Data-Driven Compensation of Unmodeled Dynamics for Complex Mechatronic Systems – Part III: Control-Relevant Neural Networks for Feedforward

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Abstract

Accurate and flexible feedforward control is essential for the performance of mechatronic systems. This research aims at developing a systematic framework for neural networks for feedforward control that explicitely considers the three basic entities involved in constructing models from data [1]: model structures, data sets and assessment criteria.

Consider a SISO control system with plant P, controller C and error e given by

$$e = Sr - SPf,$$

with reference r, feedforward signal f and system sensitivity $S = (1 + PC)^{-1}$. The feedforward signal for which the error is zero is given by

$$f = (SP)^{-1}Sr = P^{-1}r.$$

The feedforward signal is designed using a neural network $\mathcal{F}$ that maps r to f_{nn}, such that the error is minimized.

Regarding model structures, neural networks used for feedforward control of mechatronic systems should enable pre-actuation [2] and compensation of nonlinear effects. If the plant P contains delays, including sampling delays, and in particular when the plant is non-minimum phase, the inverse P^{-1} that is approximated by the neural network is non-causal. Pre-actuation in f_{nn} is achieved through non-causal time-delay neural networks that result in finite preview, and bi-directional long short-term memory layers in recurrent neural networks that result in infinite preview. In addition, nonlinear effects such as friction can be modeled through nonlinear activation functions, which are typical for neural networks.

The approximation of system nonlinearities depends on the specific input-output data set that is used, since nonlinearities manifest themselves along the used trajectories. Therefore, networks are trained using a representative closed-loop data set consisting of ten fourth-order references with corresponding feedforward signals f_{train} that are found using iterative learning control [3].

The criterion with which the networks are trained should be related to the criteria based on which the system performance is assessed [4]. This is achieved by the following control-relevant cost function

$$\mathcal{J}(f) = \left\|SP(f_{\text{train}} - f)\right\|_2^2 + w\left\|f_{\text{train}} - f\right\|_2^2,$$

in which the first term minimizes the error in terms of the squared 2-norm and the second term is added for regularization.

Experimental results on an industrial flatbed printer, see Figure 1, show that non-causal TDNNs reduce the cost by a factor three compared to polynomial basis functions. RNNs are shown to be sensitive to overfitting and as such result in relatively large errors for references outside of the training set, see Figure 2.

Figure 1: Arizona flatbed printer

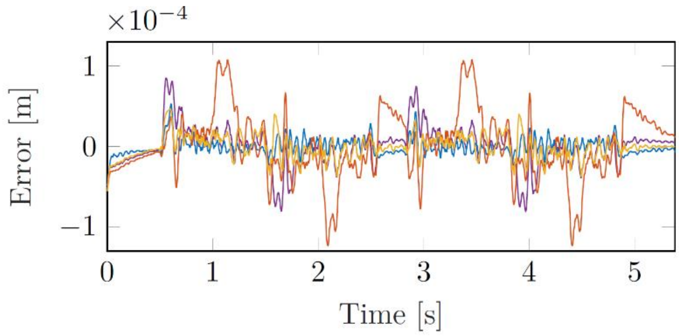

Figure 2: Errors for a reference outside the training set resulting from f_{train} (blue), polynomial basis functions (purple), a non-causal TDNN (yellow) and a non-causal RNN (red)

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