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Repetitive process based design and experimental verification of a dynamic iterative learning control law

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ABSTRACT

This paper gives new results on iterative learning control (ILC) design and experimental verification using the stability theory of linear repetitive processes. Using this theory a control law can be designed in one step to force error convergence and produce acceptable transient dynamics. Previous research developed algorithms for the design of a static control law with supporting experimental verification. Should a static law not give the required levels of performance one option is to allow the control law to have internal dynamics. This paper develops a procedure for the design of such a control law with supporting experimental verification on a gantry robot, including a comparative performance against a static law applied to the same robot. The resulting ILC design is an efficient combination of linear matrix inequalities and optimization algorithms.

1. Introduction

An often encountered industrial task involves a system, e.g., a robot, executing the same finite duration task over and over again. Once each execution has been completed resetting to the starting location occurs and the next execution can begin, either immediately after the resetting is complete or after a finite time period has elapsed from the end of the resetting operation. A particular example is a gantry robot making repeated executions of a pick and place operation where the steps are: (i) collect an object, or payload, from a given location, (ii) transfer it over a finite duration, (iii) place the payload on a moving conveyor, (iv) return to the starting location and (v) repeat (i)–(iv) as many times as required or for a finite number and then stop for maintenance. Each execution is commonly termed a trial in the literature and the time taken for a single trial is known as the trial length. Once each trial is complete, all information generated over the trial length is available for use in computing the control law for the next trial. For example, at sample instant t information from $t+\lambda, \lambda>0$, can be used. Such information is non-causal in the standard sense but not for the dynamics considered provided it has been generated on a previous trial.

The paper (Arimoto, Kawamura, & Miyazaki, 1984) introduced iterative learning control (ILC) as a method for the control of systems where the distinguishing feature is the use of information from previous trials to update the control signal applied on the next one. In particular, once the system has completed each trial, the complete information generated is available for use in computing the control signal to be applied on the next trial with the aim of sequentially improving performance from trial-to-trial.

Industrial robotics is the most natural application area for ILC but many others have also arisen in the engineering domain. The survey papers (Ahn, Chen, & Moore, 2007; Bristow, Tharayil, & Alleyne, 2006) are possible starting points for the literature. Also ILC has been applied outside engineering, most notably in robotic-assisted stroke rehabilitation where ILC, with supporting clinical trials, has been used to adjust the level of electrical stimulation applied to the relevant muscles of a stroke patient undergoing robotic-assisted upper limb rehabilitation for everyday tasks, such as reaching out to a cup over a table top or reaching out and then upwards (Freeman, Rogers, Hughes, Burridge, & Meadmore, 2012).

Let $y_{ref}(p)$ be a vector valued reference representing desired output behavior. In the case of discrete dynamics, use the notation $y_k(p)$, $0 \le p \le \alpha-1$, $k \ge 0$, where y is a vector or scalar valued variable, $\alpha < \infty$ denotes the number of samples over the trial duration and the nonnegative integer k the trial number. Then the error on trial k is

$$e_k(p) = y_{ref}(p) - y_k(p), \quad 0 \le p \le \alpha-1 \tag{1}$$

Moreover, the construction of a sequence of input functions that improves performance from one trial to the next is equivalent to the following convergence conditions on the input and error:

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$$\lim_{k\to\infty} \| e_k \| = 0, \quad \lim_{k\to\infty} \| u_k - u_\infty \| = 0, \tag{2}$$

where $\|\cdot\|$ is a signal norm in a suitably chosen function space with a norm-based topology and u_∞ is termed the learned control. These conditions ensure trial-to-trial performance and if, as in this paper, the dynamics along the trial are discrete, a commonly used setting for design is based on a form of lifting that enables the dynamic plant model in $\mathbb{R}$ to be treated, for single-input single-output (SISO) systems with a natural extension to the multiple-input multiple-output (MIMO) systems, as a static system in $\mathbb{R}^\alpha$. Once the ILC law is applied, the propagation of the error dynamics from trial-to-trial is described by a linear difference equation in k and this is the starting point for analysis and design.

Given the finite trial length, trial-to-trial (in k) error convergence can occur even if the system is unstable since such a system can only produce a bounded output over a finite time duration. Considering linear dynamics, the only option in lifting based ILC design is to first introduce a stabilizing feedback control law and then complete the ILC design for the controlled system. An alternative that allows simultaneous consideration of trial-to-trial error convergence and transient response along the trials is to formulate the design problem in the 2D systems setting, where k is one direction of information propagation and p the other. The use of 2D discrete linear systems theory in ILC design started in Kurek and Zaremba (1993) where the Roesser state-space model was used. Repetitive processes are a particular class of 2D systems where information propagation in the temporal domain occurs over a finite duration known as the pass length, where this is an inherent property of the dynamics and not an assumption.

The finite pass length makes repetitive processes a more natural match for ILC design and this setting has led to control laws that have been experimentally tested (Hladowski et al., 2010, 2012; Paszke, Rogers, Gałkowski, & Cai, 2013). These results used static combinations of state or output feedback and pass profile feed forward information with Linear Matrix Inequalities (LMIs) used to calculate the required control law parameters. Another option, frequently used in process control applications, exploits the batch process setting, e.g., Liu and Wang (2012) where an approach to robust ILC design was developed for batch processes with time-varying uncertainties and load disturbances. This is similar to the repetitive processes setting but only designs in this latter setting have been experimentally validated.

