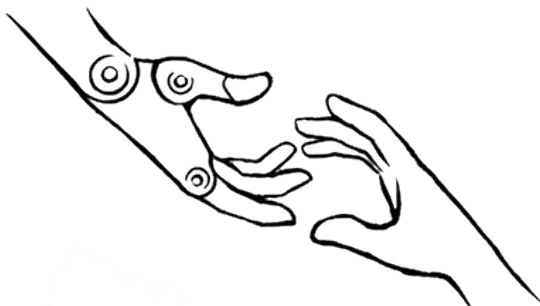


Using Geometry to Detect Grasp Poses in 3D Point Clouds



ten Pas, Platt
Northeastern University

September 15, 2015



Helping Hands Lab



Objective

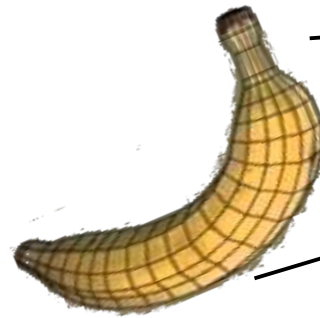
Three possibilities:

- Instance-level grasping
- Category-level grasping
- Novel object grasping

Objective

Three possibilities:

- Instance-level grasping
- Category-level grasping
- Novel object grasping



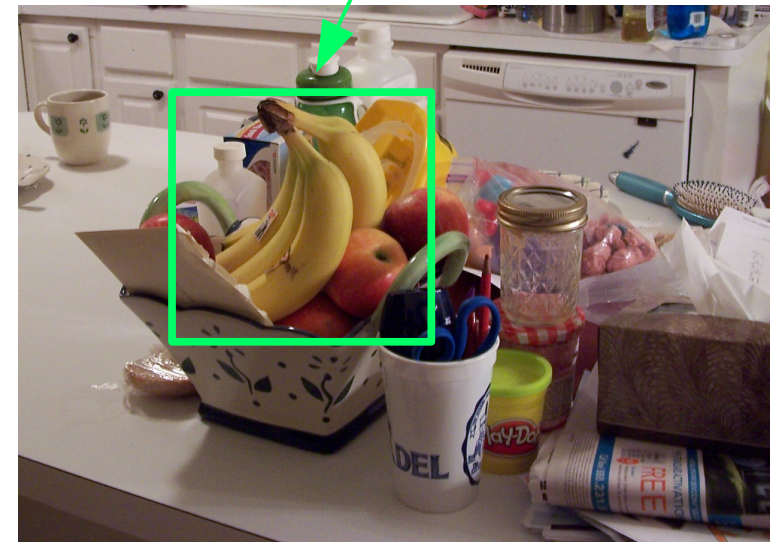
The robot has a detailed description of the object to be grasped.

Objective

Three possibilities:

- Instance-level grasping
- Category-level grasping
- Novel object grasping

Grasp the banana



The robot has general information about the object to be grasped.

Objective

Three possibilities:

- Instance-level grasping
- Category-level grasping
- Novel object grasping

Grasp the thing in the box

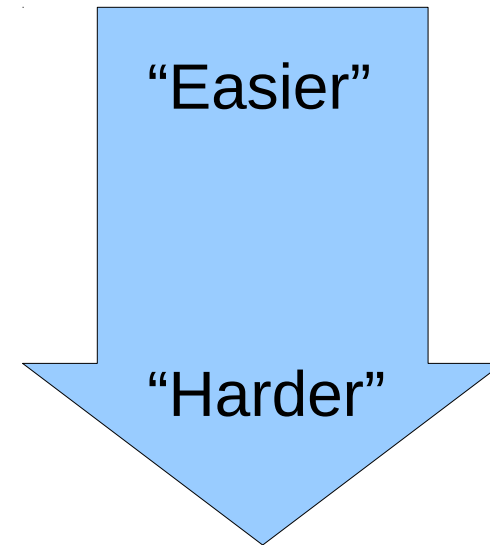


The robot has no information about the object to be grasped.

Objective

Three possibilities:

- Instance-level grasping
- Category-level grasping
- Novel object grasping

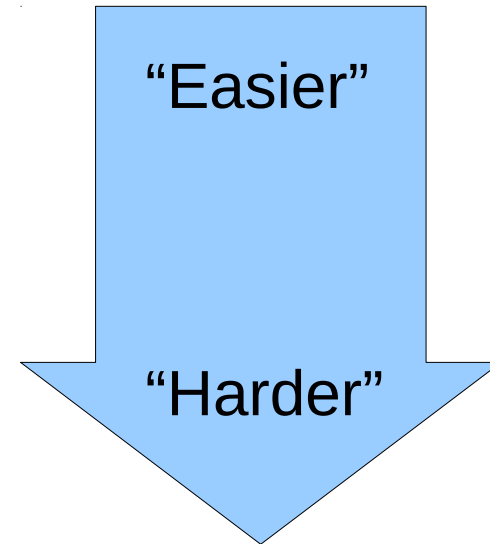


Objective

Most research
assumes this

Three possibilities:

- Instance-level grasping
- Category-level grasping
- Novel object grasping



Objective

Three possibilities:

– Instance-level grasping

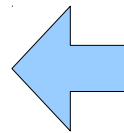
– Category-level grasping

– Novel object grasping

Our focus:

1. Grasping novel or partially known objects

2. Robustness in clutter

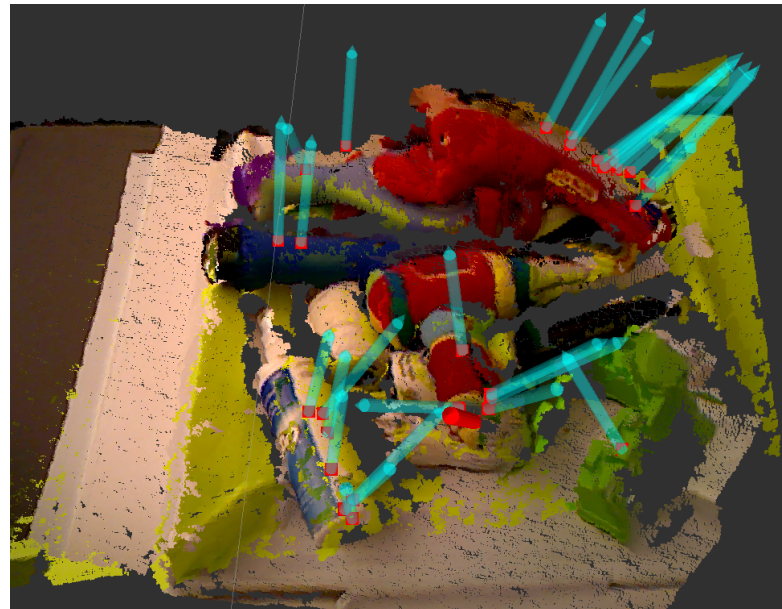


Related Work:

