Tactile Experience-based Robotic Grasping

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ABSTRACT

We propose an experience-based approach to the problem of blind grasping, stable robotic grasping using tactile sensing and hand kinematic feedback. We first collect a set of stable grasps to build a tactile experience database which contains tactile contacts for each stable grasp. Using the tactile experience database, we propose an algorithm to synthesize local hand adjustment that controls the hand pose and improves the grasp based on tactile sensor readings. Simulation experiments show that local adjustment of the hand improves the grasping performance.

1. INTRODUCTION

Stable robotic grasping is one of the most fundamental problems in the field of robotics. To enable a robot to grasp objects stably, one of the existing approaches is to decompose a grasping procedure into two stages: planning and execution. Some examples include [1, 2]. In the planning stage which is usually done in simulation, a stable grasp parameterized by the hand posture and hand-object relative pose is synthesized. In the execution stage, the planned grasp is sent to a path planner to generate a collision-free trajectory and the robot moves along the newly generated trajectory to the target grasping pose. These methods usually use geometrical models of the objects to be grasped for the planning stage. However, since grasp planning is done in a simulation world which is not an exact model of the actual workspace due to imperfect perception and robot calibration, the executed grasps can end up unstable. So these methods are sensitive to pose uncertainties.

Another approach is to treat grasping as a control problem where a set of control laws are applied to adjust the hand to achieve some preferred contact configuration on the object (e.g. antipodal grasps [3, 4, 5]). Methods along this direction are usually object model free. Since the control laws are relatively computationally inexpensive, these methods run fast. In addition, these methods usually utilize the actual sensing data from force, torque, or tactile sensors; so they do not require any specific hand-object relative pose and are more robust under pose uncertainties. However, a major issue is that these methods either ignore the hand kinematics or assume simple hand designs, such as parallel jaw grippers and their simple variants. So, it is difficult to extend these methods to complex hand designs which have more dexterity in object manipulation tasks.

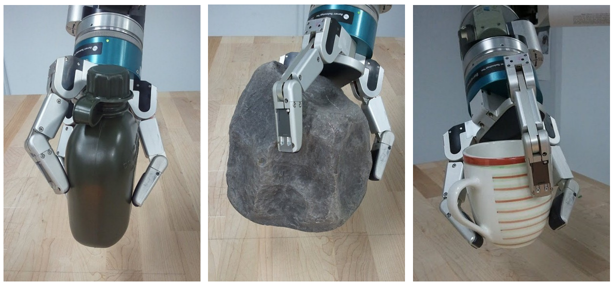


Figure 1: Blind grasping - a Barrett hand picks up everyday objects stably using only tactile and hand kinematic data as information resource.

Within a control-based stable grasping framework, the evaluation of grasp stability is a very important component, which directs the design of control algorithms. We believe the difficulty to explicitly formulate a generic evaluation criterion is a major reason for most control algorithms assuming simple hand designs or ignoring hand kinematics. In our previous work [6], we proposed a machine learning approach to estimate grasp stability, a method which does not place any constraints on the hand design. The experiments indicated that the tactile feedback along with the hand kinematic data carry meaningful information for the prediction of the stability of a robotic grasp. This approach enables a robot to blindly grasp objects using only tactile and hand kinematic data. Figure 1 shows some physical experiments where a robot picks up objects by randomly adjusting hand pose and seeking for a stable grasp based on tactile and hand kinematic data. However, to make the control loop more intelligent, one question should be addressed, which is "what is an intelligent (instead of random) hand adjustment to make if the current grasp is not a stable one?"

The focus of our presented work is to address this problem by developing a method to synthesize hand adjustment. The basic idea is that ***similar grasps share similar local object geometry at locations where contacts are established***. We consider grasps as similar if they have similar contact configurations, i.e. similar contact locations. To develop a grasping strategy utilizing contact configuration similarities, we first build a grasp database in simulation which consists of thousands of stable grasps and their corresponding tactile contacts, a database providing tactile experience which indicates the tactile knowledge of stable grasps. By comparing the tactile contacts between an actual grasp and the grasps in the experience database, we synthesize a hand adjustment command to move the wrist and re-shape the hand to explore around the object and achieve a grasp that shares similar tactile contacts with a stable grasp in the experience database.

In this paper, we discuss related work in Section 2. We design a tactile contact database in Section 3. An experience-based grasping strategy using the tactile experience database is proposed in Section 4. In Section 5, we discuss simulation experiments, followed by conclusion in Section 6.

