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Assessment of gradient-based iterative learning controllers using a multivariable test facility with varying interaction

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ABSTRACT

A multiple input, multiple output (MIMO) experimental test facility has been developed for the evaluation, benchmarking and comparison of iterative learning control (ILC) strategies. The system addresses the distinct lack of experimental studies for the multivariable case and enables controller performance and robustness to be rigorously investigated over a broad range of operating conditions. The electromechanical facility is multi-configurable with up to 3 inputs and permits both exogenous disturbance injection and a variable level of coupling to be applied between input and output pairs. To confirm its suitability for evaluation and comparison of ILC, theoretical results are derived for two popular forms of gradient-type ILC algorithm, linking interaction with fundamental performance limitations. The test facility is then used to establish how well theoretical predictions match experimental results. The analysis is then extended to provide solutions to address this performance degradation, and these are again confirmed using the test facility.

1. Introduction

Iterative Learning Control (ILC) was formally conceived 30 years ago, and has become an area of considerable research interest in both theoretical and application domains. ILC is suitable for systems which perform a repeated process defined over a finite time interval, termed a trial. It uses data recorded over previous trials to modify the control signal of the subsequent trial with the aim of sequentially improving tracking accuracy. A well established algorithmic framework has emerged for the class of gradient based algorithms whose convergence and robustness properties have been extensively studied by many groups, including Bristow (2008), Butcher, Karimi, and Longchamp (2008), Freeman, Rogers, Hughes, Burridge, and Meadmore (2012), Janssens, Pipeleers, and Swevers (2013a), Mishra, Topcu, and Tomizuka (2011), Ratcliffe, Lewin, Rogers, Hatonen, and Owens (2006), van de Wijdeven, Donkers, and Bosgra (2009) and Wang, Dassau, and Doyle (2010). A prominent member of this class is Norm Optimal ILC (NOILC) which has received considerable attention in the ILC community due to its mature theoretic basis (Amann, Owens, & Rogers, 1996; Janssens, Pipeleers, & Swevers, 2013b; Pandit & Buchheit, 1999). The framework has been applied to a range of systems including gantry robots (Ratcliffe et al., 2006), multi-axis robotic testbeds (Barton & Alleyne, 2011), rehabilitation platforms (Rogers et al., 2010), lasers (Rogers et al., 2010) and pneumatic muscle actuators (Schindele & Aschemann, 2011). Extensions have been proposed using a predictive mechanism (Bristow & Alleyne, 2006), constraints (Chu & Owens, 2010), projections (Chu & Owens, 2009), and accelerated learning (Owens & Chu, 2009). Another well established algorithm is 'gradient ILC', also termed 'adjoint ILC' which has been studied by many groups, including Furuta, Yamakita, and Kobayashi (1991), Jian-Xu and Ji (1998), Owens and Feng (2003) and Owens, Hätonen, and Daley (2009) and found to possess considerable robustness to plant uncertainty (Owens et al., 2009). This has been confirmed in applications to experimental single input, single output (SISO) systems including a non-minimum test facility (Freeman, Lewin, & Rogers, 2007).

ILC has a proven ability in providing high performance in the presence of significant modelling uncertainty and exogenous disturbance, leading to uptake within industries such as manufacturing (Freeman, Lewin, Rogers, & Ratcliffe, 2010; Kim & Kim, 1996), chemical process engineering (Hui-hai, 2009; Lee, Bang, Yi, Son, & Yoon, 1996), industrial power systems (Deng, Oruganti, & Srinivasan, 2009; Zha, Sun, & Chen, 2003), robotics (Elci, Longman, Phan, Juang, & Ugoletti, 1994; Chen & Li, 2010; Hui-hai, 2009; Norrlof, 2002), biomedical engineering (Freeman et al., 2011) and precision laser and satellite control (Rogers et al., 2010; Wu et al., 2009). While many such reported applications and cases of detailed experimental comparison and benchmarking exist for the SISO case, there are few instances involving multiple input, multiple output (MIMO) systems (Haurani, Taha, Michalska, &

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Boulet, 2001; Tyréus, 1979). These are generally more challenging due to interaction dynamics which typically increase controller demand as well as significantly complicating controller design and performance/robustness analysis. A number of studies involve multivariable systems (Barton & Alleyne, 2011; Bristow & Alleyne, 2006; Ratcliffe et al., 2006), but interaction between dynamics is negligible and is generally not considered. With mild interaction, one approach is to treat the coupling as an exogenous disturbance and to design multiple SISO ILC loops. This has yielded satisfactory results when applied to control each joint of a six degrees-of-freedom industrial robot (Wallén, Norrlof, & Gunnarsson, 2008). The approach has also been taken in stroke rehabilitation with ILC used to control the electrical stimulation applied to muscles in the lower and upper limb (Freeman et al., 2012). However, in the foregoing cases a robustness filter was required to prevent instability and the tracking accuracy was considerably larger than when controlling a single joint (with the remaining joints locked). In the case of more significant multivariable coupling, this approach may therefore be expected to lead to a further loss of tracking accuracy, and the likelihood of instability. Other practical studies have employed MIMO test facilities to tackle vibration suppression using ILC. For example in Tsai, Chen, Yun, and Tomizuka (2013) an ILC approach is applied to a 6 degree of freedom LCD substrate transfer robot to reduce end-effector vibration. Another MIMO vibration suppression approach is applied experimentally to a 3 input, 3 output flexible beam in van de Wijdeven and Bosgra (2007). In addition to a lack of MIMO application examples with significant input–output coupling there exists no comparative benchmarking between ILC algorithms, critical for thorough performance assessment prior to wider industrial implementation (Ahn, Chen, & Moore, 2007; Bristow, Tharayil, & Alleyne, 2006).

