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Brief paper

Inferential Iterative Learning Control: A 2D-system approach[☆]

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ABSTRACT

Certain control applications require that performance variables are explicitly distinguished from measured variables. The performance variables are not available for real-time feedback. Instead, they are often available after a task. This enables the application of batch-to-batch control strategies such as Iterative Learning Control (ILC) to the performance variables. The aim of this paper is first to show that the pre-existing ILC controllers may not be directly implementable in this setting, and second to develop a new approach that enables the use of different variables for feedback and batch-to-batch control. The analysis reveals that by using pre-existing ILC methods, the ILC and feedback controllers may not be stable in an inferential setting. Therefore, the complete closed-loop system is cast in a 2D framework to analyze stability. Several solution strategies are outlined. The analysis is illustrated through an application example in a printing system. Finally, the developed theory also leads to new results for traditional ILC algorithms in the common situation where the feedback controller contains a pure integrator.

1. Introduction

Increasing performance requirements on systems demand an explicit distinction between measured variables and performance variables. Performance variables may not be available for real-time feedback control due to computational constraints, physical limitations in sensor placement, delays in acquiring measurements, etc. Examples include heat exchangers (Parrish & Brosilow, 1985) and motion systems (Oomen, Grassens, & Hendriks, 2015).

In many cases, the performance variables are available offline. For instance, when the final product is inspected afterwards, the 'true' performance is revealed. This enables batch-to-batch control using performance variables. A common batch-to-batch control strategy is Iterative Learning Control (ILC) (Bristow, Tharayil, & Alleyne, 2006). In ILC, the control signal is updated trial-to-trial using measurement data of previous trials to improve performance. Traditionally, ILC is applied to the measured variables that are also available for the feedback controller. This classical approach is well-established with many results on the convergence and robustness properties (Norrlöf & Gunnarsson, 2002; Wang, Gao, & Doyle, 2009).

A direct combination of ILC acting on the performance variables while the feedback controller uses different real-time measured variables may lead to potentially hazardous situations. Indeed, the feedback controller aims to regulate the measured variables while the ILC regulates the performance variables. This may lead to a conflict in case a parallel (Bristow et al., 2006) ILC-feedback control structure is used. In Longman and Lo (1997), initial indications of such a conflict are already reported. In Wallén, Norrlöf, and Gunnarsson (2011), a related and specific approach is presented to use observers to *infer* the performance variables from the real-time measurements instead of a direct performance measurement. The main idea is that distinguishing between performance and measured variables can potentially fully exploit the use of ILC. The use of performance variables for ILC and different real-time measured variables for feedback control is referred to as *inferential ILC* in the present paper.

Although ILC is potentially promising for the mentioned inferential control applications, the direct application of pre-existing ILC design methods may not lead to satisfactory performance and stability properties. In fact, in this paper it is shown through a formal analysis that using traditional ILC design approaches such as

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Bristow et al. (2006) and Norrlöf and Gunnarsson (2002) in the inferential ILC situation can lead to implementations that are unstable.

The main result of this paper is a framework for inferential ILC, including a detailed analysis and new learning control approaches. To facilitate the analysis, the time-trial dynamics of a common ILC algorithm with dynamic learning filters is cast into a 2D Framework using discrete Linear Repetitive Processes (dLRP's) (Rogers, Galkowski, & Owens, 2007). The motivation for using 2D systems stems from the observation that the unstable behavior remains undetected in traditional approaches, e.g., as the lifted/supervector approach in Norrlöf and Gunnarsson (2002). Stability conditions are developed using 2D systems theory. Solutions are presented and analyzed using these stability conditions. The analysis is illustrated through an application example in printing systems. In addition, it can be shown that the related approach in Wallén et al. (2011) can be analyzed in the developed framework as a special case. Finally, the developed theory also leads to new results for the traditional ILC case where the performance variables are equal to the measured variables in the common situation where the feedback controller contains an integrator.

Notation. $\mathbb{Z}^*$ ($\mathbb{Z}^+$) denotes the set of positive (non-negative) integers. Discrete-time is denoted with $p \in \mathbb{Z}, k \in \mathbb{Z}$ is the trial index. For $A \in \mathbb{C}^{n\times n}$, $\rho(A) = \max_{1\leq i\leq n} |\lambda_i|$, with $\lambda = \{\lambda_0, \lambda_1, \ldots, \lambda_n\}$ the spectrum of A. Systems are discrete-time, for a system G, $G := \left[\begin{array}{c|c} A^G & B^G \\ \hline C^G & D^G \end{array}\right]$ denotes a state-space representation with state x^G, which is often assumed minimal. The real-rational transfer function for G is given by $G(z) = C^G(zI - A^G)^{-1} + D^G$, with z a complex indeterminate and $G \in \mathcal{R}^{n_y\times n_u}$. Over a finite-time interval $0 \leq p < \alpha$, $\alpha \in \mathbb{Z}^+$, the input–output behavior of G can be denoted as $\bar{y} = \bar{G}\bar{u}$ with $\bar{G} \in \mathbb{R}^{\alpha n_y\times\alpha n_u}$ a Toeplitz matrix that contains the impulse response coefficients $h(p)$, where $h(p) = C^G(A^G)^{p-1}B^G$ for $p > 0$ and $h(0) = D^G$, with $h(p) \in \mathbb{R}^{n_y\times n_u}$ (Norrlöf & Gunnarsson, 2002). The input $\bar{u} \in \mathbb{R}^{\alpha n_u}$ and output $\bar{y} \in \mathbb{R}^{\alpha n_y}$. Single-input single-output systems are assumed throughout to facilitate the presentation. The extension to multivariable systems is conceptually straightforward and many of the results in Sections 3 and 4 directly apply.

