Control Engineering Practice 37 (2015) 11–19

Contents lists available at ScienceDirect

Control Engineering Practice

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

Iterative motion feedforward tuning: A data-driven approach based on instrumental variable identification

Frank Boeren*, Tom Oomen, Maarten Steinbuch

Eindhoven University of Technology, Department of Mechanical Engineering, Control Systems Technology Group, Eindhoven, The Netherlands

ARTICLE INFO

Article history:
Received 28 May 2014
Accepted 23 December 2014
Available online 19 January 2015

Keywords:
Feedforward Control
Iterative learning control
Data-driven control
Precision motion systems
System identification

ABSTRACT

Feedforward control can significantly enhance the performance of motion systems through compensation of known disturbances. This paper aims to develop a new procedure to tune a feedforward controller based on measured data obtained in finite time tasks. Hereto, a suitable feedforward parametrization is introduced that provides good extrapolation properties for a class of reference signals. Next, connections with closed-loop system identification are established. In particular, instrumental variables, which have been proven very useful in closed-loop system identification, are selected to tune the feedforward controller. These instrumental variables closely resemble traditional engineering tuning practice. In contrast to pre-existing approaches, the feedforward controller can be updated after each task, irrespective of noise acting on the system. Experimental results confirm the practical relevance of the proposed method.

1. Introduction

Feedforward control is widely used in control systems, since feedforward can effectively reject disturbances before these affect the system. Indeed, many applications to high-performance systems have been reported where feedforward control leads to a significant performance improvement. For servo systems, the main performance improvement is in general obtained by using feedforward to compensate for the reference signal. Relevant examples of feedforward control include model-based feedforward, see, e.g., Zhong, Pao, and de Callafon (2012), Clayton, Tien, Leang, Zou, and Devasia (2009) and Butterworth, Pao, and Abramovitch (2012), and Iterative Learning Control (ILC), see, e.g., Bristow, Tharayil, and Alleyne (2006) and Moore (1993).

On the one hand, model-based feedforward results in general in good performance and provides extrapolation capabilities of tasks. In model-based feedforward, a parametric model is determined that approximates the inverse of the system. The performance improvement induced by model-based feedforward is highly dependent on (i) the model quality of the parametric model of the system and (ii) the accuracy of model-inversion, see, e.g., Devasia (2002). On the other hand, ILC results in superior performance with respect to model-based feedforward. By learning from previous iterations, high performance is obtained for a single, specific task, i.e., at the expense of poor extrapolation capabilities of tasks. In addition, ILC only requires an approximate model of the system.

Recently, an approach is presented in van de Wijdeven and Bosgra (2010) that combines the advantages of model-based feedforward and ILC, resulting in both high performance and good extrapolation capabilities. To this purpose, basis functions are introduced that reflect the dynamical behavior of the system responsible for the dominant contribution to the servo error. In Van der Meulen, Tousain, and Bosgra (2008), the need for an approximate model of the system, as is common in ILC, is eliminated by exploiting concepts from iterative feedback tuning (IFT) (Hjalmarsson, Gevers, Gunnarsson, & Lequin, 1998). This approach is extended to input shaping in Boeren, Bruijnen, van Dijk, and Oomen (2014) and multivariable systems in Heertjes, Hennekens, and Steinbuch (2010), while a comparative study of data-driven feedforward control procedures is reported in Stearns, Yu, Fine, Mishra, and Tomizuka (2008). However, by eliminating the need for an approximate model of the system, the approach presented in Van der Meulen et al. (2008) requires a significantly larger experimental cost to perform an update of the feedforward controller and puts stringent assumptions on noise acting on the system.

