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Task-Based Grasp Quality Measures for Grasp Synthesis

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***Abstract*— To facilitate manipulation tasks, grasp should be selected intelligently to fulfill different stability properties and manipulative requirements in the tasks. In this paper, two task-dependent grasp quality measures are introduced: task wrench coverage measure and the manipulator efficiency measure. The first one measures the ability of a grasp to provide required interactive wrench during a task, while the second measures the effort that the manipulator takes for the whole manipulation process in facilitating the required instrument motion, which is determined by the grasp when the motion of the instrument is defined. The proposed measures are then used in selecting grasps for three typical manipulation tasks in simulations and using a real robotic system and produced successful grasp synthesis outcomes that satisfy manipulative requirements.**

I. INTRODUCTION

Currently, most grasping approaches consider only 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 random physical interactive wrench: force and torque on the instrument in a robot's hand. In addition, for an instrument to perform a required task, certain motions need to occur; we call it "functional instrument motion," which represents the innate function of the instrument and the nature of the task. Therefore, grasps should be selected intelligently to fulfill different stability properties and manipulative requirements.

Grasping with a robotic hand gives 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 instrument motion. Thus, the grasp and the functional instrument motion decide the manipulator's motion, as well as the effort to achieve the motion.

Therefore, we propose to establish two objectives to serve the purpose of a grasp: the grasp should maintain a firm grip and withstand and provide necessary interactive wrench on the instrument during the task; and the grasp should enable the manipulator to carry out the task most efficiently with little motion effort, and then search a grasp to optimize both objectives.

To measure how firm a grasp is, one widely used quality criterion is force-closure property: the capability of a grasp to apply appropriate forces on the instrument to resist disturbances in any directions, defined as the radius of the largest wrench space ball that just fits within the unit grasp wrench space [1]. Related researches were developed in [2], [3], [4], [5], etc. Other quality measures include internal forces and stability, etc. Detailed reviews of grasp measures can be referred to [6], [7]. These quality measures are all task independent, where an evenly distributed disturbance in all directions is assumed. Alternatively, the force-closure property can be modified as task-dependent metrics, where the shape of the task wrench space is adaptable to a task instead of a uniformly distributed ball.

Works in [3], [8], [9], [10], [11] incorporated this force requirement into the grasp measure. However, the difficulty of modeling a task has been a main challenge in task-oriented grasp planning [12]. Most of the related works empirically approximate the task wrench space rather than really measuring it in the physical world.

Few works have taken the manipulation motion into consideration while planning a robotic grasp. One related measure of grasp quality is the manipulability, i.e. the ability of the manipulator to impart arbitrary motions at the end-effector [13], [14]. The measure of manipulability can help avoid the singularity situation where there is a fairly low transition rate from joint velocity to the end-effector velocity for all motion directions. But it does not consider the task-dependent requirements that could be only several dominant motion directions. The problem was addressed by Chiu [15], who defined a task compatibility index to measure the transformation ratio along some directions at a single moment. The property of manipulability was extended to multi-finger grasping in [16], [17]. However, the measures of manipulability and task compatibility index are used to compute the optimal posture at one single moment, but not to optimize over the entire sequence of continuous motion throughout an entire manipulation task. In addition, the previous works did not consider a manipulator and a multi-finger hand together in fulfilling instrument manipulation requirements.

In this paper, we consider manipulator motion in grasping evaluation given a manipulation task. We combine the manipulator efficiency measure with the task wrench coverage measure we proposed recently [18], [19] to evaluate a grasp given a human demonstrated task. The task wrench coverage criterion measures the ability of a grasp to resist the task disturbance, while the manipulator efficiency criterion measures the effort of the manipulator makes in order to accomplish the required manipulation motion.

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II. Task-Based Grasp Quality Measures

A. Data Collection

We aim to synthesize a grasp that best fulfills the task requirements. Although tasks can be semantically described, such as pouring water using a bottle, pick up the bottle and open the bottle cap, etc., they are know to be difficult in mathematically modeling. In the physical world, task requirements are separated into two parts by Li and Sastry [8]: force requirement and motion requirement. While most of the researchers placed their emphasis on grasp metric definition and computation, they assume that the task is known or approximated by experience [20].

