Using Geometry to Detect Grasp Poses in 3D Point Clouds

ten Pas, Platt
Northeastern University

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Helping Hands Lab

Objective

Three possibilities:

– Instance-level grasping

– Category-level grasping

– Novel object grasping

Objective

<u>Three possibilities:</u>

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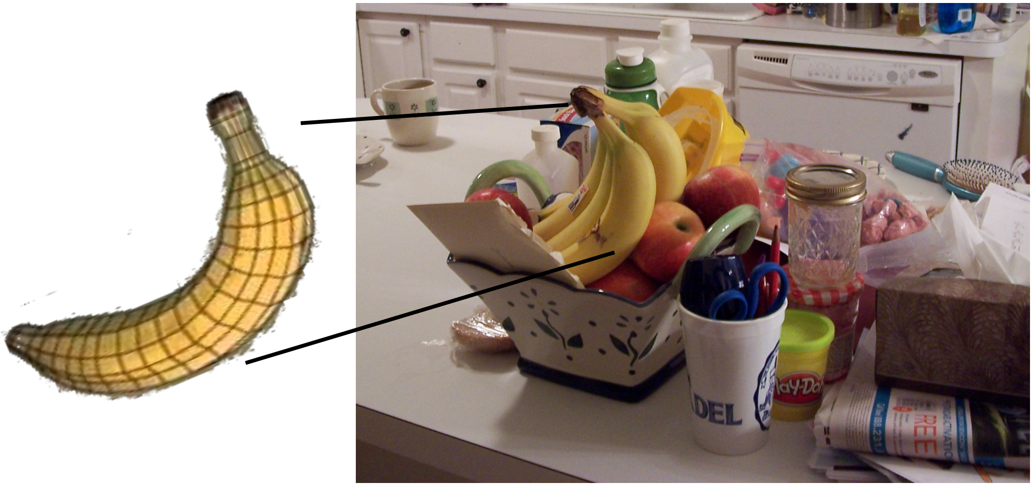
– Category-level grasping

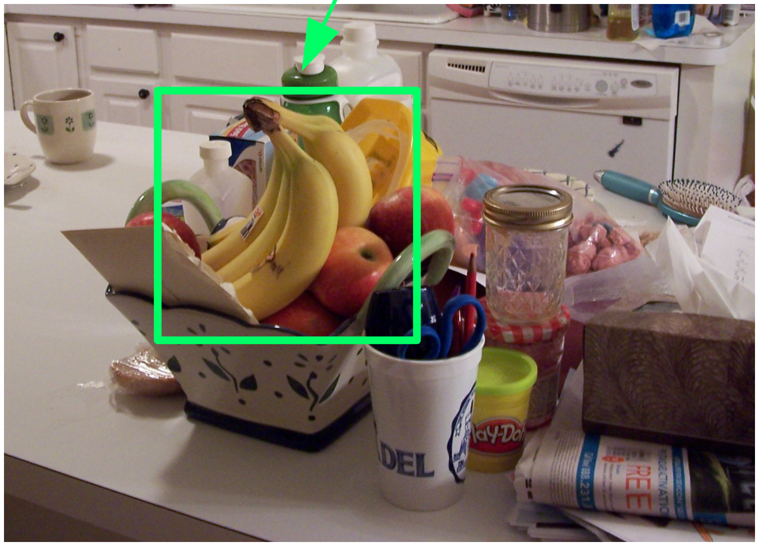
– Novel object grasping



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

Objective

Grasp the banana



<u>Three possibilities:</u>

– Instance-level grasping

– Category-level grasping

– Novel object grasping

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

Objective

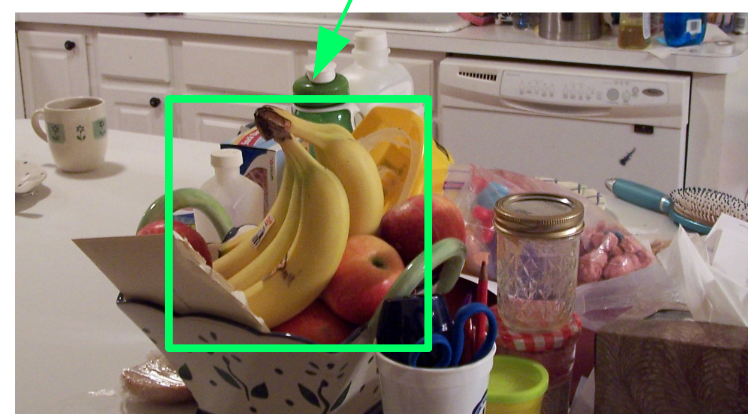
<u>Three possibilities:</u>

– 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.

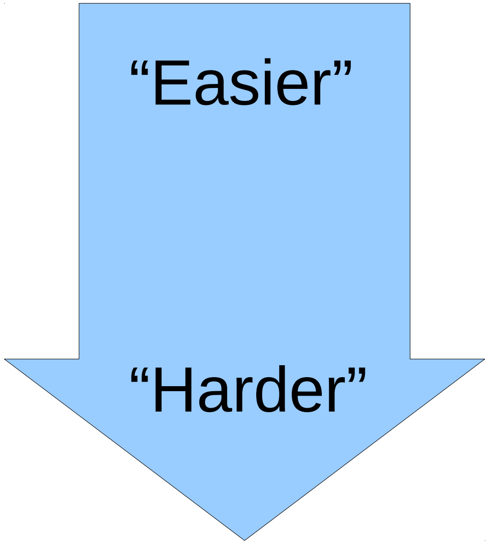
Objective

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

“Easier”

