Robotic Grasping for Instrument Manipulations

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***Abstract*—The paper focuses on the grasp requirements derived from the voluntary and involuntary physical interactions in instrument manipulations. The manipulation-oriented grasp requirements include interactive wrench requirements and motion requirements that are required to accomplish a manipulation task. The manipulation-oriented grasp requirements are directly associated with the functionality of the instrument and the manipulation task, but independent from the robotic hardware. Grasp quality measures developed from the manipulation-oriented grasp requirements can be used as search criteria for optimal grasps. Working with hardware-independent grasping strategies extracted from human demonstration including grasp type and thumb placement, optimal grasps could be located efficiently in a dramatically reduced hand configuration space.**

***Keywords*—Robotics, Grasping, manipulation, quality measure, force**

1. Introduction

Traditionally, robotic grasping and manipulation approaches have been successful in planning and executing pick-and-place tasks without any physical interaction with other instruments or the environment, which are common in an industry setting with limited uncertainty. When robots move into our daily-living environment and perform a broad range of tasks in an unstructured environment, all sorts of physical interactions will occur, which will result in physical interactive wrench: force and torque on the instrument in a robotic hand.

In addition, for an instrument to perform a required task, certain motions need to occur; we call it "functional motion," which represents the innate function of the instrument and the nature of the manipulation task. To successfully complete the task with a given instrument, the same functional motion should be carried out no matter if the instrument is in the hand of a human or a robot, and similar interactive wrench will occur.

Both the functional motion and wrench requirements can be developed into grasp quality measures to serve the purpose of finding a grasp that best facilitate the instrument manipulation. The grasp should maintain a firm grip and withstand interactive wrench on the instrument during the task; and the grasp should enable the manipulator to carry out the task most efficiently.

Works in [1], [2], [3], [4], [5] incorporated force requirement into the grasp measure. However, the difficulty of modeling a task has been a main challenge in task-oriented grasp planning [6]. Most of the related works empirically approximate the task wrench space rather than really measuring it from the physical world.

Several components of the proposed approach has been published before. The grasping force in manipulation tasks was first investigated in [7]. The grasp measure derived from the wrench distributions in interactive manipulation tasks was originally presented in [8]. Its extended version is published in [9]. Recently, we have developed the grasp measure based on the functional motion requirement and combined it with the task coverage measure from the wrench requirements [10]. Extracting hardware independent strategies such as grasp type and thumb placement are presented in [11], [12], [13], [14].

Fig. 1: Instruments are modified for recording interactive motion, force, and torque.

2. Characterizing Manipulation Tasks

We have designed and developed a physical-interaction observation system that not only observes the motion of the instruments, but also the interactive wrench between the instrument and environment in great detail. Using the observation system, we have collected the instrument motion and wrench measurements in several representative instrument manipulation tasks by a number of participants. Each manipulation task are characterized with its wrench distribution models and functional motion models.

The handles of the selected instruments are removed and replaced with a swappable 3D printed handle that is embedded with a six-axis ATI Mini40 force and torque sensor. The sensor is located at the front end of the handle to collect the interactive wrench applied to the instrument. A set of markers are mounted on the instrument and they are observed by a marker-based motion tracking system NaturalPoint OptiTrack MoCap to obtain the functional motion during interactions. The setup is shown in Figure 1.

2.1. Task wrench models and requirements

For different tasks, even for the same instrument, the wrench on the instrument could be significantly different. For example, a user was asked to perform a cutting task and a butter-spreading task with the same knife. The interactive wrench distributions in the two tasks are reported in Figure 2(a)-(d).

As shown for the cutting task in Figure 2(a), significant cutting force is applied on the cutting edge (along z axis) and along with friction force mainly along the knife's long direction (x axis). The torque generated along with the force is shown in Figure 2(b). For the butter-spreading task shown in Figure 2(c) and (d), the knife applies pressure along knife blade sides (y axis), along with friction along the z axis. As we have observed, neither of the two task wrench distributions could be represented well with a 6D ellipsoid that is usually used in traditional grasping and manipulation planning [9].

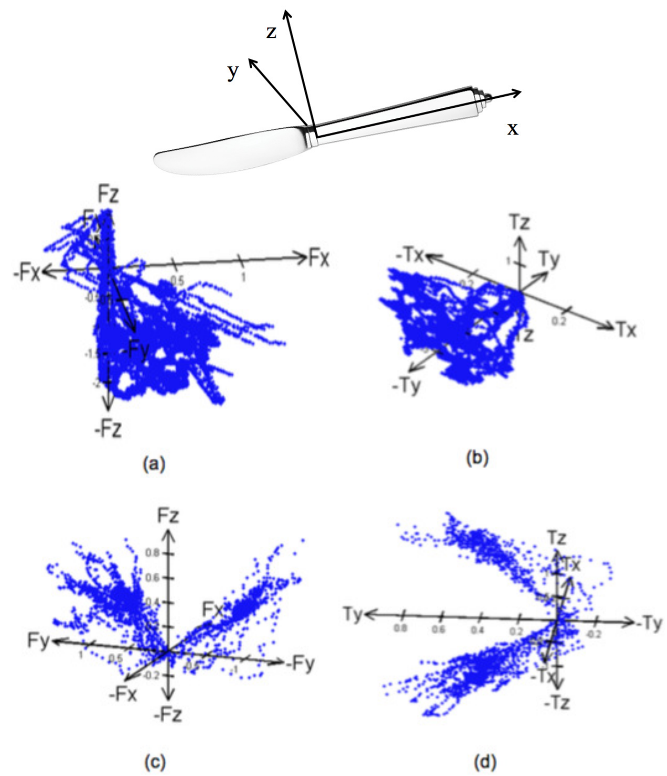

Fig. 2: (a)-(b): Cutting task distribution of task wrenches projected to Fx-Fy-Fz and Tx-Ty-Tz subspaces, respectively, where the task wrenches are distributed mainly in -Fz and Fx; (c)-(d): Corresponding task wrench distribution for butter-spreading task, where the task wrenches are distributed primarily in +Fy, -Fy, +Fz, +Tz, -Tz.

