Adaptive Dynamical Systems – A promising tool for embodied artificial intelligence

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Introduction

Nonlinear Dynamical Systems (NDS) are an interesting tool to devise locomotion controllers for mDOF robots, e.g. CPGs for quadrupeds [1]. Furthermore, this approach has a strong foundation based on the investigation of biological coordination tasks [7]. One of the difficulties that limits the usability of this approach to robots is the problem of how to design a suitable NDS to control a given robot and, if the NDS can be found, how to tune its parameters. Furthermore, one would like to have a certain flexibility and adaptivity in the controllers in order for them to adapt to changing body properties and non stationary, complex environments.

In a "proof of principle" implementation in a simulation [2] we showed that we can extend a simple dynamical system (i.e. an oscillator) with an additional state variable and the corresponding evolution law (i.e. differential equation) in order to make it adaptive to a mechanical structure. The mechanical structure (body) and the *adaptive frequency oscillator* (controller) make up a simple adaptive locomotion system. This locomotion system is capable of adapting to changing body properties or an addition of external load. In this contribution we show that we can successfully implement these concepts in the real world. As briefly discussed in [2] we consider the therein presented system as an example of a much broader class of systems. Namely, we propose that the extension of dynamical systems by state variables with different time scales could be a useful tool for many applications in robotics, machine learning and other areas were dynamic adaptive behavior is desirable. We call such dynamical systems which are extended with additional state variables, which evolve on different (normally slower) time scales than the rest of the state variables, Multiscale Dynamical Systems. In contrast to conventional adaptive control, this systems and the feedback loops are usually strongly non-linear. This allows for interesting pattern formation capabilities.

Adaptive Dynamical Systems

We implement an adaptive dynamical system by using a *plastic NDS*, as described in the following. The controller is described by the dynamical system which has four additive contributions, i.e. the *Effective flow* $\mathbf{F}_{\sum}(\mathbf{q}, t)$ is the sum of all the parts described in the following and is the effective dynamics: (1) The *Intrinsic flow:* $\mathbf{F}_0(\mathbf{q})$ describes the

part of the system that we consider fixed (i.e. constant over time). (2) The *Plastic flow* $\mathbf{F}_p(\mathbf{q}, t)$ describes the plastic part of the system, e.g. the adaptation in the neural network (learning) of a subject, metabolistic adaptation, etc. (3) *External influences*: $\mathbf{F}_e(t)$ this term describes disturbances from the environment, sensory input, feedback, etc. It can also be used to impose a training signal on the system. (4) Finally the *Noise term* $\mathbf{F}_\xi(t)$ includes thermal and other noise sources as well as not modeled dynamics.
The *adaptation of the dynamics* is modeled by the plastic flow. The idea of the plastic dynamical system is the following: The history of the phase point leaves traces in the system, i.e. history of the systems behavior *and* external influences shape future dynamics. There are two main contributions to the change of the dynamics: (1) The "memory trace function" $\mathbf{T}$ and the (2) forgetting dynamical system $\mathbf{R}$: $\dot{\mathbf{F}}_\mathbf{p} = \underbrace{\mathbf{T}(\mathbf{F}_{\sum}, \mathbf{q}, t)}_{\text{trace}} + \underbrace{\mathbf{R}(\mathbf{F}_{\sum}, \mathbf{q}, t)}_{\text{forgetting}}$

Example: Controller adapting to to body dynamics

As a concrete example of the above ideas we will show the implementation of a controller which is able to autonomously adapt to the body dynamics of a quadruped underactuated robot [5]. The robot is actuated only at his hip joints, and has springs in the knee joints. Such a robot thus has a very pronounced body dynamics in terms of resonant frequencies. From former studies on the robot (and animals) it is known that the resonant frequencies are a good choice for efficient locomotion.
We present, based on the above general concepts, a very simple online adaptive controller based on adaptive frequency oscillators [2, 6] The controller needs no complicated signal processing, no algorithmic description and there is no separation between learning substrate and learning algorithm, which makes the whole system treatable in an unified way.
By the interaction of the controller and the body-environment systems, a distinct locomotion pattern emerges, results from simulations furthermore suggest that the gait pattern and the energy consumption distribution is in line with observations in mammals [4, 3].

Outlook

Despite its application to robotic locomotion, we are convinced that the presented approach will be useful at least two ways to bring forward our understanding of intelligent processes: (1) as a mathematical framework for learning and adaptive systems which allows to formulate problems in the unified, rigorous language of dynamical systems, and (2) more specifically on the road from locomotion to cognition, it will allow us to gradually implement intelligent high-level controllers which are grounded in the real world.

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