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Sparse Learning Approach to Feedforward Filter Selection: Applied to an Industrial Flatbed Printer

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1 Background

Iterative learning control (ILC) techniques are capable of achieving outstanding tracking performance of control systems that repeatedly perform similar tasks by utilizing data from past iterations. Flexibility for multiple tasks is enabled by ILC with basis functions where the learned input signal is constructed via a feedforward parameterization. The specific choice for this parameterization affects both the performance and robustness. The aim of this paper is to investigate this feedforward filter selection while simultaneously learning the optimal system parameters in an ILC framework.

2 Problem formulation

Consider the closed-loop ILC scheme shown in Figure 1. To allow flexibility in the motion task $r_j \in \mathbb{R}^N$, the feedforward signal $f_j \in \mathbb{R}^N$ is parameterized by a set of basis functions,

$$f_j = \Psi(r_j)\theta_j,$$

where $\Psi(r_j) \in \mathbb{R}^{N\times N_\theta}$ the set of basis functions, $\theta_j \in \mathbb{R}^{N_\theta}$ the learning parameters and $j \in \mathbb{N}$ the trial index. The objective of feedforward control in ILC is to minimize the tracking error of the next trial e_{j+1}, by designing θ_{j+1} based on the measured error e_j of the previous trial.
The parameters θ_j, along with the basis $\Psi(r_j)$, aim to describe the inverse system P^{-1} to obtain zero tracking error, that is,

$$\Psi(r_j)\theta_j \approx P^{-1}r_j \quad \Rightarrow e_j \approx 0.$$

The tracking performance is limited by the ability of $\Psi(r_j)\theta_j$ to describe the inverse system and heavily relies on the selection of basis $\Psi(r_j)$. Therefore, the problem addressed is a combined automated basis function selection with ILC to obtain high performance.

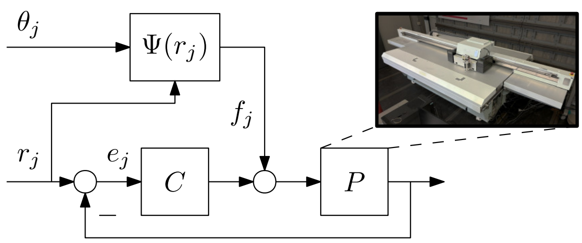

Figure 1: Control structure considered.

3 Approach

The proposed method enables automatic basis function selection via the sparsity-promoting algorithm Least Absolute Shrinkage and Selection Operator (LASSO) [1]. The convex optimization problem is written as follows

$$\min_{\theta_{j+1}} \quad \|e_{j+1}(\theta_{j+1})\|_2^2 + \lambda\|\theta_{j+1}\|_1, \tag{1}$$

where the first term enforces performance and the second term selects relevant basis functions by enforcing sparsity in the learning parameters θ_{j+1}. Problem (1) is efficiently solved for each iteration to find the relevant sparse subset of basis functions, $\Psi_S \in \mathbb{R}^{N\times n_\theta} \subseteq \Psi$, that are best in describing the inverse system P^{-1}, resulting in high ILC performance.

4 Results and Outlook

Figure 2 shows the experimental results on the flatbed printer where it can be seen that the presented approach, using only 7 parameters, equals the performance compared to a full basis with $n_\theta = 200$ parameters. Hence, the algorithm efficiently selected the relevant basis functions to obtain best performance. A next step is to extend the initial set of basis functions to allow more freedom for the algorithm.

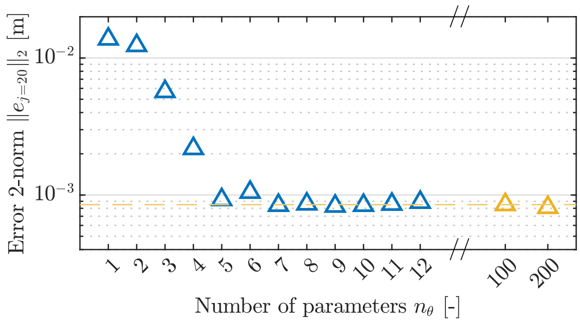

Figure 2: Experimental error 2-norm after learning, hence, the sparse basis in (△) equals performance to the full basis in (△) with significantly less parameters.

References

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