Skill Learning using Generalized Cylinders Encoding, Reproduction, Generalization, and Refinement*

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Abstract— **This paper presents a novel parameter-free geometric approach to learning and reproducing trajectory-based skills from human demonstrations. We model a skill as a Generalized Cylinder which is a geometric representation composed of an arbitrary space curve called spine and a smoothly varying cross-section. To form the spine and the cross-section function of the generalized cylinder, our approach identifies and extracts the main characteristics of the demonstrated skill. These characteristics are spatial correlations across different demonstrations. Using a geometric rule, the encoded model reproduces the skill, as a time-independent trajectory, and generalizes it to unforeseen situations while its main characteristics are preserved. We also show that with a slight modification to the reproduction rule, our approach enables a human teacher to refine the characteristics of the learned skill through physical interaction. We validate the feasibility and efficiency of the proposed approach through several real-world experiments with a Jaco robotic arm.**

I. INTRODUCTION

Learning from Demonstration (LfD) facilitates teaching new skills to robots interactively by eliminating the need for manual programming of the desired behavior [1]. By observing a set of human-provided demonstrations, LfD approaches learn a model and generalize the encoded skill to novel situations autonomously. These capabilities make LfD a powerful approach that has the potential to enable even non-experts to teach new skills to robots with little effort. However, despite the existence of several trajectory-based LfD approaches, the vast majority of the existing robotic platforms rely on motion-level actions that are either hand-coded or teleoperated by experts [2], highlighting the need for further advances in this area.

One of the main factors that make existing approaches challenging (especially for non-experts) is the level of complexity of the existing representations. The number of parameters to be tuned and their corresponding tuning methods make it almost impossible for naïve users to tune the system and also understand how the system reacts to such adjustments. The other critical factor is that most available approaches require near-optimal demonstrations in order to perform effectively, while the redundancy and complexity of the current robotic platforms (i.e. high degrees of freedom), together with uncertainty and noise from the environment, demand a significant level of expertise to perform near-optimal demonstrations.

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In addition, being able to refine the given demonstrations to improve the learned model is highly desirable. Very few attempts have been made to enable the teacher to refine the given demonstrations through incremental learning.

In this paper, we propose a novel parameter-free LfD approach with a geometric representation composed of a regular curve and a surface in 3D Cartesian space. In addition to capturing the demonstrated trajectories, the constructed model extracts and represents the main characteristics of the demonstrated skill, which are the spatial correlations across different demonstrations. These underlying characteristics are extracted from the raw data and are not specified by the user explicitly, thereby minimizing the effort of the user. Additionally, the proposed representation is visually perceivable and can reproduce the learned skill as a time-independent trajectory using a simple geometric rule. To overcome the issue of sub-optimal demonstrations, our approach enables the user to improve the learned model through physical motion refinement. Unlike other existing approaches, refinements can be applied to both the demonstrations and reproductions of the skill. Consequently, the user can start from a set of (sub-optimal) demonstrations and refine the learned model interactively to reach the desired behavior. In total, the proposed skill learning approach presented in this paper: *a*) maintains the important characteristics and implicit boundaries of the skill, *b*) generalizes the learned skill over the initial condition of the movement while exploiting the whole demonstration space to reproduce a variety of successful movements. *c*) requires no parameter tuning, *d*) enables users to provide physical feedback to improve the characteristics/quality of the learned skill interactively. We validate our approach in seven experiments using a physical 6-DOF robot, as well as demonstrate its use in comparison to prior work.

The main concept of Generalized Cylinders (and the Canal Surfaces which are Generalized Cylinders with circular cross-sections) was firstly presented in [3] and [4]. Later in [5], the method was later extended with more experiments and was compared to existing prior work.

II. RELATED WORK

Existing trajectory-based LfD approaches use various techniques to encode demonstrations and retrieve a generalized form of the skill [1]. A category of approaches use regression-based techniques to generate a probabilistic representation of the given demonstrations [6],[7]. Grimes *et. al.,* employed Gaussian Process (GP) regression to learn and generalize over a set of demonstrated trajectories [7].

