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Incremental motion learning with locally modulated dynamical systems

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HIGHLIGHTS

- A novel Dynamical Systems formulation based on reshaping an existing system is introduced.
- The system can be flexibly reshaped to accommodate demonstrations.
- Stability properties of the original dynamics are retained in the reshaped dynamics.
- Evaluation on several robot manipulation tasks.

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ABSTRACT

Dynamical Systems (DS) for robot motion modeling are a promising approach for efficient robot learning and control. Our focus in this paper is on autonomous dynamical systems, which represent a motion plan without dependency on time. We develop a method that allows to locally reshape an existing, stable nonlinear autonomous DS while preserving important stability properties of the original system. Our system is based on local transformations of the dynamics. We propose an incremental learning algorithm based on Gaussian Processes for learning to reshape dynamical systems using this representation. The approach is validated in a 2d task of learning handwriting motions, a periodic polishing motion and in a manipulation task with the 7 degrees of freedom Barrett WAM manipulator.

1. Introduction

A set of preprogrammed behaviors is insufficient for a truly versatile robot. Alternative solutions should hence be sought to provide the user with an intuitive interface that can be used to quickly and efficiently teach the robot new tasks. Robot Learning from Demonstration (RLfD) addresses this issue by endowing the robot with the capability to learn tasks from demonstrations [1,2]. The goal is that the user should be able to show the robot how to perform a task rather than programming it explicitly. A task can be demonstrated in various ways, e.g. through motion capture or Kinesthetic teaching. After a set of demonstrations has been collected, these are typically used for optimizing a parameterized representation of robot motions. While these representations can take many forms, in this paper we are interested particularly in approaches that represent motions using Dynamical Systems (DS).

In order to successfully model the robot motion, demonstrations should be provided such that they include the generic characteristics of the motion. This is however very difficult when dealing with complex and/or high dimensional motions. Incremental Learning, whereby the robot successively learns the task through several demonstrations, can alleviate this difficulty. Furthermore, incremental learning can allow task refinement (incremental adaptation of task model to improve task performance) and reuse (use of an existing task model for a completely different task) [3]. A general workflow of an incremental learning setting is described in Fig. 1. While numerous advances have been made for incremental motion learning for time-indexed trajectories, incremental learning in DS representations is still a largely unexplored area of research. In this work, we address this by proposing a novel DS representation, called Locally Modulated Dynamical Systems (LMDS), that allows to reshape DS while preserving stability properties of the original system. As hinted by the name, this is done by locally applying transformations (e.g. rotations), to the original dynamics. It is shown that this way of reshaping dynamics is suitable for robot motion modeling, since complex motions can be modeled without risking the introduction of spurious attractor points

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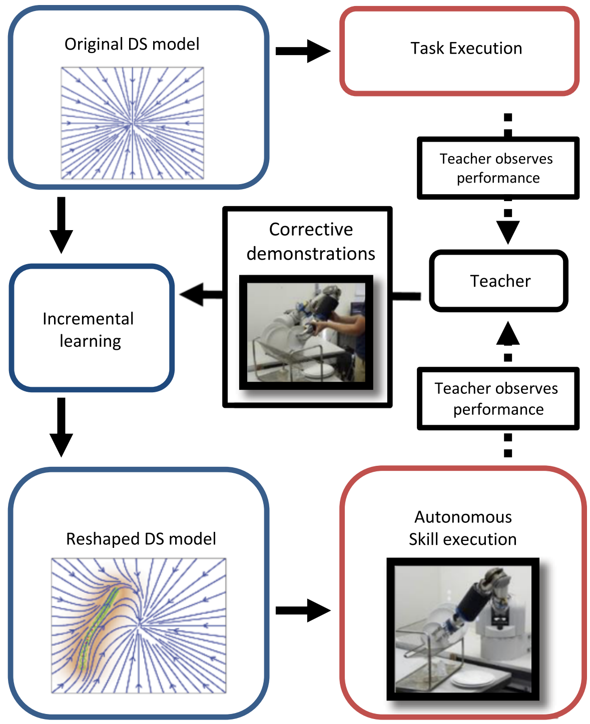

Fig. 1. The figure illustrates the incremental process of acquiring a new skill by reshaping dynamics using the proposed framework. The system can be reshaped repeatedly until satisfactory task performance has been achieved.

or unstable behavior. The LMDS representation is not constrained to a particular form of original dynamics or learning method (any *local* regression method can in principle be used, together with any representation of a first order *autonomous* dynamical system). We further propose the Gaussian Process Modulated Dynamical Systems (GP-MDS) algorithm, which uses Gaussian Process Regression (GPR) to learn reshaped dynamics. In summary, the main contributions in this paper are:

- The Locally Modulated Dynamical Systems (LMDS) formulation.
- Stability analysis of the general LMDS formulation.
- An incremental learning algorithm for LMDS based on Gaussian Processes, GP-MDS.

