Computers and Chemical Engineering 77 (2015) 10–23

Contents lists available at ScienceDirect

Computers and Chemical Engineering

journal homepage: www.elsevier.com/locate/compchemeng

# A unified data-driven design framework of optimality-based generalized iterative learning control

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ARTICLE INFO

*Article history:*
Received 1 November 2014
Received in revised form 16 February 2015
Accepted 3 March 2015
Available online 12 March 2015

*Keywords:*
Data-driven control
Norm optimal design
Iterative learning control
Point-to-point iterative learning control
Terminal iterative learning control
Nonlinear discrete-time systems

ABSTRACT

This paper proposes a unified design framework for data-driven optimality-based generalized iterative learning control (DDOGILC), including data-driven optimal ILC (DDOILC), data-driven optimal point-to-point ILC (DDOPTPILC), and data-driven optimal terminal ILC (DDTILC). First, a dynamical linearization in the iteration domain is developed. Then three specific DDOGILC approaches are proposed. Both design and analysis of the controller only require the measured I/O data without relying on any explicit model information. The optimal learning gain can be updated iteratively, which makes the proposed DDOGILC more adaptable to the changes in the plant. Furthermore, the proposed DDOPTPILC and DDOTILC only depend on the tracking error at specific points, and thus they can deal with the scenario when the system outputs are measured only at some time instants. Moreover, the proposed DDOPTPILC and DDOTILC approaches do not need to track the unnecessary output reference points so that the convergence performance is improved.



## 1. Introduction

For a repetitive control task on a finite time interval, iterative learning control (ILC) was originally formulated by Uchiyama (1978) and Arimoto et al. (1984) and it has now become an effective tool to design a dynamical control system to track all points of a desired trajectory (Xu and Tan, 2003; Bristow et al., 2006; Ahn et al., 2007).

In the real industrial applications, the tracking tasks can normally be classified into three different control scenarios, i.e., tracking an entire reference trajectory, tracking specified multiple reference points, and tracking a single terminal point at the endpoint. The first control scenario of tracking an entire reference trajectory is most common in practical applications (Uchiyama, 1978; Arimoto et al., 1984; Xu and Tan, 2003; Bristow et al., 2006; Ahn et al., 2007; Saab, 1994; Park et al., 1999; Sun and Wang, 2002; Tayebi, 2004; Xu and Xu, 2004; Rotariu et al., 2008; Chi et al., 2008; Hwang et al., 1991; Amann et al., 1996; Lee et al., 2000; Gunnarsson and Norrlof, 2001; Sun and Alleyne, 2014) and the ILC solutions mainly focus on the contraction mapping based PID-ILC (Saab, 1994; Park et al., 1999; Sun and Wang, 2002), Lyapunov function based adaptive ILC (AILC) (Tayebi, 2004; Xu and Xu, 2004; Rotariu et al., 2008; Chi et al., 2008), and optimization based optimal ILC (OILC) (Hwang et al., 1991; Amann et al., 1996; Lee et al., 2000; Gunnarsson and Norrlof, 2001; Sun and Alleyne, 2014). The optimal ILC is most popular in practice because it can reject the undesirable large transient behavior that exists in PID-ILCs and AILCs, and has a monotonic convergence performance along the iteration direction.

The second control scenario includes many practical applications where the control task is to repeatedly track multiple intermediate pass points and the tracking errors are of concern only at those specific points, instead of all the points of a complete reference trajectory. Relevant examples (Freeman et al., 2011; Freeman, 2012) include robotic 'pick and place' tasks, crane positioning, production line automation, and so on. In Freeman et al. (2011), Freeman (2012), Son and Ahn (2011), and Son et al. (2013), some optimality-based point-to-point ILC (PTP-ILC) approaches were proposed to track the intermediate pass points rather than all the points of the trajectory by using the error information at the given points only.

The third control scenario mainly focuses on the practical applications in process industry, such as rapid thermal processing (RTP) systems for chemical vapor deposition (Xu et al., 1999) and batch to batch processes (Gauthier and Boulet, 2009; Flores-Cerrillo and MacGregor, 2005). In many of the real processes, the only available

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http://dx.doi.org/10.1016/j.compchemeng.2015.03.003
0098-1354/

measurement is the terminal state or terminal output and the ultimate control objective is also the terminal state or terminal output instead of the entire trajectory of the system output. It is obvious that the conventional ILC (Uchiyama, 1978; Arimoto et al., 1984; Xu and Tan, 2003; Bristow et al., 2006; Ahn et al., 2007; Saab, 1994; Park et al., 1999; Sun and Wang, 2002; Tayebi, 2004; Xu and Xu, 2004; Rotariu et al., 2008; Chi et al., 2008; Hwang et al., 1991; Amann et al., 1996; Lee et al., 2000; Gunnarsson and Norrlof, 2001; Sun and Alleyne, 2014) cannot be applied to this type of control tasks because the exact measurement of the system state or output is not possible. Hence terminal iterative learning control (TILC) (Freeman, 2012; Son and Ahn, 2011; Xu et al., 1999; Gauthier and Boulet, 2009; Flores-Cerrillo and MacGregor, 2005) has been proposed to handle only terminal points at prescribed time instants rather than the whole trajectory over all time instants. In Xu et al. (1999), Gauthier and Boulet (2009) and Flores-Cerrillo and MacGregor (2005), a basis function terminal ILC was proposed for linear time-varying systems. However, the selection of basis function is not a trivial task in practice. Recently, some optimal TILC approaches were developed in Freeman (2012) and Son and Ahn (2011) for linear discrete-time systems by introducing the explicit optimization objective into the terminal ILC design.

