Analyzing Human Behavior and Bootstrapping Task Constraints from Kinesthetic Demonstrations

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ABSTRACT

In robot Programming by Demonstration (PbD), the interaction with the human user is key to collecting good demonstrations, learning and finally achieving a good task execution. We therefore take a dual approach in analyzing demonstration data. First we automatically determine task constraints that can be used in the learning phase. Specifically we determine the frame of reference to be used in each part of the task, the important variables for each axis and a stiffness modulation factor. Additionally for bi-manual tasks we determine arm-dominance and spatial or force coordination patterns between the arms. Second we analyze human behavior during demonstration in order to determine how skilled the human user is and what kind of feedback is preferred during the learning interaction. We test this approach on complex tasks requiring sequences of actions, bi-manual or arm-hand coordination and contact on each end effector.

Categories and Subject Descriptors

I.2.9 [**Robotics**]; I.2.6 [**Learning**]: Knowledge acquisition

Keywords

Programming by demonstration; Task constraints extraction

1. INTRODUCTION

Most common daily tasks such as mixing in a bowl or scooping ice cream require several atomic actions, each with its own set of features. For example the bowl has to be approached in a certain way, and a given force needs to be applied while mixing. For a robot it is important to extract this information for learning the task. Moreover in order to generalize the task, the motion and force profiles need to be related to the object of interest for that particular action.

However from a user perspective, this information is implicit. Therefore while demonstrating a task to a robot multiple times the users involuntarily maintain the key features unchanged while introducing variability in all the other aspects. Starting from this assumption we developed an approach for extracting task constraints. Further we use these constraints to evaluate skill across demonstrators. However when humans teach a robot kinesthetically their performance might change. Therefore in order to improve the teaching interaction we explore ways of providing feedback to make the learning process transparent to the user.

2. RELATED WORK

From a robot learning perspective we focus on extracting artificial constraints [7] that are key for properly executing complex tasks. Typically this requires segmenting the demonstration data into meaningful subactions [5], each with a corresponding set of constraints. Prior work focuses on the extraction of the frame of reference with respect to a given metric of imitation [3]. In our work we determine an attractor frame with respect to the extracted frame of reference, in which we can perform orthogonal decomposition of force and position control. Additionally we learn a stiffness modulation and a corresponding force profile.

From a user perspective, having a human in the loop requires first measures of what makes a good demonstration [2]; and second a social component that makes the teaching interaction a dual process and allows the improvement of both the robot and the user [4] by maintaining a mental model of the way the learning procedure is advancing [1].

3. APPROACH

We consider tasks that require completing several actions, such as the ones in Figure 1. We record a set of kinesthetic demonstrations. In the case of uni-manual tasks recorded data consist of robot proprioceptive information of end effector pose and wrench. When performing bi-manual demonstrations we use a data glove equipped with Tekscan tactile sensors, and a force-torque sensor mounted on the tool. This allows us to study the motion of both arms while providing additional information about the grasp being used.

3.1 Bootstrapping information for learning

We develop a criterion based on the assumption that the regions in the demonstration data where the user was coherent represent the features of the task that should be reproduced. This criterion allows us to compare different measures (like position and force) and modulate their contribution to the controller used in reproducing the motion, by using a weighting factor that adapts the robot's stiffness. We determine the suitable reference frame by weighting the

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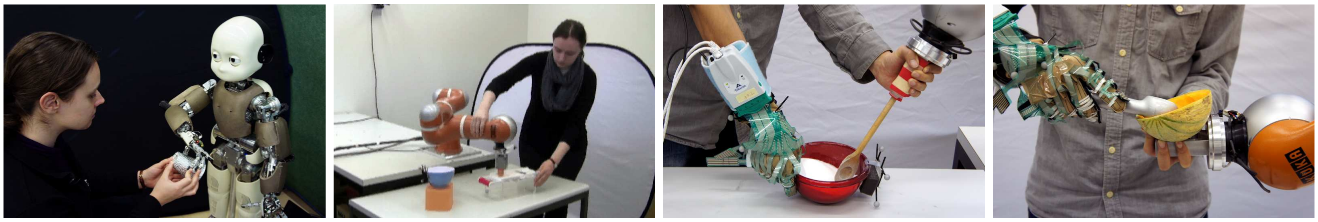