“Harder”

Objective

<u>Three possibilities:</u>

– Instance-level grasping

– Category-level grasping

– Novel object grasping

<u>Our focus:</u>

1. Grasping novel or partially known objects

2. Robustness in clutter

<u>Related Work:</u>

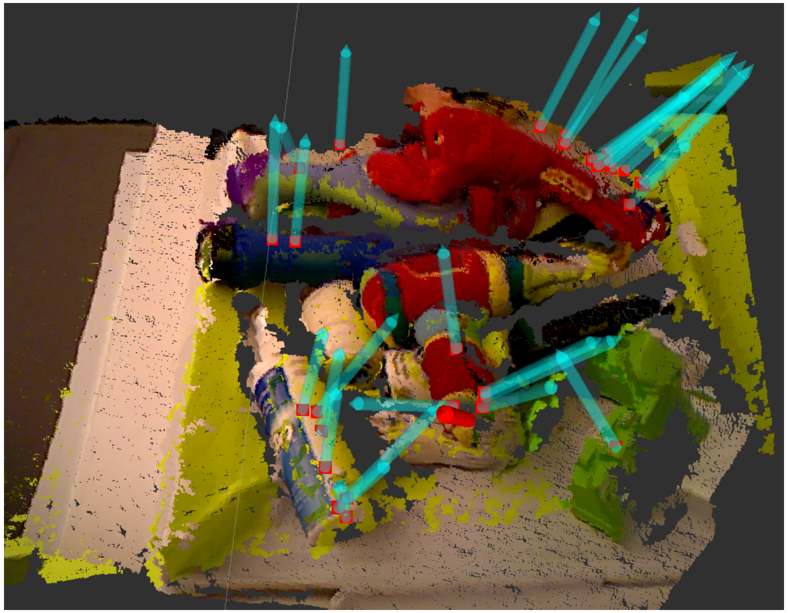
1. Fischinger and Vincze. Empty the basket - a shape based learning approach for grasping piles of unknown objects. IROS'12.
2. Fischinger et al. Learning grasps for unknown objects in cluttered scenes. IROS 2013.
3. Jiang et al. Efficient grasping from rgbd images: Learning using a new rectangle representation. 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

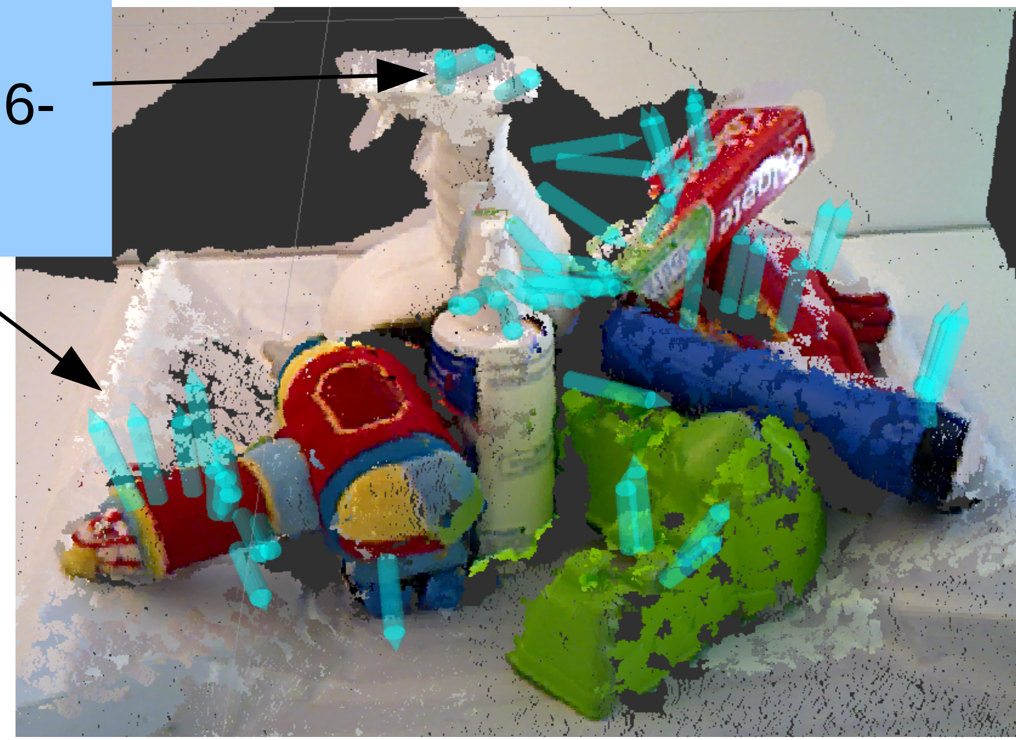
Novel Object Grasping

Input: a point cloud

Output: hand poses where a grasp is feasible.