1. Fischinger and Vincze. Empty the basket - a shape based learning approach for grasping piles of unknown objects. IROS'12.
2. Fischinger et al. Learning grasps for unknown objects in cluttered scenes. IROS 2013.
3. Jiang et al. Efficient grasping from rgb-d images: Learning using a new rectangle representation. IROS 2011.
4. Klingbeil et al. Grasping with application to an autonomous checkout robot. IROS 2011.
5. Lenz et al. Deep learning for detecting robotic grasps. RSS 2013.

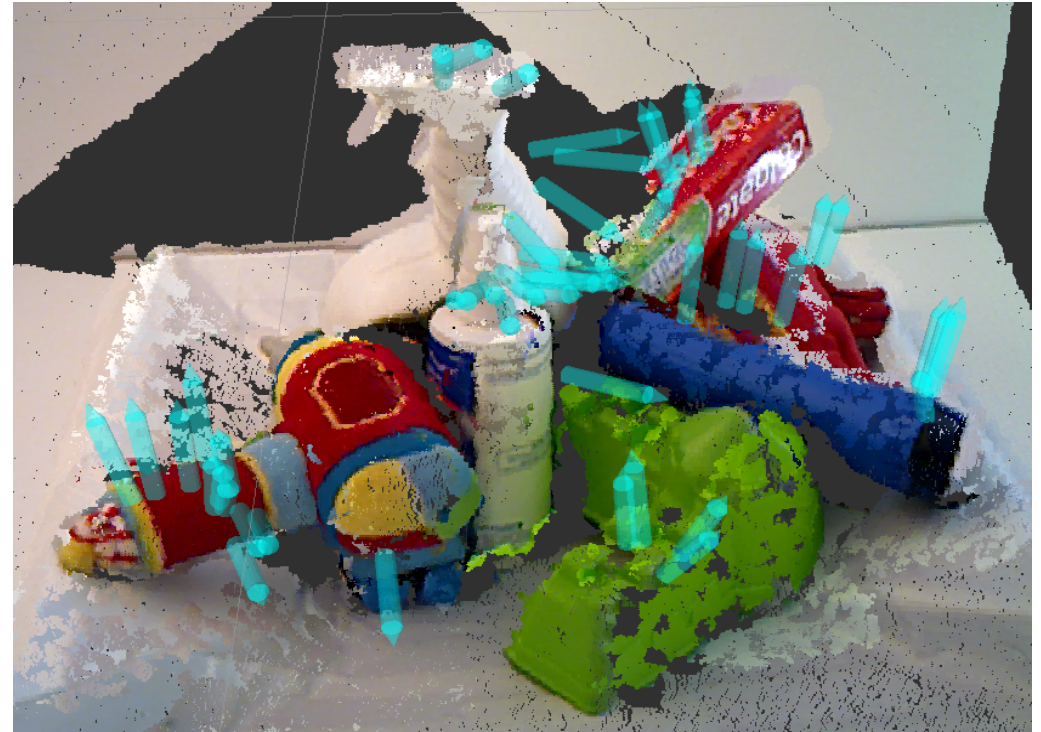
Differences to Prior Work

- Localizing 6-DOF poses instead of 3-dof grasps
- Point clouds obtained from multiple range sensors instead of a single RGBD image
- Systematic evaluation in clutter