2. RELATED WORK

Tactile sensing from direct interaction of a robotic hand with the object in touch provides local geometrical information of the object. Researchers have been using tactile sensing to improve grasping performance. Bekiroglu *et al.* used HMM to estimate grasp stability from a series of tactile data [7]. Hsiao *et al.* used tactile sensing to cope with object pose uncertainties [8]. Platt exploited force sensing to learn grasping strategies consisted of contact relative motions and tested the method on grasping a mailbox with a Robonaut hand [4]. Bierbaum *et al.* proposed a method to generate anti-podal grasps from tactile contacts while moving around the object [9]. Some earlier work also proposed methods to achieve stable grasps based on contact sensing, e.g. [3, 10].

We utilize tactile sensing to achieve stable robotic grasps. Conceptually, our work is within the category of data-driven approaches, for example, the work by Goldfeder *et al.* [11]. In this work, the authors exploited shape similarities between objects to generate grasps on objects of similar shapes. Compared to their work, we are focusing on the local object geometry where the contacts are established and using the local geometry information indicated by tactile contacts to control the hand and achieve stable grasps. Another related work is done by Steffen *et al.* where they proposed a method to control the closing procedure of the fingers during grasping [12]. Different from our work, theirs does not control the wrist pose, which adjusts the hand pose with respect to the grasping object.

3. TACTILE EXPERIENCE DATABASE

A tactile experience database is an important part of our method. It consists of stable grasps and their corresponding tactile contacts. Specifically, a grasp, $\mathcal{G}$, in the tactile experience database can be considered as $\mathcal{G} = \{\mathcal{P}, \mathcal{J}, \mathcal{T}, \mathcal{C}\}$ where

- $\mathcal{P} =< p, o >, p \in R^3, o \in R^4$ specifies the hand pose in the object coordinate system, including the position and orientation of the hand. The orientation is represented using quaternions.
- $\mathcal{J} = \{j_1, j_2, ..., j_N\}, j_i \in R$ records the N joint angles of the grasp. For a Barrett hand, we chose $N = 7$ and record the 7 joint values.
- $\mathcal{T} = \{t_1, t_2, ..., t_L, t_i \in R\}$ is the L tactile sensor readings. For a Barrett hand, there are 24 tactile sensors on each fingertip and the palm. In this case, $L = 96$.

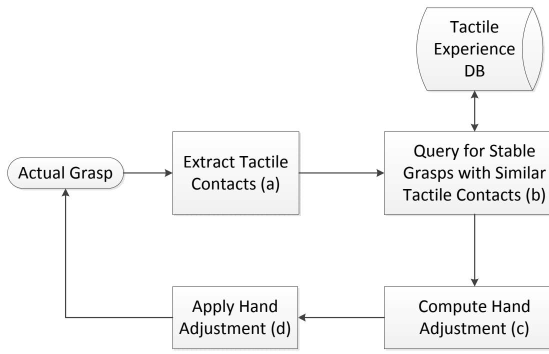


Figure 2: A hand adjustment procedure: starting from an actual grasp, tactile contacts are extracted first (a), then tactile contacts are used in querying for stable grasps with similar tactile contacts from the tactile experience database (b), once candidate stable grasps are returned hand adjustment is computed (c) and applied to control the hand (d).

- $\mathcal{C} = \{c_1, c_2, ..., c_M\}, c_i =< p_i, o_i >, p_i \in R^3, o_i \in R^4$ is the set of tactile contacts, indicating the locations, p_i, and the orientations, o_i of the M activated tactile sensors.

4. STABLE GRASPING USING TACTILE EXPERIENCE

With a tactile experience database generated, we now describe a method to utilize the tactile experience database to synthesize a hand adjustment command to improve the grasp stability by locally adjusting the hand. Generally, an adjustment to the hand consists of the changes in the hand location, orientation, and the selected degrees of freedom (DOFs) to control. $A =< p, o, s >$ where $p \in R^3$ is a 3-D vector specifying the new hand position in the current hand coordinate system, $o \in R^4$ is the new hand orientation in the current hand coordinate system represented in quaternion, and $s \in R^{S_{dof}}$ is the set of new values for the selected DOFs we want to control in a hand adjustment command.

We assume that initially contacts are established between the object and the hand so that the tactile sensors provide valid tactile data. Then, a simple grasp exploration can be driven by a hand adjustment procedure which consists of the four major steps as shown in Figure 2. First, the tactile contacts are extracted using forward kinematics and tactile sensor readings. Second, the tactile contacts are used in querying the tactile experience database for stable grasps with similar tactile contacts. Once the stable grasps with similar tactile contacts are retrieved, hand adjustment parameters are synthesized and sent to control the hand to make local movements.