The remainder of this paper is organized as follows. In Section 2, we provide a literature review. In Section 3 we detail the LMDS formalism, and propose a particular parameterized form of the modulation function which is used in this paper. In Section 4, we then address the problem of how to learn LMDS, introducing the GP-MDS algorithm. Experimental validation is presented in Section 5, with a 2d example of warping dynamics for handwriting letters, and one periodic as well as one discrete manipulation task on the KUKA LWR and Barret WAM arms. The paper is concluded with a discussion and an outlook into future directions of research in Section 6.

2. Related work

Dynamical Systems have emerged as one of the most general and flexible ways of representing motion plans for robotic applications. In contrast to classical architectures where a robot is usually programmed to track a given reference position trajectory as accurately as possible, in DS representations the static reference trajectory is replaced by one which unfolds as the task progresses, making adaptation to unforeseen events possible. Motion generation with dynamical systems is a long-standing research topic with important early approaches such as the VITE [4] model suggested to simulate arm reaching motions. Recurrent Neural Networks (RNN) have been successfully used for modeling dynamics [5–7] in various applications. However, neural network approaches typically suffer from long training times and difficulty to ensure stability.

More recently, the Dynamic Motor Primitives (DMP) framework [8,9] and variants [10] have gained popularity both in imitation learning [11] and reinforcement learning [12,13]. This class of DS has been shown to be very useful and flexible for a large variety of robotics tasks, both discrete and rhythmic. Coupling between several DS is achieved via a shared phase variable that acts as a clock, which also forces potentially unstable non-linear dynamics to decay and eventually be replaced by a linear system with known stability properties. This mechanism makes it easy to incorporate exploration and learning without risking unstable behavior, but it also means that the system is time-dependent, which for some tasks may or may not be desirable.

In contrast, autonomous DS formulations [14] can encode motions in a completely time-independent manner. By scaling the speed of motion, time-invariant models can be transformed into time-dependent models and cope with timing constraints [15,16]. Stability is arguably one of the most fundamental properties that should be ensured when using DS for modeling robot motions, both from a task performance and a safety perspective. In our previous work, this has been addressed in [17] by deriving stability constraints for a particular parametric form of DS, Gaussian Mixture Regression (GMR). A similar analysis with resulting constraints have also been performed for DS learned by Extreme Learning Machines (ELM) in [18]. A more generally applicable method was proposed in [19], which presents an approach that can stabilize any DS by online generation of an auxiliary command that ensures monotonic decay of a task-based energy function which is learned from demonstrations. This method allows more complex motions than stability constraints based on a quadratic energy function, which is used e.g. in [17], but is still limited by the energy function used as a basis for the stabilization mechanism. Task-based Lyapunov functions have also been explored in the ELM framework in [20]. All of these methods are based on using a parameterized Lyapunov function for ensuring asymptotic stability of the dynamics. In each case, this has consequences on the accuracy at which trajectories can be represented. In this work, we do not base the stability analysis on a known Lyapunov function, and instead construct a DS which is (1) inherently incapable of introducing spurious attractors and (2) guaranteed to generate bounded trajectories. These are weaker properties than asymptotic stability, with the consequence that our dynamics can converge to limit cycles or orbits (but not spurious attractors). In exchange, we can directly incorporate incremental demonstrations, which need not comply with an energy function. As will be shown later, asymptotic stability is for all practical purposes an unnecessary restriction in our framework, since it is not violated unless the demonstrations explicitly indicate orbital behavior.

Our model is based on modulating an available autonomous (time-invariant) DS with a state-dependent full-rank matrix, and strongly related to our previous work where state-dependent modulation was used to steer trajectories away from obstacles [21]. While similar in formulation of the dynamical system, here we assume a non-parametric form of the modulation and learn it from examples.

Incremental learning from demonstration can alleviate the difficulty of simultaneously demonstrating desired behavior in multiple degrees of freedom. Furthermore, it can allow refinement and reuse of a learned model for a different task. Various methodologies have been used. In [22], a neural network based approach inspired by how humans consolidate existing knowledge is presented. Gaussian Mixture Modeling (GMM) usually in