Learning through Experience
– Optimizing Performance by Repetition –

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Making a robot explore its own dynamic behavior and learn its individual dynamic characteristics represents an important step towards a robust and reliable operation; especially, when considering challenging and changing environments.

The goal of our research is to develop a strategy which enables a system, executing the same task multiple times, to use the knowledge of the previous trials to learn more about its own dynamics and enhance its future performance. Our approach, which falls in the field of iterative learning control [1, 2], combines methods from both areas, traditional model-based estimation and control and purely data-based learning. Certainly, first-principles models provide a great opportunity to understand the system's fundamental dynamic behavior; however, they never capture the whole complexity of a real system. Therefore, real operation data plays an important role in estimating unmodeled dynamics, paramteric uncertainties, and disturbances and later updating the input signal appropriately.

Taking advantage of the a-priori knowledge about the system's dominating dynamics, a data-based update rule is derived which adapts the input signal after each trial. The update is done in two steps: an error estimation followed by a control step. First, the constant overall error signal along the trajectory is estimated using optimal filtering methods as Kalman filter, least square, or (robust) convex programming [3]. The estimated error signal provides more insight in the real dynamics along the trajectory. Second, based on this information, a new input signal is calculated, e.g. by means of LQR-type control or approaches minimizing the variance of the noise. In doing so, the focus and novelty of our work lies in the direct treatment of input and state constraints as well as in the use of computational efficient algorithms which provide the opportunity to expand our approach and consider cooperative multi-vehicle learning.

Different experimental platforms are used to develop and proof our ideas. Among others, the swing-up trajectory of a pendulum is learned, which is very sensitive to model errors. Moreover, flying vehicles are taught to perform highly agile maneuvers.

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2. Hyo-Sung Ahn, Kevin L. Moore, and YangQuan Chen. Iterative Learning Control: Robustness and Monotonic Convergence for Interval Systems (Communications and Control Engineering). *Springer*, 2007.
3. Stephen Boyd and Lieven Vandenberghe. Convex Optimization. *Cambridge University Press*, 2004.