(a) Holding a cup (b) Grating vegetables (c) Mixing in a bowl (d) Scooping a mellon

Figure 1: Task constraints and user behavior were studied across different tasks that require completing several actions. In the scooping task illustrated in figure (d) these actions consist in: reaching for the mellon, scooping, reaching a bowl and emptying the scoop, reaching back.

relative importance of each of the task variables when expressed in the reference system of the objects involved in the task. A set of segmentation points are obtained by splitting the motion whenever a change in the reference frame or in the variables on interest occurs.

This information bootstrapped prior to learning a task is aimed to parameterize the learned models by automatically encoding features that are important in the execution. We encode the motion of each segment in a time independent manner using a Coupled Dynamical Systems approach [6]. We encode the force and stiffness profiles as a function of position using gaussian mixture models. The approach was validated on a common kitchen task of grating vegetables (see Figure 1(b)), and performance was compared against standard control modes.

3.2 Human factors in PbD

We assessed human factors influencing demonstrations with the underlying motivations of (1) understanding what keeps the user engaged throughout the demonstrations; (2) making the robot responsive to user actions in a way that would increase user engagement; and (3) maximizing the use of demonstrated data.

For this we conducted a user study in which the participants had to teach a robot a manipulation task (see Figure 1(a). Kinesthetic teaching was used to demonstrate a robot how to adapt its finger positions when faced with perturbations, without dropping the object. Recorded data consisted of finger joint angles and the response of tactile sensors on the robot's fingertips. First we evaluated the teaching procedure with regard to task specific metrics (i.e. showed how good the robot's response was when the object's position was perturbed). Second we evaluated the human performance in four different conditions: the robot provided no feedback at all; a GUI feedback of the tactile response was provided on a screen; verbal feedback by a knowledgable person; and direct feedback by the robot through the use of facial expressions mapped to the intensity of the contact. Results showed that the last two setups improved the teaching, while the last one reduced user fatigue.

3.3 Consistent user behavior in bimanual tasks

Ongoing work focuses on asymmetrical bi-manual tasks, as seen in Figures 1(c) and (d). We extend the approach described in Section 3.1 to determine arm dominance. This has an impact on the way the task is encoded as typically the passive arm follows the active arm and therefore the motion is relative to its reference frame. Second we assess how coordination occurs between arms, between each arm and hand and between the fingers of the hand. For this we study the causality structure in the demonstration data. This allows us to understand what determines a change in the task flow and to retain the important set of variables.

For evaluating user performance during the demonstration we make the assumption that the extracted uni-manual and bi-manual constraints remain invariant across demonstrators for the same task. However while the motion of the two arms in the scooping task should be coordinated, still during demonstration multiple instances of decoupling may occur. Similarly a user might use a grasp that is suitable for the task (i.e. for applying a force or a torque in a certain direction), or might show a different level of coordination between the fingers and the hand while switching between grasps. Therefore users' skill can be evaluated based on these metrics to determine a preferred demonstrator.

4. CONCLUSIONS

We proposed an approach for automatically extracting task constraints from uni-manual and bi-manual tasks. This represents a bootstrapping process that precedes learning a task model, and consists of determining features of the task that should be encoded. From a control point of view we use a hybrid impedance controller throughout the task. We extract the constraints from variables that can be directly used for control. Current work focuses on applying this approach to bi-manual tasks, and using the extracted constraints as a metric that would help the robot evaluate the skill of the user and therefore choose a preferred demonstrator.

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