Available online at www.sciencedirect.com

ScienceDirect

IFAC-PapersOnLine 48-28 (2015) 368–373

A Simultaneous Iterative Learning Control and Dynamic Modeling Approach for A Class of Nonlinear Systems ⋆

Zhongsheng Hou * . **Qiongxia Yu** * . **Jian-Xin Xu** ** . **Chenkun Yin** *

* *Advanced Control Systems Laboratory, Beijing Jiaotong University, Beijing 100044, China (e-mail: zhshhou@bjtu.edu.cn;12111044@bjtu.edu.cn;chkyin@bjtu.edu.cn)*
** *Department of Electrical and Computer Engineering, National University of Singapore, Singapore 117576, (e-mail:elexujx@nus.edu.sg)*

Abstract: This paper presents a novel simultaneous iterative learning control and dynamic modeling (SILCDM) approach. For a class of unknown and repeatable nonlinear discrete-time systems, a model-free iterative learning control (ILC) method is applied first. Meanwhile, by using the data generated during the repetitive operations, a novel iterative learning parameter estimation algorithm is proposed to calibrate the unknown time-varying parameter in the nonlinear system with known structure simultaneously. After the model parameter is well identified, the accurate dynamic model of the controlled plant is obtained. With this identified model, the model-free ILC method is then switched to a model-based optimal ILC method in order to get much better control performance. The theoretical analysis shows that the proposed approach guarantees the convergence of both the system state and the parameter identification. The effectiveness of the SILCDM is further demonstrated through simulations.

Keywords: iterative learning control, learning identification, dynamic modeling, train control.

1. INTRODUCTION

In many real systems, such as robot manipulators (Chien and Tayebi (2008); Freeman et al. (2012)), linear motor systems (Freeman et al. (2010); Butcher and Karimi (2010)), and train operation systems (Hou et al. (2011); Sun et al. (2013)), two prominent features can be found, including (1) the system executes a given task repeatedly; (2) the accurate system model is difficult to obtain.

Iterative learning control (ILC)(Arimoto et al. (1984)) is a specially developed and systematic control method for addressing the control problem of a repeatable system in a finite time interval. It is a data-driven model-free control approach, which means ILC methods, such as P-type or PID-type ILC (Chen et al. (1999)), can be used to tackle the control issue when the plant model is unavailable. For these ILC methods, the systematic analysis tool has been established in the sense of λ-norm, but the introduced λ-norm may be not proper to evaluate the actual learning control performance. Recently, the model-based optimal ILC (Son et al. (2013); Janssens et al. (2013)) has been proposed for achieving much better control precision, and convergence property can be guaranteed by means of the more reliable 2-norm. However, a perfect linear model should be known exactly for this kind of ILC method. In lack of an accurate model, satisfactory control performance can not be achieved.

Moreover, over 90% engineers and researchers in the field of control engineering and control theory believes that the model-based control methods are more reliable comparing to the data-driven control methods. Besides, it is a pity that the data generated in the past operations by applying the model-free ILC to unknown systems are not fully used although it contains lots of valuable information about the dynamics of the controlled plant. Thus, for an unknown nonlinear plant, when the ILC controller is in the closed loop, how to design a method which can make full use of the process data and meanwhile can build an accurate input-output model to cater the traditional engineers and researchers for the practical control task is a significant issue to be solved and has not been well addressed before.

Usually, the accurate input-output model of real plants is hard to establish since the precise calibration of the model parameters is not an easy task, although the dynamic model structure can be obtained using the first principle knowledge. For example, the high-speed train dynamics in operation influenced dominantly by aerodynamics resistance which contributes to the total resistance in a scale of the square of the train speed. The aerodynamics resistance is with a known structure according to the Newtonian mechanics, but the accurate resistance coefficient is difficult to obtain due to the complicated operating environment of the train system. Thus, accurate identification of the

⋆ This work was supported by National Science Foundation of China (61120106009, 61433002, 61403025). Corresponding Author: Zhongsheng Hou.

10.1016/j.ifacol.2015.12.155

resistance coefficient in the aerodynamics model is an important role for safety operation.

The traditional parameter identification method needs collecting the system input and output data off-line, that means we should operate the train many times in different speed and traction force in order to obtain all the dynamics modes, and then use the least square or projection algorithm (Goodwin and Sin (1984); Maruta and Sugie (2009); Guo and Zhao (2013)) to estimate model parameters. These processes would cost too much time and too much effort. Further, the air resistance coefficient in the aerodynamics model is time-varying since the high-speed train always operates in a very long distance, which implies that the train will go through different climate zones, different air density areas, and on the tracks in open air and tunnel. Theoretically, the traditional parameter identification algorithm can not perform this task well due to the essential time-variation. In recent years, some works on iterative learning identification technique (ILIT) have been proposed (Campi et al. (2008); Sun et al. (2012); Cao et al. (2014); Liu and Alleyne (2014)). The ILIT can improve the transient identification results by using information learned from previous iterations to anticipate parameter changes for subsequent trials, and is capable of estimating time-varying parameters. However, the existing works on the ILIT are all analysed for linear systems. Little work has been reported to estimate time-varying parameters for nonlinear systems.

