

# Connecting 6D Object Pose Estimation with Robot Manipulation



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Assistant Professor

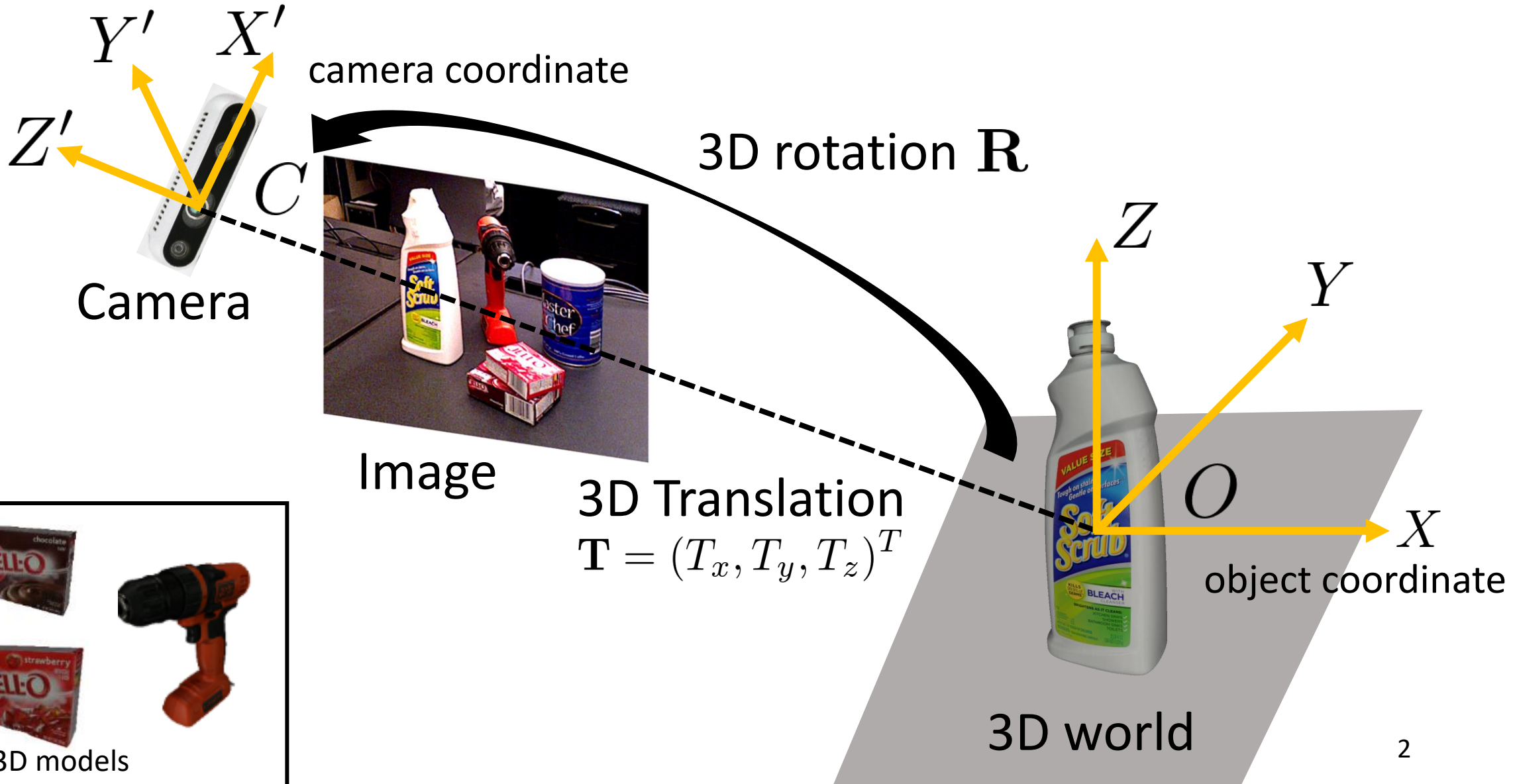
Computer Science

The University of Texas at Dallas

10/3/2023

8<sup>th</sup> International Workshop on Recovering 6D Object Pose @ ICCV 2023

# Model-based 6D Object Pose Estimation



# Model-based 6D Object Pose Estimation

- What information can be obtained from 6D object pose estimation?
  - Object position in camera frame  $\mathbf{T} = (T_x, T_y, T_z)^T$
  - Object orientation in camera frame  $\mathbf{R}$