We model the task with the data collected in observation of the instrument being manipulated. The interactive wrench between the environment and the instrument, as well as the instrument's motion are captured during human demonstration in a virtual reality environment. We provided a user interface consisting of a haptic device Phantom Omni, and a virtual reality environment. For each task, a user is asked to manipulate an instrument using the haptic device (see Figure 1 for example). Detailed experimental setting and evaluation of the simulation is explained in [19]. The haptic device Phanton Omni is not used to teach the robotic grasping, but used to collect manipulation features of instrument forces and motions.

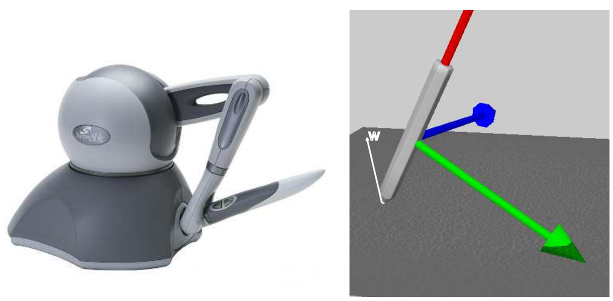


Fig. 1: A user interface for human users to perform manipulation tasks in a virtual environment. Left figure: a haptic device, PHANTOM Omni, to manipulate a virtual instrument. Right figure: a virtual pen is being manipulated in the virtual environment. The motion sequence of the instrument and the disturbance wrench is being captured.

The forces and torques exerted to the instrument in the environment can be grouped as a wrench vector $w = [w, \tau]^T$, where f is a 3-d force vector and τ is a 3-d torque vector. Gravity and the wrench generated by acceleration are non-contact wrench that are not acting on the surface of the instrument, but acting on the center of mass of the instrument. The collision force of the instrument is captured in the environment in every iteration.

Similarly, the task sequential motion of the instrument is described by a sequence of vector $u \in R^m$ representing the position and orientation of the instrument in task coordinate.

$$TMS = \{u(t), \dot{u}(t), \ddot{u}(t) | t = t_0, t_1, ..., t_n\} \tag{1}$$

Given the force and motion requirements modeled from human demonstration, we formulate two criteria, the task wrench coverage measure and the manipulator efficiency measure to evaluate a grasp in terms of satisfying the force and motion requirements.

B. Task Wrench Coverage Measure

The measure of the ability of a grasp to resist the disturbance wrench can be analyzed based on the contact points formed by a grasp. Given n contact points of a grasp, the grasp can be modeled as a Grasp Wrench Space (GWS) – the space of all wrenches that be applied to the instrument from the contacts. If the magnitude of the contact force is constrained to unitary, it is called unit GWS (UGWS). Similar to the grasp wrench space, a task can also be described as a task wrench space (TWS) – the space of all disturbance wrenches the instrument has to resist or provide during a manipulation task. If no task-oriented information is provided to form a subset of the whole space of wrenches, a typical task wrench space assumed to be a 6D ball T_{ball} centered at the wrench space origin, where external disturbance is uniformly weighted (Left of Figure 2).

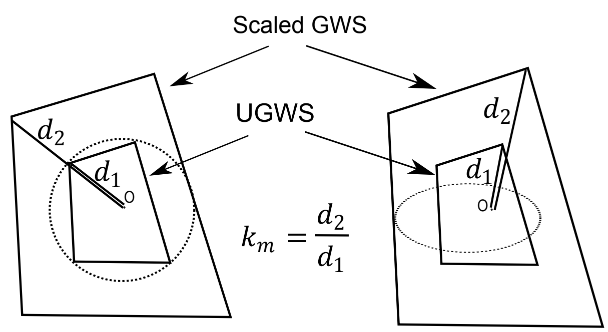


Fig. 2: Grasp quality measures for (a) task ball (b) task ellipsoid.