4.1 Querying for stable grasps with similar tactile contacts

Once the set of tactile contacts are extracted from the actual grasp, we query the tactile experience database for grasps that share similar tactile contacts. To this end, we define a distance function which measures the similarity between two grasps $\mathcal{G}_1$ and $\mathcal{G}_2$. This distance function considers both the tactile contact configuration and the hand posture between two grasps. In our work, we only used the location of a contact in the distance metric. The distance metric can be expressed as the following equation

$$dist(\mathcal{G}_1, \mathcal{G}_2) = \frac{1}{2} \cdot \sum_{m=1}^{N_1} \min_n (||c_m^1 - c_n^2||) + \frac{1}{2} \cdot \sum_{m=1}^{N_2} \min_n (||c_m^2 - c_n^1||) + \alpha ||s_1 - s_2|| \quad (1)$$

where c_m^k is the m^{th} contact of the grasp k, N_k is the number of contacts of grasp k, and s_k is the values for the selected DOFs of the grasp k. α is a scaling factor for the euclidean distance between selected DOFs. We empirically chose the value $\alpha = 100$ so that 0.01 radian difference in joint angles is equivalent to 1 mm in euclidean distance. The first two parts of the right side of the equation measure the euclidean distance between the two sets of contacts in terms of their positions. The third part measures the difference between the hand DOFs.

According to this distance function, we query the tactile experience database for the k nearest neighbors for the current actual grasp using tactile contacts.

4.2 Calculating hand adjustment

All the k nearest neighbors are stable grasps with positive epsilon qualities and they share similar tactile contacts with the actual grasp. In this case, it is reasonable to assume that the local geometry is similar where the contacts are established. Although the actual grasp shares similar tactile contacts with stable grasps, it is not close enough to be a stable one. The goal of this step is to find a hand adjustment to achieve a grasp which has closer contact configuration to the stable grasps.

In order to find a reasonable adjustment, we first localize the actual grasp around each of the nearest neighbors (stable grasps). To do this, we start from each of the k nearest neighbors, perturb the hand around the nearest neighbor and locate a sample grasp which is closest to the actual grasp using distance as in Equation 1. In this perturbation test, we sample wrist orientation (yaw, pitch, roll), wrist position (approaching depth) and selected DOFs to generate perturbed hand posture. Once the offset transform is determined, the relative pose between the stable grasp and the actual grasp is determined. Then the reverse of the offset transform is returned as the ideal hand adjustment. The detailed procedure we take to search for a hand adjustment is described in Algorithm 1.

4.3 Applying hand adjustment

Once an adjustment $A^* =< p, o, s >$ is found, we need to apply this adjustment to the hand: change the hand pose and reshape the joints. We decompose this process into three steps.

First, the hand opens its fingers so that it lets go the object and backs up to have some safe margin between the palm and the object before the following movement.

Second, the selected DOFs change to the values specified by s. The hand moves to a location $5cm$ (subject to change for different hands) backed from the goal position with the goal orientation o.

Third, the hand moves in guarded mode towards the goal position. The hand will either reach the goal position or stop if it hits anything before it reaches the goal.

Algorithm 1: Computing a hand adjustment

Input: A robotic grasp $\mathcal{G}_x$, and a tactile experience database $\mathcal{D}$
Output: A hand adjustment $A =< p, o, s >$

Initialize A^*: $p = [0, 0, 0]$, $o = [1, 0, 0, 0]$, $s = s(\mathcal{G}_x)$
Look for k nearest neighbors to $\mathcal{G}_x$ in $\mathcal{D}$
$min\_dist = MAX$
foreach *neighbor* $\mathcal{G}_i$ **do**
  $pose\_list = Perturb(Obj(\mathcal{G}_i))$
  $s\_list = Sample(s(\mathcal{G}_i), s(\mathcal{G}_x))$
  foreach $s \in s\_list$ **do**
    foreach $< p, o > \in pose\_list$ **do**
      Perturb the hand according to $< p, o, s >$
      Synthesize the grasp information, $\mathcal{G}_p$, of the grasp after perturbation
      if $dist(\mathcal{G}_p, \mathcal{G}_x) < dist(\mathcal{G}_i, \mathcal{G}_x)$ *and* $dist(\mathcal{G}_p, \mathcal{G}_x) < min\_dist$ **then**
        $A^* =< p, o, s >$
        $min\_dist = dist(\mathcal{G}_p, \mathcal{G}_x)$
      end
    end
  end
end
Return A^*

The reason we decompose the movement into these three parts is that the adjustment A may end up with potential collision. So we want to first go to a safe place that is backed from the goal location with the goal orientation and then approach the goal position using guarded motions.

