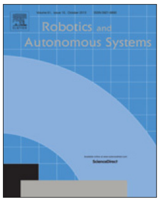
Robotics and Autonomous Systems 103 (2018) 222–235

Contents lists available at ScienceDirect

Robotics and Autonomous Systems

journal homepage: www.elsevier.com/locate/robot



Constraints extraction from asymmetrical bimanual tasks and their use in coordinated behavior

Lucia Pais Ureche *, Aude Billard

Learning Algorithms and Systems Laboratory (LASA), École Polytechnique Fédérale de Lausanne (EPFL), Switzerland

HIGHLIGHTS

- Automatic extraction of coordination constraints from asymmetrical bimanual tasks.
- Autonomous execution on a bimanual platform following a constraint-based task representation.
- Collaborative execution with stiffness modulation in response to the change in the hand shape while using the tool.

ARTICLE INFO

Article history:
Received 20 January 2017
Received in revised form 19 November 2017
Accepted 21 December 2017
Available online 31 January 2018

Keywords:
Task representation
Dual arm manipulation
Force and tactile sensing
Learning and adaptive systems

ABSTRACT

In this paper we focus on extracting a parametrization of asymmetrical bimanual tasks from human demonstration. Two arms coordinate while being in physical contact and fulfilling complementary aspects of the task: one arm is mostly assistive while the other performs active manipulation. Such a task can be executed either autonomously by a bimanual robot, or collaboratively by a single robotic arm performing the assistive or active role in collaboration with a human. We thus decompose the demonstrated task in a set of actions and for each action we extract: the role of the arms as *master* or *slave*, the type of coupling as *force–motion* or *motion–motion* coupling with the corresponding stiffness modulation, and the transition condition. We discuss how this applies to the three execution cases mentioned above. Additionally for the collaborative case we study hand-related features that allow the robot to anticipate and adapt to the user's actions. We validate our approach on common daily tasks.

1. Introduction

Bimanual tasks rely on the coordination between the arms. In particular, asymmetrical bimanual tasks are both common and natural for humans: i.e. we can scoop a fruit with one hand, but the task becomes easier when the other hand is holding it. The hands interact indirectly, transmitting a desired relative movement or contact force through an object. Thus the action of each arm is characterized by a motion profile, and use of force which we automatically determine using our previously proposed approach [1]. However these unimanual features are interrelated as one arm adapts to the other, switching their *roles* as master and slave, and changing the type of *coupling* from motion coordination to force–motion coordination.

In this paper we focus on extracting bimanual *coordination features* from human demonstrations. We then use these features in 3 execution cases: (1) autonomous execution by a bimanual robot, (2) collaborative execution with a human partner in which the human acts as master, or (3) the robot acts as master.

In the last two cases a reliable interaction requires the robot to anticipate and adapt to the counterpart's intention to apply a force before this is actually applied in the task. For example in the scooping task a robot arm holding the fruit can adapt its stiffness in response to a force that the human arm is expected to exert. We thus analyze the way humans use the tools in relation to the constraints extracted before. Based on the hand shape and tactile signature we compute a grasping quality metric. A high value of this metric in the direction in which force is a constraint indicates that the user is ready for the task and his hand is shaped appropriately. This allows the robot to update its stiffness according to the user's state. The approach is summarized in Fig. 1.

We address these aspects by taking advantage of factors implicit in human behavior when employing tools with high dexterity, and working towards a goal. The role of the dominant and non-dominant hands is not hardcoded, but assigned depending on the task constraints [2]. Therefore it can change during manipulation, based on a force–motion relationship [3]. With respect to handedness, position control is often employed by the non-dominant hand while force control is commonly used by the dominant hand [4].

---

* Corresponding author.
E-mail addresses: lucia.pais@epfl.ch (L.P. Ureche), aude.billard@epfl.ch (A. Billard).

https://doi.org/10.1016/j.robot.2017.12.011

Table 1
Summary of our approach wrt. existing literature, contrasting the action sequence, task representation, arm control and coupling.

Paper	Action sequence	Task representation	Arm control	Coordination	Encoding
[9]	Extracted: stable postures	HMM	Joint position	Relative distance and time	Time-dependent
[10]	Extracted: key points	HMM	N/A	Temporal	Time-dependent
[11]	Single action	TP-GMM	Position	Spatial	Time-independent
Our work	Extracted: continuous	Constraint-parameterized FSM	Impedance	Spatial, force, temporal	Time-independent

