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IFAC-PapersOnLine 49-21 (2016) 213–221

Design Techniques for Multivariable ILC: Application to an Industrial Flatbed Printer

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Abstract: Iterative Learning Control (ILC) can significantly improve performance of systems that perform repeating tasks. Although in practice many systems are multivariable, frequency-domain ILC design procedures often involve multi-loop single-input single-output (SISO) filters which do not explicitly address interaction in dynamics. The aim of this paper is to i) analyze multi-loop SISO ILC designs, ii) point out the importance of multivariable ILC design, and iii) develop the required multivariable design algorithms. Benefits of the proposed approaches over multi-loop SISO ILC are demonstrated on an industrial printer model example.

Keywords: Iterative learning control, multivariable control, zero phase-error tracking control, non-minimum phase systems, motion control, $\mathcal{H}_\infty$ control, preview control

1. INTRODUCTION

Iterative Learning Control (ILC) (Bristow et al. (2006)) is widely used in control systems, since it can significantly improve the performance of systems that perform repeating tasks. Many successful applications have been reported, including additive manufacturing (Barton et al. (2011); Hoelzle et al. (2011)), industrial robots, printing systems (Bolder et al. (2015)), and wafer stages (Mishra et al. (2008)).

Important design frameworks in ILC include frequency-domain design, and time-domain norm-optimal design. The time-domain norm-optimal framework often uses advanced synthesis tools from optimal control, and requires detailed uncertainty models to provide robustness, see, e.g., Ahn et al. (2007); Van de Wijdeven et al. (2009). In contrast, frequency-domain ILC design can be based on nonparametric frequency response function (FRF) measurements, and performance and robustness requirements can be enforced by means of standard frequency-domain loop-shaping methods, see, e.g., Bristow et al. (2006, 2010); Moore (1993); Boeren et al. (2016). These are important advantages for industrial motion control applications. Hence, the present paper focuses on frequency-domain ILC design techniques.

Although in practice many systems are multivariable, i.e., multi-input multi-output (MIMO), design techniques for ILC often consider multi-loop single-input single-output (SISO) controllers, see, e.g., Bristow et al. (2006); Moore (1993); Wallén et al. (2008). In these multi-loop SISO design techniques, interactions in MIMO systems are not explicitly taken into account, which potentially can lead to non-convergent algorithms. To deal with these ignored dynamics, performance of the ILC may have to be sacrificed due to the more severe demand on robustness. This is a well known trade-off between performance and robustness.

Noncollocated sensors and actuators, and fast sample rates with plants having high relative degree can lead to non-minimum phase (NMP) dynamics which complicate the ILC design. For NMP systems, inputs obtained through standard inversion techniques typically yield unbounded outputs. Solutions to compute bounded outputs include stable inversion (Blanken et al. (2016a); Boeren et al. (2015); Bolder et al. (2015)), and heuristic stable designs such as the widely used zero phase-error tracking control (ZPETC) of Tomizuka (1987), the related zero magnitude-error tracking control (ZMETC), see, e.g., Butterworth et al. (2012), and perfect tracking control, see, e.g, Fujimoto et al. (2001). Recently, in Blanken et al. (2016b) an intuitive procedure is proposed for computing full MIMO controllers which provide phase cancellation for NMP zeros. Though, this procedure requires performing pole-zero cancellations, which can be numerically troublesome.

In this paper, two approaches for multivariable ILC design are proposed. First, an alternative implementation is presented with improved numerical properties compared to the heuristic design of Blanken et al. (2016b). This procedure is applicable to MIMO systems, and recovers the traditional ZPETC for SISO systems. Second, a procedure is presented for $\mathcal{H}_\infty$-optimal ILC synthesis with finite preview. For zero preview, this approach recovers the results of De Roover and Bosgra (2000). This approach potentially outperforms heuristic designs in terms of achievable performance, and numerical properties.

The aim of this paper is to point out the importance of multivariable ILC design techniques related to the performance-robustness trade-off, and develop the re-

10.1016/j.ifacol.2016.10.552

quired algorithms. By explicitly incorporating interactions in multivariable ILC design, performance can potentially be improved, see, e.g., De Roover and Bosgra (2000). The contributions of this paper are fourfold. First, a design-oriented analysis is presented of multi-loop SISO ILC, related to robustness for ignored dynamics. Second, an algorithm is proposed to design a multivariable learning filter for NMP systems, which cancels the phase shifts induced by unstable zeros. Third, an $\mathcal{H}_\infty$-based approach is presented for the optimal synthesis of ILC systems, including finite preview. Fourth, the benefits are demonstrated of explicitly designing the ILC for interaction on an industrial printer model example.

The outline of this paper is as follows. In Section 2, the MIMO frequency-domain ILC design problem is formulated. In Section 3, a design-oriented analysis of multi-loop SISO ILC is presented. In Section 4, a heuristic MIMO ILC design is presented, and in Section 5 an $\mathcal{H}_\infty$-based approach is presented for the optimal synthesis of ILC systems with finite preview. In Section 6, the industrial flatbed printer used for simulations is introduced, for which MIMO ILCs are designed in Section 7. In Section 8, the benefits of MIMO ILC are demonstrated by use of simulations. Finally, conclusions are provided in Section 9.