Motivated by above discussion, in this work, we propose a novel simultaneous iterative learning control and dynamic modeling (SILCDM) approach based on a new iteration learning identification method—a modified projection algorithm (MPA) along the iteration axis. The proposed MPA identifies the time-varying model parameter in the unknown nonlinear system when the model-free ILC is implemented in the closed loop, rather than using identical input signal to control the system in each iteration for identification purpose only like in the aforementioned ILIT. In addition, the MPA is more efficient than the traditional identification method since massive and time-consuming off-line running tests are not needed. Based on this new MPA, the control and the dynamic modeling can be conducted simultaneously. When the model parameter has been well identified, the proposed SILCDM will switch from the mode-free ILC to a model-based optimal ILC for an improved tracking precision and a guaranteed convergence in terms of 2-norm.

The other parts of this paper are organized as follows. Section 2 introduces the problem formulation. The proposed SILCDM approach with rigorous convergence analysis is presented in Section 3. Simulation results are provided in Section 4. Last section concludes the paper.

2. PROBLEM FORMULATION

Consider the following repeatable affine nonlinear discrete-time system

$$x_n(k+1) = f(x_n(k), \theta(k)) + bu_n(k) \tag{1}$$

where the subscript $n \in \mathbf{Z}$ denotes the index of the iteration number and $k \in \{0, 1, \ldots, K\}$ represents the time index. $x_n(k) \in R$ and $u_n(k) \in R$ are the measurable system state and input at time k of the n-th iteration, respectively. b is a known control input gain and is either positive or negative. Without loss of generality, assume that $b > 0$ in this paper. $\theta(k) \in R$ is an unknown time-varying parameter. $f(\cdot)$ is a continuously differentiable nonlinear function with a known structure. Its differential is uniformly bounded by a positive constant b'.

Remark 1. The dynamic model (1) is widely used in many real plants such as gantry robot systems (Freeman et al. (2010)), freeway traffic flow processes(Hou et al. (2008)), and train operation systems(Sun et al. (2013)), etc.

To restrict our discussion, the following assumptions are made on the nonlinear discrete-time system (1).

Assumption 1. The re-initialization condition i.e., $x_n(0) = x_d(0)$ is satisfied, where $x_d(0)$ is the initial value of the desired state $x_d(k)$.

Assumption 2. There exists a control input $u_d(k)$ that can exactly drive the system state to track the desired trajectory $x_d(k)$ for the system (1) over the finite time interval $\{0, 1, \ldots, K\}$.

Remark 2. Assumption 1 demands the initial state value to be consistent with the desired one. In practice, if this condition is not met, we can always revise the target trajectory aligned with the actual one at the initial stage of tracking (Sun and Wang, 2003). Assumption 2 is a reasonable assumption that the task assigned for control should be feasible.

3. SIMULTANEOUS ITERATIVE LEARNING CONTROL AND DYNAMIC MODELING

In this section, the proposed SILCDM is presented.

3.1 Model-free ILC for unknown nonlinear system

The following model-free P-type ILC is applied to the unknown nonlinear system (1) at the first stage

$$u_n(k) = u_{n-1}(k) + \beta_u e_{n-1}(k+1) \tag{2}$$

where β_u is a positive learning gain. $e_{n-1}(k+1)$ is the state error defined as $e_{n-1}(k+1) = x_d(k+1) - x_{n-1}(k+1)$.

Theorem 1. For the nonlinear discrete-time system (1) satisfying Assumptions 1-2, choosing the learning gain β_u satisfying $|1 - \beta_u b| < 1$, the P-type ILC (2) guarantees that the state of the system $x_n(k)$ converges to the desired state $x_d(k)$ iteratively, i.e.,

$$\lim_{n\to\infty} |x_d(k) - x_n(k)|_\lambda = 0 \tag{3}$$

where $|\cdot|_\lambda$ is λ-norm denoted as $|\cdot|_\lambda = \sup_{k\in[0,K]} h^{-\lambda k}|\cdot|$ with $\lambda > 1$ and $h > 1$.

Proof. See Appendix A.

Remark 3. In Theorem 1, the convergence of the model-free P-type ILC is obtained in the sense of λ-norm, with a sufficiently large λ being required. However, λ is neither a system parameter nor a control parameter. It is introduced only for convergence analysis. The larger the λ is chosen, the more the system dynamics will be ignored. Therefore, it is not suitable for assessing the