Neural Networks for Motion Feedforward: Control-Relevant Training and Non-Causality

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1 Background

Neural networks are universal function approximators and, as such, offer large potential for flexible and accurate motion feedforward. Motion feedforward involves several important aspects, including control-relevance [2] and non-causal feedforward for non-minimum phase systems that require pre-actuation to achieve zero error [1].

2 Problem formulation

Consider a SISO control system with error $e \in \mathbb{R}$ given by

$$e = Sr - SPf \tag{1}$$

with reference $r \in \mathbb{R}$, feedforward signal $f \in \mathbb{R}$ and system sensitivity $S = (1 + PC)^{-1}$ with plant P and controller C. The feedforward signal for which $e = 0$ is given by

$$f = (SP)^{-1}Sr \tag{2}$$

Neural networks are used to find a mapping $f_{\text{nn}} = \mathcal{F}(r)$ such that the error e in (1) is minimized for $f = f_{\text{nn}}$. The aim is to investigate the implications of the invertibility of P, in particular when P has non-minimum phase zeros, and the use of closed-loop data, i.e., the role of SP in (1).

3 Approach

The training data needed to find the mapping from r to f consists of a representative set of ten references with corresponding feedforward signals f_{train}, found using iterative learning control [3]. The neural network-based feedforward f_{nn} that minimizes the error in terms of the squared 2-norm is the minimizer of the control-relevant loss function

$$\mathcal{J}_{\text{CR}}(f_{\text{nn}}) = \|SP(f_{\text{train}} - f_{\text{nn}})\|_2^2, \tag{3}$$

to which a term $w\|f_{\text{train}} - f_{\text{nn}}\|_2^2$ with weighting $w = 1e^{-3}$ is added as regularization.

Non-causal mappings between r and f_{nn} are generated by two types of networks. Non-causal time-delay neural networks (TDNN) take a shifted finite sequence of reference samples as input, resulting in finite preview. Bi-directional long short-term memory (biLSTM) layers in recurrent neural networks (RNN) receive both forward and time-reversed data, giving infinite preview.

Figure 1: Arizona flatbed printer

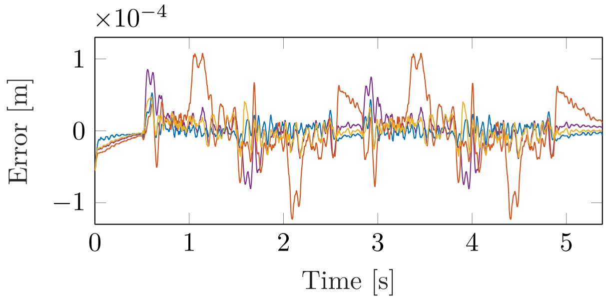

Figure 2: Errors for a reference outside of the training set resulting from f_{train} (—), polynomial basis functions (—), a non-causal TDNN (—) and a non-causal RNN (—).

4 Results

Neural networks for motion feedforward are applied to the industrial flatbed printer shown in Figure 1. The input of the networks consists of a fourth-order reference with its derivatives. Non-causal TDNNs reduce the loss by a factor 3 compared to a linear feedforward neural network (FNN) that is equivalent to polynomial basis functions. RNNs are sensitive to overfitting, reducing the performance, see Figure 2.

References

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