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Predictive iterative learning control with experimental validation

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ABSTRACT

This paper develops an iterative learning control law that exploits recent results in the area of predictive repetitive control where a priori information about the characteristics of the reference signal is embedded in the control law using the internal model principle. The control law is based on receding horizon control and Laguerre functions can be used to parameterize the future control trajectory if required. Error convergence of the resulting controlled system is analyzed. To evaluate the performance of the design, including comparative aspects, simulation results from a chemical process control problem and supporting experimental results from application to a robot with two inputs and two outputs are given.

1. Introduction

Many systems complete the same finite duration task over and over again. The sequence is that the task is completed, the system resets to the starting location, the next one is completed and so on. In this paper each execution is termed a trial and the duration is termed the trial length. Once each trial is complete, the system resets to the original location and the next trial can begin, either immediately after the resetting is complete or after a stoppage time has elapsed.

Such systems arise in many industrial applications, where a generic example is a gantry robot undertaking a pick and place task and the sequence of operations is (i) collect the object from a fixed location, (ii) transfer it over a finite duration, (iii) place it at a static location or on a moving conveyor, (iv) return to the starting location and (v) repeat the previous four steps for as many times as required or until a halt is needed for maintenance or other reasons. Similar operations exist in the field of chemical process control such as the operation of batch chemical reactors, see, for example, Lee, Bang, Yi, Son, and Yoon (1996, 2000, 2001), Chin, Qin, Lee, and Cho (2004), and Liu, Gao, and Wang (2010), where the output of the reactor is required to follow a given trajectory over a finite time interval.

Once a trial is complete all information generated during its production is available for use in computing the control signal to be applied on the next trial. Iterative Learning Control (ILC), where the first work is widely credited to Arimoto, Kawamura, and Miyazaki (1984), uses information generated on the previous trial, or a finite number thereof, in the computation of the input to be applied on the next trial. The survey papers Bristow, Tharayil, and Alleyne (2006) and Ahn, Chen, and Moore (2007) are a starting point for the literature.

One extensively studied class of ILC laws is based on the minimization of an objective function constructed from the addition of two sums of squares terms and the result summed over the trials, such as Amann, Owens, and Rogers (1996) and Lee et al. (2000). The first of these is formed from the current trial error, that is, the difference between the supplied reference signal and the current trial output, and the second from the difference between the control signals used on successive trials, or the current trial signal alone. This class of algorithms is termed norm optimal, and experimental verification of its performance has also been reported (Barton & Alleyne, 2011; Ratcliffe, Lewin, Rogers, Hatonen, & Owens, 2006; Rogers et al., 2010).

This paper develops a predictive ILC design that uses a similar cost function to the one in norm optimal ILC, but embeds the reference signal/disturbance model in the controller and employs the receding horizon control principle. The idea of embedding the reference signal information in the controller has been successfully used in model predictive control, for example, Wang (2009) and in other ILC related research (Moore & El-Sharif, 2009). The design allows for the practically motivated case where the reference signal has dominant frequencies and it is decided to only include these in control design as opposed to all frequencies. Also it is assumed that the system dynamics can be adequately modeled, at least for initial control related studies, as linear and time-invariant.

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The duration of each trial in ILC is finite and the trial-to-trial error sequence can converge as the number of trials increases even if the system has unstable along the trial dynamics, since over a finite duration only bounded dynamics can be produced. The control design in this paper stabilizes the dynamics on each trial and allows for the rate of convergence to be controlled.

Simulation results from a chemical process control example and supporting experimental data from application of the new results to a two-input two-output robot complete the paper. The next section gives the required background.

2. Background

The design in this paper is based on a frequency domain decomposition of the supplied reference signal or vector in the single-input single-output (SISO) and multiple-input multiple-output (MIMO) cases. Once these are selected they are embedded in the process state-space model in accordance with the internal model principle as described next.

Consider the SISO case for simplicity with an obvious generalization to the MIMO case, and suppose that the frequency components of the reference signal to be included in the design have been selected, for details see Wang, Chai, Rogers, and Freeman (2012, 2013). This results in the annihilator polynomial

$$\begin{aligned} D(z) &= (1 - z^{-1}) \prod_{i=1}^{l} (1 - 2\cos(i\omega)z^{-1} + z^{-2}) \\ &= 1 + d_1 z^{-1} + d_2 z^{-2} + d_3 z^{-3} + \ldots + d_\gamma z^{-\gamma}. \end{aligned} \quad (1)$$

Here 0 and $i\omega$, $i = 1, 2, \ldots, l$, for some chosen positive integer l, denote the frequencies to be included.

