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Proactive Grasp Adaptation of Disembodied Barrett Hand

Neil Traft and Jolande Fooken

University of British Columbia

Abstract

The overall goal of this project is to implement the adaptive grasping algorithms of Humberston and Pai [1] on the Barrett robotic arm and hand. There, stable grasps were sampled and then used to "seed" later grasps with a similar shape, to establish a more "natural" grasp. The goal in the original context was to achieve a more realistic appearance in the animation of precision hand manipulations. As opposed to this, our goal in achieving more natural grasps is slightly different: we wish to generate a more reliable and flexible grasp by mimicking human prehensile behavior. The implementation of the grasp adaptation will be based on the tactile read out in subsequent grasping tasks. We hope to thereby increase grasp stability and dexterity.

I Introduction

When humans perform simple grasping task in every day life, they depend on a combination of their visual system as well as their sensorimotor memory. Hereby, the human hand relies on about 17000 mechanoreceptive tactile units [2] embedded in the hairless skin of the palm that are able to give feedback in response to e.g. touch, pressure or vibrations, constantly adapting fingertip forces and grasping strength. Lifting up an object, such as a cup or a pen, is consequently followed by a cascade of sensory signal generation and processing [3].

In humans, visual information of the objects properties during grasping is important, however not essential [4]. Consequently, a lot of research effort has been put into tactile-driven approaches for robotic grasp control [5] [6]. The main challenge remains yet to find a dexterous robotic grasping technique that can cope with the wide range of different grasping contexts. In other words, to mimic natural human grasping behavior as accurate as possible.

Conventionally, there are two approaches to develop grasping strategies and algorithms. While the first one uses geometric object models, i.e. calculates a geometry-based object specific optimal hand posture, the second approach solely depends on tactile feedback upon contact with the object being grasped. Both approaches have the drawback that each grasp will be performed independently of the previous grasp experience. In contrast to this, humans use previous grasping information to *preshape* their grasp. (The simple example of a person lying in bed at night and reaching for a glass of water as opposed to a phone or a book illustrates this.) Accordingly, more recent ideas integrate some kind of *grasp experience* into the planning of the subsequent grasp [7] [8].

The main idea of grasp adaptation is to use previously acquired grasping knowledge to improve future grasping strategies. This can, for example, be achieved by storing hand postures of successful grasping trials in a database. Upon initial finger contact with the object, a suitable hand posture can then be chosen from the database. Consequently, the grasp is more likely to succeed [7].

In our approach we want to make use of the tactile feedback of the Barrett hand. As we expect the tactile feedback to be distinct for individual shapes, we plan to implement an adaptation of the hand posture for repetitive grasping based on the respective previous task. To put it in simpler words, we want to see the hand fail to grasp on an initial trial, however, teach it to learn from its failure.

II Methods

System

The system we will use to conduct our experiments consists of the 7-DOF Barrett WAM robot arm and 4-DOF Barrett BH-280 Hand from Barrett Technology, Inc. The robot is equipped with one 6-DOF wrist torque sensor, three 1-DOF finger joint torque sensors, and four 24-DOF tactile pressure sensors, making for a total of 105 independent sensor inputs. Given such rich sensory input, we hope to invent feature vectors which exhibit statistically significant differences between different grasp shapes. Such a feature vector could be used to augment the grasp preshaping algorithm of Humberston and Pai [1].

All the sensors described above read at 125 Hz. Most afferent inputs in humans run at less than 60 Hz, so this rate is enough for any biologically motivated algorithms we decide to implement [9].

Experimental Setup

We will begin the project with a basic implementation and an experiment. First, we will implement a robotic controller which mirrors the adaptive grasp shaping algorithm of [ben] as closely as possible. When complete, we will use this controller to conduct some simple grasp and lift experiments with simple, known objects.

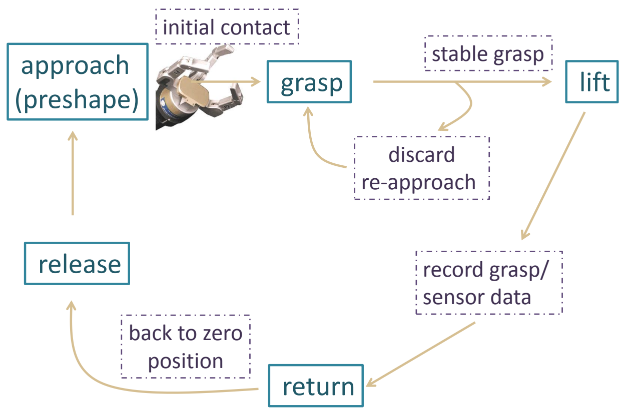

Figure 1 Overview of experimental succession. Bold solid boxes indicate the active phases of the Barrett hand, while dashed boxes represent the grasp adaptation mechanisms.

The basic workflow of our project is as follows (see also Figure 1):

1. Approach the object from a nearby location (possibly by a pre-recorded trajectory).

2. When close to the object (or when contact is detected), close the hand's fingers. Possibly iterate this step a few times.

3. When the fingers stop closing or contact is detected, slowly lift upward.

4. Stop when some predetermined height is reached.

5. Return to table height and release the grip on the object.

Sensor data will be recorded throughout this process, but especially in steps 2 and 4. This will give us a good picture of what sensor readout is like (1) when contact is first established and (2) during a stable grasp.

