# Learning and Force Adaptation for Interactive Actions

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Abstract—Dynamic movement primitives prove to be a useful and effective way to represent an action of a given agent. However, current DMP formulations do not take the interaction among multiple agents into the consideration. We propose a new formulation called Coordinate Change Dynamic Movement Primitive (CC-DMP), which explicitly represents the relationship between leader and follower in multi-agent collaborative tasks. The formulation of the CC-DMP is motivated by the idea of learning the relationships among interacting agents instead of learning single agent movements. We extend this idea in our previous work further to include a coupling term into the formulation, which is initially learned to adapt the CC-DMP to the current environment and context and is subsequently refined to account for dynamic changes perceived by the agent's sensor system. The incorporation of the coupling term in the formulation allows learning and adaptation of CC-DMPs for interaction tasks as well as encoding the complexity of the learned actions and their adaptation to dynamic changes in the scene, specifically caused by another agent. We demonstrate our approach in the context of learning wiping movements for dynamically changing task constraints.

#### I. INTRODUCTION

Learning actions from human observation and sensorimotor experience is an essential skill in order to enable a humanoid robot towards assistance of a human within its environment, especially in the case of interaction tasks which might involve physical contacts or coupled actions. Skill learning for a single agent has been thoroughly addressed in previous approaches in the field of imitation learning or programming by demonstration [2], [3]. In this context, generic models and representations have been proposed which are capable of encoding a demonstrated trajectory and which can be parameterized in order to adapt the encoded task to different situations such as Gaussian Mixture Models (see [4]) and Hidden Markov Models (see [5], [6]). In recent years, a popular approach using dynamical systems has been introduced in [7], [8] and [9] in the form of the Dynamic Movement Primitives (DMPs). A DMP describes a movement using a goal attractor whose shape is encoded by a nonlinear perturbation force term based on a demonstrated trajectory. With regression algorithms such as locally weighted regression, this force term can be learned from a single demonstration. A DMP has several beneficial properties. Due to the spring damping system, attraction to a different goal configurations is guaranteed. In addition, the force term profile encodes task-specific characteristics which allow the reproduction of topologically



Fig. 1: Wiping system based on KIT motion database [1]. A wiping movement is extracted from the motion database. After trajectory analysis, the periodic pattern is learned using the original DMP formulation. With the CC-DMP formulation, the learned wiping pattern is adapted to the movement of human's back. The novel coupling term applies force adaptation of the wiping movement and generates a desired constant pressure on the surface as depicted in the bottom-right image.

similar trajectories for different goal and start positions. In order to consider interactions, a new coupling term is usually added to the DMP formulation. This coupling term explicitly defines a mapping from the sensor feedback to the immediate reaction, as an example, a force field is constructed to avoid obstacles or keep distance between two agents. Furthermore, the parameters of the coupling term can be learned with reinforcement learning strategies from multiple interactive demonstrations, such as lifting an object with an another agent several times. However, such strategies can only handle relatively static environments, where crucial task-specific parameters must remain constant, e.g. the height of the agent involved in the lifting task.

In fact, the feature space in which we describe the motions for multi-agent systems is high-dimensional, much larger and has more variance than the feature spaces describing single-

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agent motions. However, the mutual consideration of both agents is essential in order to capture the important aspects of interaction task. Thus, to simplify the learning of interaction actions, we focus on learning the relationships among agents instead of learning the agents' motions. The formulation of the CC-DMP is motivated by this idea. It directly learns the relationships among agents for a special skill in the task space. This relationship is described as the follower's local movement in the leader's coordinate system.

In this paper, we introduce a coupling term which is used to enrich the CC-DMP formulation. The coupling term facilitates the learning of actions in complex situations and environments and allows the gradual refinement of a CC-DMP based on sensorimotor experience. In other words, CC-DMP captures the variance in interaction tasks while the coupling term learns specific variations influenced by the current situation and environment. For example, in a wiping system, CC-DMP is used to encode the relationship between a wiping movement and a moving wiping surface, while the coupling term adapts to the roughness, which is different but relatively static for different surface. We will discuss this idea in more detail in this paper and describe how to achieve force adaptation using coupling term in the CC-DMP formulation.