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 3(a)-(d). As shown for the cutting task in Figure 3(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 3(b). For the butter-spreading task shown in Figure 3(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. Therefore, instead of covering the regular artificial 6D wrench space, a GWS should cover the measured task wench space to guarantee a firm grasp in the task.

However, in reality, due to uncertainty in physical interactive manipulation tasks, the interactive wench distribution

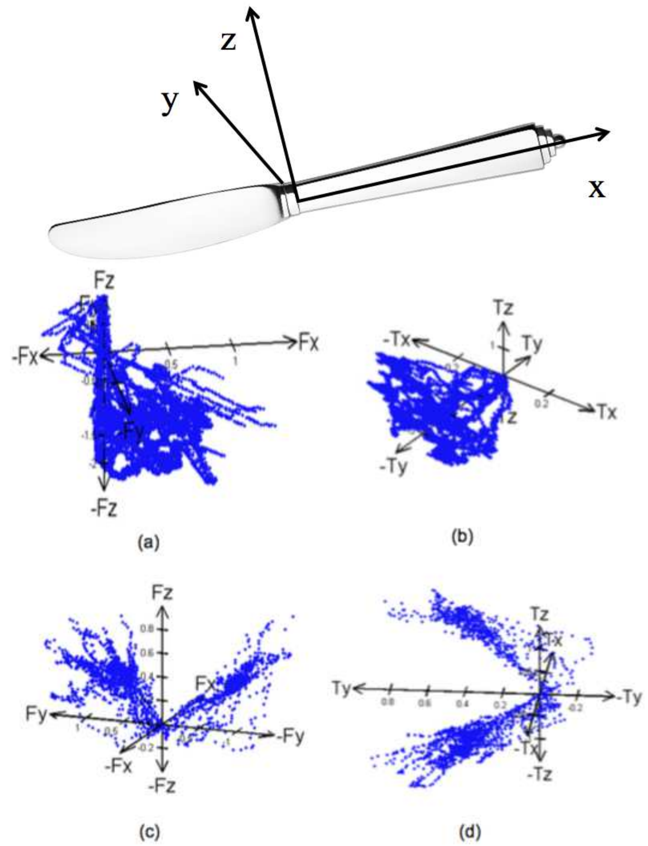


Fig. 3: (a)-(b): cutting task distribution of task wrenches projected to Fx-Fy-Fz and Tx-Ty-Tz subspaces, respectively, where the task wrenches are distributed mainly in -Fz and Fx; (c)-(d): corresponding task wrench distribution for butter-spreading task, where the task wrenches are distributed primarily in +Fy, -Fy, +Fz, +Tz, -Tz;

varies in different trials. Some wrench samples, especially large spikes, rarely occur, but stretch the TWS and make it difficult to cover. Because a robotic hand has limited capability in grasping force, it is reasonable to allocate the robotic hand's capability to prioritize the coverage of the most frequent wrench, especially for daily living tasks, in which dropping instruments occasionally is not catastrophic.

Instead of focusing on the shape of the TWS, we take the density of the task wrench samples into account. Since the task wrench distributions are irregular and different, we cannot assume the task wrench samples are drawn from a given probability distribution. Therefore, we estimate task wrench density distribution with a nonparametric model by assigning equal probability to each wrench observation (O).

Based on the nonparametric task wrench density distribution, we propose to define the task wrench coverage measure as:

$$Q_w = \frac{Count\{\mathrm{O}|O \in \mathrm{GWS} \cap \mathrm{TWS}\}}{Count\{\mathrm{O}|O \in \mathrm{TWS}\}} \quad (2)$$

where $Count\{\mathrm{O}|O \in \mathrm{GWS} \cap \mathrm{TWS}\}$ is the count of task wrench observations in the TWS that are covered by GWS, while the $Count\{\mathrm{O}|O \in \mathrm{TWS}\}$ provides the count of the total task wrench observations in the TWS. Q_w measures the percentage of task wrench observations covered by GWS. The greater Q_w is, the higher chance the grasp will have in preventing dropping the held instrument during the task.