Novel Object Grasping

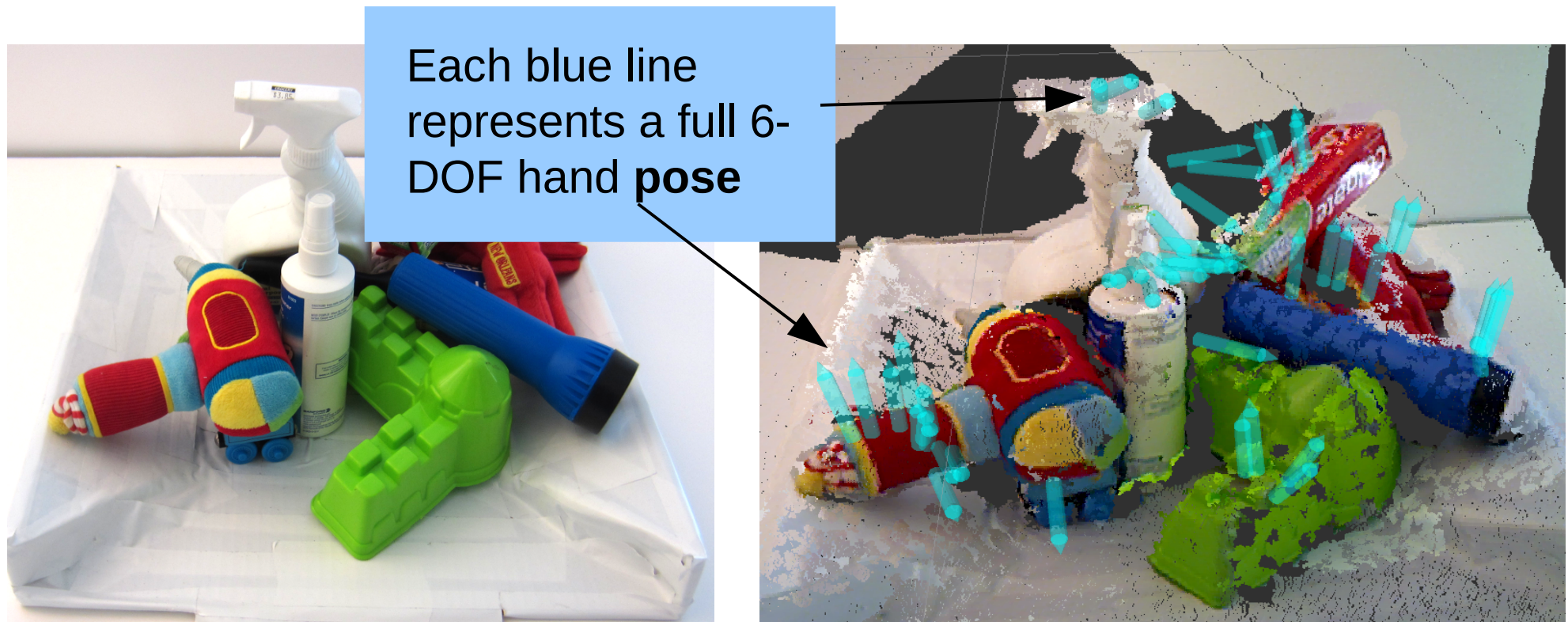
Novel Object Grasping



Input: a point cloud

Output: hand poses where a grasp is feasible.

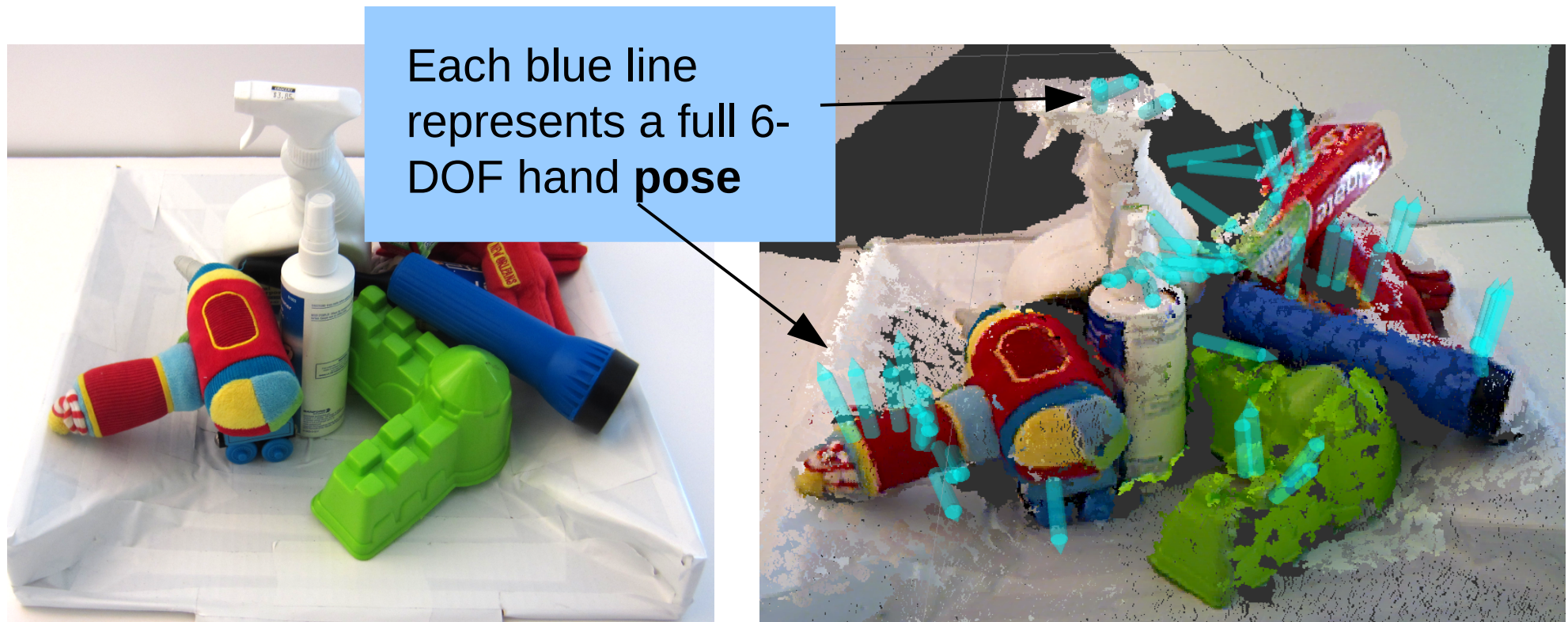
Novel Object Grasping



Input: a point cloud

Output: hand poses where a grasp is feasible.

Novel Object Grasping



Input: a point cloud

Output: hand poses where a grasp is feasible.
– don't use any information about object identity