The paper is organized as follows. Section II provides an overview of existing approaches which have addressed the representation and encoding of coordinated multi-agent tasks. In Section III, we briefly mention our previous work on Coordinate Change Dynamic Movement Primitive [10]. After that, we will introduce a coupling term into the CC-DMP formulation and discuss its learning strategy in Section IV. Subsequently, a complete force sensor based wiping system is constructed and described in Section V. In conclusions, the work is summarized and an outlook is given.

#### II. RELATED WORK

Recent research efforts, in particular, related to the field of learning from human observation have been dedicated to the modelling and the representation of complex manipulation and cooperative actions which involve mostly two agents. In this context, the original DMP formulation has been extended in several works to address the requirements imposed by interactive actions. [11] introduced interactive DMPs for the representation of cooperative tasks by incorporating two dynamical systems in order to encode the movements of the involved agents. To ensure that both agents reach a common goal configuration, the dynamical systems are extended by a force term which emerges from a virtual spring with a fixed, task-specific length or distance spanned between the two agents. In [12], the interaction forces between agents are encoded in a continuous coupling term which is added to the DMP formulation. The coupling term is gradually learned through interactive learning control (ILC) based on sensory feedback. The coupling term is merely phase-dependent and does not consider the relation between the agents in task space which makes the adaptation of the proposed DMP formulation to different scenarios more difficult. In [13],

interactive movement primitives are presented which combine separately trained DMPs for each agent in cooperative tasks with a predictive distribution. However, the presented approach is restricted to a single interaction pattern and not easily generalizable. In [16], the force adaptation is realized by learning z-direction offset. This offset is learned incrementally, because it should be adjusted on-the-fly for different wiping surface. However, the described method does not support the surface movement, and it is difficult to adjust the amplitude of the periodic pattern, because the z-offset is dependent on the canonical value but not on the contact position. If the amplitude is changed, the zoffset must also be changed and learned from the beginning. Moreover, it is not intuitive to control the pressure on the surface, which is achieved by increasing or decreasing the virtual z-offset.

# **III. LEARNING INTERACTIVE ACTIONS**

# A. Dynamic Movement Primitives

Dynamic Movement Primitives 1 are action representations based on a dynamical system combined with a nonlinear shape attractor which is capable of encoding the characteristics of arbitrary complex trajectories.

$$\begin{aligned} \tau \cdot \dot{v} &= K \cdot (g - y) - D \cdot v + f \cdot scale \\ \tau \cdot \dot{y} &= v, \end{aligned} \tag{1}$$

where y is the current state, v is the derivative or the velocity, f is the force term which is scaled by the scaling term *scale*.

A DMP can be also considered as a high-level PD controller with an additional control term. In the PD controller, the error is the offset between the goal and the current position. Thus, the goal movement is also taken into the consideration.

In Eq. 2,  $K_p$  is corresponding to the spring factor K and  $K_d$  is the damper factor D. In the original DMP, the goal is fixed, thus,  $\dot{g} = 0$ .

$$\tau \cdot \ddot{y} = K_p \cdot (g - y) + K_d \cdot (\dot{g} - \dot{y}) + scale \cdot f. \quad (2)$$

#### B. Coordinate Change Dynamic Movement Primitive

The works mentioned in section II consider one agent at a time and try to introduce as much dynamic environmental information as possible into the formulation, which increases the learning complexity and decreases the generalization capability. For example, reinforcement learning adjusts DMP parameters for a relatively static environment, which allows only minor changes in a short period.