Input image

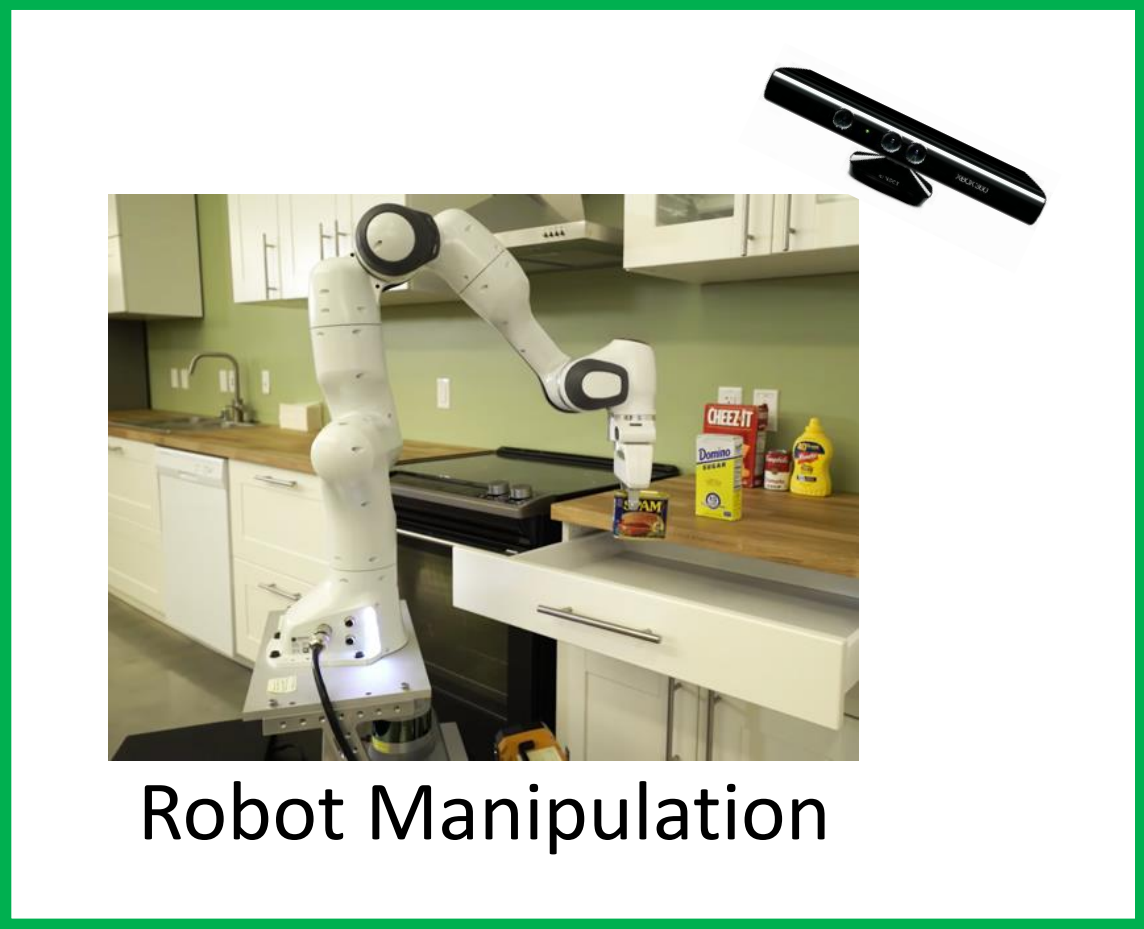


Point cloud and object axes in camera frame

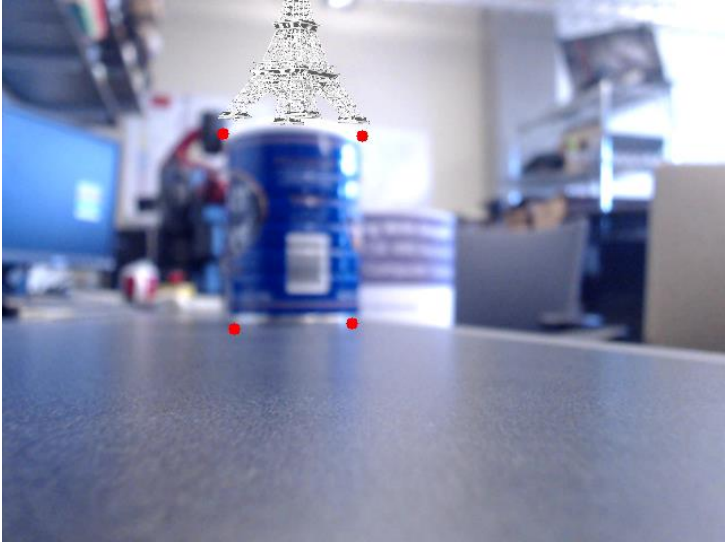


Projection of 3D models onto the input image

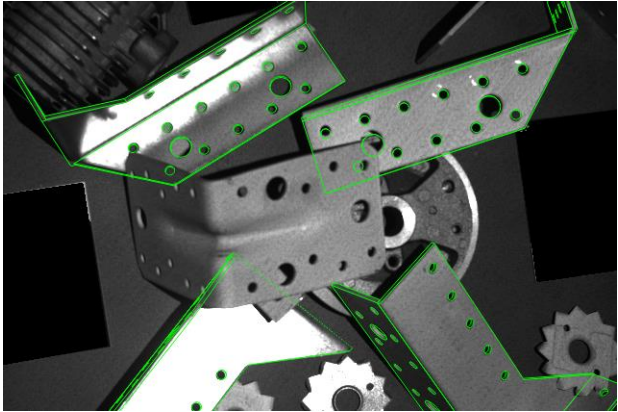
# Applications



Robot Manipulation



Augmented Reality



<https://www.mvtec.com/company/research/datasets/mvtec-itodd>

Industrial Object Inspection

