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Adaptation and coaching of periodic motion primitives through physical and visual interaction

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HIGHLIGHTS

- An intuitive and user friendly system for transferring of skills from a person to a robot.
- It allows online learning and adaptation of motion trajectories.
- It allows adaptation of trajectories through human coaching, from either force or visual feedback.
- It is based on the dynamic motion primitives framework.
- Surface wiping use-case through non-rigid contact is demonstrated and evaluated.

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ABSTRACT

In this paper we propose and evaluate a control system to (1) learn and (2) adapt robot motion for continuous non-rigid contact with the environment. We present the approach in the context of wiping surfaces with robots. Our approach is based on learning by demonstration. First an initial periodic motion, covering the essence of the wiping task, is transferred from a human to a robot. The system extracts and learns one period of motion. Once the user/demonstrator is content with the motion, the robot seeks and establishes contact with a given surface, maintaining a predefined force of contact through force feedback. The shape of the surface is encoded for the complete period of motion, but the robot can adapt to a different surface, perturbations or obstacles. The novelty stems from the fact that the feedforward component is learned and encoded in a dynamic movement primitive. By using the feedforward component, the feedback component is greatly reduced if not completely canceled. Finally, if the user is not satisfied with the periodic pattern, he/she can change parts of motion through predefined gestures or through physical contact in a manner of a tutor or a coach.

The complete system thus allows not only a transfer of motion, but a transfer of motion with matching correspondences, i.e. wiping motion is constrained to maintain physical contact with the surface to be wiped. The interface for both learning and adaptation is simple and intuitive and allows for fast and reliable knowledge transfer to the robot.

Simulated and real world results in the application domain of wiping a surface are presented on three different robotic platforms. Results of the three robotic platforms, namely a 7 degree-of-freedom Kuka LWR-4 robot, the ARMAR-IIIa humanoid platform and the Sarcos CB-i humanoid robot, depict different methods of adaptation to the environment and coaching.

1. Introduction

Learning by demonstration, as an approach of acquiring trajectories in robotics [1], can only be effective if it enables adaptation of the demonstrated policy to the current situation of

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the task or the environment [2]. For example, when learning a wiping behavior, which is a rather trivial skill for humans, the robot must acquire the correct characteristics of motion, but must also maintain contact with the surface it is wiping. Such skill transfer from a human to a robot, where not only the motion but also the constraints imposed by the task are important, is the motivation behind this paper. We propose a system that enables a robot to learn actions which require continuous non-rigid contact with the environment through human demonstrations and interactive coaching. The coaching mechanisms enable a human teacher to efficiently guide the robot towards a goal-directed execution.

Learning by demonstration often exploits the means of encoding the motion characteristics of an action by generalizing demonstrated trajectories from the performing subject and the current situation. Different approaches exist, for example splines and wavelets [3,4], which are effective for imitation learning, but do not allow easy online modulation. Another options are Gaussian Mixture Regression [5] and Gaussian Mixture Models [6,7], used to estimate the entire attractor landscape of a movement skill from several demonstrations. To ensure stability of the dynamical system towards an attractor point, a constraint optimization problem in a nonconvex optimization landscape needs to be solved. Yet another option is the use of Hidden Markov Models [8]. Different dynamical systems can also be used.

Another type of dynamical systems are dynamic movement primitives (DMPs) [9], which focus on the representation of single movements by a set of differential equations. A DMP can represent a control policy in a compact way and its attractor landscape can be adapted by only changing a few parameters. Compared to representations proposed in [6,7], only a simple system of linear equations needs to be solved. DMPs can be used for representing classes of movements using statistical learning techniques [2,10], for combining trajectories in a dynamic way [11,12], and for reinforcement learning [13–16]. In this paper we exploit the DMP framework to enable continuous non-rigid contact with the environment, based on force feedback.

Adaptation of learned trajectories to external feedback was previously discussed in different settings and applications, using different trajectory representations. The use of force feedback to learn and improve task execution was widely considered in robotics, see for example the book chapter by Villani and De Schutter [17]. One of the best known approaches is the method proposed by Hogan [18], where force feedback is used to change the output velocity of a manipulator. This technology is the basis for the DMP adaptation proposed in this paper.