Notation: $\mathbb{R}[z]$ denotes the polynomial ring in indeterminate z with coefficients in $\mathbb{R}$. $\mathcal{R}(z)$ denotes the field of real rational functions. The space consisting of all square summable sequences is denoted ℓ_2. Given $f(z), g(z) \in \mathbb{R}[z]$, $g(z)$ divides $f(z)$ if there exists a $h(z) \in \mathbb{R}[z]$ such that $f(z) = g(z)h(z)$. A polynomial is called monic if it has leading coefficient 1. A polynomial matrix $U(z) \in \mathbb{R}^{n\times n}[z]$ is called unimodular if and only if $U^{-1}(z) \in \mathbb{R}^{n\times n}[z]$. A_d denotes the diagonal matrix containing the diagonal elements of A. Furthermore, $\mathrm{diag}\{a_1, a_2, \dots, a_n\}$ is the diagonal matrix with diagonal elements $a_1, a_2, \dots, a_n$. Throughout, all systems are assumed to be discrete-time, multi-input multi-output (MIMO), and linear time-invariant. The complex indeterminate z is omitted when this does not lead to any confusion.

2. PROBLEM FORMULATION

In this section, the multivariable ILC design problem is formulated, and design challenges are indicated motivating the analysis and development of multivariable ILC design techniques in Sections 3 and 4, respectively.

Consider the control configuration depicted in Figure 1, consisting of the true system $P(z) \in \mathcal{R}^{p\times q}(z)$ and a stabilizing feedback controller $C(z) \in \mathcal{R}^{q\times p}(z)$. The system is repeatedly excited by a reference signal r. Each repetition of r is called a task, denoted by subscript j. Furthermore, f_j denotes the feedforward, u_j the controller output, y_j the output, and e_j the error in task j, given by

$$e_j = Sr - SPf_j,$$

with sensitivity $S = (I + PC)^{-1} \in \mathcal{R}^{p\times p}(z)$. The objective of ILC is to minimize e_j in terms of an appropriate norm. To this purpose, e_j is measured in task j and used to construct f^{j+1} in task $j + 1$. Typically, the following general ILC algorithm is invoked:

$$f_{j+1} = Q(f_j + Le_j), \tag{1}$$

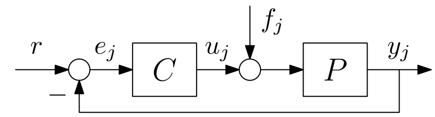

Fig. 1. ILC control configuration.

with learning filter $L \in \mathbb{R}^{q\times p}$ and robustness filter $Q \in \mathbb{R}^{q\times q}$. A condition for monotonic convergence of f_j is given in the following theorem.

Theorem 1. Consider the control configuration in Figure 1, and suppose $u_j, e_j \in \ell_2$, then the ILC algorithm (1) converges monotonically to a fixed point f^* if

$$\|Q(I - LSP\|_\infty < 1 \tag{2}$$

where $\|H\|_\infty = \sup_{\omega\in[0,\pi]} \bar{\sigma}(H(e^{j\omega}))$ is the $\mathcal{L}_\infty$-norm, and $\bar{\sigma}$ denotes the maximum singular value.

Proof. A proof of Theorem 1 is omitted, since it follows along similar lines as (Moore, 1993, Theorem 3.1) for the $\mathcal{H}_\infty$-norm, and can be appropriately extended to the $\mathcal{L}_\infty$-norm to account for noncausal L, Q using (Chen and Gu, 2000, Theorem 2.1.10). □

If (2) is satisfied, the fixed point f^* is given by

$$f^* = (I - Q(I - LSP))^{-1} QLSr,$$

and the resulting fixed point of the error is given by

$$e^* = \left(I - SP\,(I - Q(I - LSP))^{-1} QL\right) Sr. \tag{3}$$

For (2) to be satisfied and (3) minimal, it can be seen that L should be chosen equal to $(SP)^{-1}$ with $Q = I$. However, NMP dynamics of SP can complicate the control design.

Although convergence analysis results as Theorem 1 have received considerable attention in literature, practical procedures for the design of multivariable filters L and Q are difficult to find. Often, L and Q are designed as multi-loop SISO filters, see Bristow et al. (2006); Moore (1993). This design choice for ILC is analyzed in the next section. This analysis will motivate to develop design procedures for *full* multivariable L-filters in Sections 4 and 5.

3. ANALYSIS & DESIGN OF MULTI-LOOP SISO ILC

In this section the design of multi-loop SISO, or diagonal, ILC is addressed. Though this makes the design procedure relatively simple, interaction in the closed-loop system is ignored. Hence, the robustness filter Q must not only be designed for model uncertainty, but also for interaction.

A multi-loop SISO learning filter is of the form

$$L = \mathrm{diag}\{L_1, L_2, \dots, L_p\}, \tag{4}$$

with $L_i \in \mathcal{R}(z)$. Each element L_i can, e.g., be designed as the zero-phase error tracking controller for the corresponding element of $(\widehat{SP})_\mathrm{d}$, as in Tomizuka (1987). Given this design approach for L, the design of robustness filter Q is investigated in the following sections.

3.1 Multi-Loop SISO Design for Q Ignoring Interaction

In this section, the design of a multi-loop SISO robustness filter Q is analyzed, with attention to model uncertainty and interaction in the dynamics. Here, model uncertainty refers to $\Delta = (SP)_\mathrm{d} - (\widehat{SP})_\mathrm{d}$, i.e., the model error in the