Grasp Adaptation Control with Finger Vision
Verification with Deformable and Fragile Objects

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1. Introduction

In order to establish a strategy to learn robotic grasping behaviors with external vision (e.g. cameras on a robot head) and tactile perception obtained by FingerVision, we develop a grasp adaptation control that grasps unknown objects with adequate grasping force. FingerVision proposed by Yamaguchi and Atkeson [1, 2] is a vision-based tactile sensor that gives robots a tactile sensation and visual information of nearby objects. When grasping objects, humans are combining vision and tactile perception. However, use of tactile perception is not considered as essential in robotics. For example, in the recent work of learning robotic grasping with deep learning [3], robots learned grasping without tactile sensing. This was possible because there is a consistent relation between the state before grasping (visual scene of the object and the gripper) including the grasping parameters and the outcome of grasping. Tactile sensing is intermediate information, which is not necessary to use in learning grasping behavior.

However tactile perception is useful in many manipulation scenarios. When grasping a container whose contents are unknown, visual information is not sufficient to decide the grasping force, while tactile sensing can handle this problem. Romano *et al.* created a tactile-based grasping behavior using a PR2 robot that grasped a range of unknown objects including deformable ones [4]. From our experience of peeling banana with a Baxter robot teleoperated by a human, we noticed that the absence of tactile feedback makes teleoperation difficult [5]. Since peeling a banana is a dual-arm manipulation task and bananas are deformable, estimating force applied by the other hand is not easy, which makes it difficult to avoid slipping or crushing.

We explore combining external vision and tactile perception in learning grasping behaviors. This approach should make the acquired grasping behavior more robust, and the required number of samples might be decreased. We consider a grasping behavior model consisting of two components: one is a predictor of grasp parameters such as a grasp pose using external vision, and the other is a controller to adapt the grasp to hold an object using tactile sensing. We refer to them as the grasp pose estimator and grasp adaptation controller respectively.

This paper reports on an implementation of grasp adaptation controller with FingerVision and the results of preliminary experiments. We consider the grasping task as holding an object without crushing it. Since holding an object is achieving a state where the object is not slipping in a gripper, controlling the grasp to avoid slippage would be the most straightforward approach. We use FingerVision [1] to detect slip, and propose a grasp adaptation controller that modifies the grasp to avoid slip.

Fig.1 Left: Robotiq gripper with FingerVision sensors. Right: 30 objects used in the experiment.

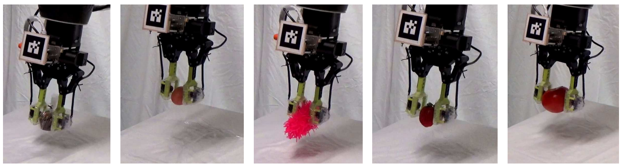

Fig.2 Examples of grasp (cup cake, raw egg, hairy rubber toy, strawberry, tomato).

2. Related Work

Similar ideas of using slip sensing in grasping are explored in [4, 6, 7, 8]. There are many papers on slip detection such as [9]. The major advantage of our approach is that since FingerVision provides vision-based slip detection, it does not depend on the force between the fingers and an object. It can sense slip even when the object is very lightweight, such as grasping origami objects. This approach can control grasping when the force is too small to measure. Such a grasping strategy is adequate especially for grasping deformable and fragile objects such as vegetables, raw eggs, and origami objects.

3. Grasp Adaptation Controller

We use FingerVision to detect slip. The image sequence obtained by FingerVision is processed using a background subtraction method. Since the background subtraction perceives both the object movement and the background movement (including gripper movement), we need to distinguish the object from the background. First we build a background model, and then we adaptively construct an object model. Finally we use the object model as a mask to extract the object movement from the image. Both the background and the object models are represented as HSV color histograms. We use an implementation of OpenCV (`cv::BackgroundSubtractorMOG2`) for the background subtraction.

The grasp adaptation controller is modeled with a finite state machine. We assume a two-finger parallel gripper. It has two phases: (1) Moving the object upward slightly (5 mm) and waiting for a short time (0.4 s). If slippage is detected, moving the object to the initial height and closing the gripper slightly (0.7 mm). These are repeated until no slippage is detected. (2) Moving the object upward to a target height (15 cm from the initial height). If slippage is detected, we go back to the phase (1). In both phases, a feedback control is activated: when slip is detected, closing the gripper slightly (0.7 mm).

4. Preliminary Test of Grasp Adaptation Controller

We conduct a preliminary test of the grasp adaptation controller. We verify that when the grasp pose estimator gives an adequate pose, the grasp adaptation controller can grasp an object robustly. We let a human operator decide a good grasping pose to a given object with a joystick controller, and then run the grasp adaptation controller to pick up the object. We do not tune the parameters of the controller for each object.

We tested with 30 deformable and fragile objects shown in Fig. 1 including vegetables, fruits, origami objects, and a raw egg. We use a Baxter robot with a Robotiq 2-Finger Adaptive Robot Gripper where two FingerVision sensors are installed as shown in Fig. 1. Initially each object is placed on a table.

We conducted 36 trials: Origami box, Origami crane, Badminton ball, Hairy rubber toy, Cup cake, Chocolate, Strawberry, Tomato-medium-1, Eggplant@1, Eggplant@2, Zucchini-yellow, Mushroom-1@1, Mushroom-1@2, Egg(raw), Pepper-red-1, Oyster mushroom-1, Peach-1, Mushroom-2, Potato-1, Kiwi-1, Tomato-medium-2, Broccoli@1, Broccoli@2, Oyster mushroom-2, Green pepper-1, Kiwi-2, Pepper-red-2, Tomato-big, Banana-1@1, Banana-1@2, Banana-1@3, Green pepper-2@1, Green pepper-2@2, Peach-2, Potato-2, Banana-2. A label with @N denotes an N-th trial of the same object. Examples of successful grasping are shown in Fig. 2. There were several failures: (1) Dropped after bringing up: Oyster mushroom-1, Potato-1. (2) Slippage could not be detected due to a computer vision failure: Eggplant@1 (the skin was black), Broccoli@1 and Green pepper-2@1 (the color was similar to the fingers). (3) Closing gripper did not stop in Banana-1@1 because detecting the deformation of object as slip. Since the contact force from the table disappeared when bringing up the banana, the banana skin was deformed slightly. (4) In Banana-1@2, dropped during bringing up, and failed to re-grasp since the fingers got stuck at the edge of the object, and the passive joints of the gripper bent. Note that (2) was solved by grasping the green part (Eggplant@2), helping the object detection manually (Broccoli@2), and just trying again (Green pepper-2@2).

The issues of (2) and (3) will be solved by improving the computer vision method for: (A) a better object detection and (B) distinguishing slippage and deformation. The issues of (1) and (4) will be solved by improving the behavior. For example, testing the grasp stability by shaking the object after grasping will avoid (1). (4) can be solved by optimizing the trajectory of fingertip in re-grasping.

5. Conclusion

We explored a grasp adaptation control that grasps unknown objects with adequate grasping force without crushing them. The controller is a feedback control of slip where FingerVision [1] is used to detect slip. Since this slip detection is vision-based, it can sense slippage of very lightweight objects such as origami objects. The results of preliminary experiments showed that although slight improvements are necessary for the slip detection and the grasp adaptation, this approach is promising toward the goal of learning grasping a range of objects.

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