Why Novel Object Grasping is Hard

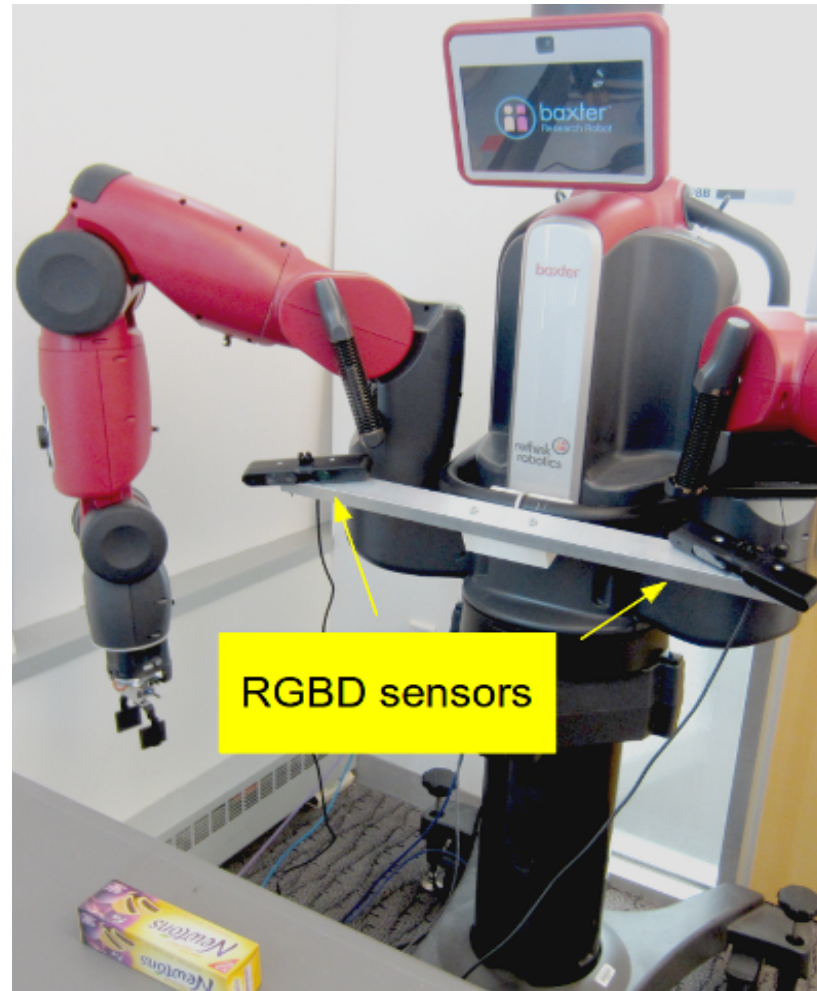


what was there



what the robot saw

Why Novel Object Grasping is Hard



Why Novel Object Grasping is Hard



what was there



what the robot saw
(monocular depth)

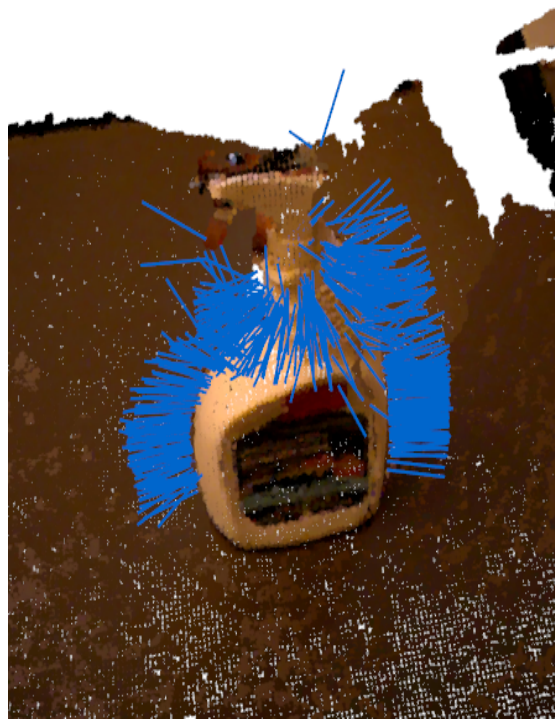


what the robot saw
(stereo depth)

