Data-Driven Inverse-Model Feedforward Control using Non-Causal Rational Basis Functions

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Background

Feedforward can compensate for known disturbances before these affect the system, enabling high performance. This is typically achieved by inverting a model of the system. In view of the achievable control performance, the quality of the parametric inverse model is crucial. Especially for lightly damped mechatronic systems such as flatbed printers, see Figure 2, such accurate parametric models can be difficult and expensive to obtain due to, e.g., complex dynamics, and numerical issues. This motivates to directly estimate the inverse model based on measured input/output data, obtained in the same setting as the model is going to be used in, i.e., a feedforward control configuration.

Data-Driven Feedforward: Non-Causal Control

In data-driven feedforward control, measured data is used to iteratively determine a fixed-structure controller $F(\theta)$, such that the tracking error $e = \frac{1}{1+PC}(1-PF(\theta))r$ is minimized when $F(\theta)$ is applied, see Fig. 1. Optimal tracking performance, i.e., $\mathbb{E}e = 0, \forall r$, is achieved if $F(z,\theta) = P^{-1}(z)$. The key difficulty is to choose a compact parametrization for $F(\theta)$, capable to accurately model the *inverse* system P^{-1}.

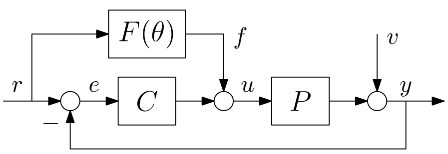

Figure 1: Control configuration for data-driven feedforward: the parameters θ are iteratively optimized based on measured data.

Crucially, if P has non-minimum phase (NMP) zeros, then P^{-1} has poles outside the typical stability region. Interestingly, this can effectively be dealt with in feedforward, where non-causality can be exploited to compensate 'unstable' poles. The aim of this research is to enable non-causal control using a suitable parametrization for $F(\theta)$.

The main contribution of the presented research is the development of a compact parametrization for inverse systems, that is suited for inverse-model feedforward control. Crucially, the developed parametrization builds on the use of general *non-causal* rational orthonormal basis functions (ROBFs) in $\mathcal{L}_2$ [1], to compensate poles outside the usual stability region. As special cases, *causal* ROBFs in $\mathcal{H}_2$ [2] and finite impulse response (FIR) models are recovered.

Experimental Results: Industrial Flatbed Printer

The developed approach is applied to the Arizona flatbed printer, shown in Fig. 2, which has 3 NMP zeros with input F_L $[N]$ and output x_R $[m]$. The results in Fig. 3 show that:

- *non-causality*, through basis functions in $\mathcal{L}_2$, is crucial to compensate poles outside the typical stability region;
- *rational* functions enable high performance using compact models, in contrast to polynomial (FIR) functions.

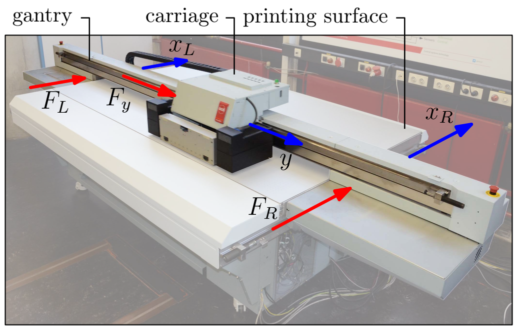

Figure 2: Océ Arizona flatbed printer @TU/e CST Motion Lab.

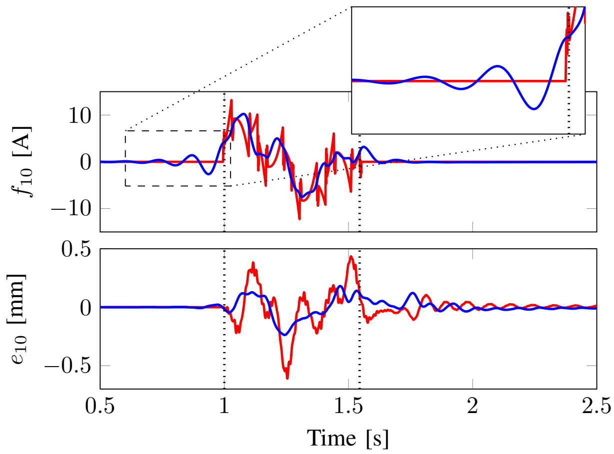

Figure 3: Experimental results: non-causal ROBFs (—) enable infinitely long pre-actuation and post-actuation. Compared to (non-causal) FIR basis functions (—), which enable only a small and finite amount of preview, the error e_{10} is significantly reduced.

References

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[2] P. Heuberger, P. Van den Hof, and B. Wahlberg. "Modelling and identification with rational orthogonal basis functions," Springer-Verlag, London, UK, 2005.