Autonomous Iterative Learning Control for Systems with Unknown Dynamics

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At the Institute of Mechatronic Systems at Leibniz University Hannover, we investigate how data-driven and AI-based methods can help overcome fundamental limitations of classical model-based approaches in system identification, sensor fusion, state estimation, and control. Many established estimators and controllers rely on sufficiently accurate model knowledge and carefully tuned parameters, while their performance may deteriorate under model uncertainty, changing operating conditions, or transfer to a different system. Our goal is therefore to develop learning-enabled methods that infer missing system knowledge from data and rapidly adapt to previously unknown dynamics and environmental conditions. The methodological spectrum ranges from physics-informed neural networks and fast non-autoregressive models for system identification to pluripotent sensor-fusion schemes and data-driven control algorithms. One concrete focus is the autonomous learning of repetitive motion tasks, where performance can be improved from trial to trial in a way that is reminiscent of human motor learning.

This talk provides an overview of recent research on autonomous iterative learning control for such repetitive reference-tracking tasks. Iterative Learning Control (ILC) is a well-established approach for improving tracking performance from trial to trial and is supported by a broad body of results on convergence, robustness, and high-performance tracking [1]. In practice, however, classical model-based ILC typically relies on prior model information and on learning parameters that must be selected and tuned for the system at hand, while data-driven control aims to reduce the dependence on explicit plant models [2].

One line of work combines iterative learning with data-driven modeling of unknown nonlinear dynamics in Autonomous Iterative Motion Learning (AI-MOLE). AI-MOLE repeatedly applies an input trajectory, trains a Gaussian process model from experimental data, and uses the learned model to update the input trajectory until the desired tracking performance is achieved; the necessary learning parameters are determined automatically, enabling plug-and-play operation without manual parameter tuning [3]. Extensive experiments demonstrate this concept on different real-world robots and reference-tracking tasks using only input/output information when required.

Building on this idea, more recent work introduces Iterative Model Learning (IML) and Dual Iterative Learning Control (DILC) as a unified framework for data-driven ILC [4]. IML learns models of unknown dynamics from input/output trajectory pairs, while DILC combines model learning and control learning so that established model-based ILC methods can be employed without prior model information and with systematic self-parametrization. The latest extensions address multiple-input/multiple-output dynamics and show that autonomous tracking and model learning can be achieved without prior system knowledge or manual parameter tuning in complex robotic systems [5]. Related work additionally considers constraint-aware motion adaptation and application-specific extensions of these learning control concepts.

The talk will place these developments along a continuum from classical model-based ILC to data-driven and increasingly self-configuring learning control. Particular attention will be given to the practical questions that determine whether such methods can be used beyond carefully tuned laboratory examples: the amount of prior knowledge required, the number of repetitions needed, the availability of formal convergence properties, and the transfer of the same learning mechanism between different systems and tasks. Application examples include different real-world robotic testbeds, multi-axis manipulators, and high-fidelity simulations of industrial robotic systems. The overall aim is to illustrate how repetitive mechatronic systems can learn accurate reference tracking from experimental data with progressively less commissioning and manual control-design effort.

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