Our Algorithm has Three Steps



1. Hypothesis generation



2. Classification

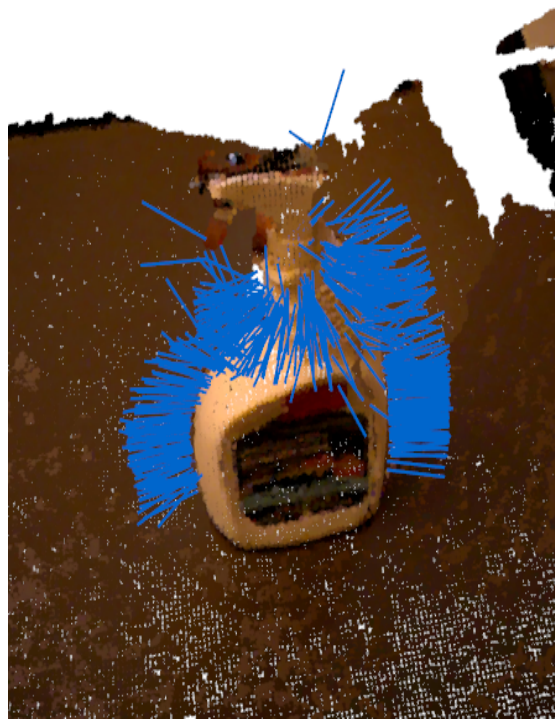


3. Outlier removal

Our Algorithm has Three Steps



1. Hypothesis generation

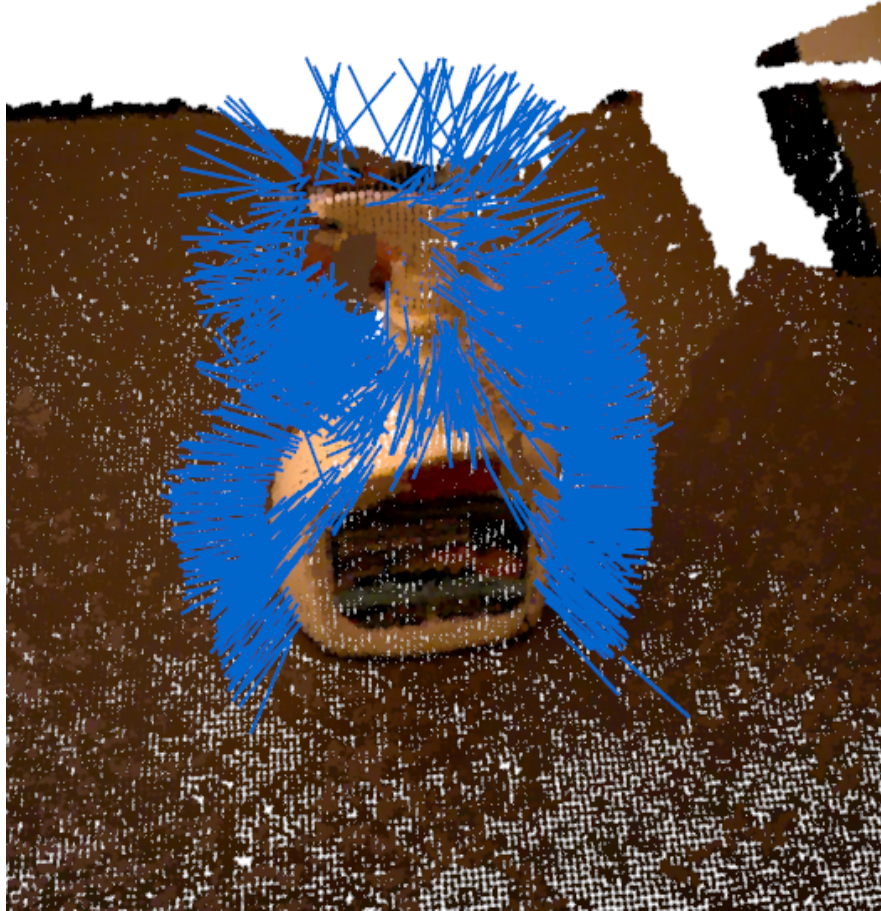


2. Classification



3. Outlier removal

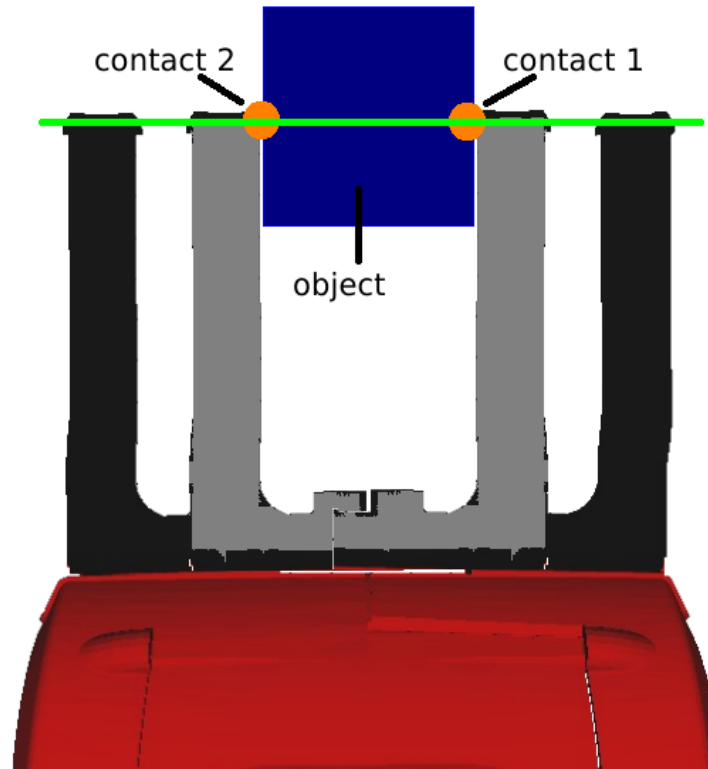
Step 2: Grasp Classification



We want to check each hypothesis to see if it is an antipodal grasp

If we had a “perfect” point cloud...

... then we could check geometric sufficient conditions for a grasp



We would check whether an *antipodal* grasp would be formed when the fingers close

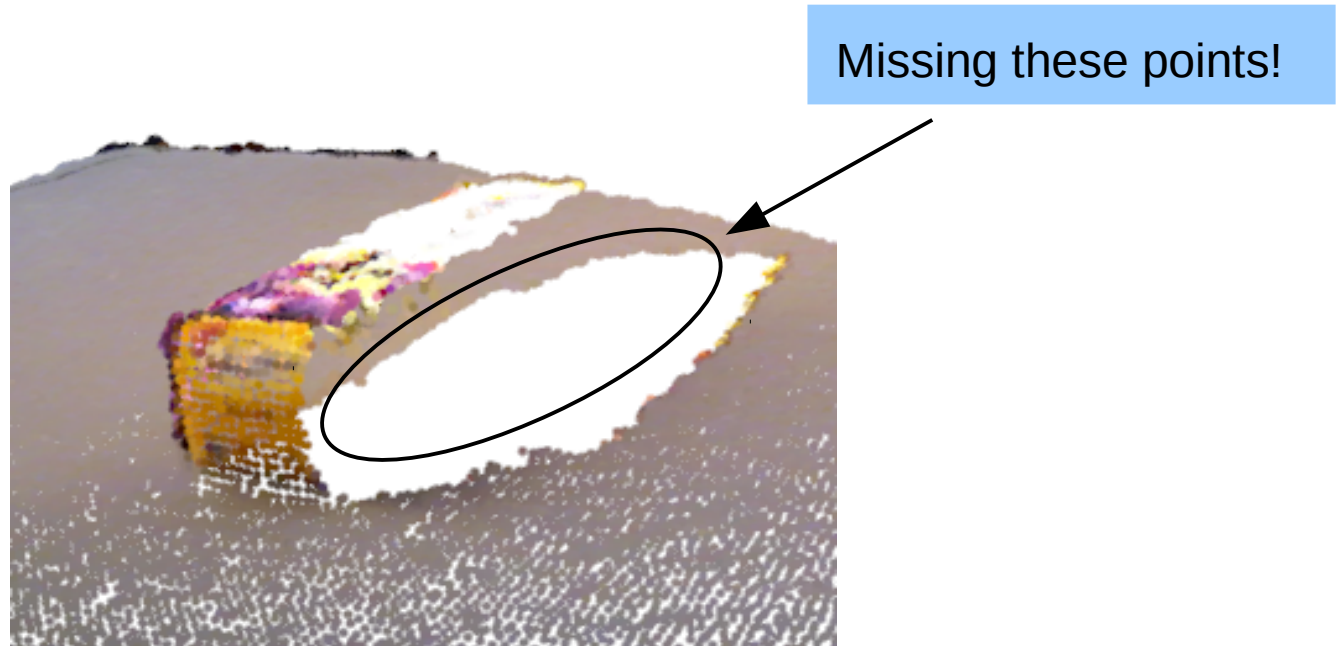
If we had a “perfect” point cloud...



But, this is closer to reality...

So, how do we check for a grasp now?

If we had a “perfect” point cloud...