C. Task Manipulator Efficiency Measure

In addition to providing a firm grasp, humans also decide where and how to grasp an instrument according to the task to be performed. For example, when humans grasp a hammer, we mostly will grasp the head to carry and the end of the handle to swing, because humans desire to reach a large swing motion with a relatively small arm motion as well as to generate a large impact force. The grasp optimization should not consider only the ability to apply force but also the arm and wrist motions.

To perform a task, the instrument motion trajectory can either be computed by a motion planner or generated from a learned motion model. If the instrument is rigidly mounted on the robot's wrist, to achieve the desired instrument motion trajectory, the instrument position and orientation vector can be mapped to joint angle vector $\mathbf{q}$ with inverse kinematics.

A grasp can be described by $\mathbf{g} = [\mathbf{p}, \mathbf{x}]^T$, where $\mathbf{p} \in R^d$ is the vector of hand joints in joint coordinate, and $\mathbf{x} \in R^m$ is the vector of wrist position and orientation in Cartesian coordinate. The hand joints and the relative wrist position to the instrument are fixed given a grasp, so the wrist position and orientation $\mathbf{x}(t)$ is changing together with the instrument motion.

Given a grasp $\mathbf{g}$ and the target instrument trajectory $\mathbf{u}(t)$, the wrist motion $\mathbf{X} = \{\mathbf{x}(t)|t \in [0, t_n]\}$ can be computed via kinematic transformation in Cartesian coordinate, as shown in Figure 4. From the wrist motion, using inverse kinematics, the corresponding joint motions $\mathbf{Q} = \{\mathbf{q}(t)|t \in [0, t_n]\}$. Various approaches have been developed to solve inverse kinematics problems. In our experiments, we utilized the analytic approach in Matlab Robotic Toolbox [21].

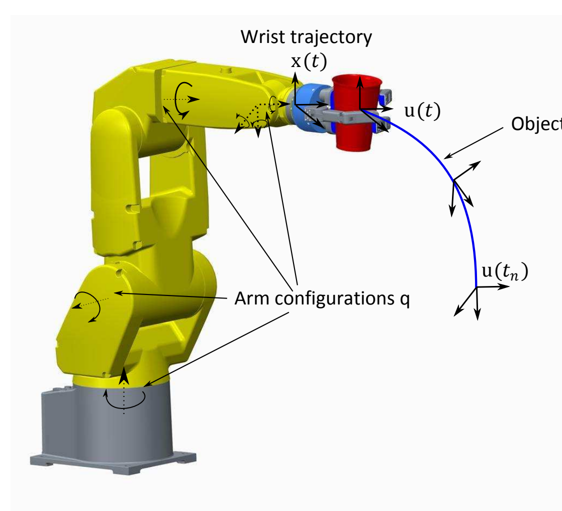


Fig. 4: An example of grasp and manipulation.

When the instrument trajectory is defined by the required task motion, different grasps $\mathbf{g}$'s will require different joint motions $\mathbf{Q}$'s. The arm motion is controlled by outputting joint torque from joint actuators, written as the dynamic equation:

$$\tau = M(\mathbf{q})\ddot{\mathbf{q}} + C(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + F(\dot{\mathbf{q}}) + G(\mathbf{q}) + J(\mathbf{q})\mathbf{f} \quad (3)$$

where τ is the m-joint vector of torques from the actuator, $\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}$ are respectively the vector of joint, velocities and accelerations of the arm. The first term is the inertial forces due to acceleration of the joints, and M is the symmetric positive definite mass-inertia matrix. $C(\mathbf{q}, \dot{\mathbf{q}})$ is the Coriolis and centripetal coupling matrix, $F(\dot{\mathbf{q}})$ is the friction force; $G(\mathbf{q})$ is the gravity term. $J(\mathbf{q})$ is the Jacobian matrix, $\mathbf{f}$ is the external load applied to the end-effector. The last term $J(\mathbf{q})\mathbf{f}$ is the joint torque transmitted from the end-effector.