One approach is to find a better way to describe the task, which can capture as many variations as possible. We rely on the fact that the relationship of multiple agents plays an important role in an interactive task and that this relationship almost always changes in the same way for different variations. As a simple example, in a handover task, two agents tend to reach the same attractor point in the task space, no matter where they start and where the object exchange position is. Taking into account the relative position and orientation between a leader and a follower in the task space, we have proposed a new formulation called Coordinate Change Dynamic Movement Primitive (CC-DMP) [10], which allows to learn a follower's DMP in the leader's local coordinate system and execute it while considering the leader's movement. The CC-DMP is formulated as coupled multi-dimensional dynamical system as given in eq. 3.

$$\tau \cdot R_G^L \cdot \ddot{y}^G = K_p \cdot (g^L - R_G^L \cdot y^G) + K_d \cdot (\dot{g}^L - R_G^L \cdot \dot{y}^G) + scale^L \cdot f^L,$$
(3)

where  $R_G^L$  is a transformation matrix from the global to local coordinate system.  $g^L$  is the local goal which describes the final leader-follower configuration. E.g., a zero local goal indicates that the follower and leader tend to reach the same point attractor in the task space, if the follower executes a discrete movement. The local scaling matrix  $scale^L$  and local force term  $f^L$  determines the additional control signal which is needed to ensure that the relationship follows a task-specific path in the configuration space.

In our CC-DMP formulation, the leader's position and orientation determine the follower's position, while the follower's orientation is not taken into the consideration. In many tasks, the orientation relationship between the follower and the leader remains unchanged. For example, the follower's hand has the similar pose as the leader's hand during the hand-over task, where the follower's orientation is against the leader's orientation in general. The CC-DMP described here represents only a controller or kinematic path planner for the follower's position. However, it is not difficult to construct another CC-DMP which determines the follower's orientation. In other words, we are able to learn a DMP representing orientation relationship. Then, the follower's orientation is calculated by this DMP based on the leader's orientation.

The proposed CC-DMP is suited for tasks, where the leading agent's movement is demonstrated beforehand, such as a bi-manual task or a hand-over task with at least one demonstration. Moreover, CC-DMPs can also be used for on-the-fly changing leader's state, for example, for a moving goal in the hand-over task as we showed in [10]. Given continuous and reliable sensory feedback for detecting the leader's state, the CC-DMP would work without leader's DMP formulation. But if such sensory feedback fails to provide continuous leader's state change, the follower's formulation cannot adjust to sudden changes in the leader's behaviour such as a jump of the leader's coordinate system causing high acceleration and eventual damage to robot. Hence, the leader's DMP cannot be ignored. In on-the-fly applications, there is no rule defining leader's movement from one place to another, because it is not observed beforehand, hence, the force term of the leader's DMP should be set zero. In this case, the leader's DMP is a simple PD controller controlling a virtual leader towards the current

leader's position.

# IV. ADAPTATION OF INTERACTIVE ACTIONS

## A. Coupling term in Dynamical System

Here, we introduce the coupling term which is used to extend DMP formulation in order to allow a DMP to accommodate environmental changes. Instead of directly adjusting the learned parameters of the nonlinear perturbation force term with regard to dynamic environments, we add an external coupling term which provides a more flexible solution. Thus, the extended DMP is a combination of a goal attractor (PD controller), a shape attractor (internal force term) and an environment adaptor (coupling term). Based on the extended DMP formulation, the original CC-DMP formulation presented in [10] changes as follows:

$$\begin{aligned} \tau \cdot R_G^L \cdot \ddot{y}^G &= K_p \cdot (g^L - R_G^L \cdot y^G) \\ &+ K_d \cdot (\dot{g}^L - R_G^L \cdot \dot{y}^G) \\ &+ scale^L \cdot f^L + \tau \cdot R_G^L \cdot scale_C^L \cdot C , \end{aligned}$$
(4)

where C is the external coupling term, which is given as:

$$C(u) = \frac{\sum_{i=1}^{M} \Phi_i(u)\theta_i}{\sum_{i=1}^{M} \Phi_i},$$
(5)

where u is a phase vector,  $\Phi_i$  is the ith kernel function and  $\theta$  is the parameter to learn. The phase vector u is a multi-dimensional vector describing the local environment, for example, a 2D vector representing the relative contact position in the wiping task. The multiplier  $\tau$  for the coupling term in Eq 4 guarantees that the change of execution speed will not affect the value of the coupling term, because it only depends on the local environment. The scaling term  $scale_C^L$ in Eq. 4 changes for different initial configurations and its effect is similar to the scaling term  $scale^L$  of the force term. As an example, it enables different initial z-offsets for the force adaptation during the wiping task.