Machine Learning
(i.e. classification)

Classification

We need two things:

1. Learning algorithm + feature representation
2. Training data

Classification

We need two things:

1. Learning algorithm + feature representation
 - SVM + HOG
 - CNN
2. Training data

Classification

We need two things:

1. Learning algorithm + feature representation

- SVM + HOG
- CNN

2. Training data

- automatically extract training data from arbitrary point clouds containing graspable objects

Training Set

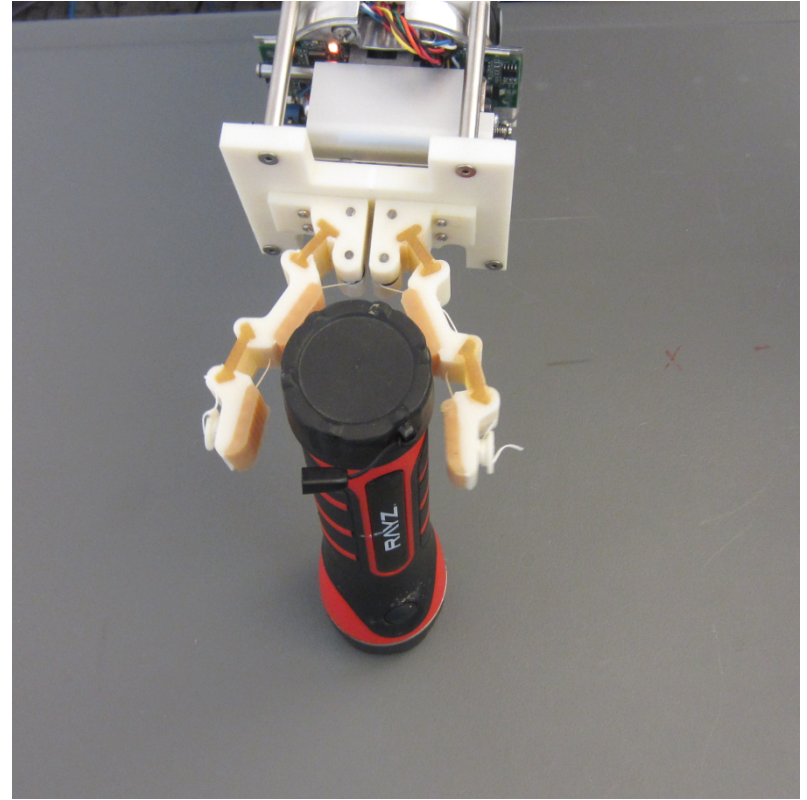
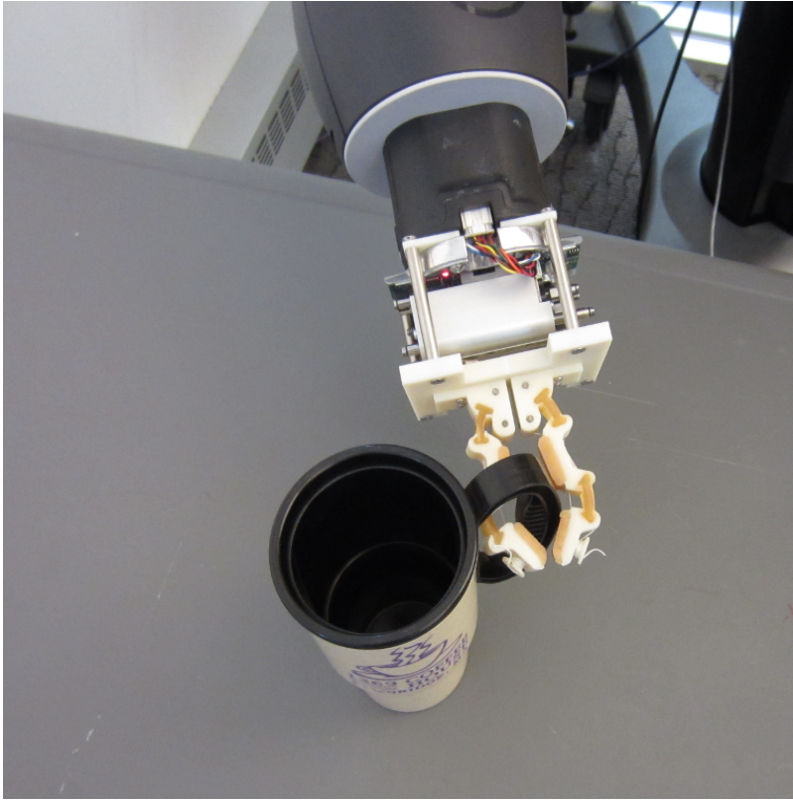


Training Set



97.8% accuracy (10-fold cross validation)

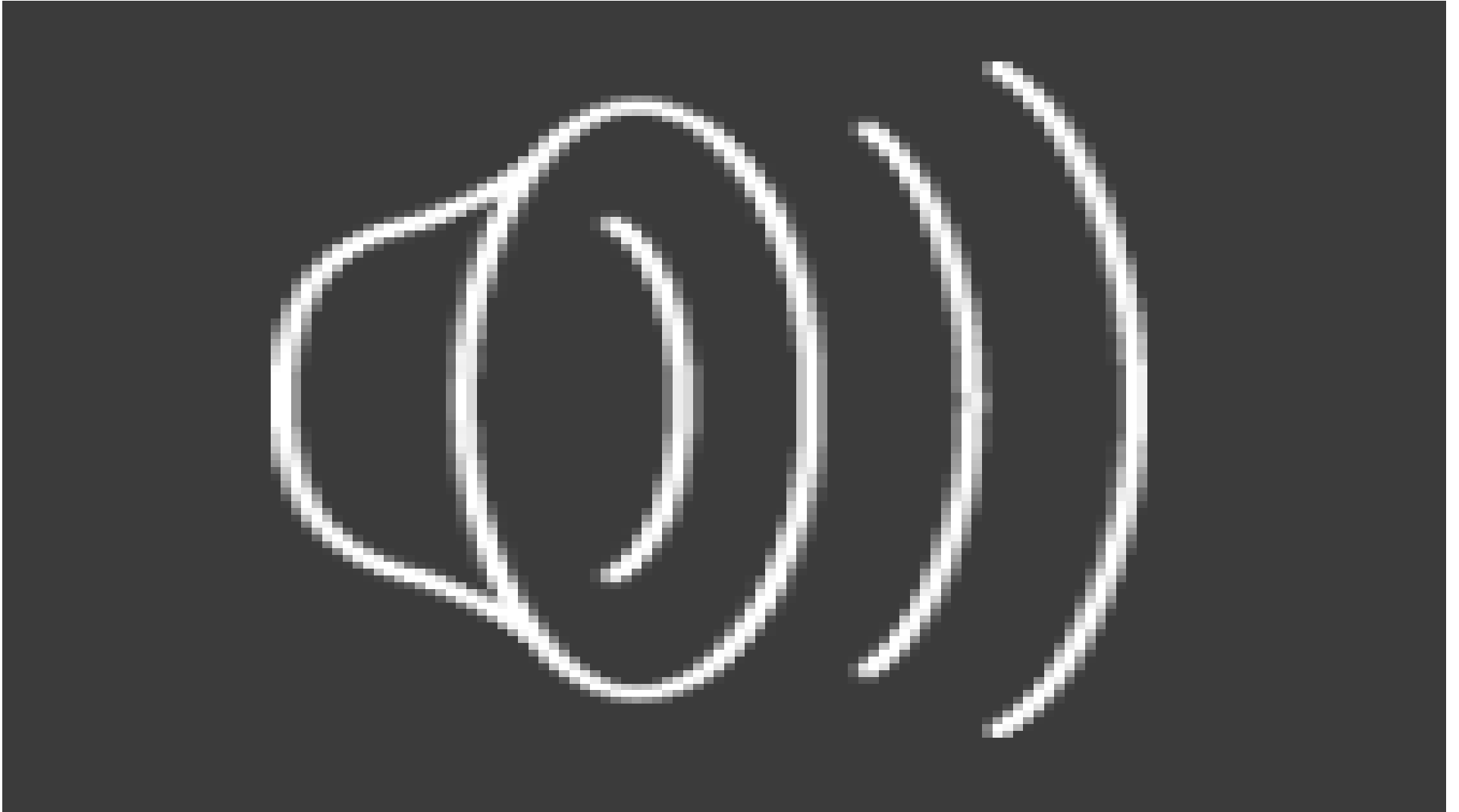
Experiment: Grasping Objects in Isolation