There are various performance measures to the manipulative motion used as the cost function in the literature, such as energy consumption, motion jerks, effort, or their combinations[22]. Here, we define the manipulator efficiency by the manipulator's motion effort:

$$Q_e = \int_{t_0}^{t_n} \tau(t)^T \tau(t) dt \quad (4)$$

The vector of torques τ are applied to each joint by the actuators, and it can be derived from the joint space dynamics. The manipulator efficiency represents a measure of the effort given by the sum of every squared joint torque integrated over time for the entire manipulation process. According to the dynamics equation, optimizing it represents a search to find the optimal grasp that results in the smallest arm motion that yields smooth trajectories and avoids large motion changes. When applied to a real robot, it minimizes the stresses to its actuators and its energy consumption.

D. Grasp Planning to Fulfill the Task Requirement

Hence, we describe the problem by finding the optimal grasp measured by the wrench coverage measure Q_w and the manipulator efficiency measure Q_e, subject to the kinematics constraints and the dynamics constraints.

The force and motion criteria evaluate the grasp from two distinct aspects independently or combined in several ways. For example, the grasp can be selected by either sequential evaluations under these two criteria, or a global criterion combining them together. The way of selecting the optimal grasp should take into concerns both applications and the hand capability.

In this paper, we compute the set of preliminary candidate grasps using wrench coverage measure, first without computing arm configurations. The candidate grasp set is, therefore, independent of the arm kinematic model, as well as the position and orientation of the target instrument relative to the manipulator, so it can be generated off-line. Then, each grasp in the candidate grasp set is measured by the manipulator efficiency criterion. The grasps that cannot meet the reachability and acceleration constraint are rejected. The optimal grasp is then selected under the measure of the manipulator efficiency. This computation of a grasp is in coincidence with the intuitive consideration in physical world, because the grasp should be stable, in the first place, to ensure the instrument not to be dropped under the outside disturbance; then the manipulator efficiency is considered, in the second place, to yield a small and smooth arm motion. Further dimensionality reduction can be performed to reduce the search space for the grasp planning [23], [24], [25].

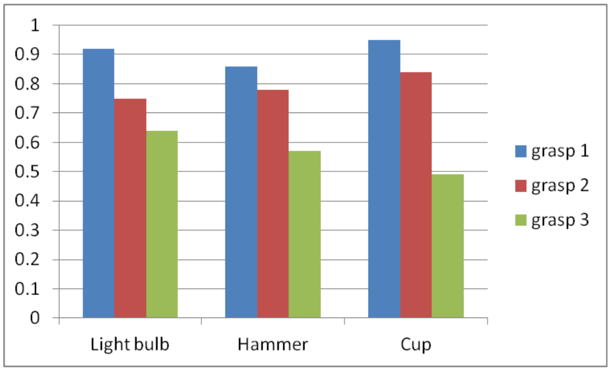
III. Comparing Measures in Experiments

We describe the grasp planning problem by finding the optimal grasp in terms of both wrench and motion requirements, measured by the wrench coverage Q_w and the arm motion effort Q_e, subject to the physical constraints such as velocity and accelerations. We compared the two grasp measures Q_w and Q_e for different grasps and instruments, as summarized in Figure 5. The execution process can be seen in the video attachment. The comparison was tested with a Barrett hand and a FANUC LR Mate 200iC robotic arm that is a 6-axis robotic arm with a spherical wrist. The instrument motions in the experiments are predefined. However, manipulation motions could be generated automatically using motion planners or motion harmonics [26].