Note that if all of the system states and outputs are measurable, the standard ILCs Park et al. (2006), van de Wijdeven and Bosgra (2008), and Ding and Wu (2007) could be applied to the second and the third control scenarios by employing a designed reference passing through the desired points, and the PTP-ILC could also be applied to the third control scenario since the TILC is a special case of the PTP-ILC when there is only one single terminal point to track. However, it is difficult to select an optimal reference trajectory passing the specified points for the second control scenario and the optimal reference may no longer be the optimal one if there is change in the controlled plant. It is equally difficult to determine the proper pass points related to the specified terminal point if one wants to apply the PTP-ILC to the third control scenario.

Another drawback of using standard ILCs to the second and the third control scenarios or using the PTP-ILC to the third control scenario is that they fail to utilize the extra freedom available to secure additional performance demands. In practice, it is often expected that we only need to track the given constrained multiple intermediate pass points or a single terminal point like the second and the third control scenarios respectively rather than a whole trajectory at all time instants. If removing the unnecessary constraint that the plant has to follow, some additional control performance, such as the reduced control effort and faster convergent speed could be expected.

In addition, the issue of memory size and computation time is also an important issue for realization of a control algorithm. Supposing the number of data is $N$ for tracking the desired trajectory in the first control scenario, then for the second control scenario, the number of data is $M$, $M < N$, and the number of data is 1 for the third control scenario. It is clear that the size of memory and computation time can be reduced greatly by choosing only necessary control at certain time instants.

Therefore, the PTP-ILC and TILC approaches are not a simple extension of the traditional ILC. In this work, the term of "generalized ILC (GILC)" is used as a general name for methods of the standard ILC, PTP-ILC and TILC. It is worth pointing out that the ILC (Arimoto et al., 1984) was originally proposed for nonlinear uncertain systems directly using I/O data for the controller design without requiring the exact knowledge of the system model and thus is classified as data-driven control as illustrated in Hou and Wang (2013). However, the above optimal GILC Hwang et al. (1991), Amann et al. (1996), Lee et al. (2000), Gunnarsson and Norrlof (2001), Sun and Alleyne (2014), Freeman et al. (2011), Freeman (2012), Son and Ahn (2011) and Son et al. (2013) can only be categorized into "model-based control" because the knowledge of an accurate linear model of the controlled system is required for the controller design. When the model is inaccurate, the monotonic convergence of optimal GILC is no longer guaranteed, and learning transients with large, rapid growth of the error or even instability can occur.

Pracaltically, it is difficult to gain an explicit process model, especially in large scale and complex industrial processes such as in oil refinery plants, traffic and communication networks, power grids, aeronautics and astronautics (Hou and Jin, 2013). Even if a mathematical model may be obtained by first-principles or identification techniques with a significant amount of effort, some other theoretical and practical difficulties exist. For example, these difficulties can include (i) the unmodeled dynamics and the poor robustness are inevitable problems; (ii) the structure of the plant is often difficult to determine; (iii) often, the more accurate the model is, the more complex control law might be, which may lead to poorer robustness and lower reliability of the controlled system, and difficulties would be brought into practical implementation and application of the designed control system.

Thus, model-based control strategies may not be always able to produce satisfactory performance. It is desirable to have a control method that is less dependent on an explicite model. This motivates us to study a data-driven or data-based control method, which means that the controllers design merely uses the input and output measurement data of a plant and the controller itself does not contain any explicite model information about the controlled plant (Hou and Wang, 2013; Hou and Jin, 2013; Yin et al., 2014).

Motivated by the above discussion, the objective of this paper is to develop a unified data-driven design framework of optimal GILC, including optimal ILC, optimal PTPILC, and optimal TILC, for a class of nonlinear discrete-time repetitive systems by considering different practical applications. To achieve our goal, first, a dynamical linearization in the iteration domain is used by using the *Differential Mean Value Theorem* and the supervector approach, and an iteration-dependent linearization data model (LDM) is derived by a gradient matrix mapping the input vector to the output vector. Different from other linearization methods, such as Taylor expansion, the LDM is completely equivalent to the original nonlinear system. Then the optimal learning control law and parameter updating law of the proposed NOGILC are designed by introducing the index functions of the control input and parameter estimation under a unified design framework.

The main contributions of this work are summarized as: (a) The proposed optimal GILC is a data-driven approach where the controller design and analysis require only the measurement I/O data without using any explicit model information of the plant. (b) The learning gain of the optimal control law is derived from the estimation of the gradient parameter, which is updated iteratively using the measured I/O data only. (c) The proposed data-driven optimal PTP-ILC (DDOPTPILC) utilizes only the error measurements at the given specified points, and thus it can also deal with the scenario when only the system outputs at the given time instants are measured. (d) Similarly, the proposed data-driven optimal TILC (DDOTILC), updated only from terminal output tracking error, can deal with the scenario when the only available measurement is the terminal state or terminal output. (e) The proposed DDOPTPILC and DDOTILC do not need to track the unnecessary output points, and thus their convergence performance and control effort can be improved, as well as the required size of memory can be reduced.

The rest of this paper is organized as follows. Section 2 presents a data-driven optimal ILC approach for nonlinear systems with rigorous mathematical analysis. Section 3 proposes a data-driven optimal PTP-ILC to track the given multiple intermediate pass points, instead of an entire reference trajectory. Section 4 considers the applications to the control scenario of tracking a single terminal