Data-Driven Feedforward Control for Mechatronic Systems: Analysis, New Approach and Application

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1 Background

Learning control enables substantial performance improvement in control applications. For instance in mechatronic systems substantial performance enhancements are envisaged, e.g., learning is a key aspects of I-MECH [1]. Typical learning algorithms are batch-wise, disconnecting time-domain and iteration-domain [2]. Recently, learning control methods are extended with basis functions, i.e., learning feedforward parameter instead of a specific signal enabling task flexibility. Indeed, flexibility is essential in mechatronic systems and one of the reasons that hampers industrial deployment [1].

2 Problem formulation

Batch-to-batch learning, where performance benefit is only possible after each subsequent task, is becoming too slow. To improve learning speed the aim is to learn during tasks, i.e., current iteration learning. This is done in conjunction with basis function, enabling fast learning combined with task flexibility.

3 Approach

To optimize feedforward parameters, the connection between feedforward control and online system identification is established. Approaches have been developed, estimating feedforward parameters using recursive least squares optimization, essentially estimating the inverse of the system dynamics. However, in existing approaches biased estimates can be obtained as in closed-loop estimation problems [3]. In this work, a detailed statistical analyses is provided showing that biased estimates are obtained if measurement noise is present [4]. Furthermore, a new approach is presented which mitigates the effect of noise.

4 Results

Current iteration learning is applied to a benchmark motion system. The results confirm theoretical conclusion, i.e., that biased estimates are obtained. In Fig. 1, the positioning error with feedback (—) and with the proposed approach (—) are shown. Despite of the biased estimate a major performance improvement is obtained within the first motion task, showing the benefit of direct learning.

[1]European project driven by industrial applications, see www.i-mech.eu

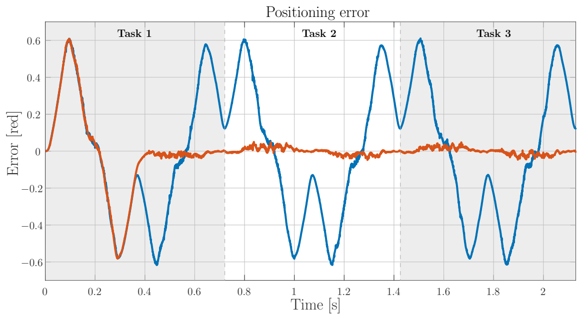

Figure 1: Experimental results of current iteration learning (—) compared to only feedback control (—) .

5 Conclusions & Ongoing research

A detailed statistical analyses of the proposed framework is provided to show that biased estimates are obtained in existing approaches. Furthermore, the proposed method is applied to a benchmark motion system confirming its potential despite the presence of a bias. Ongoing research focuses on fundamental bias elimination along the lines of [5].

6 Acknowledgments

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