# Template-Based Exploration of Grasp Selection

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Autonomous robotic grasping is one of the pre-requisites for personal robots to become useful when assisting humans in households. Seamlessly easy for humans, it still remains a very challenging task for robots. The key problem of robotic grasping is to automatically choose an appropriate grasp configuration given an object as perceived by the sensors of the robot. An algorithm that autonomously provides promising grasp hypotheses has to be able to generalize over the large variations in size and geometry of everyday objects (for examples see Fig. 1).

Object model-free approaches have been proposed that directly operate on point clouds provided by 3D sensors (for example a stereo camera system, or the Microsoft Kinect). Hsiao et. al. developed an algorithm that searches among feasible top and side grasps to maximize the amount of object mass between the finger tips of the robot gripper [1]. This and similar approaches use a fixed heuristic for grasp computation and thus lack the ability to adapt and improve the ranking of grasp hypotheses based on previous grasp executions. In [2] success rate of grasps is learned by trial-and-error from local descriptors extracted from 2d images. However, local 2d features for grasping are often not descriptive enough to select a 6d grasp configuration.

In this paper, we propose a model free grasp selection algorithm that generates grasps for a wide variety of differently shaped objects and is able to improve from experience. In addition the repertoire of grasps can be extended by kinesthetic teaching. We propose an object part representation, the grasp heightmap, which (i) better generalizes over local features and (ii) also represents holistic features (see Fig. 2). Further, it is not restricted to specific hands, but performs well on different robots. Our approach is based on the simple assumption that similar objects can be grasped with similar grasp configurations. For example, a pen can be grasped from the table with a strategy similar to that used to grasp a screwdriver of the same size. The algorithm is initialized by teaching the robot a set of grasp configurations and storing a heightmap for each grasped region in form of a *template* along with the associated gripper pose into a template library. Grasp hypotheses for a new object are generated by computing candidate heightmaps from the perceived object point cloud and matching them against the templates stored in the library. The grasp configuration associated with the best match is used as a grasp hypothesis for the new object. After the grasp was executed we store heightmaps that resulted in failures as negative templates in order to improve ranking for next trials.

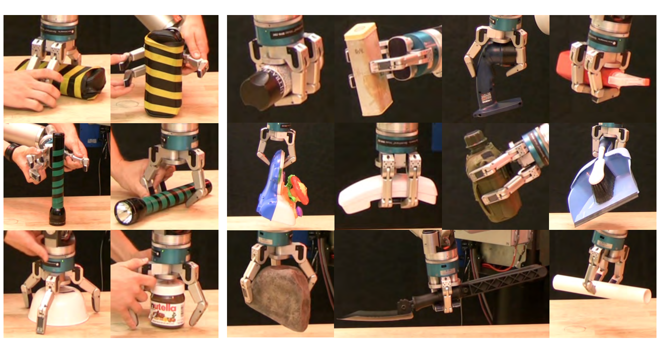

Fig. 1. Left: A user demonstrating grasps to the Barrett WAM robot. Right: A subset of achieved grasps by the robot.

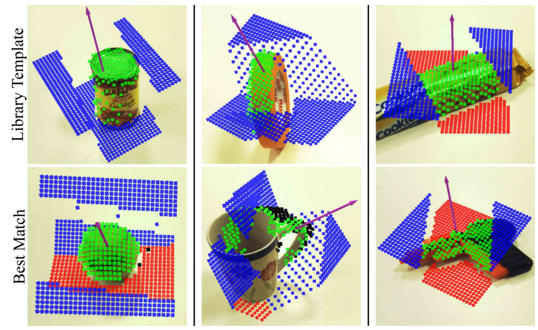


Fig. 2. A *grasp heightmap* consists of a raster of height values. Additionally, each tile also contains information about whether it is one of (1) *object surface*: points on the object (green), (2) *background*: points that do not belong to the object, e.g. table (red), (3) *empty regions*: points that are outside the bounding box of the gripper (blue), or (4) *self-occluded regions*: points that may or may not be part of the object and are not directly visible from the current view angle (black). The top row shows templates contained in the library that have been learned from demonstration; the bottom row shows the best corresponding match for new objects.

We evaluated the performance of the proposed grasp selection algorithm on the Willow Garage PR2 robot and the Barrett WAM robot. In our experiments a set of grasps were demonstrated to the robots. Then they had to perform grasps on a difficult set of variously shaped objects (see Fig. 1). In an additional experiment we made the robots grasp one object over and over again and observed an increase of the success rate of grasps over time.[1]

Future work includes incorporating information from tactile sensors.

## References

[1] K. Hsiao, S. Chitta, M. Ciocarlie, and G. E. Jones, "Contact-reactive grasping of objects with partial shape information," in *Proc. IEEE/RSJ Intl Conf. on Intelligent Robots and Systems*, 2010.

[2] L. Montesano and M. Lopes, "Active learning of visual descriptors for grasping using non-parametric smoothed beta distributions," *Robotics and Autonomous Systems*, vol. 60, no. 3, Mar. 2012.

[1] A summary of the experiments: www.youtube.com/watch?v=noRv2gsy2u0