2. Problem definition and application motivation

First, the control setup is motivated from an application perspective. Next, the considered problem is presented.

2.1. Application motivation and control setup

Printing systems are an important example where performance variables cannot be measured directly in real-time. The paper positioning drive of a printer, see Fig. 1, is traditionally controlled through feedback using inexpensive encoder position measurements. High tracking accuracy using the encoder measurement y does not imply good printing performance z due to mechanical deformations in the drive.

Recently, a scanner has been mounted in the printhead, which enables line-by-line measurements of the printing performance z (Bolder, Oomen, Koekebakker, & Steinbuch, 2014). This direct measurement of the performance is not available to real-time feedback, but can directly be used for batch-to-batch control strategies including Iterative Learning Control (ILC). This leads to the situation where the variables for feedback control y are not equal to variables for ILC z, see Fig. 2. Here, $\begin{bmatrix} z_k & y_k \end{bmatrix}^T = Pu_k$. System P has two outputs: the performance variable z_k and the measured variable y_k. The input to the system equals $u_k = u_k^C + f_k$.

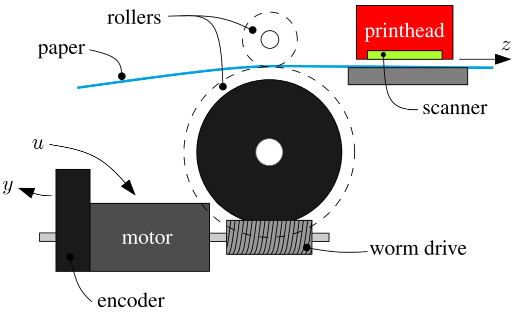

Fig. 1. Side-view of the positioning drive in a printer. The paper position z is controlled using the motor. The feedback controller uses real-time encoder measurements y. The performance z is measured line-by-line using the scanner.

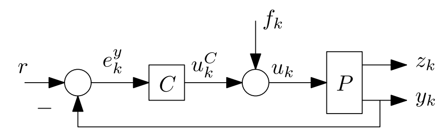

Fig. 2. Traditional feedback control setup.

Here, $u_k^C(r, y_k)$ is the feedback control signal. In traditional printing systems, it is assumed that $y_k \approx z_k$, in which case a feedback controller is implemented as $u_k^C = C(r - y_k)$, with C assumed fixed and designed such that the closed-loop system is internally stable. In the setting considered in the present paper, the feedforward signal f_k results from a batch-to-batch control algorithm. For instance, standard ILC approaches (Bristow et al., 2006) consider an algorithm of the form

$$f_{k+1} = Q(f_k + Le_k^z), \tag{1}$$

where $e_k^z = r - z_k$, L is a learning filter, Q is a robustness filter, and k is the trial index. Appropriate substitution of e_k^z in (1) using $P = [P^z\ P^y]^T$, $z_k = P^z u_k$, $u_k = Ce_k^y + f_k$, $e_k^y = r - y_k$, and $y_k = P^y u_k$ leads to iteration domain dynamics $f_{k+1} = Q(1 - LJ)f_k + L(1 - JC)r$, where

$$J = \frac{P^z}{1 + CP^y}. \tag{2}$$

Next, a simplified inferential ILC example is presented.

2.2. Illustrative example

In the following example, it is shown that using the traditional ILC approach of Bristow et al. (2006) in the batch-to-batch inferential setting where $y_k \neq z_k$ can lead to an undesirable situation.

Example 1. Let

$$P = \begin{bmatrix} P^z \\ P^y \end{bmatrix} = \begin{bmatrix} 1 \\ 3 \end{bmatrix} \quad \text{and} \quad C = \left[\begin{array}{c|c} 1 & 1 \\ \hline 0.5 & 0 \end{array}\right].$$

Thus, P is a static system and C an I-controller. The stable closed-loop system is given by

$$\begin{bmatrix} z_k \\ y_k \end{bmatrix} = \left[\begin{array}{c|cc} -0.5 & 1 & 3 \\ \hline -0.5 & 0 & 1 \\ -1.5 & 0 & 3 \end{array}\right] \begin{bmatrix} r \\ f_k \end{bmatrix}.$$

Next, an ILC algorithm (1) is designed following Bristow et al. (2006) and Norrlöf and Gunnarsson (2002), with $Q = 1$ and L such that the trial-to-trial dynamics converge. The converged command signal f_∞ is given by

$$f_\infty = \lim_{k\to\infty} f_{k+1} = (1 + CP^y - CP^z)P^{z^{-1}} r, \tag{3}$$