# B. Learning Coupling Term

According to the sensor feedback, a closed-loop controller is designed to adjust the required coupling term. The controller's result is learned with respect to the local environment. A function approximator is trained and later used to predict the required coupling term based on the current local environment, and the predicted coupling term is iteratively adjusted by the controller. This function approximator should be updated after each execution, thus, it must support incremental learning. In this paper, we use Locally Weighted Projection Regression (LWPR) [17] to learn the coupling term. As a result we obtain a multi-agent system consisting of 1) a CC-DMP which adapts the motion to the leader's behaviour and 2) a learned coupling term which adapts the motion to relatively static local environment, which does not change at least for a short period.



Fig. 2: Wash-back movement in the simulator. The movement of human's back is manually controlled. CC-DMP formulation enables the wiping pattern adapting to the movement of the human's back.

## C. Sensor-based Force Adaptation

In the above CC-DMP formulation, it is easy to generate an extra force by adding a coupling term. CC-DMP is a second-order dynamical system. Hence, the generated force is proportional to the coupling term. In many cases, however, there is no knowledge about how strong the external force should be in order to ensure the required pressure on the surface, because the original TCP's position has an offset to the target surface. And it is difficult to directly determine the contact position without the object's model or an accurate vision system. The basic idea is to gradually adjust the coupling term until the force sensor gives reasonable signals.

In order to guarantee the stability of the force control, we use the following controller 6 to derive the next coupling term  $C_{t+1}$  based on the current one  $C_t$ .

$$C_{t+1} = C_t + k_C \cdot (k_F \cdot (F_g - F_t) - d_F \cdot \dot{F}_t) , \quad (6)$$

where  $F_g$  is the required pressure on the target surface and  $F_t$  is the sensor feedback.  $k_C$  defines the relationship between real force and the coupling term.  $k_F$  and  $d_F$  are parameters for proportional and derivative parts separately. The change of the coupling term is proportional to the result given by a PD-like controller, which avoids significantly large overshoots which may damage the robot.

## V. APPLICATION: ROBOT WIPING SYSTEM

One important task for a service robot is to help people do housework, such as wiping the table. Hence, a wiping system which is able to adapt to different wiping surface is required in this context. A general wiping movement is a coupling between the wrist's periodic movement and the arm's discrete movement. In this case, the arm is naturally considered as the leader and the wrist as the follower. The leader determines the setting point of the periodic wiping pattern, while the follower is the executor. In an adaptable wiping system, the wiping pattern must be adjustable for different, sometimes complicated, wiping surface. At the same time, the arm as the follower must react to the movement of the wiping surface as the leader, which leads to a stable wiping system in a dynamic environment. These two difficult requirements are accomplished by using a two-layer CC-DMP framework with coupling term .

## A. Wiping System

Consider that the target surface is the leader of the wiping motion, whose local coordinate system is the playground, where the wiping pattern is executed. On the other hand, the setting point of a wiping pattern must follow a path in order to cover the whole surface. The reason to separate the whole wiping motion into the setting point's motion and the wiping pattern is to make wiping more flexible and adaptable. The combination of different setting point's movements and wiping patterns meets requirements of different wiping tasks.

As mentioned before, CC-DMP is a good framework to realize a leader-follower system, where the follower's local movement is learned without considering its possible global movement, which is decided by the leader's movement. For example, the wiping pattern generator does not need to know the target surface's movement in the wiping system. A great benefit of this set-up is that the direction of the coupling term, in which pressure must be added on the surface is unchanged in the local coordinate system, even when the target surface is rotated during wiping. Once a wiping system is constructed, any wiping pattern and wiping path can be chosen to generate different wiping motion, which also adapts to the target surface's movement on the fly (see Fig. 2).