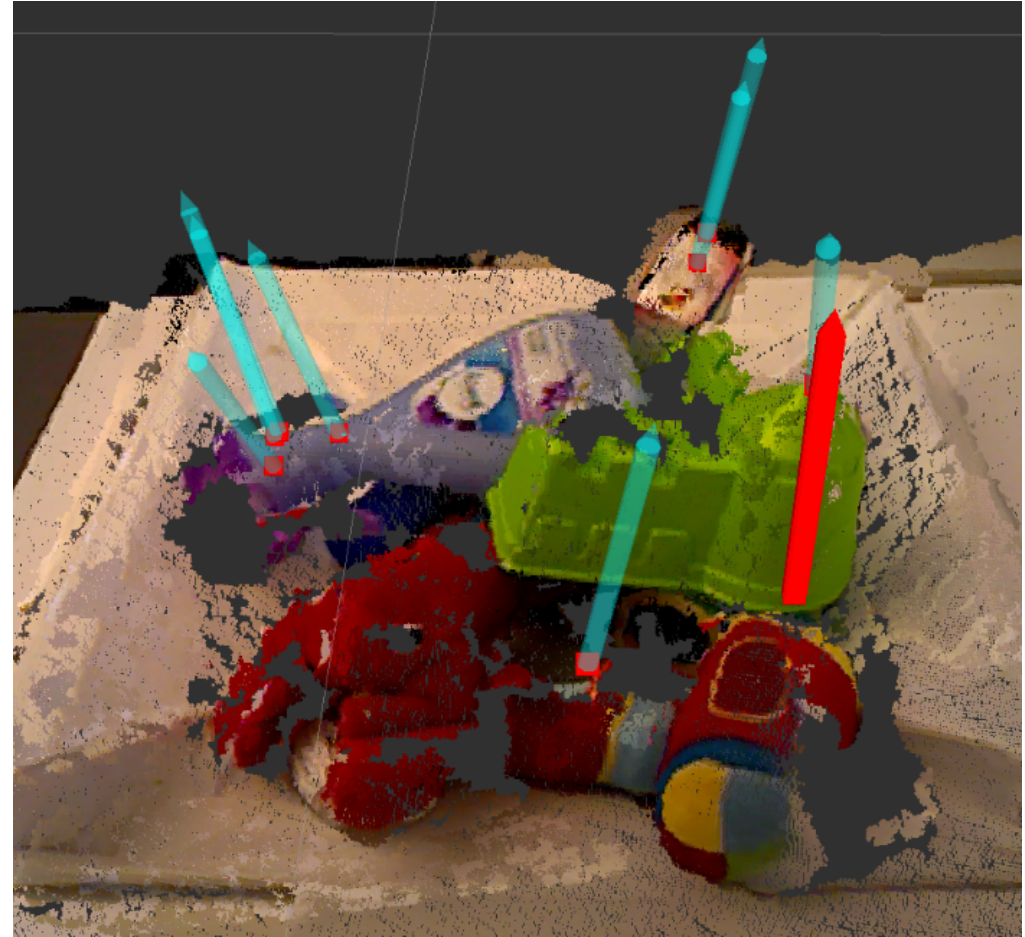
Results: Objects Presented in Isolation

| Object | number of poses | Succ. Rate A, 2V | number of poses | Success Rate | | | |
|---------------------|-----------------|------------------|-----------------|---------------|---------------|---------------|---------------|
| | | | | NC, 1V | NC, 2V | SVM, 1V | SVM, 2V |
| Plush drill | 3 | 100.00% | 6 | 50.00% | 66.67% | 100.00 | 66.67% |
| Black pepper | 3 | 100.00% | 8 | 62.5% | 62.50% | 75.00 | 100.00% |
| Dremel engraver | 3 | 100.00% | 6 | 33.33% | 50.00% | 66.67 | 100.00% |
| Sand castle | 3 | 100.00% | 6 | 50.00% | 33.33% | 83.33 | 83.33% |
| Purple ball | 0 | NA | 6 | 66.67% | 100.00% | 83.33 | 100.00% |
| White yarn roll | 3 | 100.00% | 8 | 87.50% | 87.50% | 87.50 | 75.00% |
| Odor protection | 0 | NA | 8 | 50.00% | 87.50% | 87.50 | 75.00% |
| Neutrogena box | 3 | 66.67% | 8 | 25.00% | 87.50% | 87.50 | 87.50% |
| Plush screwdriver | 3 | 100.00% | 6 | 83.33% | 87.50% | 83.33 | 100.00% |
| Toy banana box | 3 | 100.00% | 8 | 100% | 83.33% | 87.50 | 75.00% |
| Rocket | 3 | 100.00% | 8 | 50.00% | 87.50% | 100.00 | 87.50% |
| Toy screw | 3 | 100.00% | 6 | 100.00% | 100.00% | 83.33 | 100.00% |
| Lamp | 3 | 100.00% | 8 | 62.50% | 83.33% | 87.50 | 87.50% |
| Toothpaste box | 3 | 66.67% | 8 | 87.50% | 100.00% | 87.50 | 87.50% |
| White squirt bottle | 3 | 66.67% | 8 | 25.00% | 12.50% | 75.00 | 87.50% |
| White rope | 3 | 100.00% | 6 | 66.67% | 83.33% | 83.33 | 100.00% |
| Whiteboard cleaner | 3 | 100.00% | 8 | 62.50% | 75.00% | 100.00 | 100.00% |
| Toy train | 0 | NA | 8 | 87.50% | 100.00% | 87.50 | 100.00% |
| Vacuum part | 3 | 100.00% | 6 | 33.33% | 66.67% | 100.00 | 83.33% |
| Computer mouse | 0 | NA | 6 | 33.33% | 33.33% | 66.67 | 83.33% |
| Vacuum brush | 1 | 100% | 6 | 50.00% | 83.33% | 66.67 | 50.00% |
| Lint roller | 3 | 100.00% | 8 | 75.00% | 75.00% | 87.50 | 100.00% |
| Ranch seasoning | 3 | 100.00% | 8 | 50.00% | 75.00% | 100.00 | 100.00% |
| Red pepper | 3 | 100.00% | 8 | 75.00% | 75.00% | 100.00 | 100.00% |
| Crystal light | 3 | 100.00% | 8 | 25.00% | 37.50% | 75.00 | 75.00% |
| Red thread | 3 | 100.00% | 8 | 75.00% | 100.00% | 100.00 | 100.00% |
| Kleenex | 3 | 100.00% | 6 | 33.33% | 33.33% | 83.33 | 83.33% |
| Lobster | 3 | 66.67% | 6 | 16.67% | 83.33% | 66.67 | 83.33% |
| Boat | 3 | 100.00% | 6 | 83.33% | 100.00% | 83.33 | 100.00% |
| Blue squirt bottle | 2 | 100% | 8 | 25.00% | 50.00% | 75.00 | 62.50% |
| Average | | 94.67% | | 57.50% | 72.92% | 85.00% | 87.78% |

Experiment: grasping objects in clutter



Results: Clutter



