Learning for data-intensive industrial machines

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Learning for data-intensive industrial machines

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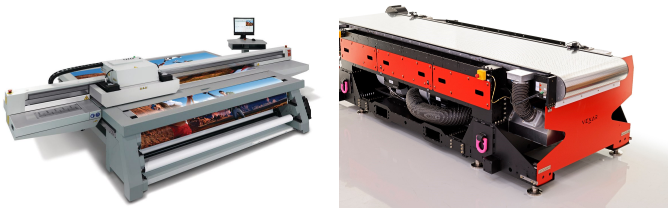
I. RESEARCH OVERVIEW

The productivity and product quality of many manufacturing systems hinge on the performance of mechatronic positioning systems. Examples include large-format printing systems, see Fig. 1a, and the intelligent substrate carrier for industrial printing, see Fig. 1b. To meet future requirements on accuracy, speed, and product dimensions, it is foreseen that a significant increase is required in the complexity of positioning systems. This leads to the manifestation of pronounced disturbances and complex dynamical behavior, including large numbers of dynamic modes, inherently multivariable behavior, and position-dependent behavior, which potentially restrict performance of control systems.



(a) Large-format printing system (b) Intelligent substrate carrier

Fig. 1: Data-intensive mechatronic positioning systems.

A new control design paradigm is foreseen to manage the increasing system complexity. The key observation is that over the operational lifetime of a machine, huge amounts of data becomes available, while this data is often not exploited in control. The aim of this research is to enable radical performance improvements in future positioning systems by improving control systems through learning from data. By exploiting the abundance of data in mechatronic systems, in potential performance can be achieved up to the limit of reproducibility, far beyond what can be achieved with traditional model-based control approaches.

The key challenge in successful application of learning algorithms to industrial machines lies in managing their extreme systems complexity, while guaranteeing fast and safe learning to avoid machine downtime and production losses.

Multivariable learning control designs: balancing modeling effort with performance [1]–[3].

Although learning control is conceptually promising for complex mechatronic systems, it is not often employed in industrial environments due to associated high modeling requirements. To this end, developments have been made for multivariable learning controllers, including Iterative Learning Control (ILC) [1] and Repetitive Control (RC) [2], [3], that explicitly address trade-offs between modeling and performance requirements. This is done by judiciously combining limited parametric model knowledge with the use of non-parametric frequency response function (FRF) models, and the development of various user-friendly design techniques, ranging from decentralized approaches to centralized designs.

Learning for feedforward control: the use of prior knowledge [4]–[7].

To enable extreme performance in the presence of varying tasks, a parametrized feedforward control structure can be adopted whose parameters are to be learned from data. The key difficulty lies in selecting a suitable model structure and order, particularly in view of the extreme system complexity of future industrial machines. A crucial aspect is the use of system knowledge, i.e., prior information, while retaining sufficient freedom to effectively learn from data. In particular, prior knowledge is exploited to

- construct parsimonious parametrizations [4], [6] with beneficial properties for control (non-causality) and optimization (convexity);
- address model order selection for (non-causal) feedforward control in a systematic manner [5]; and
- construct physics-motivated parametrizations for position-dependent feedforward that facilitate engineering interpretation [7].

Identification above the Nyquist frequency [8], [9].

The performance and convergence properties of learning control algorithms heavily rely on the used models. This is especially crucial for learning control since the control action is potentially effective over the entire frequency range up to the Nyquist frequency, and high-frequency dynamics, including intersample behavior, can hence not be ignored. A method is developed for fast and accurate FRF identification up to and beyond the Nyquist frequency of multirate systems [8], [9]. The key aspect is that aliased contributions can be uniquely distinguished and disentangled by exploiting local smoothness of the system response.

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II. SEMINAR TOPIC - REPETITIVE CONTROL DESIGN FOR INDUSTRIAL MACHINES

Repetitive control (RC) can significantly improve the control performance of systems that are subject to dominantly periodic disturbances. The control action is periodically updated on the basis of past measurement data in combination with a model of the system to guarantee closed-loop stability, see Fig. 2 for a typical implementation.

The aim of this seminar is to present a tutorial on RC design, that has enabled successful applications in industrial machines.

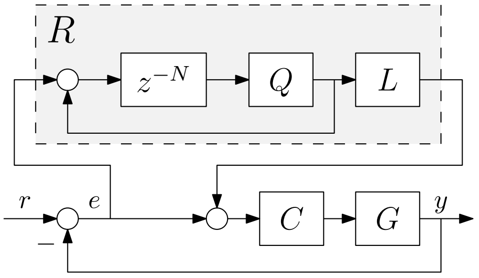

Fig. 2: Add-on repetitive control configuration.

A. Robust Design for Industrial Machines

Robust stability of RC algorithms is crucial to deal with inevitable, and often deliberate, modeling errors. A technical analysis is presented that facilitates robust RC design while taking into account the trade-off between performance and modeling requirements. In particular, a systematic design approach is presented that uses low-order approximate nominal models for control design, and considers the deliberate modeling errors as uncertainty, i.e., through robust stability, which can be directly evaluated using inexpensive nonparametric FRF measurements, see Fig. 3.

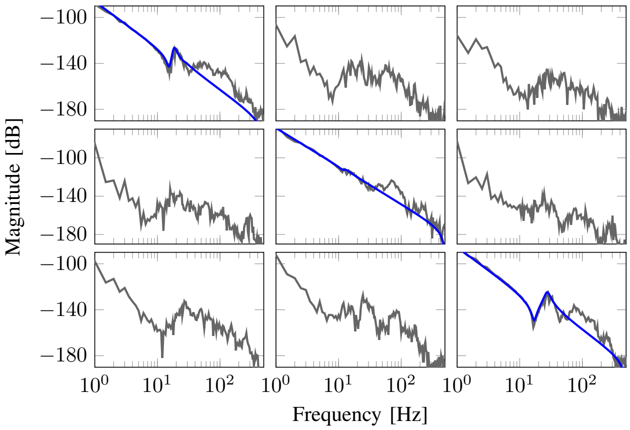

Fig. 3: Models for robust RC design: low-order parametric models (blue) for nominal control design, and non-parametric multivariable FRF measurement (grey) that enables direct evaluation of robust stability.

B. Application to Large-Format Printing System of Fig. 1a

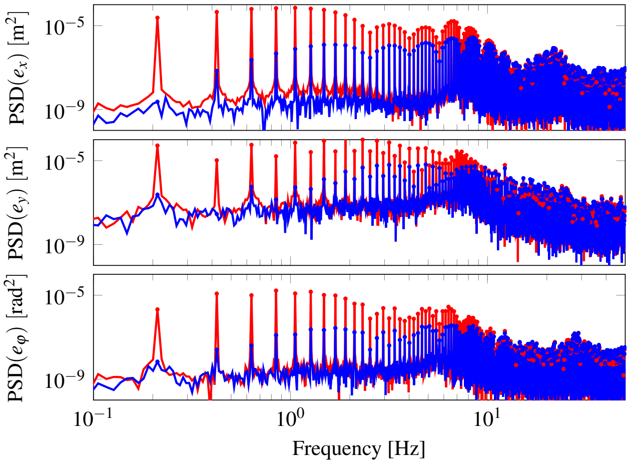

Fig. 4: Power spectral density (PSD) of servo errors before (red) and after RC convergence (blue), visualizing the performance increase.

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