The control law is to be designed to track the reference signal and hence, by the internal model principle (Francis & Wonham, 1975), the corresponding $D(z)$, that is, a particular case of (1) must be included in the denominator of the z transfer-function description of the controller dynamics. In this paper, the method used is to add a vector term ($\mu(p)$ in the state-space model (2) below) to the state dynamics in the plant state-space model as described next, but alternatives exist.

Remark 1. To put this particular design in context, the basic premise is that in many cases the reference signal will have a finite number of dominant frequencies and it suffices to enforce tracking of these frequencies instead of the complete frequency spectrum. This can be viewed as selecting a number of basis functions to approximate the reference signal and there has been other work on such ideas for ILC, see, for example, Sugie and Sakai (2007), van de Wijdeven and Bosgra (2010), and Hamamoto and Sugie (2001). In van de Wijdeven and Bosgra (2010) the problem considered is that the learned command signal is optimal for the specific fixed task only and, in general, extrapolation of the learned command signal to other tasks leads to a significant performance deterioration. Basis functions are used to enhance the extrapolation to a class of reference signals. The approach in Sugie and Sakai (2007) and Hamamoto and Sugie (2001) is to restrict the input/output space to an appropriate finite dimensional space spanned by basis functions derived from the reference signal. These are valid alternatives and the question of which one to chose for a given application is discussed again in the last section of this paper.

Suppose that the plant to be controlled has m_u inputs and m_y outputs and consider the following state-space model at sampling instant p,

$$\begin{aligned} x_m(p+1) &= A_m x_m(p) + B_m u(p) + \mu(p) \\ y(p) &= C_m x_m(p) \end{aligned} \quad (2)$$

where $x_m(p)$ is an $n_1 \times 1$ state vector, $u(p)$ is an $m_u \times 1$ input vector and $y(p)$ is an $m_y \times 1$ output vector of the plant. Also each entry in the $n_1 \times 1$ vector $\mu(p)$ is the inverse z-transform of $\frac{1}{D(z)}$ and let q^{-1} denote the backward shift operator and $D(q^{-1})$ the shift operator interpretation of $D(z)$. Then applying $D(q^{-1})$ to $x_m(p)$ and $u(p)$ gives

$$x^s(p) = D(q^{-1})x_m(p), \quad u^s(p) = D(q^{-1})u(p).$$

Also $D(q^{-1})\mu(p) = 0$ (since $D(z)$ contains all frequencies in $\mu(p)$) and from (2)

$$\begin{aligned} x^s(p+1) &= A_m x^s(p) + B_m u^s(p) \\ D(q^{-1})y(p+1) &= C_m A_m x^s(p) + C_m B_m u^s(p). \end{aligned} \quad (3)$$

Introducing the state vector

$$x(p) = \begin{bmatrix} (x^s)^T(p) & y^T(p) & \ldots & y^T(p-\gamma+1) \end{bmatrix}^T$$

gives the following augmented state-space model for design

$$\begin{aligned} x(p+1) &= Ax(p) + Bu^s(p) \\ y(p) &= Cx(p) \end{aligned} \quad (4)$$

where

$$A = \begin{bmatrix} A_m & 0 \\ \hat{C} & A_d \end{bmatrix}, \quad \hat{C} = \begin{bmatrix} C_m A_m \\ 0 \end{bmatrix}$$

$$A_d = \begin{bmatrix} -d_1 I & -d_2 I & \ldots & -d_{\gamma-1} I & -d_\gamma I \\ I & 0 & 0 & \ldots & 0 \\ 0 & I & 0 & \ldots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & 0 & \ldots & I & 0 \end{bmatrix}$$

and 0 and I denote the zero and identity matrices, respectively, of compatible dimensions ($\gamma m_y \times \gamma m_y$). In addition

$$B = \begin{bmatrix} B_m^T & (C_m B_m)^T & 0 & \ldots & 0 & 0 \end{bmatrix}^T,$$

$$C = [0 \quad I \quad 0 \quad \ldots \quad 0 \quad 0].$$

The poles of (4) are the union of those of the system model and those arising from the structure of $\mu(p)$.

3. Prediction-based ILC design

In the ILC setting $k \geq 0$ is used to denote the trial number and the notation for variables is of the form $y_k(p)$ where y is the scalar or vector valued variable under consideration and $p < \infty$ is the number of samples along the trial. The plant dynamics are again described by a state-space model triple. Let $r(p)$ be the supplied reference vector that does not vary from trial-to-trial. Then

$$e_k(p) = y_k(p) - r(p) \quad (5)$$

is the error on trial k and the basic ILC problem is to force the sequence $\{e_k\}$ to converge in k.

Suppose that the frequency domain decomposition given in the previous section is applied to $r(p)$ and $D(z)$ of (1), where the latter polynomial is constructed from the frequencies to be included. Then the ILC problem can be formulated by following identical steps to those used to obtain (4), resulting in a state-space model for design of the form