SEDS-II: Generating Stable, Reactive, and Robust Robot Motions with Smooth Regression Techniques

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I. Motivation

We consider Dynamical Systems (DS)-based modeling of a class of robot motions which ends at a given target point, i.e. the so-called point-to-point motions [2], [1], [3]. Typical examples of such motions are reaching out for an object, closing fingers in a particular grasping configuration, stepping motion, etc. When modeling robot point-to-point motions with DS, ensuring stability of the learned DS (from a set of demonstrations of the task) is a key requirement to provide a useful control policy. There are numerous nonlinear regression techniques to estimate nonlinear DS. Each of these techniques has its own pros and cons which make their use very task-dependent. However, the majority of these techniques cannot be used directly to model DS-based robot motions because they do not ensure stability of DS. In this paper we present an extension to our previous work Stable Estimator of Dynamical Systems (SEDS) [2] so as to ensure stability of DS-based motions independently of the choice of the regression technique. Therefore the new approach, called SEDS-II, allows adopting the most appropriate technique based on the requirements of the task at hand without compromising DS stability. SEDS-II also provides the possibility of online learning and using a combination of two or more regression methods, which could be helpful to satisfy the requirements of more advanced robot tasks.

II. Dynamical Systems-Based Robot Motions

We formulate the encoding of reaching motions as a control law driven by autonomous dynamical systems. Consider a state variable $\boldsymbol{\xi} \in \mathbb{R}^d$ that can be used to unambiguously define a discrete motion of a robotic system (e.g. $\boldsymbol{\xi}$ could be a robot's joint angles, the position of an arm's end-effector in the Cartesian space, etc):

$$\dot{\boldsymbol{\xi}} = \boldsymbol{f}(\boldsymbol{\xi}), \quad \boldsymbol{f} : \mathbb{R}^d \mapsto \mathbb{R}^d \tag{1}$$

where $\boldsymbol{f}(\boldsymbol{\xi})$ is a continuous function. Starting in an initial configuration $\boldsymbol{\xi}^0$, the robot motion $\dot{\boldsymbol{\xi}}^t$ is given by Eq. (1). We seek to derive an estimate of $\boldsymbol{f}(\boldsymbol{\xi})$ that is globally asymptotically stable at this attractor, so as to ensure that, even when perturbed, the system will ultimately reach the goal. Furthermore, we seek to have an estimate that follows a particular dynamics demonstrated by the user.

We will start by building an estimate of $\boldsymbol{f}(\boldsymbol{\xi})$ based on a set of N demonstrations $\{\boldsymbol{\xi}^{t,n}, \dot{\boldsymbol{\xi}}^{t,n}\}_{t=0,n=1}^{T^n,N}$ using any of our favorite nonlinear regression method. In our experiments, the training points are provided by a human demonstrator, passively guiding the robot through the motion. This initial estimate of $\boldsymbol{f}(\boldsymbol{\xi})$ will be likely unstable because standard regression techniques do not consider stability of $\boldsymbol{f}(\boldsymbol{\xi})$ during their training. In this work we first derive sufficient conditions to ensure global asymptotic stability of $\boldsymbol{f}(\boldsymbol{\xi})$ at its unique attractor $\boldsymbol{\xi}^*$, and then propose a constrained optimization problem to build an estimate of $\boldsymbol{f}(\boldsymbol{\xi})$ from the demonstrations under the constraint of the derived stability conditions.

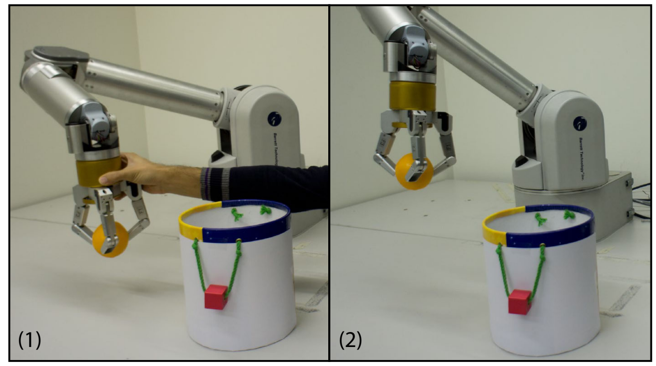

Fig. 1: Online learning of a DS model of the placing task, i.e. putting oranges inside the bucket (left). The execution of the task by the 7-DoF Barrett WAM arm (Right).

We evaluate the performance of the proposed approach in two ways: 1) On a set of complex planar motions that are inferred from human demonstrations. With this experiment, we illustrate one of the main properties of the proposed method that it can be used to stabilize unstable DS that are modeled with different regression techniques such as GPR, GMR, LWPR, and SVR. 2) In a robot experiment performed on the 7-DoF Barrett WAM arm that requires online/incremental learning. In this experiment, we demonstrate that our approach allows combining two different regression techniques in order to benefit from the advantages of both approach (see Fig. 1).

Acknowledgments

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References

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