Novel Object Grasping

Each blue line represents a full 6-DOF hand **pose**

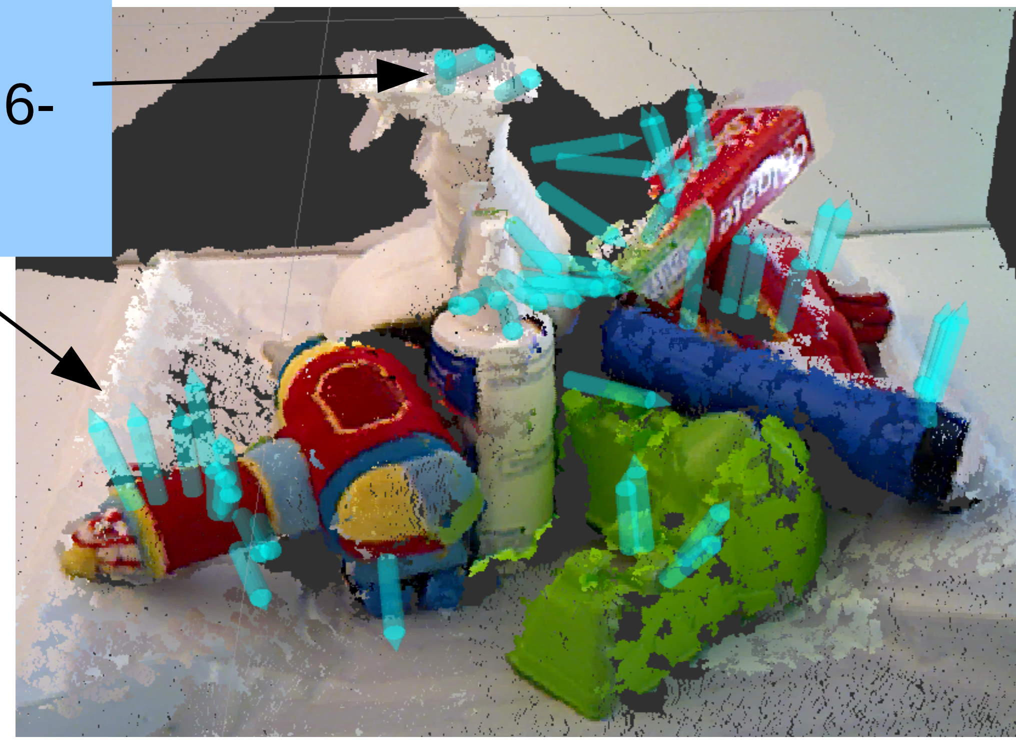


<u>Input</u>: a point cloud

<u>Output</u>: hand poses where a grasp is feasible.

Novel Object Grasping

Each blue line represents a full 6-DOF hand **pose**



Input: a point cloud

Output: hand poses where a grasp is feasible.

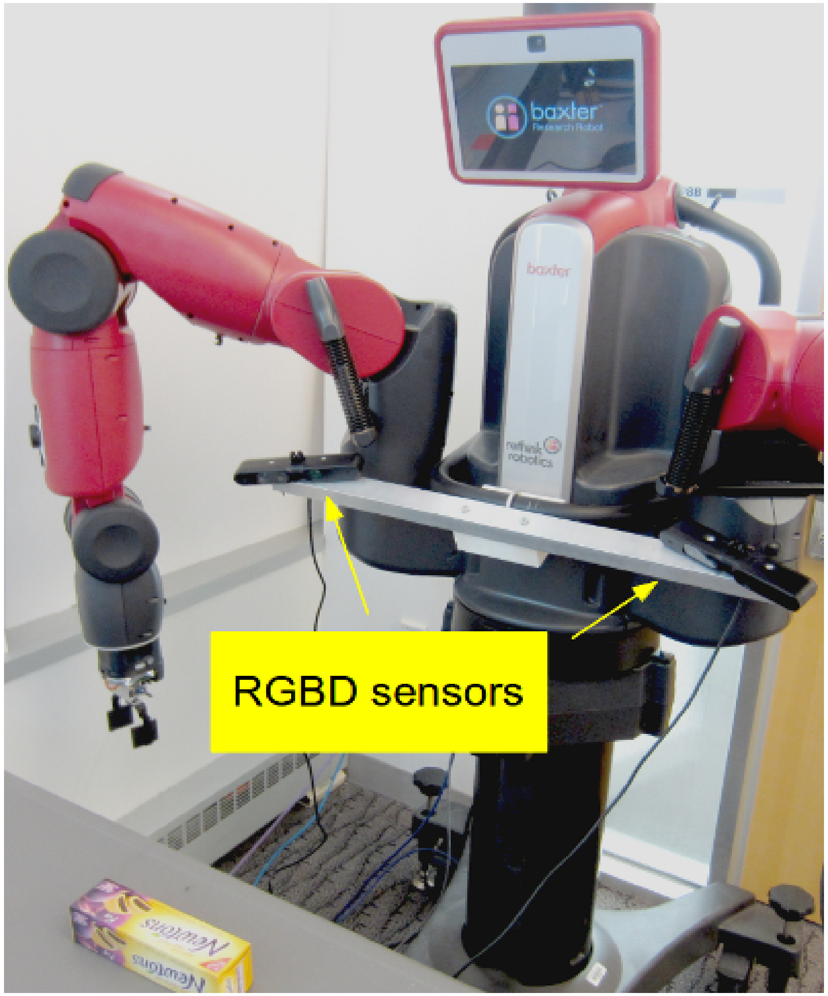
– don't use any information about object identity