DMPs themselves were already used for adaptation to forces. In [19] the authors used an interaction force and the parallel force/position control law to modulate the velocity of the dynamical system. Pastor et al. [20,21] have also combined force controllers and DMPs in an approach for modifying DMPs at the acceleration level, allowing for reactive and compliant behaviors. They used the demonstrated trajectory profiles as reference, while [22] applied reinforcement learning to further optimize the behavior. A modulation approach at the acceleration level of a DMP for physically coupled dual-agent tasks was reported by Kulvicius et al. [23], but the learning was applied to acquire appropriate feedback gains instead of reference trajectories. On the other hand, Gams et al. [24] utilized coupled DMPs with force feedback at the velocity level. Combined with iterative learning control, their approach can achieve the desired force interaction for rigid contacts. Iteratively approaching a desired behavior has been applied for in some programming by demonstration approaches. For example, Sauser et al. [25] showed grasp adaptation through human corrections, while Calinon and Billard [26] showed gesture learning. On the other hand, iteratively approaching a desired behavior was also shown in combination with DMPs in a peg-in-hole task [27], where reference force-torque profiles were used as means for autonomously improving the execution performance. In this work the force controller was not applied within the DMP framework. Haptic feedback for improving the teacher demonstration was also used by Rozo et al. [28], who addressed the problem of what to imitate based on the mutual information between perceptions and actions. HMMs and GMR were used to encode the demonstrations and for the robotic execution of the learned tasks. The method was augmented in order to be applicable also for the task of pouring [29]. Adaptation of trajectories is not limited to one-arm behaviors. An approach for bimanual operation based on dynamical systems by adding local corrective terms was discussed by Calinon et al. [30].

In this paper we consider the transfer of skills from a human to a robot through coaching. The transfer is not limited to the motion, but includes the execution of the task in contact with the environment. We consider two problems of on-line motion adaptation for the actual completion of the task. The first is the adaptation to the external environment in order to achieve desired forces of non-rigid contact throughout the complete trajectory. The second is adapting the trajectories to the interventions of an instructor, modifying the trajectories through physical contact or with the use of predefined gestures. The interaction puts the instructor into the role of a tutor who coaches the robot to achieve the desired performance. Both adaptation to the environment and coaching rely on the use of a unified trajectory representation, i.e. the dynamic movement primitives (DMPs). The combination creates an intuitive and user-friendly interface to learning and modifying robotic trajectories with the potential of creating complex object-interaction trajectories.

Not many papers describe adaptation of learned trajectories for non-rigid contacts. Initial results of DMP adaptation methods, expanded on in this paper, were presented in [31,32]. The approach was expanded on by Ernesti et al. [33] to include transient motions and [34] to include structural bootstrapping from experience. Wiping with a robot has also been studied from other perspectives, including using dynamic models and operational space dynamics [35].

Coaching has been applied also in context of other robotic tasks. Gruebler et al. [36] used voice commands as a reward function in their learning algorithm. Verbal instructions of non-experts were used to modify movements obtained by human demonstration [37]. Physical contact was also used, for example, by Lee and Ott [38] who used kinesthetic teaching with iterative updates to modify the behavior of a humanoid robot. Coaching based on gestures and obstacle avoidance algorithms was applied to DMPs [39]. This approach is expanded on in this paper with force feedback.

In the next section we provide the basics of DMPs and the algorithm of encoding them. Section 3 provides the core algorithm of the adaptation approach. Three different methods are explained. Coaching, as the means to adapt parts of the trajectory based on the user input is explained in Section 4, followed by the results in Section 5 and a discussion with conclusions.

2. Learning of periodic dynamic movement primitives

In this paper we build on periodic dynamic movement primitives. For the sake of completeness we provide the basics of the DMP notation and an algorithm for extracting the frequency of the demonstrated signals. The algorithm of learning of weights that encode a DMP follows. It is the basis for both adaptation to external force and the coaching algorithms.

2.1. Periodic DMPs

The formulation of DMPs in this paper is based on [2]. For a complete DMP overview see [9]. The description is for clarity