More generally, multivariable test facilities have been developed for the purpose of benchmarking and comparison of control strategies, such as a 2 input, 2 output quadruple-tank process (Johansson, 2000), however, to the authors' knowledge no modular facility exists which enables full control over the degree of coupling between input–output pairs, or which enables noise/disturbance injection to be applied. To address this problem, a multi-configurable experimental test facility is developed in this paper to enable MIMO ILC approaches to be rigorously evaluated. This platform provides a variety of possible inputs and outputs, enables disturbance injection and encompasses variable dynamic interaction. In addition, its modular structure will enable principled analysis of many relevant phenomena in a comprehensive manner (e.g. the inclusion of non-minimum phase zeros can be realised by modifying the spring-mass-damper sections to assume the non-minimum phase form used in Freeman et al. (2007)).

To confirm the system's utility for both benchmarking and for evaluation of new theoretical results, this paper provides novel analysis which links the level of interaction with fundamental performance limitations within both NOILC and gradient ILC. These algorithms are then implemented on the system and experimental results are found to match theoretical predictions over a broad range of operating conditions. To address these limitations, the analysis is extended and it is shown that the performance limitations are directly mitigated by relaxing the tracking requirement to comprise only a subset of points over the trial duration. Using the test facility, these results are then confirmed experimentally over a range of interaction levels.

This paper is arranged as follows: Section 2 describes the specification, design and parameter selection of the test facility and Section 3 details its physical realisation. ILC algorithms are derived and summarised in Section 4 together with performance measures, and experimental results follow in Section 5. Conclusions and future work are given in Section 6.

2. System specification and design

Given the popularity of ILC within robotic and automation application domains, the test bed will comprise electromechanical components. One of the most prevalent mechanisms providing dynamic coupling between drive trains in industry is a differential gearbox. Hence to capture dynamics of broad practical relevance, these will be incorporated in the design of the MIMO facility, connected via spring-mass-damper components, and driven by motors of different types. Such a modular structure enables future extension, to include, for example, non-minimum phase dynamics. An internal representation of a differential gearbox is shown in Fig. 1, where I_A, I_B, I_C are the inertial values of the bevel gears of ports A, B, C respectively with B_A, B_B, B_C the associated viscous damping coefficients. Likewise θ_A, T_A are respectively the rotational angle and torque applied to port A, θ_B, T_B are the rotational angle and torque of port B, and θ_C, T_C are the rotational angle and torque of port C. Lagrangian analysis yields the relationships

$$I_A\ddot{\theta}_A + B_A\dot{\theta}_A - T_A + 2I_C\ddot{\theta}_C + 2B_C\dot{\theta}_C - 2T_C = 0 \tag{1}$$

$$I_B\ddot{\theta}_B + B_B\dot{\theta}_B - T_B - I_C\ddot{\theta}_C + B_C\dot{\theta}_C - T_C = 0 \tag{2}$$

$$2\theta_A - \theta_B - \theta_C = 0 \tag{3}$$

A representation of one of the spring-mass-damper components is shown in Fig. 2, where, in this case, the system is connected to port B of the differential gearbox with T_B the torque from the differential gear, and ϕ_B the angle of the free end. The transfer-function linking variables at port B is

$$\frac{\theta_B(s)}{T_B(s)} = \frac{I_{B2}s^2 + B_{B2}s + K_B}{(I_Bs^2 + B_Bs + K_B)(I_{B2}s^2 + B_{B2}s + K_B) - K_B^2}. \tag{4}$$

The MIMO system must have an easily adjustable level of interaction, as well as exogenous noise/disturbance injection and

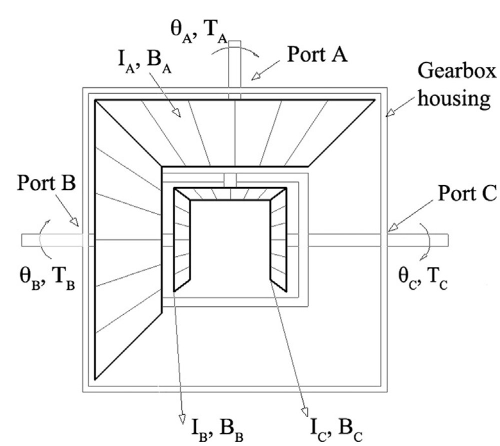

Fig. 1. Differential gearbox.

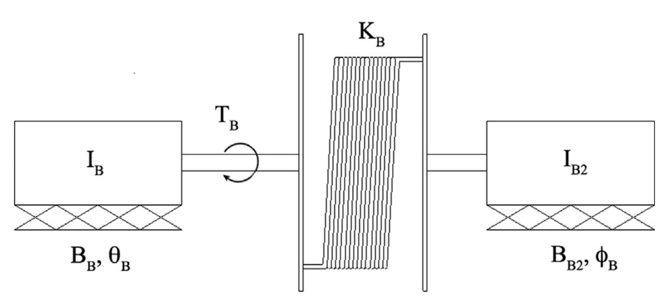

Fig. 2. Spring-mass-damper module attached to output B.