A Unifying Computational Framework for Optimization and Dynamic Systems Approaches to Motor Control

Peyman Mohajerian, Jan Peters, Auke Ijspeert, Stefan Schaal

Computer Science & Neuroscience
University of Southern California
ATR Human Information Sciences Laboratory

Theories of biological motor control have been pursued from at least two separate frameworks, the “Dynamic Systems” approach and the “Control Theoretic/Optimization” approach. Control and optimization theory emphasize motor control based on organizational principles in terms of generic cost criteria like “minimum jerk”, “minimum torque-change”, “minimum variance”, etc., while dynamic systems theory puts larger focus on principles of self-organization in motor control, like synchronization, phase-locking, phase transitions, perception-action coupling, etc. Computational formalizations in both approaches have equally differed, using mostly time-indexed desired trajectory plans in control/optimization theory, and nonlinear autonomous differential equations in dynamic systems theory. Due to these differences in philosophy and formalization, optimization approaches and dynamic systems approaches have largely remained two separate research approaches in motor control, mostly conceived of as incompatible.

In this poster, we present a novel formal framework for motor control that can harmoniously encompass both optimization and dynamic systems approaches. This framework is based on the discovery that almost arbitrary nonlinear autonomous differential equations can be acquired within a standard statistical (or neural network) learning framework without the need of tedious manual parameter tuning and the danger of entering unstable or chaotic regions of the differential equations. Both rhythmic (e.g., locomotion, swimming, etc.) and discrete (e.g., point-to-point reaching, grasping, etc.) movement can be modeled, either as single degree-of-freedom or multiple degree-of-freedom systems. Coupling parameters to the differential equations can create typical effects of self-organization in dynamic systems, while optimization approaches can be used numerically safely to improve the attractor landscape of the equations with respect to a given cost criterion, as demonstrated in modeling studies of several of the hall marks of dynamics systems and optimization theory. We believe that this novel computational framework will allow a first step towards unifying dynamic systems and optimization approaches to motor control, and provide a set of principled modeling tools to both communities.