(Machine) learning for feedforward in precision mechatronics

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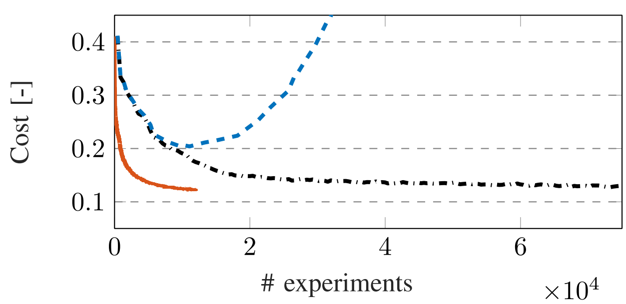
Leontine Aarnoudse[1] and Tom Oomen[1,2]

I. Research Overview

High tracking performance for mechatronic systems requires accurate feedforward control, which can be learned from data through dedicated efficient algorithms. This research is positioned at the intersection of machine learning (neural nets, random learning), controls (feedforward), and precision mechatronics. First, an overview of three different research topics is given, and secondly the topic of nonlinear filters in iterative learning control (ILC) is elaborated upon.

Randomized experiments lead to efficient learning of MIMO feedforward signals [1]

A trick using adjoints allows gradient-based ILC to be run fully model-free, yet this does not extend well to multivariable systems: generating gradients requires $n_i \times n_o$ experiments per iteration and is comparable to tuning by turning one knob at a time. Instead, an unbiased gradient estimate can be generated through one experiment for any MIMO system. All experiments are run simultaneously ('turn all knobs') in randomized directions. These gradient estimates lead to fast convergence of a stochastic gradient descent algorithm (—), which is much more efficient than deterministic approaches (-·-) that may diverge when data is noisy (- -).

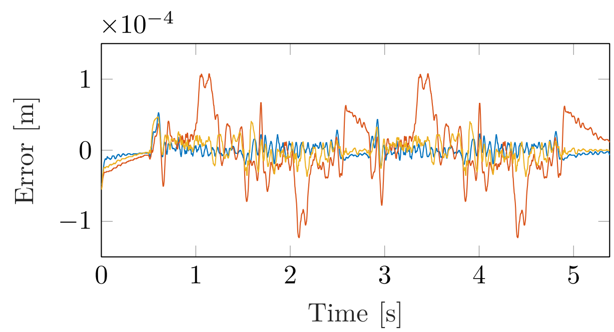


Neural networks for flexible feedforward: cost functions, model structures and training data [2]

Neural networks are promising for flexible feedforward control, but combining them in a harmonious way with state-of-the-art feedback control is subtle and requires care:

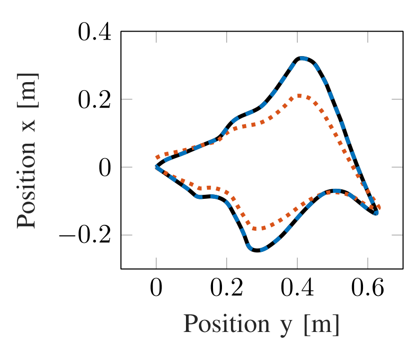
- The cost function used for training should reflect the aim of minimizing the tracking error, as $\|f_{\text{train}} - f_{\text{nn}}\|$, with $e(f_{\text{train}}) = 0$, being small does not necessarily mean that $e(f_{\text{nn}})$ will be small.
- The model structure should allow for non-causal feedforward, as many systems contain delays.
- Training data, consisting of references and feedforward signals, should be generated in closed-loop, for example using ILC, as nonlinearities manifest along trajectories.

The figure compares the performance of f_{train} (—), and non-causal time-delay (—) and recurrent neural networks (—).



Weighting the errors that matter: cross-coupled iterative learning control [3]

For contour tracking applications, the error in time domain is less important than the deviation from the contour. Cross-coupled ILC can be used to design feedforward signals for these specific cases, by using a cost function that weights this contour error explicitly. The cost function also weights the error tangential to the contour error, to allow for specifying different aims in different parts of the trajectory. For example, one might want to slow down in sharp corners and make up for lost time when moving straight. The figure shows contour tracking (—) with (- -) and without (·····) cross-coupled ILC.



*This work is part of the research programme VIDI with project number 15698, which is (partly) financed by the NWO.

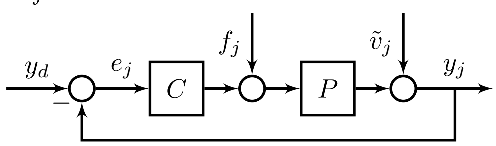
[1]The authors are with the Dept. of Mechanical Engineering, Control Systems Technology, Eindhoven University of Technology, Eindhoven, The Netherlands. l.i.m.aarnoudse@tue.nl

[2]Tom Oomen is also with the Delft Center for Systems and Control, Delft University of Technology, Delft, The Netherlands.