# Model-Based Robot Manipulation

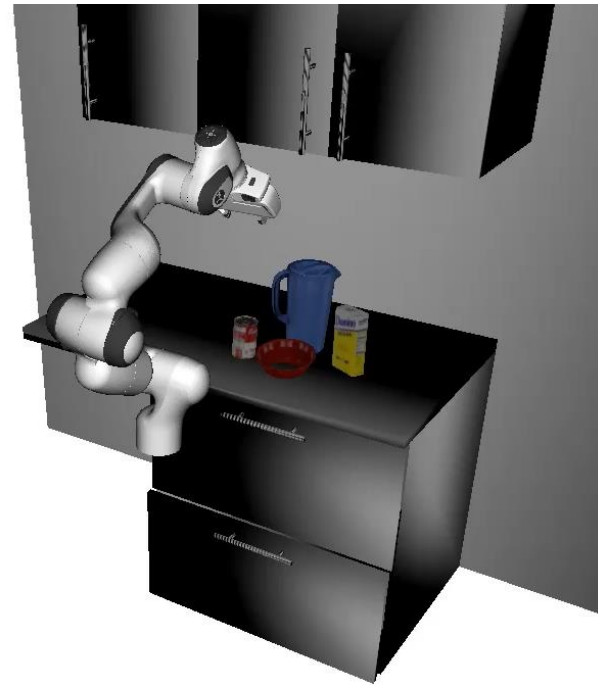
Perception

6D object pose estimation



Planning

Grasp planning and motion planning



Control

Manipulation trajectory following

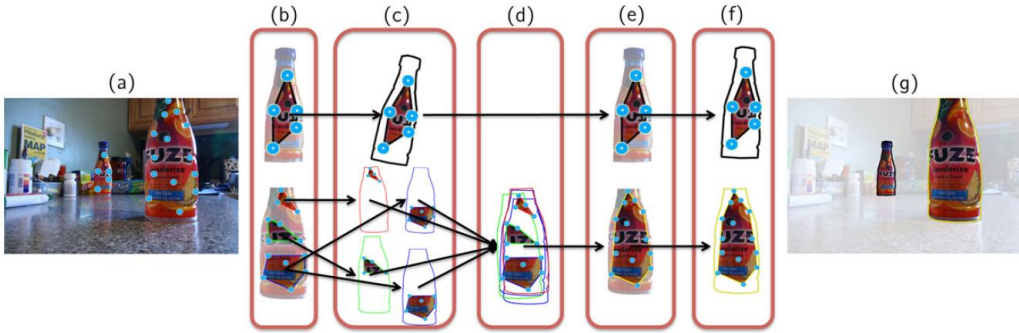


# Traditional Methods for 6D Object Pose Estimation

- Feature matching-based methods

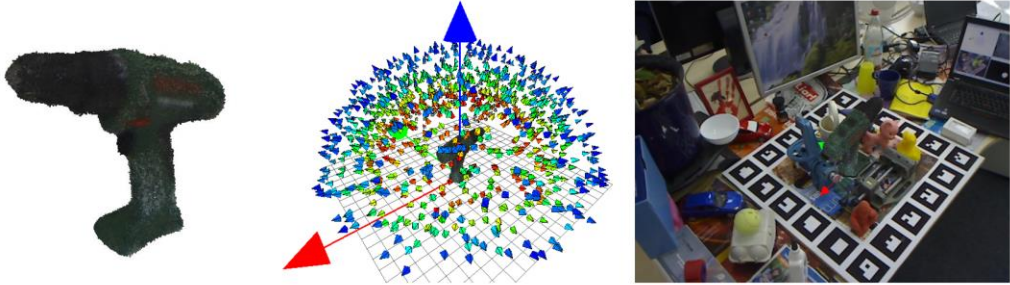


Rothganger-Lazebnik-Schmid-Ponce, IJCV'06