Why Novel Object Grasping is Hard

what was there

what the robot saw

Why Novel Object Grasping is Hard



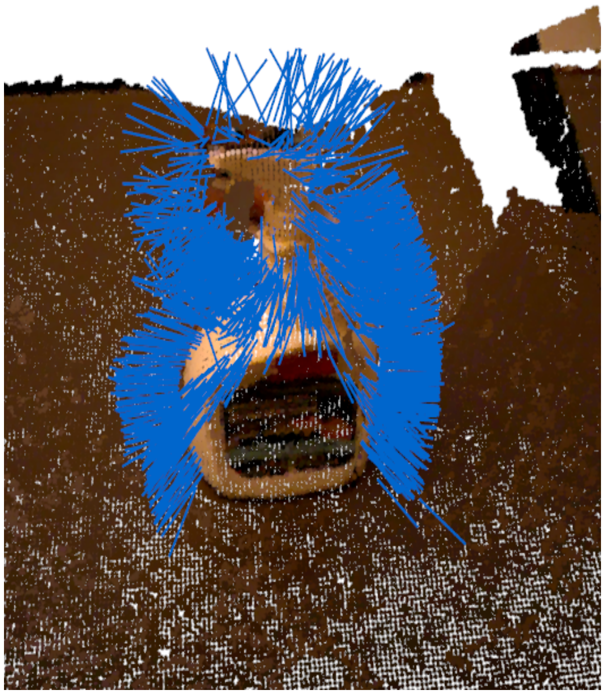
Why Novel Object Grasping is Hard

what was there

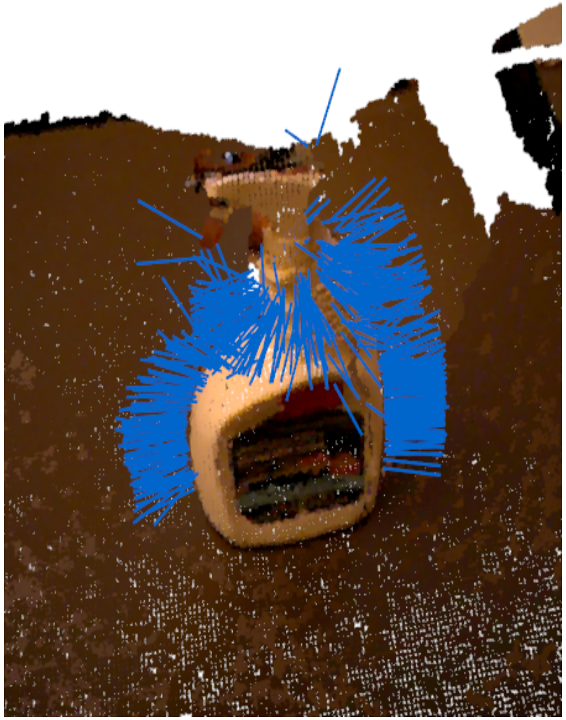
what the robot saw
(monocular depth)

what the robot saw
(stereo depth)