Although iterative feedforward tuning is widely successful to improve the performance of motion systems, existing tuning procedures (i) impose stringent requirements on noise acting on the system, (ii) require two tasks for each iterative update of the feedforward controller and (iii) can lead to a bias error. In this paper, it is shown that these deficiencies can be removed by connecting iterative feedforward tuning to system identification, and exploit

* Corresponding author. Tel.: +31 402474517.
E-mail address: f.a.j.boeren@tue.nl (F. Boeren).

http://dx.doi.org/10.1016/j.conengprac.2014.12.015
0967-0661/

concepts from closed-loop system identification in iterative feedforward tuning. In fact, in contrast to pre-existing procedures in Van der Meulen et al. (2008), Boeren, Bruijnen et al. (2014) and Heertjes et al. (2010), the proposed procedure closely resembles manual feedforward tuning procedures for motion systems, see, e.g., Boerlage, Tousain, and Steinbuch (2004). This immediately confirms the practical relevance of the proposed approach for industrial motion systems.

The main contribution of this paper is an iterative feedforward tuning approach that is efficient, i.e., it requires measured data from only a single task, and accurate, i.e., attains optimal performance for feedforward control in the presence of noise. The proposed approach is closely related to Söderström and Stoica (1983), Gilson and Van den Hof (2005), Jung and Enqvist (2013) and Karimi, Butcher, and Longchamp (2008), and extends this work to iterative tuning of feedforward controllers. Furthermore, the motivation for the proposed approach is similar to the approach in Kim and Zou (2013), i.e., combine the advantages of model-based feedforward and ILC without the need for an approximate model of the system. The key difference is that in Kim and Zou (2013) a nonparametric model for the feedforward controller is constructed, while this work aims to determine a parametric model. This paper is an extension of Boeren and Oomen (2013) that includes experimental results, and a complete explanation and analysis.

This paper is organized as follows. In Section 2, the problem formulation is outlined. Then, in Section 3, it is shown that in the presence of noise, existing procedures suffer from a closed-loop identification problem. In Section 4, a new feedforward control procedure is proposed which requires only a single task to update the feedforward controller in the presence of noise. Then, in Section 5 the proposed approach is embedded in the iterative feedforward tuning framework. In Section 6, the experimental results of the proposed approach are presented. Finally, a conclusion is presented in Section 7.

Notation: For a vector x, $\|x\|_2^2 = x^T x$. The vector u is defined as $u = [u(1), u(2), \ldots, u(N)]^T \in \mathbb{R}^N$, where $u(t)$ is a measurement at time instant t for $t = 1, 2, \ldots, N$ with N being the number of samples. The symbol q denotes the forward shift operator $qu(t) = u(t+1)$. Furthermore, the expected value $\mathbb{E}(x)$ is defined as $\mathbb{E}(x) = \int_{-\infty}^{\infty} x f(x)\, dx$, with probability density function $f(x)$. The correlation function based on a finite number of samples N is defined as $R_{xy}(N) = (1/N) \sum_{t=1}^{N} x(t) y(t)$.

2. Problem formulation

2.1. Feedforward control goal

Consider the two degree-of-freedom control configuration as depicted in Fig. 1. The true unknown system is assumed to be discrete-time, single-input single-output and linear time-invariant, and is denoted as $P(q)$. The control configuration consists of a given stabilizing feedback controller $C_{fb}(q)$ and feedforward controller $C_{ff}(q)$. Let r denote a known nth−order multi-segment polynomial trajectory with constraints on the first n derivatives, generated by a trajectory planning algorithm that takes system dynamics into account, see, e.g., Biagiotti and Melchiorri (2012), Lee, Kim, and Choi (2013) and Lambrechts, Boerlage, and Steinbuch (2005). A typical reference r in a single task is depicted in Fig. 3. Furthermore, v denotes a disturbance, u_{ff} the feedforward signal, and e the servo error. The unknown disturbance v is assumed to be given by $v = H(q)\epsilon$, where $H(q)$ is monic and ϵ is normally distributed white noise with zero mean and variance λ_ϵ^2. Hence, v and r are uncorrelated.