After performing this experiment and collecting substantial sensor data, we will analyze the data to determine our next course of action. See the Future Work section for a discussion of some possibilities.

Difficulties and Limitations

The Barrett Hand only has 4 degrees of freedom: one rotational axis of motion for each of the three fingers, plus the angle of the two outer fingers. Though each finger has two joints, these joints cannot be controlled directly by software using the libbarrett API; instead, the second joint is automatically controlled by a "torque switch" algorithm [10] . This limits our ability to preshape grasps: our shapes will consist only of these 4 DOFs and will not match the shapes we sample while lifting an object. Nevertheless we believe it will be worthwhile to apply preshaping to the task of manipulation with the Barrett.

Ben Humberston has made significant progress in the area of adaptive grasp shaping, but we cannot use much of his specific algorithms. Our methods must be significantly different because we do not have the luxury of working in a virtual environment where we can place fingers at arbitrary locations within the grasp frame. Instead, given some target grasp shape, we must use forward kinematics to calculate the necessary joint angles to achieve such a grasp. As a result, our definition of grasp shape will necessarily be very different.

Another difference between Humberston's work and ours is that his is a human-in-the-loop system. Essentially, the human performs the work of "controller" under his experimental setup. In our setup, the robot must be autonomous. We can alleviate some of the difficulty by executing motions that were prerecorded by a human. The libbarrett example code includes a "Teach and Play" system that makes it easy to teach the robot such predefined movements.

Still, we will have to program a custom controller for much of the grasping task. For this, we intend to use a state machine, as has been successful in much of the past grasping research [11] [12].

III Future Work

Our future work will take the discussed ideas into practice. Weekly goals are summarized in figure 2. We will spend approximately three weeks on implementing and testing our algorithm. Subsequently, we will test and optimize our algorithm depending on first results and applicability.

In general, two different subsequent directions for our research are possible:

1. Build context c from some tactile feature vector.

2. Use tactile feature vector to determine "good" sample grasps and "bad" sample grasps.

Further research ideas will depend on the quality of the tactile read out as well as the distinctiveness of these tactile feedback maps with respect to different shapes and grasps.

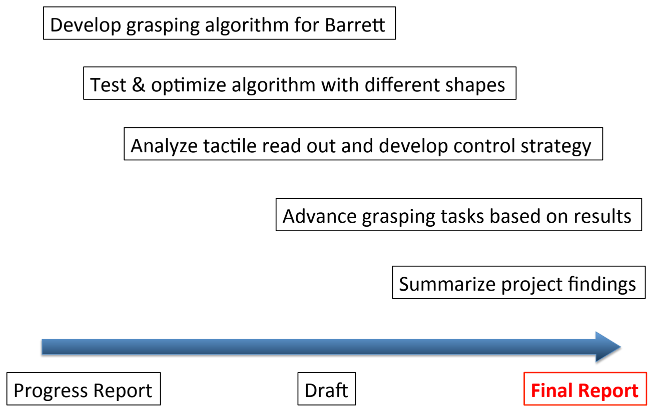

Figure 2 Approximate timeline of term project.

References

[1] B. Humberston and D. Pai, "Interactive Animation of Precision Manipulations with Force Feedback," *Draft*, 2013.

[2] S. Lederman, *Encyclopedia of human biology*, vol. 8. 2 ed., 1997.

[3] G. Tortora and B. Derrickson, *Principles of Anatomy and Physiology*. 13 ed., 2011.

[4] P. Jenmalm and R. Johansson, "Visual and Somatosensory Information about Object Shape Control Manipulative Fintertip Forces," *The Journal of Neuroscience*, vol. 17, pp. 4486–4499, 1997.

[5] M. Lee and H. Nicholls, "Tactile sensing for mechatronics – a state of the art survey," *Mechatronics*, vol. 9, pp. 1–31, 1999.

[6] H. Yousef, M. Boukallel, and K. Althoefer, "Tactile sensing for dexterous in-hand manipulation in robotics – A review," *Sensors and Actuators A: Physical*, vol. 167, pp. 171–187, 2011.

[7] J. Steffen, R. Haschke, and H. Ritter, "Online Movement Adaptation Based on Previous Sensor Experiences," *International Conference on Intelligent Robots and Systems*, vol. 17, pp. 2938–2943, 2007. San Diego.

[8] P. Pastor, L. Righetti, M. Kalakrishnan, and S. Schaal, "Online Movement Adaptation Based on Previous Sensor Experiences," *International Conference on Intelligent Robots and Systems*, vol. 17, pp. 365–371, 2011. San Francisco.

[9] R. Howe, "Tactile sensing and control of robotic manipulation," *Advanced Robotics*, vol. 8, pp. 245–261, 1993.

[10] Barrett and Technologies, *BH8-Series User Manual Firmware Version 4.4.x.*

[11] F. Leoni, M. Guerrini, and C. Laschi, "Implementing robotic grasping tasks using a biological approach," *Robotics and Automation*, pp. 2274–2280, 1998.

[12] P. Sikka and H. Zhang, "Tactile servo: Control of touching-driven robot motion," *Experimental Robotics III*, 1994.