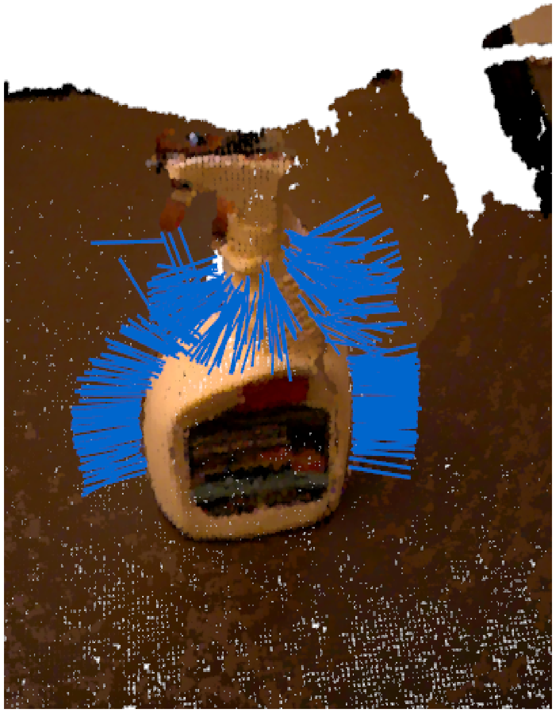
Our Algorithm has Three Steps



1. Hypothesis generation

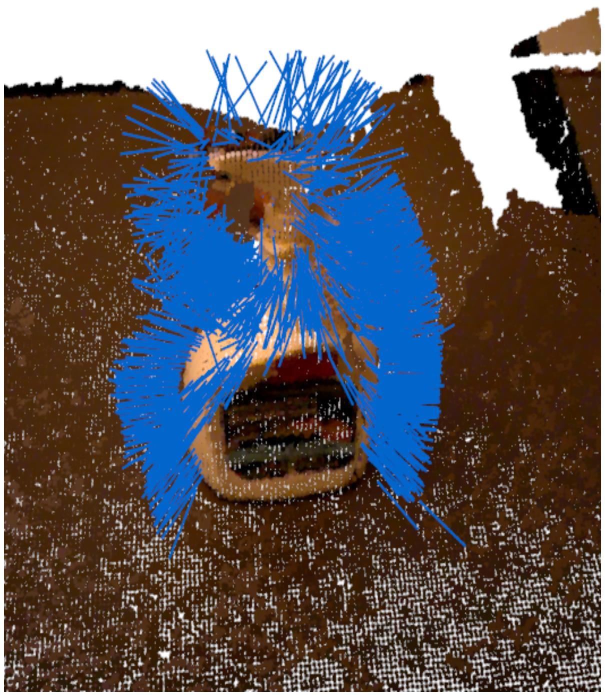


2. Classification

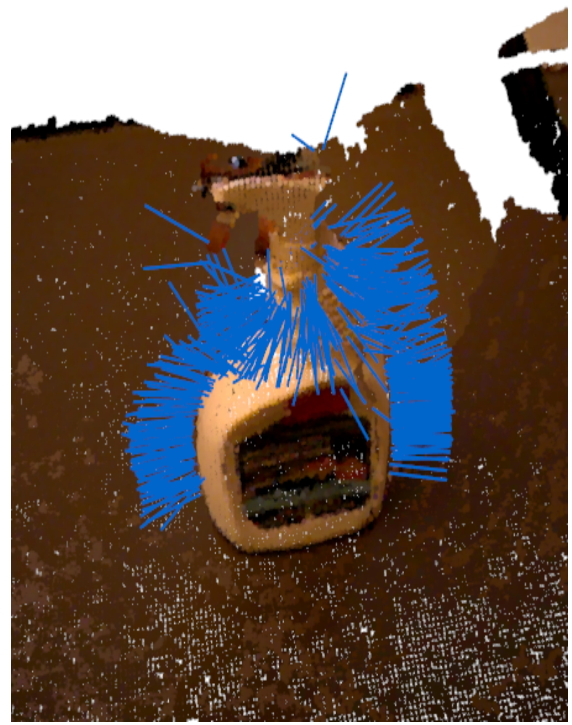


3. Outlier removal

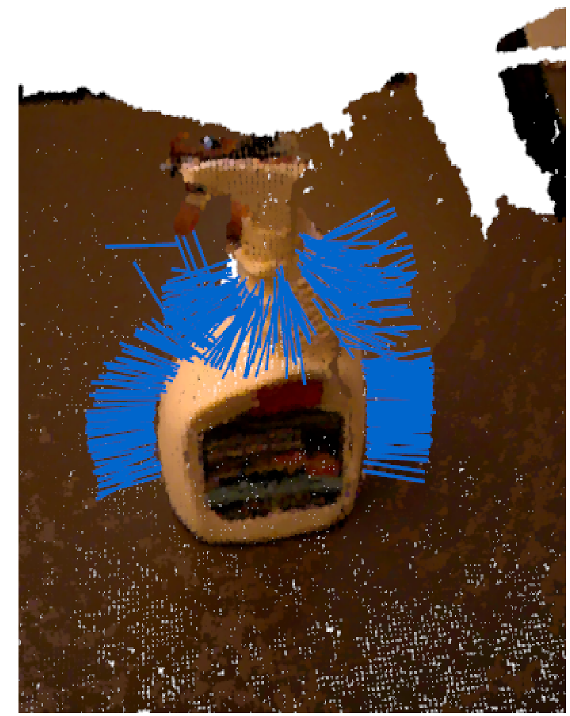
Our Algorithm has Three Steps



1. Hypothesis generation

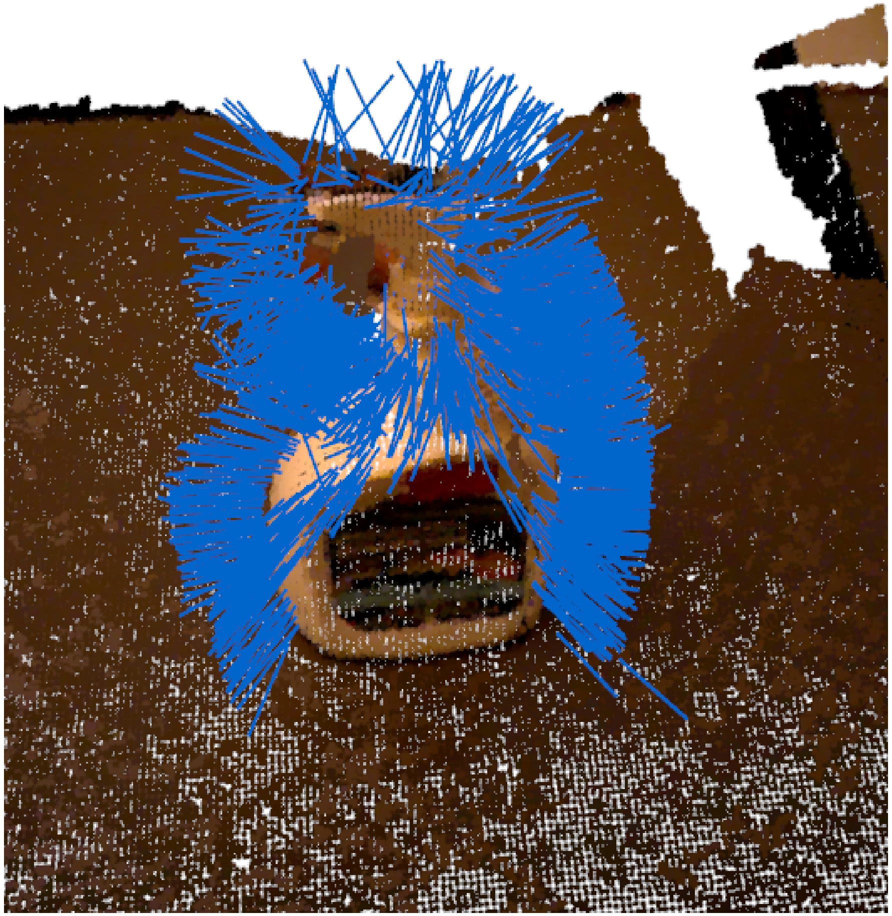


2. Classification



3. Outlier removal

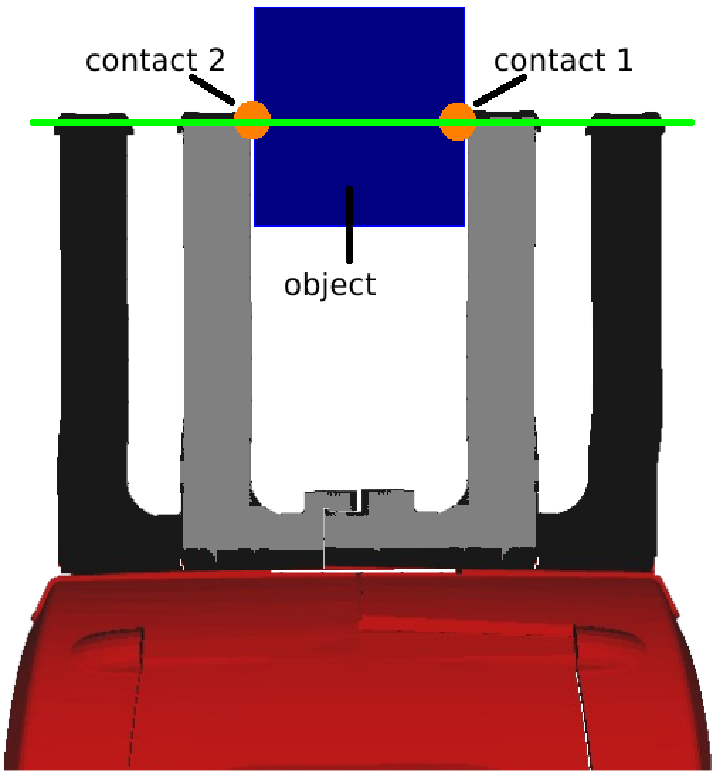
