

ROYAL INSTITUTE OF TECHNOLOGY

HIGHLIGHTS

Efficient Bounding Box Approximation of 3D Data Points

Grasping Hypotheses Generation from Box **Representations**

Bridging Geometrical Features with Grasp Properties as Parts and Tasks Geometric Features (Visibility, Reachability,

Evaluation and Learning of Stability criteria in GraspIt! Simulator

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Grasping by Parts: Robot Grasp Generation from 3D Box Primitives

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perception, action and cognition through learning of object-action complexes

Abstract

Robot grasping capabilities are essential for perceiving, interpreting and acting in arbitrary and dynamic environments. While classical computer vision and visual interpretation of scenes focus on the robot's internal representation of the world rather passively, robot grasping capabilities are needed to actively execute tasks, modify scenarios and thereby reach versatile goals. Grasping is a central issue of various robot applications, especially when unknown objects have to be manipulated by the system. We present an approach aimed at the object description, but constrain it by performable actions. In particular, we will connect box-like representations of objects with grasping, and motivate this approach in a number of ways.

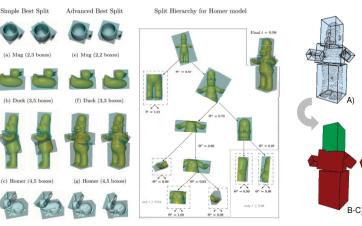
The contributions of our work are two-fold; in terms of shape approximation, we provide an algorithm for a 3D box primitive representation to identify object parts from 3D point clouds. We motivate and evaluate this choice particularly toward the task of grasping. As a contribution in the field of grasping, we present a grasp hypothesis generation framework that utilizes the box presentation in a highly flexible manner.

Method

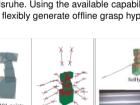
The necessary input for box decomposition is an arbitrary point cloud. The method results in intuitive part decomposition and in grasp hypotheses that still feature good grasp stability [1]. Classically, a "good" grasp is very often described in terms of stability criteria only. In our approach, we are aiming at defining a "good" grasp also depending on the task at hand or the robot embodiment. The algorithm is sketched as follows:

A) Run the decomposition method that generates a number of oriented bounding boxes from a point cloud. B) Rank the boxes **B**_i and select grasp pre-shape (e.g. spherical, cylindrical) according to a given task, C) restrict the produced face set F(B) according to a given viewpoint, and generate grasp hypotheses for each facet (approach vector = inside-facing facet normal; 4 orientations = 4 clockwise facet edge vectors). D) Restrict the thereby produced hypothesis set H by removing occluded faces and blocked hypotheses E) Also reduce the new hypotheses set **H** by removing those that are wider than the gripper aperture.

F) (For the hypotheses that remain from the selective process, use a trained neural network (trained towards estimating grasp stability [2,3], by simulating grasps in the GraspIt! simulator [Miller & Allen, 2004]) to order or select the best hypotheses.)



(h) Bunny (2.3 boxes) (d) Bunny (2.4 boxes)



D-E)

Applications

I. Natural Grasp Hypotheses for Learning of Task Constraints

When grasping a cup, applicability of grasp hypotheses clearly depends on the task, i.e. "for what to grasp the cup for." Since robots can be equipped with different hands, extraction of significant task constraints is a key to generalize tasks, e.g. "leave enough free space for handing it over." An approach to learn such task constraints by human expert labeling is presented in [5]. Our framework supports this approach by automatic generation of intuitive grasps on arbitrary object models and parts, using arbitrary hand models.



* Grasps are automatically generated from box-based representations, the labels have been assigned manually.

II. Grasping Known Objects with a Humanoid Robot

Grasping known objects using a box-based grasp generation technique on 3D shape representations was proposed in [4]. The experiments were implemented on the humanoid platform ARMAR-III, Universität Karlsruhe. Using the available capabilities of the platform (object pose estimation, visual servoing), ARMAR can flexibly generate offline grasp hypotheses from the KIT Object Models Web Database. Univ. Karlsruhe.



References

[1] K. Huebner, S. Ruthotto, D. Kragic (2008). Minimum Volume Bounding Box Decomposition for Shape Approximation in Robot Grasping. In Proc. of the IEEE International Conference on Robotics and Automation (ICRA'08), pp. 1628-1633.

[2] K. Huebner, D. Kragic (2008). Selection of Robot Pre-Grasps using Box-Based Shape Approximation. In Proceedings of the IEEE International Conference on Intelligent Robots and Systems (IROS'08), pp. 1765-1770.

[3] S. Geidenstam, K. Huebner, D. Banksell, D. Kragic (2009). Learning of 2D Grasping Strategies from Box-Based 3D Object Approximations. In 2009 Robotics: Science and Systems Conference (RSS'09).

[4] K. Huebner, K. Welke, M. Przybylski, N. Vahrenkamp, T. Asfour, D. Kragic, R. Dillmann (2009). Grasping Known Objects with Humanoid Robots: A Box-based Approach. In Proc. of the International Conference on Advanced Robotics (ICAR'09).

[5] D. Song, K. Huebner, V. Kyrki, D. Kragic. Learning Task Constraints in Robot Grasping. Poster Contribution to International Conference on Cognitive Systems (CogSys 2010).