]}, u_{\mathrm{eq}}^{[i]}) + \dfrac{\partial f}{\partial x}(x_{\mathrm{eq}}^{[i]}, u_{\mathrm{eq}}^{[i]})\Delta x^{[i]}(t,k) \\ \qquad + \dfrac{\partial f}{\partial u}(x_{\mathrm{eq}}^{[i]}, u_{\mathrm{eq}}^{[i]})\Delta u^{[i]}(t,k) \\ y^{[i]}(t,k) = g(x_{\mathrm{eq}}^{[i]}) + \dfrac{\partial g}{\partial x}(x_{\mathrm{eq}}^{[i]})\Delta x^{[i]}(t,k) \end{cases}$$
$$\begin{aligned} &\Delta x^{[i]}(t,k) = x(t,k) - x_{\mathrm{eq}}^{[i]}(t,k), \\ &\Delta u^{[i]}(t,k) = u(t,k) - u_{\mathrm{eq}}^{[i]}(t,k). \end{aligned} \tag{2}$$

Alternatively, such linear affine models can be derived using a piecewise model identification method (Liu & Gao, 2012; Ljung, 1999).