Step 2: Grasp Classification



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

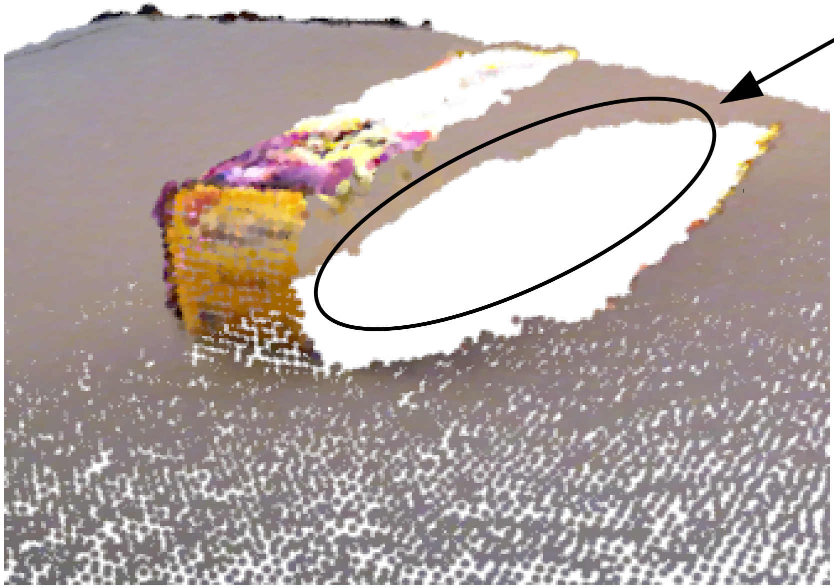
If we had a “perfect” point cloud...

… 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...



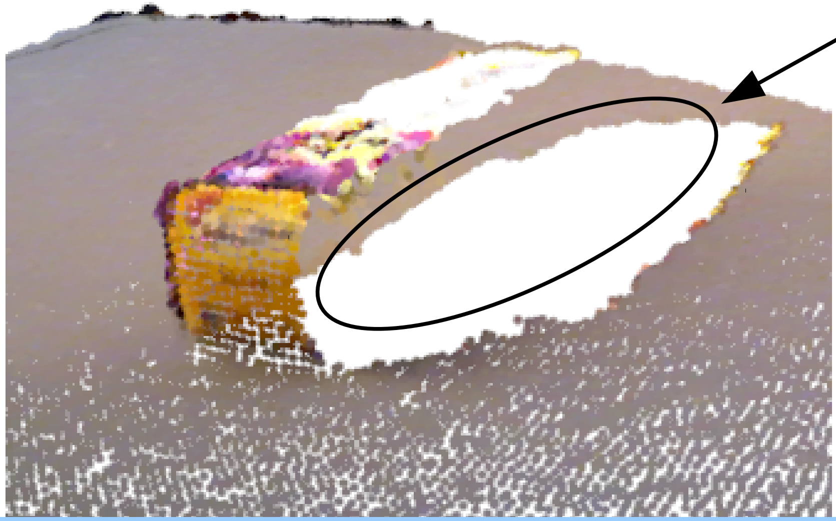
Missing these points!

But, this is closer to reality...

So, how do we check for a grasp now?

If we had a “perfect” point cloud...

Missing these points!



