Encoding Bi-manual Coordination Patterns From Human Demonstrations

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ABSTRACT

Humans perform tasks such as bowl mixing bi–manually, but programming them on a robot can be challenging specially in tasks that require force control or on-line stiffness modulation. In this paper we first propose a user-friendly setup for demonstrating bi–manual tasks, while collecting complementary information on motion and forces sensed on a robotic arm, as well as the human hand configuration and grasp information. Secondly for learning the task we propose a method for extracting task constraints for each arm and coordination patterns between the arms. We use a statistical encoding of the data based on the extracted constraints and reproduce the task using a cartesian impedance controller.

Categories and Subject Descriptors

I.2.9 [**Robotics**]; I.2.6 [**Learning**]: Knowledge acquisition; H.5.2 [**User Interfaces**]: Interaction styles

General Terms

Robot Learning

Keywords

Programming by demonstration; Task constraints extraction

1. INTRODUCTION

Daily activities, such as dish washing or preparing a meal, require completing tasks that are implicitly bi-manual. A challenge in programming such tasks is accounting for all the task variables, for the motion of each arm, as well as for their coordinated behavior. Here we take a Programming by Demonstration (PbD) approach in which a human can directly demonstrate the task, and propose a method for determining and encoding bi-manual coordination patterns.

We exemplify this on a task (stirring in a bowl, as shown in Fig. 1) that requires completing a sequence of actions for each arm. According to a taxonomy of bi-manual actions proposed in [6], the task subparts can be described as: (1) a discrete reaching motion from the initial position of each arm to the proper configuration to start mixing; (2) an asymmetrical coordinated motion, in which one arm is actively stirring while the other is passively assisting; (c) an uncoordinated reaching back action. The stirring action requires coordination not only in arm movement, but also with respect to the force and stiffness applied by each arm.

To be able to record the interaction forces perceived on each hand in coordination and in conjunction with measurements of the arm and finger displacement, we developed an experimental setup displayed in Fig. 1 (see Section 3 for a description). We analyze the demonstration data and extract (1) continuous constraints for each arm, consisting of the variables of interest in each part of the task, expressed in the local frame of reference of the object on which we perform manipulation and a stiffness modulating factor; (2) coordination patterns between the variables of interest in each part of the motion. We represent the motion using a time independent statistical encoding which allows using the extracted features as continuous task constraints that can be embedded online in the robot's motion. For reproducing the task on a bi–manual robotic platform we use a cartesian impedance controller for each arm, parameterized with the extracted constraints.

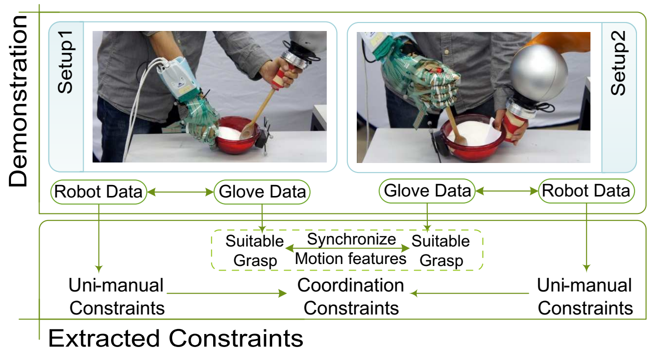

Figure 1: The two setups used in the demonstration phase. We alternate between the active/passive arms in the tasks, and record complementary information from the glove and robot arm.

2. RELATED WORK

In our previous work [1], we proposed a method for encoding arm–motion in discrete bi–manual tasks based on determining key postures during the demonstration. However

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in the present work we focus on tasks that require coordinated force control. We determine continuous constraints that apply throughout the task or in parts of the task.

For each arm we extract task constraints using the method prosed in [7], based on analyzing the variance in the data. We extend this approach to determine arm dominance (i.e the relative importance of each arm). We further encode the whole task as a sequence of states describing each action. Alternative representations are graph-based [2], or Markov-model based [5].

3. METHOD

To execute the task on a robotic platform we consider a cartesian impedance controller for each arm, given by $\tau = J^T \cdot RF \cdot (\lambda K(x - x_d) + F)$. The desired position $x_d \in \mathbb{R}^3$, the force to be applied $F \in \mathbb{R}^3$, and a factor $\lambda \in \mathbb{R}^3$ that modulates the arm's stiffness K, are extracted from demonstration (as explained below) and are expressed in the local reference frame of the object of interest RF.