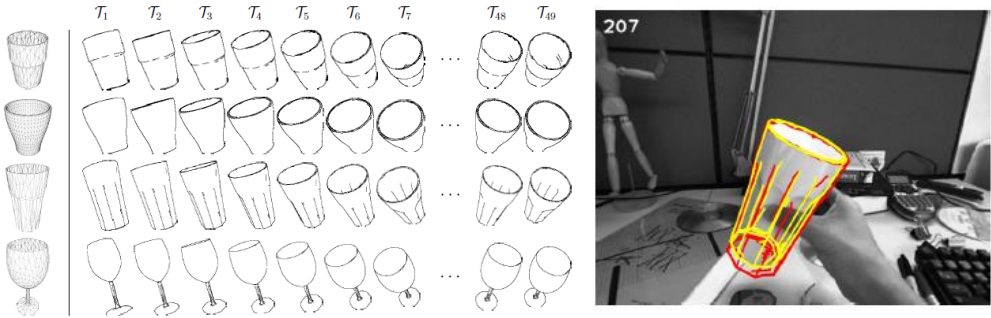


Collet-Martinez-Srinivasa, IJRR'11

- Template matching-based methods



Hinterstoisser-Lepetit-Ilic-Holzer-Bradski-Konolige-Navab, ACCV'12



Choi-Christensen, IROS'12

# PoseCNN: the First End-to-end 6D Pose Estimation Network

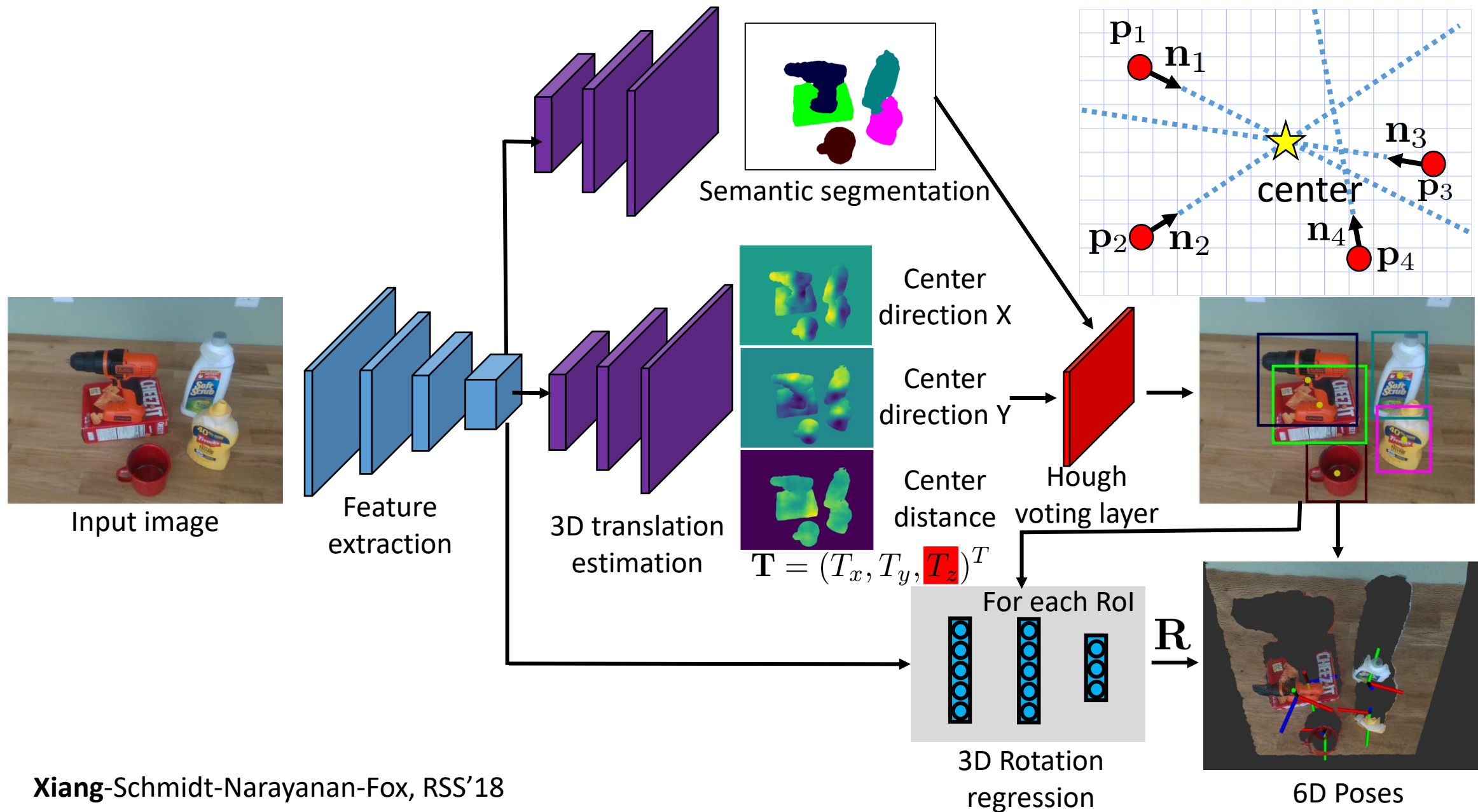


PoseCNN



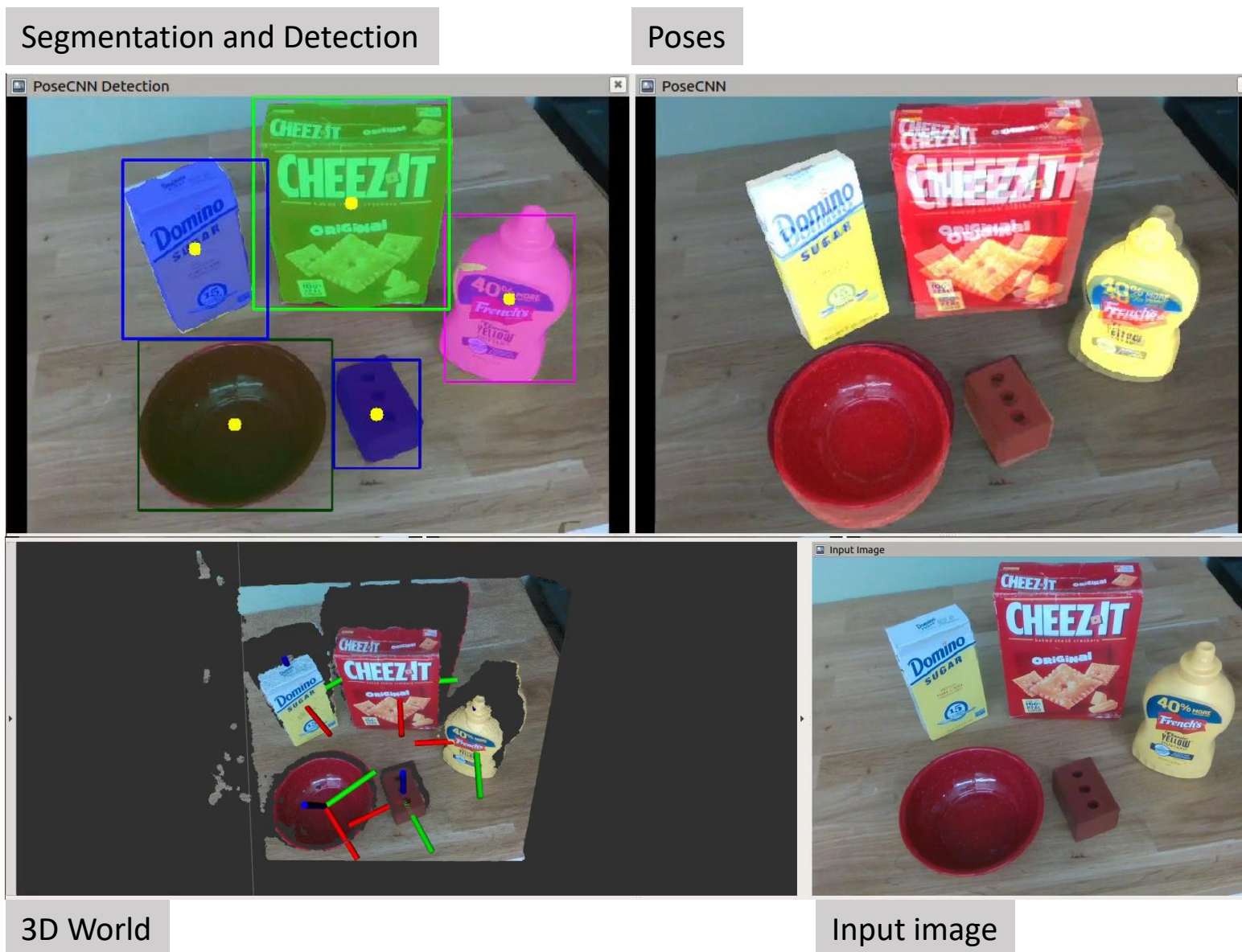
- ✓ Texture-less objects
- ✓ Symmetric objects
- ✓ Occlusions