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)

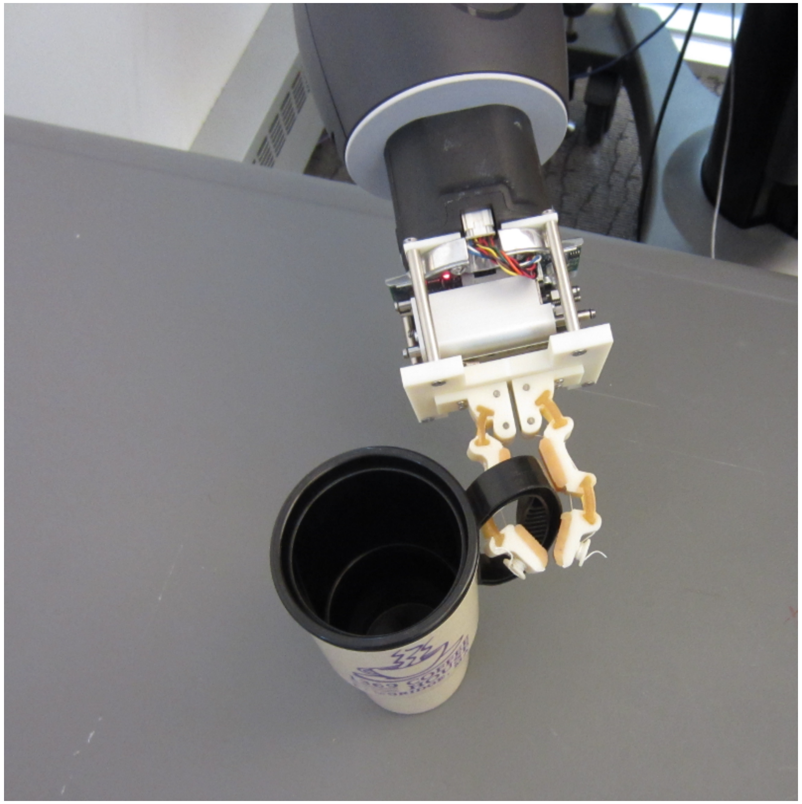
Test Set

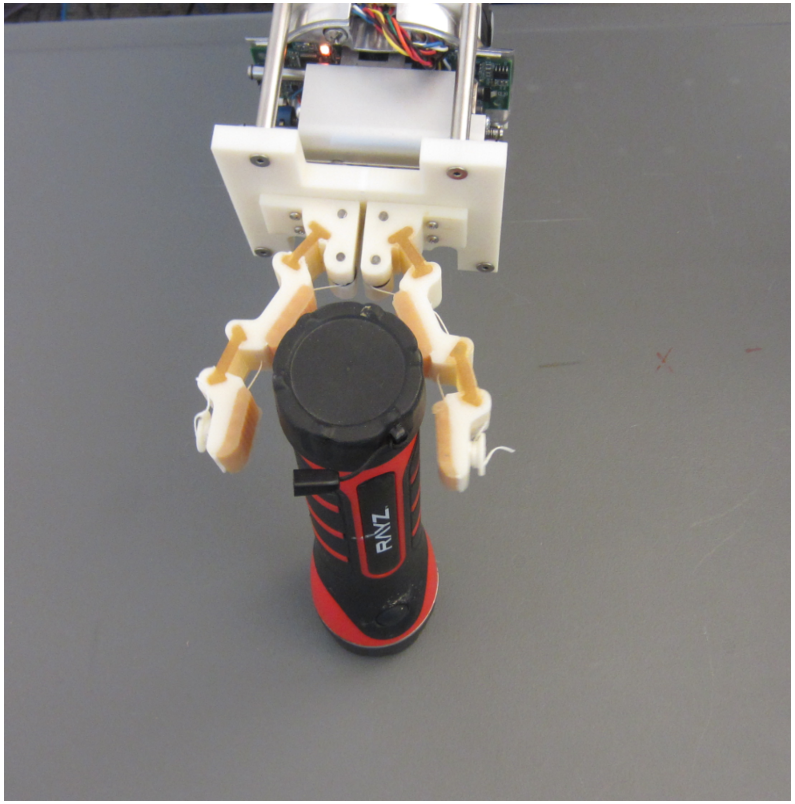
Say yes to delicious!
White Board Cleaner
Nettoyant de Tableau Blanc
EXPO
seventh GENERATION
febreze
Kernel Season's
Ranch
NEW ORLEANS
SPARKLING WHITE
with Baking Soda
Colgate