To demonstrate the task we designed the setup shown in Fig. 1, in which the user can perform the task by kinesthetically guiding the robotic arm with one hand and by wearing a data glove on the other hand. This particular configuration has two main advantages: (1) it makes it easy for the user to provide demonstrations (i.e. rather than handling multiple degrees of freedom from two robot arms); (2) it allows simultaneously recording complementary information: end effector cartesian positions ($x_R \in \mathbb{R}^3$) and forces ($F_R \in \mathbb{R}^3$), from a KUKA LWR arm; hand configuration ($\theta_G \in \mathbb{R}^{23}$ joint angles), and wrist position ($x_G \in \mathbb{R}^3$) from the data glove. Additionally we recorded the object's cartesian position ($x_o \in \mathbb{R}^3$) using an Optitrack vision system.

The user performed the task in two phases, by alternating the roles of the active and passive hands. This allowed us to record both robot data and glove data for both the active and the passive arm. We recorded N = 6 demonstrations in each phase. We aligned the recorded data using Dynamic Time Warping (DTW). The final data set for phase 1 is $\xi^1 = \{x_R^A, F_R^A, x_G^P, \theta_G^P, x_o\}$, where the upper indices refer to the hand performing an active (A) or passive (P) task. Similarly a data set ξ^2 is obtained in the second phase.

Uni-manual constraints.

To extract the constraints of each arm, we consider for each phase $i = 1..2$, a subset $\xi_R^i = \{x_R, F_R\}$ of ξ^i. The glove wrist position x_G is used for aligning the robot motion in the two phases. We analyze the robot data in the reference frame of the object (i.e. the bowl), as described in [7]. For each recorded variable (position and force), across each dimension, we compute a criterion based on the observed variance in the data [7]. This allows us to compare in a relative manner variables of different types. We consider at each time step the variable of interest to be the one with the maximum computed criterion. When this changes a segmentation point is created, resulting in a set of states ψ_s. For the current task representation see Fig. 2. The arm motion in each segment is encoded as a non-linear dynamical system [4]. The force components are encoded in a Gaussian Mixture Model (GMM) as a function of position. We compute a stiffness modulation factor λ as the difference between the criterion computed for position and the one computed for force on each axis. Additionally for each state we determine a corresponding hand configuration $\theta_{G,s}$.

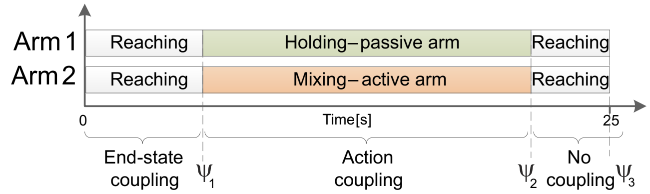

Figure 2: The identified motion segments for each arm, and corresponding coupling.

Bi-manual coordination.

Comparing the obtained criteria between the two arms allows us to determine at each time step which arm is dominating in either position or force applied in the task. This is similar to results on human subjects showing that the arms can change the active and passive roles during manipulation and this is caused by a force-motion relation, rather than prior knowledge or routine in executing the task [3].

Hand dominance thus influences the way we model the task subparts. For the active arm we encode the motion and force profile as described above. However for the passive arm the motion is insignificant, while the forces sensed on the arm are reaction forces responsible for keeping the object in place. Therefore we choose to encode using a GMM model its force $p(F_R^P, F_R^A)$, and stiffness profiles $p(K_R^P, F_R^A)$ as dependent on the forces sensed on the active arm. This allows the passive arm to apply compensating forces to the ones applied by the active arm.

4. CONCLUSION AND FUTURE WORK

We presented a procedure for recording bi–manual demonstrations that reduces user's effort and maximizes the obtained information. We analyze the data to extract constraints for each arm and encode coordination patterns.

Future work involves determining a two levels encoding of the task: (1) *skill level* as general knowledge about the action, and (2) *task level*, as a parametrization of the learned skill. This enables policy reusability for similar tasks, such as stirring in a bowl of dough, and applying the same skill for stirring coffee.

5. ACKNOWLEDGMENTS

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