II. Seminar Topic - Nonlinear Iterative Learning Control [4]

Iterative learning control (ILC) can attenuate repeating disturbances completely, yet it also amplifies iteration varying disturbances up to a factor two [5]. The aim of this research is to develop a nonlinear ILC framework that achieves fast convergence, robustness, and low converged error values in ILC. To this end, a nonlinear deadzone is added to the learning filter, which differentiates between varying and repeating disturbances based on their amplitude characteristics and applies different learning actions: fast attenuation of repeating disturbances, and slow averaging of varying disturbances.

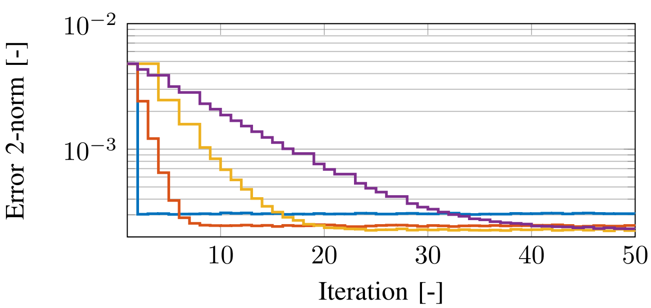
A. Problem formulation



ILC is applied to the SISO LTI system above, according to

$$e_j = S(y_d - \tilde{v}_j) - Jf_j, \quad f_{j+1} = Q(f_j + \alpha L e_j) \tag{1}$$

with $S = (1 + PC)^{-1}$, $J = SP$ and $L \approx J^{-1}$. Robustness filter Q is typically a low-pass filter. The learning gain $\alpha \in (0, 1]$ influences both the number of iterations required to compensate the iteration-invariant disturbance y_d, and the amplification of iteration-varying disturbance v_j, as illustrated for $\alpha = 1$ (—), 0.5 (—), 0.2 (—) and 0.1 (—). The aim is to achieve both small converged errors and fast convergence.



B. Approach: nonlinear ILC

To achieve both fast convergence and limited amplification of varying disturbances, a deadzone nonlinearity φ is included in the feedforward update, such that

$$f_{j+1} = Q(f_j + \alpha L e_j + L\varphi(e_j)), \tag{2}$$

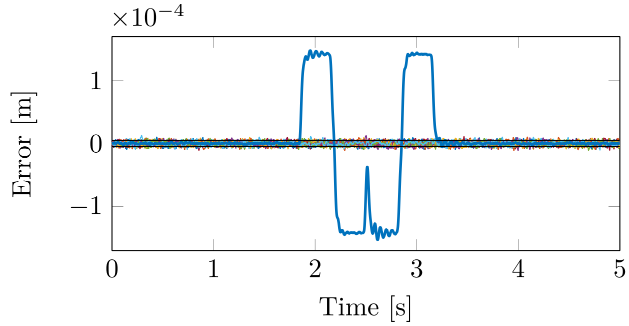
with, for deadzone width δ and gain $\gamma > 0$,

$$\varphi(e_j(k)) = \begin{cases} 0, & \text{if } |e_j(k)| \leq \delta \\ \left(\gamma - \frac{\gamma\delta}{|e_j(k)|}\right) e_j(k), & \text{if } |e_j(k)| > \delta. \end{cases} \tag{3}$$

The deadzone nonlinearity satisfies an incremental sector condition with γ, which enables convergence analysis, leading to the following convergence condition:

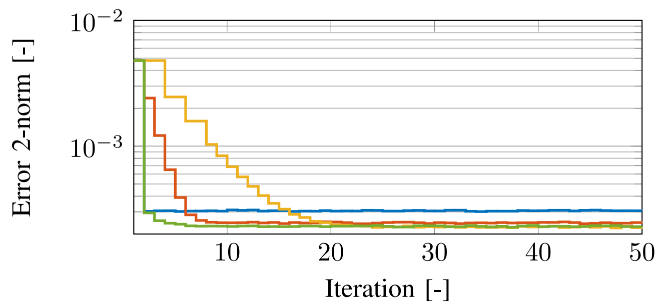
$$\left\| Q\left(1 - \alpha JL - \frac{\gamma}{2} JL\right) \right\|_{\mathcal{L}_\infty} + \frac{\gamma}{2} \|QJL\|_{\mathcal{L}_\infty} < 1. \tag{4}$$

Through the deadzone with width δ (—), a high learning gain is applied to the iteration-invariant disturbance (—) and the amplification of iteration-varying disturbances is limited.



C. Conclusions and future work

A nonlinear frequency-domain ILC algorithm (—) is developed that achieves both fast convergence and a small converged error in the presence of iteration-varying disturbances, as compared in simulation to standard ILC with $\alpha = 1$ (—), 0.5 (—) and 0.2 (—). Ongoing research is aimed at extending this approach to lifted ILC and repetitive control.



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Leontine Aarnoudse received the B.Sc degree (2017) and M.Sc degree (cum laude) (2019) in Mechanical Engineering from the Eindhoven University of Technology, Eindhoven, The Netherlands. She is currently pursuing a Ph.D. degree in the Control Systems Technology group within the department of Mechanical Engineering at Eindhoven University of Technology. Her research interests are centered around the development of learning control theory for precision mechatronics.