Test Set

94.3% accuracy on novel objects

Experiment: Grasping Objects in Isolation

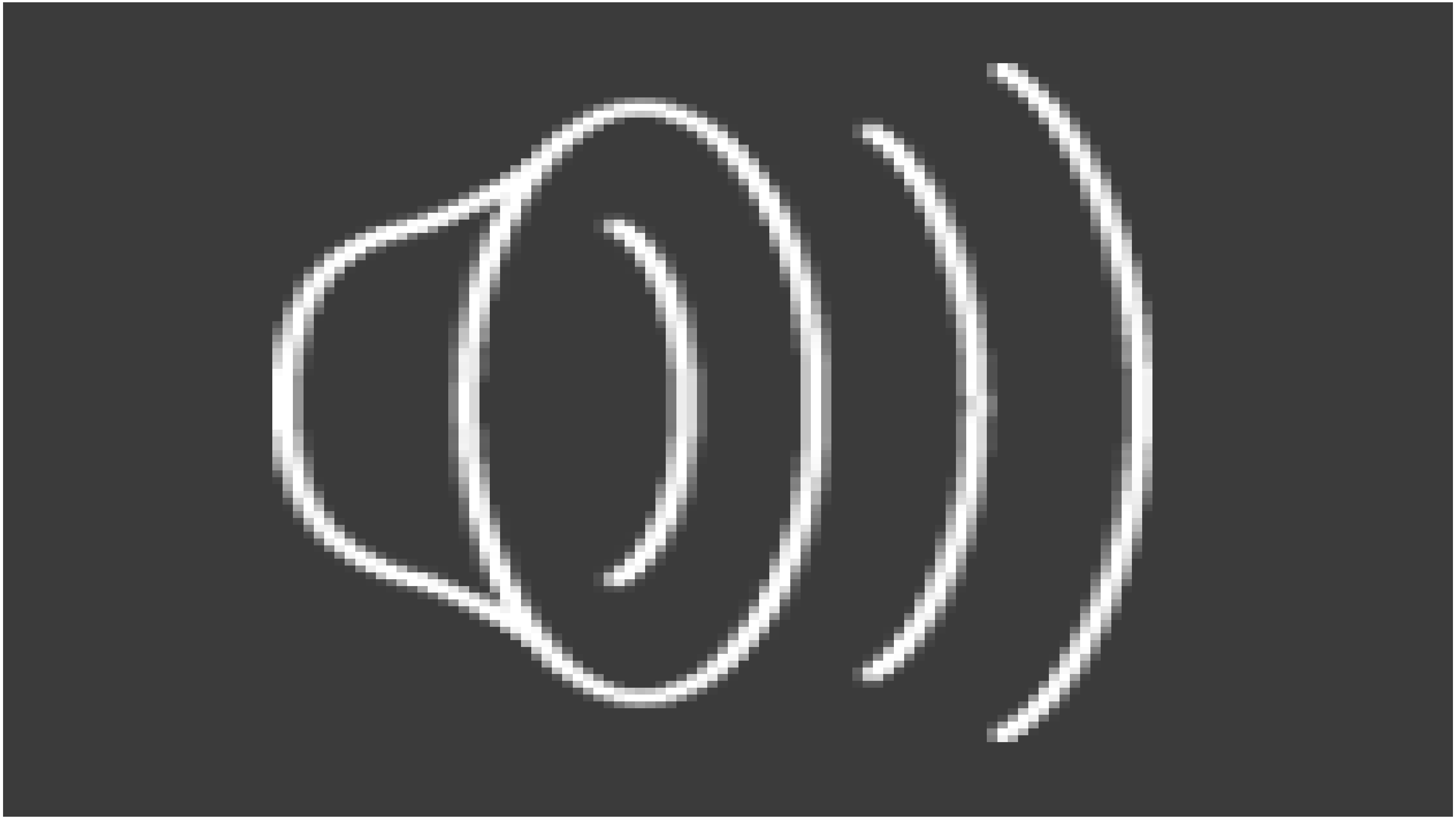




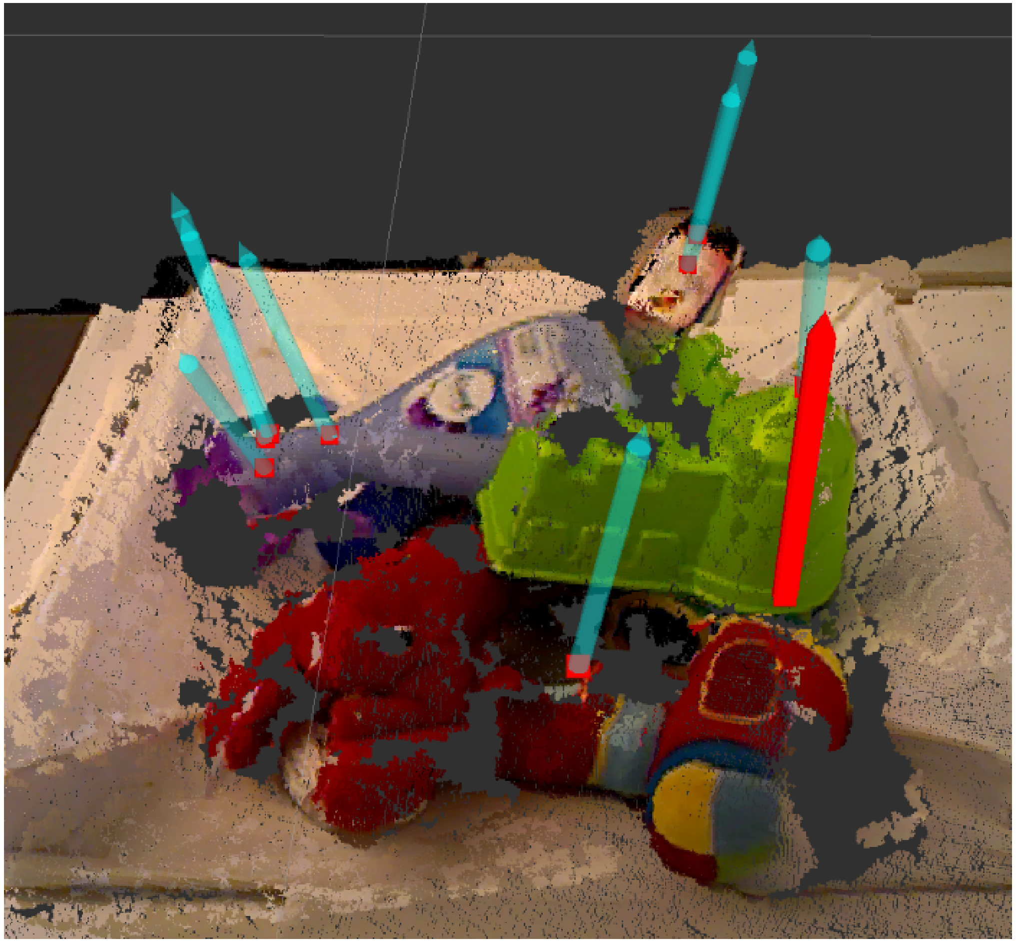
Results: Objects Presented in Isolation

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