73% average grasp success rate in 10-object dense clutter

Conclusions

- New approach to novel object grasping
- Use grasp geometry to label hypotheses automatically
- Average grasp success rates:
 - 88% for single objects
 - 73% in dense clutter

Questions?

atp@ccs.neu.edu
http://www.ccs.neu.edu/home/atp

ROS packages

- Grasp pose detection: wiki.ros.org/agile_grasp
- Grasp selection: github.com/atenpas/grasp_selection

ROS.org [About](#) | [Support](#) | [Status](#) | [answers.ros.org](#) **ROSCon**

Documentation **Browse Software** **News**

agile_grasp

hydro indigo Documentation Status

Package Summary

Released **Continuous integration** **Documented**

The agile_grasp ROS package. AGILE stands for Antipodal Grasp Identification and LEarning. The package finds antipodal grasps in point clouds.

- Maintainer status: maintained
- Maintainer: Andreas ten Pas <atp.ccs.neu.DOT.edu>
- Author: Andreas ten Pas
- License: BSD
- Source: git https://github.com/atenpas/agile_grasp.git (branch: master)

Package Links

- Code API
- Msg API
- FAQ
- Changelog
- Change List
- Reviews

Dependencies (15)

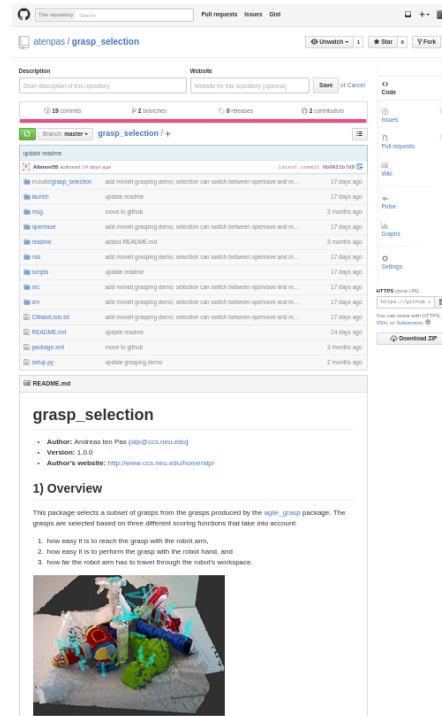
Jenkins jobs (7)

Contents

1. Overview
2. Requirements
3. Installation
 1. From Source, ROS Indigo
 2. From Source, ROS Hydro
4. Localize Grasps with a Robot
 1. Instructions for Asus Xtion Pro
 2. Launch File Parameters
5. Localize Grasps in a Point Cloud File
 1. Usage
 2. Parameters
6. Training the SVM
 1. Method A
 2. Method B
 3. Parameters
7. Citation

1. Overview

This package localizes antipodal grasps in 3D point clouds. AGILE stands for Antipodal Grasp Identification and LEarning. The reference for this package is: [Using Geometry to Detect Grasps](#).



The screenshot shows the GitHub repository page for 'atenpas/grasp_selection'. It displays the repository name, a search bar, and navigation options like 'Unwatch', 'Star', and 'Fork'. Below this, there's a list of commits with details like author, message, and time. The main content area shows the 'README.md' file, which includes the package name 'grasp_selection', author information, version, and an overview section. The overview section describes the package's purpose: selecting a subset of grasps from the 'agile_grasp' package based on three different scoring functions. It also lists three key points: how easy it is to reach the grasp with the robot arm, how easy it is to perform the grasp with the robot hand, and how far the robot arm has to travel through the robot's workspace. At the bottom, there is a small image showing a robot arm interacting with a cluttered table.