# PoseCNN: the First End-to-end 6D Pose Estimation Network

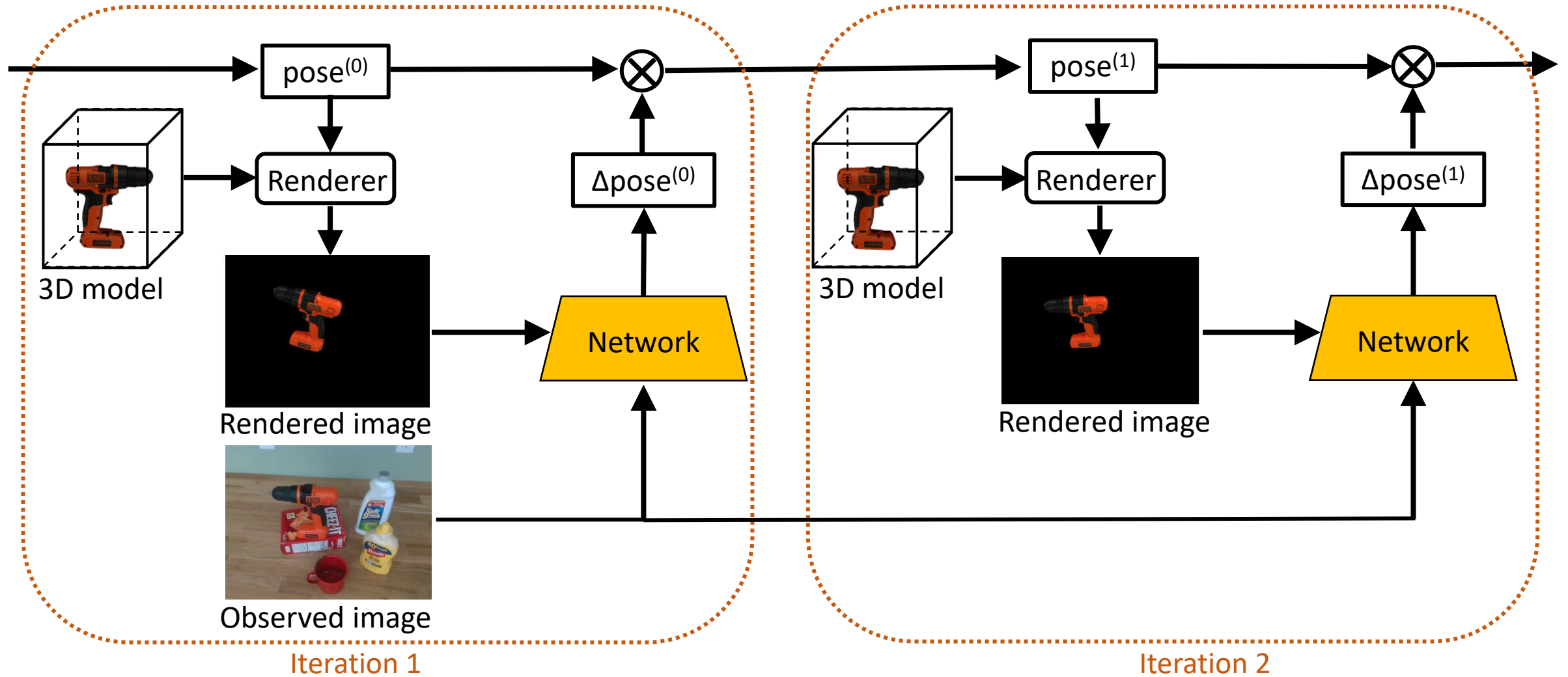




# PoseCNN: the First End-to-end 6D Pose Estimation Network



# DeepIM: Deep Iterative Matching for 6D Pose Estimation



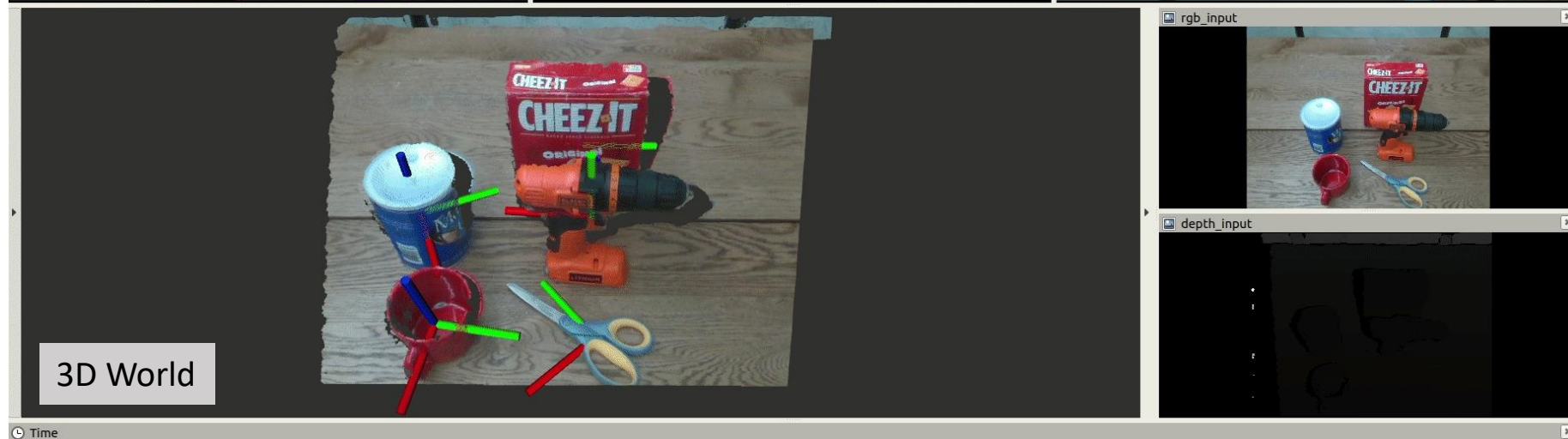
# DeepIM: Deep Iterative Matching for 6D Pose Estimation