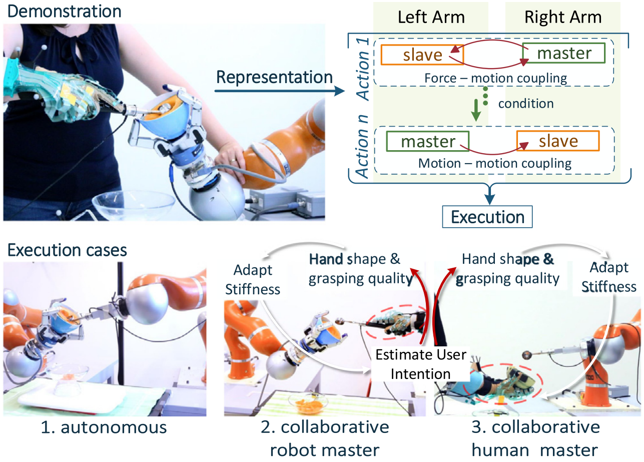


Fig. 1. We record bimanual demonstrations of asymmetrical tasks, using a custom setup that consists of a kinesthetically guided robot arm, and a human arm wearing a sensorized glove. We extract a task representation encoding arm coordination features and human's dexterous use of the tool. We execute the task autonomously or collaboratively using this representation.

However the force coordination is stronger within rather than between arms [5,6]. A change in the task is typically initiated by the non-dominant hand [7]. However the passive arm sets the frame of reference for the active arm [8], establishing a master–slave relationship .

Additionally when explaining to someone how to perform an action which requires maneuvering a new tool, people often indicate that the tool should be held in a certain way, thus making the hand features explicit. The grasp that the humans use is often adapted for applying forces and torques across a desired direction [12]. The same tool is held differently when used in different actions, adopting distinctive hand shapes and making contact with particular parts of the hand [12]. In the tasks we study in this paper (scooping, peeling and mixing), the tool is always in hand, but the grasp changes continuously, as the hand adapts to the requirements of the current action: i.e. enclosing on the tool before applying a force or switching from a precision to a power grasp.

This paper builds upon our previous work on automatic task segmentation and constraints extraction [1] for unimanual tasks. Here we extend the framework to target the extraction of bimanual constraints. In particular, we focus on learning the change in the master–slave relationship between the two arms, on determining coupled dimensions that ensure coordination and the transition conditions between the actions. Additionally we use this constraint based representation for both autonomous and collaborative execution. We achieve this by analyzing the human grasping behavior and updating the robot's stiffness for ensuring an intuitive interaction in collaborative mode.

Consequently our approach is applicable as a middle layer between planning and control. In summary it contributes to:

(1) abstracting a representation of the coordinated behavior applicable to different asymmetrical bimanual tasks
(2) using a common representation when executing the task autonomously and in physical coordination with a human
(3) validating the approach on a real robotic platform.

We tested the approach (described in Section 3) on real life tasks, Section 4. We discuss our results and conclusions in Sections 5 and 6, and the state of the art in Section 2.

2. Related work

Demonstrating bimanual tasks is often problematic as recording data requires kinesthetically driving two robots, potentially with hands. This can be demanding given the high number of DOF (i.e. a demonstrator needs to use both hands for unscrewing a light bulb, using a 16 DOF Allegro hand on a stationary robotic arm [13]). Conversely the lack of kinesthetic interaction leads to a correspondence problem.

Common approaches are: teleoperation [14], suitable for arm motions, but not for manipulation; or demonstrating gestures using motion sensors and refining them kinesthetically [15]. Alternatively custom setups allow directly demonstrating force patterns. One such example is transmitting stiffness patterns through a coupling device that connects the human and robot arm in conjunction with EMG for detecting the grasping state of the hand [16]. In our work we also use a custom setup for kinesthetically demonstrating the task. The setup consists of a robotic arm from which we record pose and force–torque information, in conjunction with the hand shape and tactile signature from a glove covered with pressure sensors. We modified the tool to embed a 6 axis force–torque sensor. This setup allows the human to freely manipulate the tool in a dexterous way. We analyze the forces applied both as a feature of the task, as well as in conjunction with the tool use. Based on a grasp quality metric we show that the position of the tool in hand changes continuously as it adapts to the requirements of the current action, unlike having only two discrete states: hand opened or closed. This information facilitates the interaction during collaborative execution.

2.1. Coordination in bimanual tasks

Coordinated behavior can be represented through features such as: stable postures [9]; keyframes (or keypoints) as important "snapshots" of the task [10]; the grasping state of the hand [17]; or spatial and temporal constraints [10,15,18,19]. While coordination is typically continuous, there are instances when it can be represented through discrete stable postures at the trajectory level, i.e. in symmetrical tasks (see Table 1).

In Ref. [9] the authors extract stable postures by analyzing the rate of change in the demonstrations. The movement is described by a generic variable (e.g. the relative distance, or phase between the arms), which remains constant during an action [9] and the encoding is time-dependent. However in our work, the spatial constraints are not rigid, the coordination is action–specific and continuous, done with respect to different reference frames. We use a time-independent encoding in which the synchronization between the arms becomes implicit.

Similarly to the stable postures approach, keypoints of a task and time dependencies between the arms are identified as features using an HMM (Hidden Markov Model) approach [10]. In our work we focus on the importance of the continuous coordination between the arms throughout an action, especially required during manipulation actions. Additionally in our case the spectrum of task