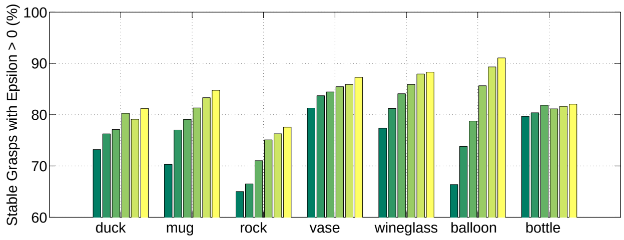
5. EXPERIMENTS

5.1 Building a tactile experience database

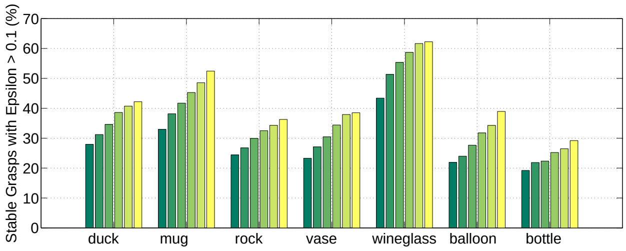
A tactile experience database consists of stable grasps and their corresponding tactile contacts. To generate stable grasps, we used a subset of objects from the Princeton Shape Benchmark (PSB) [13], which are often encountered in our everyday life. These objects range from mugs, vases, and bottles to screwdrivers, wrenches, and hammers. The robotic hand we used in our work is a Barrett hand. An Eigen-grasp planner developed by Ciocarlie and Allen [14] was used to plan stable grasps on these objects. Tactile contacts of each grasp were extracted using the *Graspit!* simulator [15]. These tactile contacts record the locations and orientations of the activated tactile sensors in the hand coordinate system. The detailed method we used to simulate tactile sensor readings from a grasp could be found in our previous work in [6].

5.2 Simulation

Seven objects were used in simulation to test our hand adjustment method. The tactile experience database includes 19,800 grasps with quality $\epsilon > 0.1$ on everyday objects. The goal of the simulation experiment is to quantitatively evaluate the improvement of the grasping performance by applying local hand adjustments. To this end, we first generated a set of initial grasps for each object by uniformly sampling the relative hand-object pose. The parameters we varied during the sampling process were 1) the pitch, yaw, and roll



(a) stable grasps with $\epsilon > 0$



(b) stable grasps with $\epsilon > 1$

Figure 3: Improvement of grasping performance measured by an increase in stable grasps after each local hand adjustment (grouped by object). Each figure has seven groups of bars, corresponding to seven objects. Each group contains six bars, corresponding to the percentages of stable grasps ($\epsilon > 0$ or $\epsilon > 1$) after executing the initial grasp and the following five hand adjustments.

of the palm of the hand, 2) the depth along the approaching direction, and 3) the spread angle of the hand. For a hand adjustment $A = <p, o, s>$, the pitch, yaw, and roll of the palm determine the o component; the depth along the approaching direction and the o component together determine the p component; the s component is selected as the spread angle of a Barrett hand.

The evaluation procedure starts by closing the hand at a sampled pose, followed by five consecutive local hand adjustments to test how the local hand adjustment could influence the grasp stability. We chose epsilon quality, ϵ, as an indicator to the stability of a grasp.

Figures 3(a) and 3(b) show the improvement of grasping performance (ϵ) after each local hand adjustment is applied. Figure 3(a) shows the percentage of grasps with epsilon quality $\epsilon > 0$ while Figure 3(b) shows the percentage of grasps with epsilon quality $\epsilon > 0.1$. From the figures, it is seen that after each local adjustment, the number of stable grasps increases. This indicates that the local hand adjustment does improve the grasping performance by achieving stable grasps locally.

6. CONCLUSION

This extended abstract discussed an experience based approach to the stable robotic grasping problem. In essence, we designed a method to synthesize hand adjustment which drives a dynamic stable grasp exploration process using tactile sensing data. A tactile experience database is designed and built for the method, which is considered as prior tactile contact knowledge of stable grasps. Using the experience-based approach, this method does not have any constraints concerning the kinematic design of the robotic hand, making this algorithm more potential to work with complex hands. The simulation experiment results show that making local hand adjustment improves the overall grasping performance. Current, we are working on a physical experiment with a Barrett hand to test the algorithm in practical robotic systems.

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