Real World



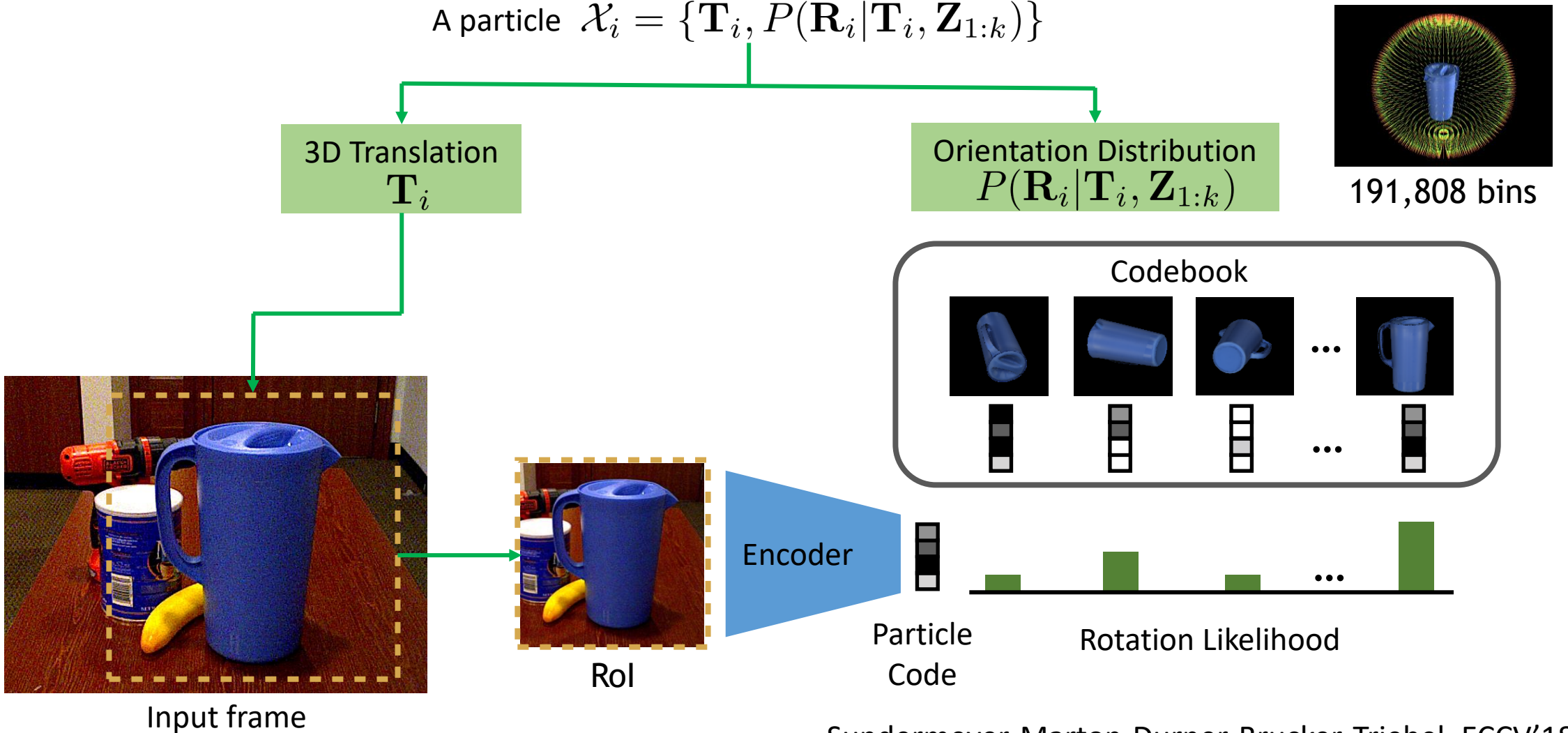
	RGB	
YCB Video	PoseCNN	PoseCNN+ DeepIM
Accuracy	75.9	<b>88.1</b>