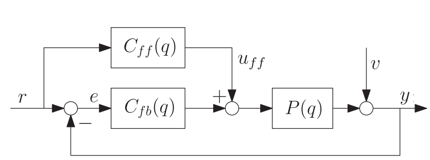

Fig. 1. Two degree-of-freedom control configuration.

The goal in feedforward control is to attain high performance by compensating for known exogeneous input signals that affect the system. The servo error e in Fig. 1 as given by

$$e = S(q)(1 - P(q)C_{ff}(q))r - S(q)v,$$

where $S(q) = (1 + P(q)C_{fb}(q))^{-1}$, reveals that the contribution of e induced by r is eliminated if $C_{ff}(q) = P^{-1}(q)$. For motion systems with dominant rigid-body dynamics, a parametrization for $C_{ff}(q)$ is proposed in Lambrechts et al. (2005) which compensates for the dominant component of the reference-induced error. The corresponding u_{ff} is given by

$$u_{ff} = \theta_a a + \theta_j j + \theta_s s, \tag{1}$$

where a, j and s correspond to respectively acceleration, jerk and snap, i.e., the 2nd, 3rd and 4th derivative of the multi-segment polynomial trajectory r, and θ_a, θ_j, θ_s are the corresponding parameters.

To illustrate this parametrization, consider the acceleration profile a and measured error e_m as depicted in Fig. 2. In manual tuning of a feedforward controller, the optimal value for θ_a is such that the predicted error

$$\hat{e}(\theta_a) = e_m - S(q)P(q)\theta_a a,$$

and a are uncorrelated, where $e_m = S(q)r - S(q)v$. Likewise, the optimal values for θ_j and θ_s are obtained if $\hat{e}$, and j and s are uncorrelated, respectively. The results in this paper enable an iterative and automated estimation of the optimal values for θ_a, θ_j and θ_s.

2.2. Iterative feedforward control

In iterative feedforward control, measured data is exploited to update $C_{ff}(q)$ after each task. For the considered class of systems, a sequence of finite time tasks, denoted as $j = 1, 2, \ldots$, with length N samples is executed. In a single task, the system starts at rest in the initial position, followed by a point-to-point motion, before the system comes to a rest in the final position of a task. A typical reference r in a single task is shown in Fig. 3. A sequence of such tasks is executed during normal operation of the system, where r is not necessarily identical for each consecutive task.

The measured signals e_m^j and y_m^j in the jth task are given by $e_m^j = e_r^j - e_v^j$, where $e_r^j = S(q)(1 - P(q)C_{ff}^j(q))r$ and $e_v^j = S(q)v^j$, and $y_m^j = y_r^j + y_v^j$, where $y_r^j = S(q)P(q)(C_{fb}(q) + C_{ff}^j(q))r$ and $y_v^j = S(q)v^j$. Note that since $P(q)$, $S(q)$ and v^j are unknown, it is not possible to construct e_r^j and e_v^j from the measured signal e_m^j. This also holds for y_m^j. For clarity of exposition, the index j is omitted if only a single task

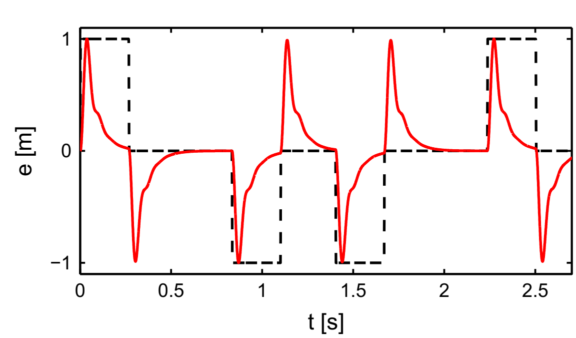

Fig. 2. Manual tuning of feedforward parameters—The normalized acceleration profile a (dashed black) and normalized error e_m (red) obtained in the previous task are used to determine θ_a such that the predicted error $\hat{e} = e_m - S(q)P(q)\theta_a a$ and a are uncorrelated. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)