Representing the Variability of Human Movement with Probabilistic Movement Primitives

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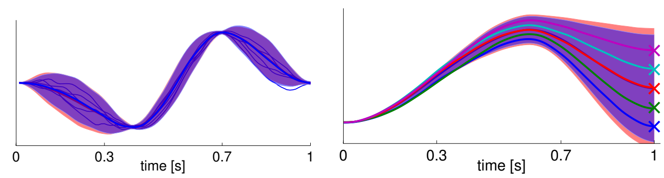
I. Introduction

Reproducing human-like movements is an essential requirement for rendering robot movements more efficient, safer, easier to train, and more appealing. Human movements have a high degree of complexity as they demonstrate variability and high-order coupling between the joints, while at the same time are able generalize to new locations, incorporate external feedback, and adjust the execution speed. We propose a probabilistic approach for generating, learning, and re-using movement primitives that exhibit most of the properties of human-like movements. We evaluate our approach on simulated and real robot experiments.



(a) Trajectory Distribution

(b) Conditioning

Figure 1. (a) Trajectory distribution learned by the ProMP approach plotted in blue, overlaid over desired distribution (red). (b) Reproduced generalization to different target states by conditioning.

II. Probabilistic Trajectory Generators

We introduce a probabilistic approach to Movement Primitives (MPs) [1] which we name Probabilistic Movement Primitives (ProMP) [3]. ProMPs represent a movement primitive as a distribution over trajectories $p(\boldsymbol{\tau})$. For controlling the robot with ProMPs, we obtain a stochastic feedback controller that exactly reproduces the given distribution over trajectories, as we depict in Figure 1(a). The stochastic controller does not require a parametric representation and is computed in closed form for each time point. We use kinesthetic teach-in to train the ProMPs, that is to obtain the distribution $p(\boldsymbol{\tau})$ over the trajectories, by providing a set of demonstrations. The parameters of $p(\boldsymbol{\tau})$ are extracted from the demonstrated trajectories by likelihood maximization, e.g. the expectation maximization algorithm. The use of trajectory distributions enables us to accurately model the variance of the movement continuously over the time, a crucial component for representing human-like movements. Our MPs can be used for both point-to-point and rhythmic movements, and the speed of the movement can be adapted by replacing time by a phase variable. After training the distribution over the trajectories, we can still modify the desired variance at any given time point, by conditioning the distribution. The distribution adapts to the new desired position while simultaneously trying to stay close to the demonstrations. As a result, generalization to new targets or via-points is also learned from demonstrations. The generalization to different desired target positions is shown in Figure 1(b). Furthermore, by using a distribution over the trajectories from multiple DoFs [2], ProMPs can capture the correlations between the state dimensions, e.g. the joint angles. Thus, our approach captures the inherent correlation of the joints, for example at task space movements. Here, our approach learns to generate movements that lie inside the null space of the task. Moreover trajectory distributions can easily be combined by calculating the "intersection" of two distributions, enabling ProMPs to continuously co-activate and blend primitives.

III. Experiments

We evaluated our approach on a real robot task with a 7-DoF KUKA anthropomorphic arm. We generated demonstrations for hitting a ball with a table tennis racket at two different locations. For each target location, we demonstrated five trajectories. After learning the primitives, the robot hit each of the target locations independently with the corresponding primitive, while it reproduced the same variability as in the demonstrations. We, subsequently, activated both primitives simultaneously to get the combination of both primitives. The robot hit both targets with one stroke.

References

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[3] A. Paraschos, G Neumann, and J. Peters. A probabilistic approach to robot trajectory generation. In *Proceedings of the International Conference on Humanoid Robots (HUMANOIDS)*, 2013.