Due to possible LMI conservativeness, a design may fail for a given example. One approach to remove or lessen the effects of this problem is to include further noncausal finite-time interval data (Cichy, Galkowski, & Rogers, 2014) in the ILC law and/or use parameter dependent Lyapunov functions (Cichy, Galkowski, & Rogers, 2015). Another approach in such cases is to use a dynamic controller, which is the subject of this paper where the results are on the structure, design and experimental verification of such a control law in the repetitive process setting for discrete dynamics.

Throughout this paper, the null and identity matrices of compatible dimensions are denoted by 0 and I respectively. Also, a symmetric positive definite (respectively negative definite) matrix, say M, is denoted by $M \succ 0$ (respectively $M \prec 0$). The symbol $*$ represents transposed entries in a symmetric matrix and the next section gives an overview of the relevant results from the modeling and stability analysis of linear repetitive processes.

2. Background

The analysis and control law design in this paper is based on the stability theory for linear repetitive processes whose dynamics and unique control problem are best introduced in terms of a physical example. In coal mining the coal is extracted by the cutting machine as it makes repeated traverses along the coal face, termed passes. Once each pass is complete, the machine is returned to the starting location and the next pass can begin, either immediately or after a period of time has elapsed. During the production of each pass, where the output is termed the pass profile, the machine rests on a semi-flexible structure that lies over the previous pass profile. Hence the previous pass profile acts as a forcing function on, and hence contributes to, the dynamics of the next pass profile. Variables in a repetitive process are functions of two indeterminates and the notation used is of the form $y_k(p)$, $0 \le p \le \alpha - 1$, $k \ge 0$, where y is the scalar or vector valued variable, $\alpha < \infty$ is the pass length and the subscript k denotes the pass number.

Let $\{y_k\}$ denote the sequence of pass profiles generated by an example. Then the control problem is that this sequence can contain oscillations that increase in amplitude from pass-to-pass, i.e., with k. The original references are in Rogers, Galkowski, and Owens (2007) for the coal mining application and establish that the oscillations in the pass profile sequence are due, in the main, to the weight of the cutting machine. Without control action the only option is to halt productive work to enable their manual removal and in this application the interaction between successive pass profiles is due to the physics of the application area. In other cases, including ILC, this interaction arises from the control action applied. Another example in this latter class is OL-Nash games in gas dynamics problems (Azevedo-Perdicoulis & Jank, 2012).

A stability theory for linear constant pass length repetitive processes has been developed (Rogers et al., 2007). This is based on an abstract model in a Banach space setting that includes are very wide range of such processes as special cases. Given the control problem, this theory demands that a bounded initial pass profile produces a bounded sequence of pass profiles, with boundedness defined in terms of the norm on the underlying function space. Moreover, this property can be enforced over the finite and fixed pass length, termed asymptotic stability, or for all possible values of the finite pass length, termed stability along the pass. This last property can be analyzed by considering $\alpha \to \infty$ and this is the form of repetitive process stability theory required in this paper.

The analysis and ILC design in this paper is based on discrete linear repetitive processes whose state-space model over $0 \le p \le \alpha - 1$, $k \ge 0$, is

$$\begin{aligned} x_{k+1}(p+1) &= \overline{\mathbf{A}}x_{k+1}(p) + \overline{\mathbf{B}}u_{k+1}(p) + \overline{\mathbf{B}}_0 y_k(p),\ y_{k+1}(p) \\ &= \overline{\mathbf{C}}x_{k+1}(p) + \overline{\mathbf{D}}u_{k+1}(p) + \overline{\mathbf{D}}_0 y_k(p), \end{aligned} \tag{3}$$

where on pass k, $x_k(p) \in \mathbb{R}^n$ is the state vector, $y_k(p) \in \mathbb{R}^m$ is the pass profile vector and $u_k(p) \in \mathbb{R}^r$ is the control input vector. The boundary conditions are the state initial vector on each pass and the initial pass profile. In this work the boundary conditions can be taken as zero without loss of generality.

As discussed above, stability of these processes is defined in terms of the contribution of the previous pass profile to the next pass. For processes described by (3) the pass-to-pass coupling is described by the convolution operator, denoted by L_α, for a discrete standard linear system with state-space model matrices $\{\overline{\mathbf{A}}, \overline{\mathbf{B}}_0, \overline{\mathbf{C}}, \overline{\mathbf{D}}_0\}$. Hence the contribution from pass k to pass $k+1$ can be written as $y_{k+1} = L_\alpha y_k$, $k \ge 0$. Also let $y_k \in E_\alpha$, where E_α is a suitably chosen Banach space with norm denoted by $\|\cdot\|$ and let the same symbol denote the induced norm on the bounded linear operator L_α.

Asymptotic stability for linear repetitive processes is equivalent to the existence of finite real scalars $M_\alpha > 0$ and $\lambda_\alpha \in (0, 1)$ such that $\| L_\alpha^k \| \le M_\alpha \lambda_\alpha^k$, $k \ge 0$. For examples described by (3), asymptotic stability requires that $\rho(\overline{\mathbf{D}}_0) < 1$ and if this condition holds the