# B. Learning Wiping Motion

A wiping movement is chosen from the KIT motion database [1] (see Fig 1). We extract discrete anchor point's movement and periodic wiping pattern separately [10]. The periodic wiping pattern is used later to generate a new wiping motion. Note that our interest does not focus on the reproduction of the original movement, because it can be done by just learning a discrete DMP, however, it is difficult to generalize. An approximated reproduction of the original movements requires the amplitude profile, because the human demonstration does not follow exactly the same periodic pattern [10].



Fig. 3: The wiping pattern is adapted to the horizontal inclined plane with target contact force 5 units. The corresponding diagram is shown in Fig. 4



Fig. 4: The diagrams are generated in the force adaptation experiment (see Fig. 3). The top diagram shows the force magnitude from the force sensor. The red dotted line represents the end of one period. The coupling term which is given by the force controller 6 and shown in the bottom diagram tries to realize the force adaptation.

#### C. Learning External Force Term

The other difficulty of a complete wiping system is how to generate pressure on the target surface. Because it is assumed that there is no wiping surface model, it is difficult to directly generate a wiping movement attaching to the surface. In this paper, instead of creating a new DMP for z-direction like in [16], the coupling term is learned directly with respect to the local position of the contact points. And with the CC-DMP formulation, the wiping movement with pressure on the surface is automatically adapted to the rotation or displacement of the wiping surface, which is not possible while using the process described in [16].

In order to use the Eq. 6, the derivative of the force sensor signal is required. It is not difficult to just keep the old value for a position and calculate the difference between the



Fig. 5: One period of force adaptation experiment (see Fig. 3) is extracted. The above diagram shows the result force value while the bottom one shows the coupling term given by the proposed force controller.

new signal and the old one. However, it is not guaranteed that the same contact point is revisited. One solution is to use a two-dimensional Radial Basis Interpolator learned by locally weighted learning strategy, thus, the force value of an unvisited contact point is interpolated based on its neighbourhood.

In our experiment, we use an inclined plane for force adaptation demonstration in order to make the diagram of the force values intuitive. However, using CC-DMP, we have a simple way to adapt the wiping movement to the inclined plane. We can train CC-DMP and orientation relationship DMP on the original plane firstly and rotate the plane before the execution. It is simply noticed that not only the follower's position (CC-DMP) but also its orientation (orientation relationship DMP) are automatically adjusted.

In Fig. 3, a force adaptation process is shown. The diagrams (see Fig. 4) show the force value and the corresponding required coupling term given by the designed force controller. The bottom diagram in Fig. 5 shows that the coupling term drops in the first half period, because the robot's arm is wiping the higher part of the plane. In the second half period, the coupling term raises back because of the smaller force value detected in the above diagram.

After learning the force adaptation coupling term, the robot can immediately adapt to the same inclined surface with the required force.

#### D. Results

The presented wiping system guarantees that the wiping movement is adapted to the online movement of the target



Fig. 6: The wiping pattern is adapted to the vertical inclined plane. After a simple goal parameter adjustment, CC-DMP enables the robot to execute the same wiping movement (see Fig. 3) on the vertical plane. The similar force adaptation process is executed by the robot.

surface, while the external force term C is learned for relatively static local environment. The combination of these two techniques enables us to create a complete force-based wiping system.

## VI. CONCLUSION AND FUTURE WORK

In this work, we presented an extension of our CC-DMP formulation by introducing a coupling term into the formulation. The combination of the CC-DMP and coupling term does not only capture the comprehensive variations of interaction actions but also enables the adaptation to specific local environment which can only be captured based on sensorimotor information from the execution of interaction tasks. The resulting action representation can be used to learn a wide range of different actions such as wiping as it has been demonstrated in this paper. In the future, we will extend this work and show how our approach generalizes to other interaction tasks, such as hand-over or bi-manual manipulation. Regarding the leader-follower system, one problem remains unsolved, namely how to decide which agent is the leader and which is the follower, which is usually provided by a high-level decision-making framework.

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