	RGB-D	
YCB Video	PoseCNN+ ICP	PoseCNN+ DeepIM
Accuracy	93.0	<b>94.0</b>



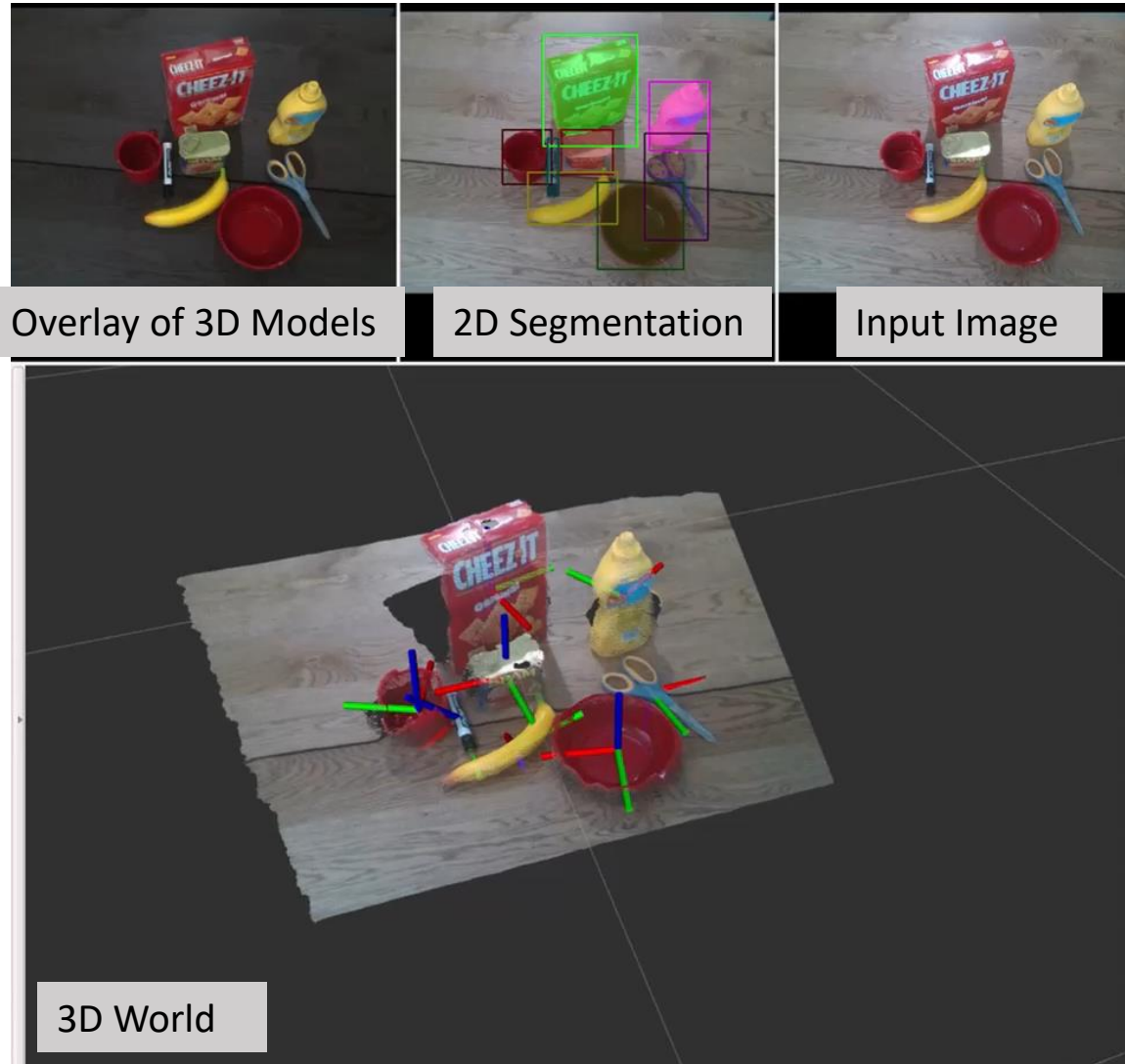
# PoseRBPF: A Rao-Blackwellized Particle Filter for 6D Object Pose Tracking

A particle  $\mathcal{X}_i = \{\mathbf{T}_i, P(\mathbf{R}_i | \mathbf{T}_i, \mathbf{Z}_{1:k})\}$

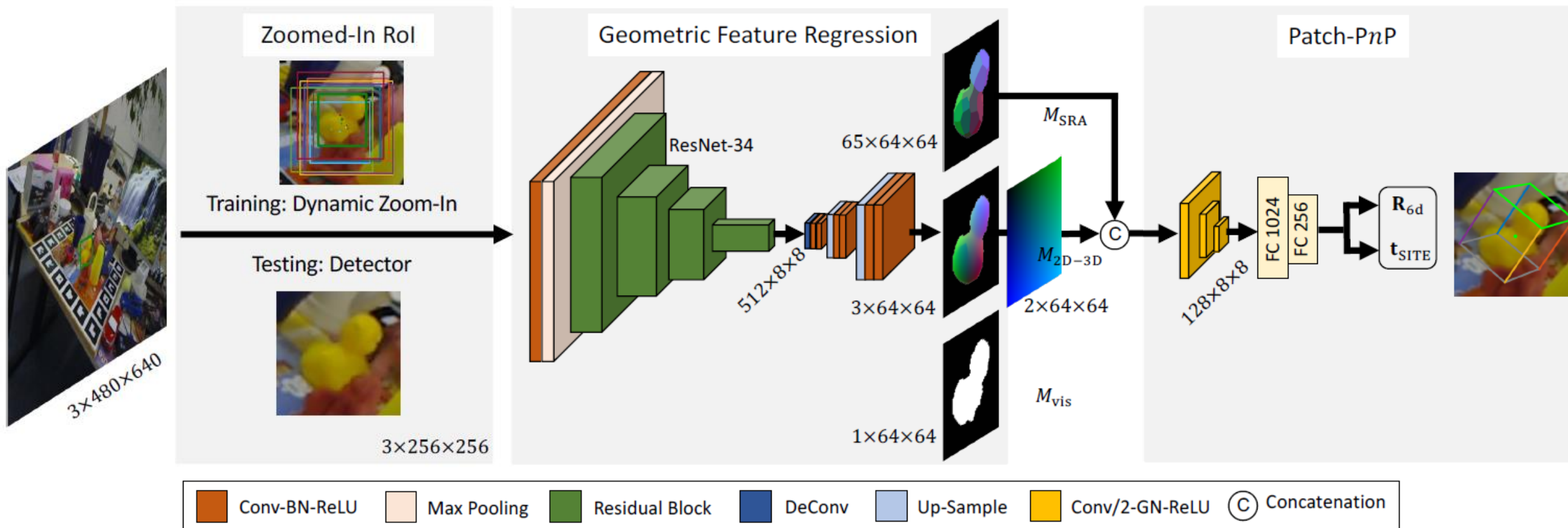


Sundermeyer-Marton-Durner-Brucker-Triebel, ECCV'18

# PoseRBPF: A Rao-Blackwellized Particle Filter for 6D Object Pose Tracking



# GDR-Net: Geometry-guided Direct Regression Network



Overall best method in the BOP Challenge 2022

G. Wang, F. Manhardt, F. Tombari, and X. Ji, GDR-Net: Geometry-guided direct regression network for monocular 6d object pose estimation, in CVPR, 2021.