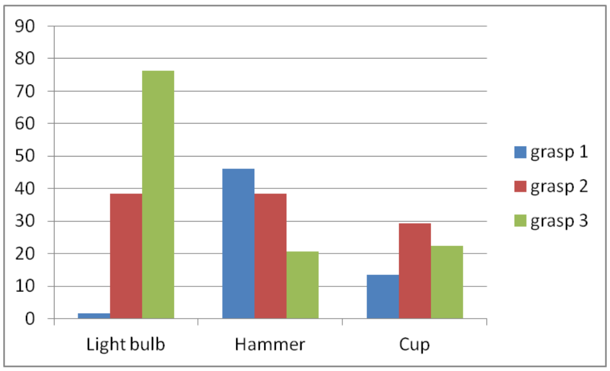
Three grasps were selected for each instrument, sorted by the wrench coverage measure in a descending order, as shown in Figure 5(a). It can be observed in bottom figure that the order of motion effort with the corresponding grasps differs from instrument to instrument. For the light bulb task, grasp 1 is the best of the three if measured by task wrench coverage, but if measured by the manipulator efficiency, grasp 3 is the best of the three; for the hammer task, grasp 1 is the best evaluated by both measures; and for the cup task, grasp 2 is the best if measured by the manipulator efficiency. Since there is no correlation between the two grasp measures as shown in the examples, the two measures should be considered comprehensively.

Two selected grasps of each instrument are visualized in Figure 6 as detailed illustrations. Each grasp is marked by three grasp measures: force-closure property ϵ and the two proposed quality measures. In the left column, the "screw in a light bulb" task, grasp measure $Q_w = 0.92$ for the grasp shown in the upper figure, meaning it has a larger task coverage than that in the lower figure. The task independent force-closure property is not coincident with the proposed task wrench coverage measure. Although ϵ value of the lower grasp is higher than the higher grasp, it has a lower ability to resist disturbance occurred in the specific screwing task. The manipulator efficiency measure $Q_e = 1.54$ of the upper grasp is also much less than the lower grasp, because it requires only wrist motion to screw the light bulb. Therefore, the upper grasp is "better" than the lower grasp, in terms of both task wrench coverage and motion effort.

In the middle column, the upper grasp has a higher ability than the lower to resist the disturbance occurred on the head of the mallet, but it requires the larger motion effort to achieve the striking motion. Different grasps can be selected



(a)



(b)

Fig. 5: Measures of wrench coverage and motion effort of different grasps: (a) wrench coverage measure; (b) motion effort measure.

in different situations. For example, the lower grasp may be chosen for a weak hand to better resist both heavy gravity as well as striking force. Whereas for the lower grasp, a larger torque is applied to the hand from the head of the mallet, but the manipulation can be achieved with less motion effort.

In the right column, all three measures of the grasp in the upper figure is "better" than the lower grasp. Figure 7 shows the manipulation process of a cup as an example to compare the two different grasps. To achieve the same cup manipulation, the grasp shown in the top row figures only requires wrist rotation while the grasp shown in the bottom row figures requires larger arm motion than the grasp in the top row.

According to the results, there is no correlation between the two grasp measures. The two quality measures can be combined in different ways according to the applications and task requirements. For example, they can be combined as one global measure using weighted sun, so the performance depends on different weights. If the execution efficiency is of more concern, then a larger weight can be put to the motion measure.

IV. Conclusion

In this paper, two task-oriented grasp quality measures are introduced for grasp synthesis given a manipulation task. A quality grasp should not only maintain a firm grip and withstand required interactive wrench in the task, but also enable the manipulator to carry out the task most efficiently with little motion effort from the manipulator. Both task-oriented grasp quality measures are formulated and compared.

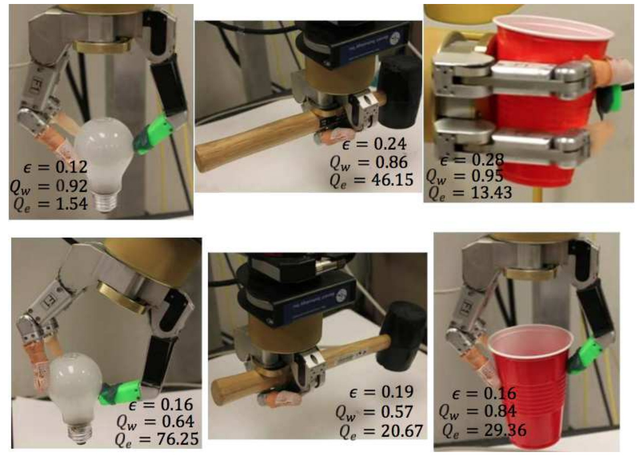


Fig. 6: Example of grasps compared by different quality measures for the three tasks.