In follow-on work, to overcome the computational cost of GP, Schneider and Ertel used local Gaussian process regression [8]. Another approach similar to GP called LfD by Averaging Trajectories (LAT), uses only one-dimensional normal distributions [9]. Both GP and LAT cannot extract constraints from the demonstrations with objects aligned parallel to a Cartesian coordinate axis. A well-known work in this category by Calinon *et. al.,* builds a probabilistic representation of the skill using a Gaussian Mixture Model (GMM) and retrieves a smooth trajectory using Gaussian Mixture Regression(GMR) [10]. GMM/GMR, GP, local GP, and LAT are time-dependent approaches that require explicit time-indexing and are useful for encoding skills that are deemed to be performed in a fixed amount of time. The skills learned using time-independent approaches, on the other hand, can be temporally scaled [11]. Another drawback of these approaches is that they require parameter tuning (e.g. number of Gaussian components, scale, weight, kernel).

Another category of approaches uses dynamical systems to encode and reproduce trajectories [12], [13]. Dynamic Movement Primitives (DMPs) represent demonstrations as movements of a particle subject to a set of damped linear spring systems perturbed by an external force [12]. The shape of the movement is approximated using Gaussian basis functions and the weights are calculated using locally weighted regression. DMPs are implicitly time-dependent and this makes the system sensitive to temporal perturbations. In addition, one has to tune the parameters of the dynamical systems, such as time constants and scaling factors.

The real-time motion planning approach proposed by Majumdar and Tedrake approximates a boundary around a trajectory, which is visualized as a funnel [14]. By computing a library of funnels and their corresponding controllers off-line, their approach generates trajectories from the library using a closed-loop system. The generated funnels illustrate a similar representation to our approach, however, we do not require extensive off-line computation. Dong and Williams proposed probabilistic flow tubes to represent trajectories by extracting covariance data [15]. The learned flow tube consists of a spine trajectory and 2D covariance data at each corresponding time-step. Although the approach was applied to extract a human's intention, the flow tube representation can be seen as a special case of our approach in which the cross-sections are formed using covariance data.

Regardless of the technique used for learning from demonstration, the capability of improving the learned model by refining its shape or spatial constraints is highly desirable. This can become available through human-robot physical interaction. There exist few approaches that enable the human to refine the initially given demonstrations. Argall *et. al.,* used tactile feedback for refining a given set of demonstrations and reusing the modified demonstrations to reproduce the skill through incremental learning [16]. They apply this approach to teaching a robot to position its hand for grasping of different objects. Lee and Ott proposed an incremental learning approach for iterative motion refinement. Their approach combines kinesthetic teaching with impedance control and represents the skill using a Hidden Markov Model (HMM) [17]. Our proposed approach, on the other hand, can be applied in both task-space and joint-space, and also it can be used to refine both demonstrations and reproductions interactively.

III. CONCLUSIONS

We have presented a novel LfD approach for learning and reproducing trajectory-based skills. Our geometric representation maintains the important characteristics and implicit boundaries of the skill and generalizes it over the initial condition of the movement. By exploiting the whole demonstration space, it reproduces a variety of successful movements. In addition, the proposed approach requires no parameter tuning that not only simplifies the usage of the algorithm and makes the result consistent, but also can makes the approach more convenient for non-expert users. We also have shown that our approach enables users to refine the learned skill interactively through kinesthetic correction. We demonstrated that the skill refinement can be performed both on demonstrations and reproductions. During the demonstration refinement process the algorithm updates the learned model. While in the reproduction refinement the model stays intact and the applied physical corrections form a constraint that affects the reproduction rule. Our representation also facilitates the visual interpretation of the reproductions and refinements. Further work will concentrate on applying our method to more complex skills such as bimanual and collaborative tasks, and compare it to other existing approaches. We also plan to conduct a user study to measure the efficiency of the proposed approach for non-expert users as well as experts.

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