From the collected data, we model the task wrench distribution (TWD) with the following two approaches: nonparametric modeling and Gaussian mixture modeling. The nonparametric model does not make any assumption about the task wrench density distribution and allows the distribution shape to be determined entirely from the collected data. We compute and use a histogram to estimate the density distribution and then use a kernel density estimation with Gaussian kernels to provide a smooth and continuous representation of the distribution.

A grasp of the instrument in the interactive task should be able to hold on to the instrument and provide the interactive wrench during the task. Therefore, how much the desired task wrench space is covered by the grasp wrench are used to evaluate how good the grasp is. The detailed formula is in [9].

2.2. Functional motion model and requirements

Instead of dealing with human motions, we directly record, analyze, and understand the innate functional motions of the instrument [15], [16], [17]. The instrument's functional motion can be decomposed into a sequence of events that have a natural physical interpretation. We apply a statistical approach and model a sequence of events from collected data.

To perform a task, the instrument motion trajectory can either be computed by a motion planner or generated from a learned motion model. Grasping with a robotic hand give flexibility in "mounting" the instrument onto the robotic arm – a different grasp will connect the instrument to the robotic arm with a different pose, then the inverse kinematics approach will result in a different joint motion to achieve the same functional motion. Therefore, the grasp and the functional motion decide the manipulator's motion. With a desired functional tool motion, the grasp determines the manipulator's motion. Since different manipulator motions will have different efficiency rates in transferring the motion from joints to the instrument, the efficiency of the manipulation motion should be used to evaluate the grasp.

Transformation from the robotic wrist to a held instrument is decided by the grasp matrix $\mathbf{G}$. The forward kinematics from the manipulator joint angles to the instrument is $\mathbf{T}_I = \mathbf{T}(\theta)_W \mathbf{G}$, where $\mathbf{T}_I$ is the total forward kinematics and $\mathbf{T}(\theta)_W$ is the forward kinematics from joint angles θ to the robotic wrist. With different grasps (different grasp matrices), to generate the same function motion of the instrument, it would require different sequences of manipulator joint angles. Since the joint angles determine the manipulator's configuration and the motion transmission efficiency (manipulability), different grasp would results different manipulabilities. Therefore we use the manipulability ellipsoid to measure the effectiveness of a grasp. The detailed formula is in [10].

3. Learning Grasp Strategies

The quality measures in both wrench coverage and manipulation efficiency are determined by contact points of the robotic hand on the tool, and contact points are further determined by the hand posture as well as the relative hand position and orientation. Therefore, a grasp G can be defined with an array of finger joint angles and hand position and orientation. When a robotic hand with high DOF is used, strategies learned from demonstrations are introduced to reduce the search space.

Previously researchers imposed appropriate contact points on the object (e.g. [18], [19], [20], [21], [22]). The constraint on contact points, however, is assumed to be independent of physical constraints of a given hand. It raises the problem of solving the inverse kinematics that satisfies the constraints imposed by contact points [23], which in many cases resolved no solution due to the limitations of the robotic hardware.

Instead of learning grasping points, we extract and use two more abstract strategies: grasp types and thumb placement. They confine the configuration space, but leave enough room for grasp planning to find the optimal stable grasp that is adapted to different robotic hands.

3.1. Grasp types

A grasp type abstracts the manner in which a human grips an object for a manipulation. It can either be input by a user or recognized in a demonstration. Our previous works [14], [12], [7] have shown that using hand joint trajectories are more effective than static poses since it disambiguates different grasp types that share similar static poses.

For robotic hands with less DOF, fewer grasp types can be defined. Taking the Barrett hand as an example, we defined only five grasp types, much fewer than the human hand: power grasp, power sphere, precision grasp, precision sphere, and lateral pinch. To map from the learned grasp types from human grasps, some grasp types can be grouped into one. Detailed grouping is in [14].

For a particular instrument manipulation task, a grasp type is learned from human demonstration and then mapped to the robotic hand's grasp type.

3.2. Thumb placement

There is general agreement in anthropology that thumb plays a key role in gripping an object efficiently. The crucial feature distinguishing human hand from other apes is the opposable thumb. The same situation applies to robots that almost all robotic hands have a long and strong opposable thumb. Mapping only thumb position from a human hand to a robot hand is simple because there is little correspondence problem and it can be easily generalized to different robotic hand models.

Both the grasp types and the thumb placement dramatically reduce the hand configuration space for searching an optimal grasp. For example, the constrains introduced by the thumb placement of a Barrett Hand reduces its configuration dimension from ten (six for the wrist and four for the fingers) to two or three depending on grasp types. More detail is in [13], [14].

4. Conclusion

To facilitate the physical interaction in an instrument manipulation task, robotic grasp should meet the interactive wrench and motion demands that are required to accomplish the manipulation. Those demands are independent from the robotic hardware, but are directly derived from the functionality of the instrument and the manipulation task and represent the dynamics of the interaction. Two grasp quality measures are developed from the interactive wrench and motion requirements and then used as search criteria for optimal grasps. The search or optimizing process can be dramatically improved by narrowing down the optimization search space using prior grasping strategies that are independent from robotic hardware, including grasp type and thumb placement.

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