The current work assumes the manipulation is performed with one grasp. In many situations, the manipulation cannot be fulfilled by only one grasp, but requires transition from one grasp to another grasp. Moreover, with multi-finger robotic hands, in-hand dexterous manipulation becomes possible. New research will be able to plan dexterous manipulation that connects several optimal task-wrench-coverage grasps at different stages of the task without sacrifice the manipulator efficiency.

When computing the task motion effort in our current experiments, we only tested it with one non-redundant robotic arm that has 6 DOFs, where there are only a finite number of solutions to the path tracking problem. For redundant robotic arms that have more than 6 DOFs, since there may be an infinite number of solutions, a more general approach is necessary to find the optimal solution given a grasp. Therefore, a another future direction is to combine motion planning together with grasp planning.

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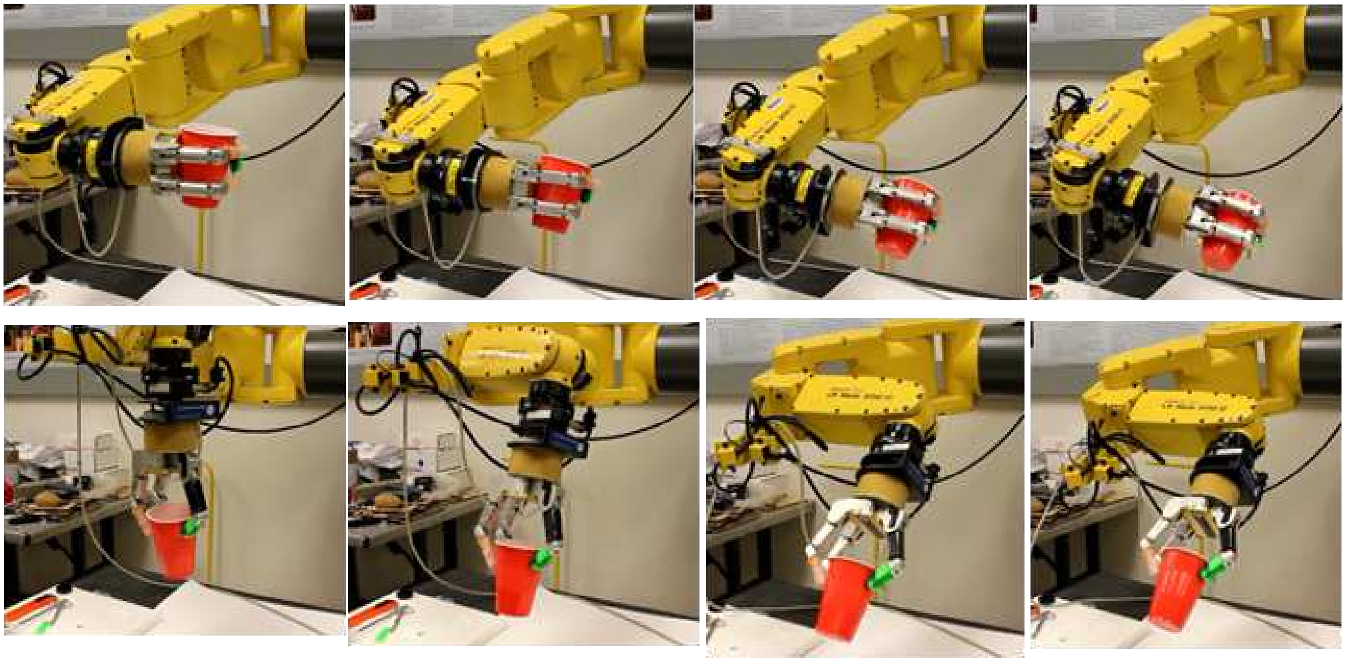

Fig. 7: Compare two different grasps to execute the same manipulation motion of a cup.

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