# Model-Based Robot Manipulation

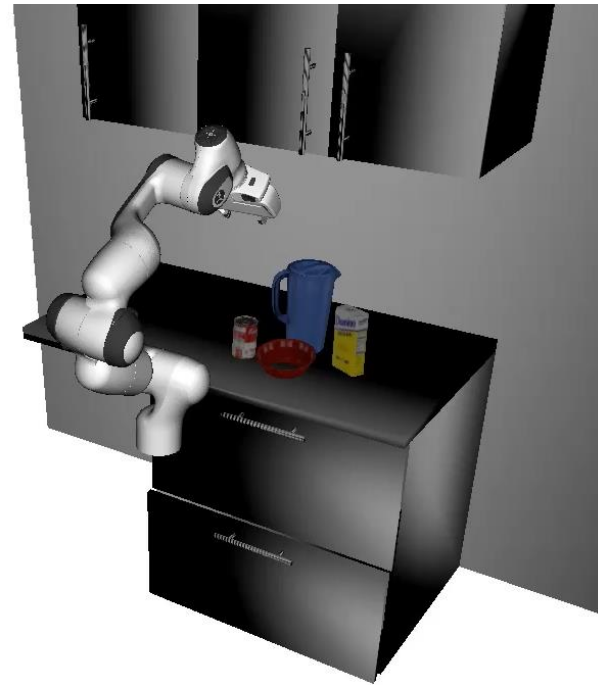
Perception

6D object pose estimation



Planning

Grasp planning and motion planning

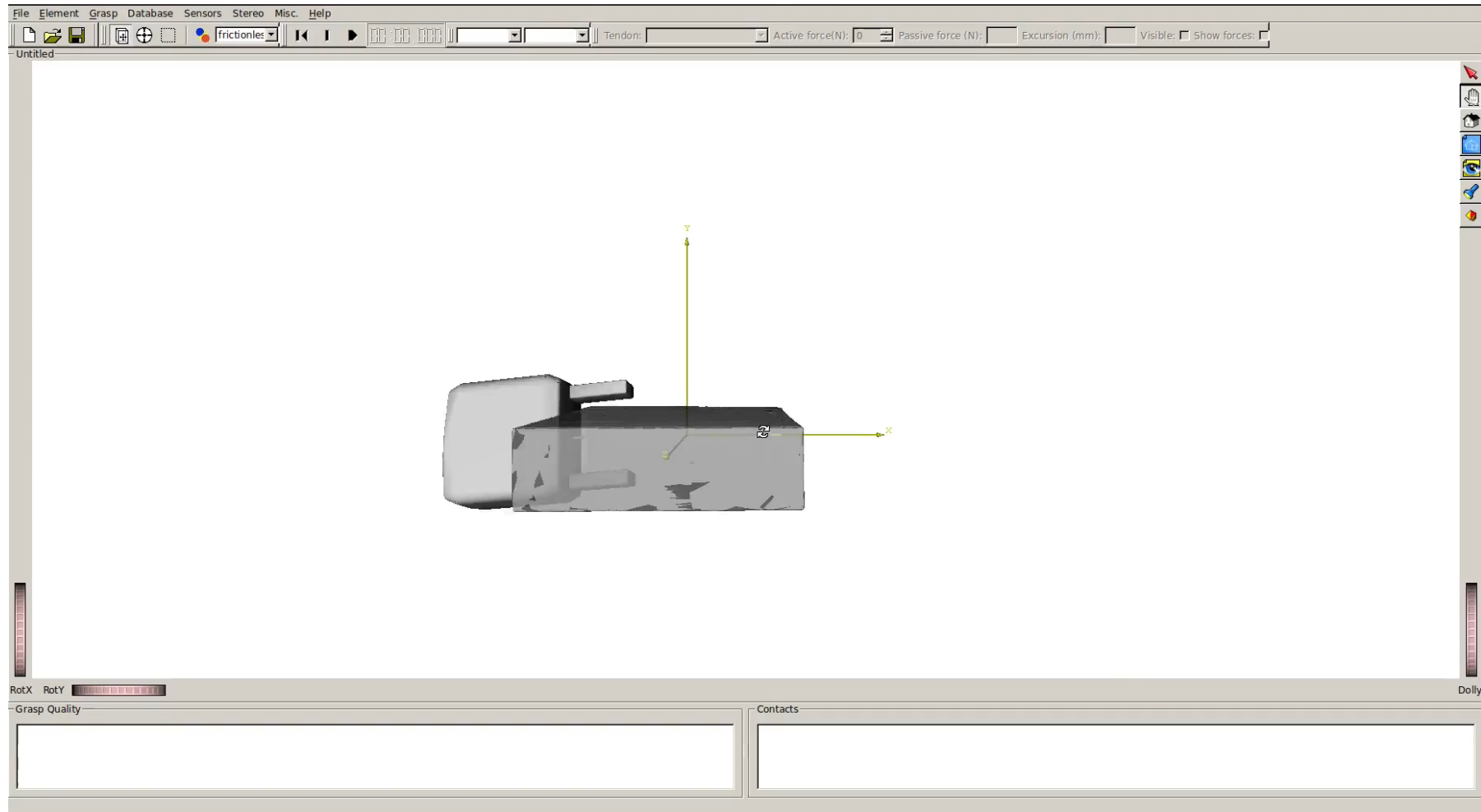


Control

Manipulation trajectory following



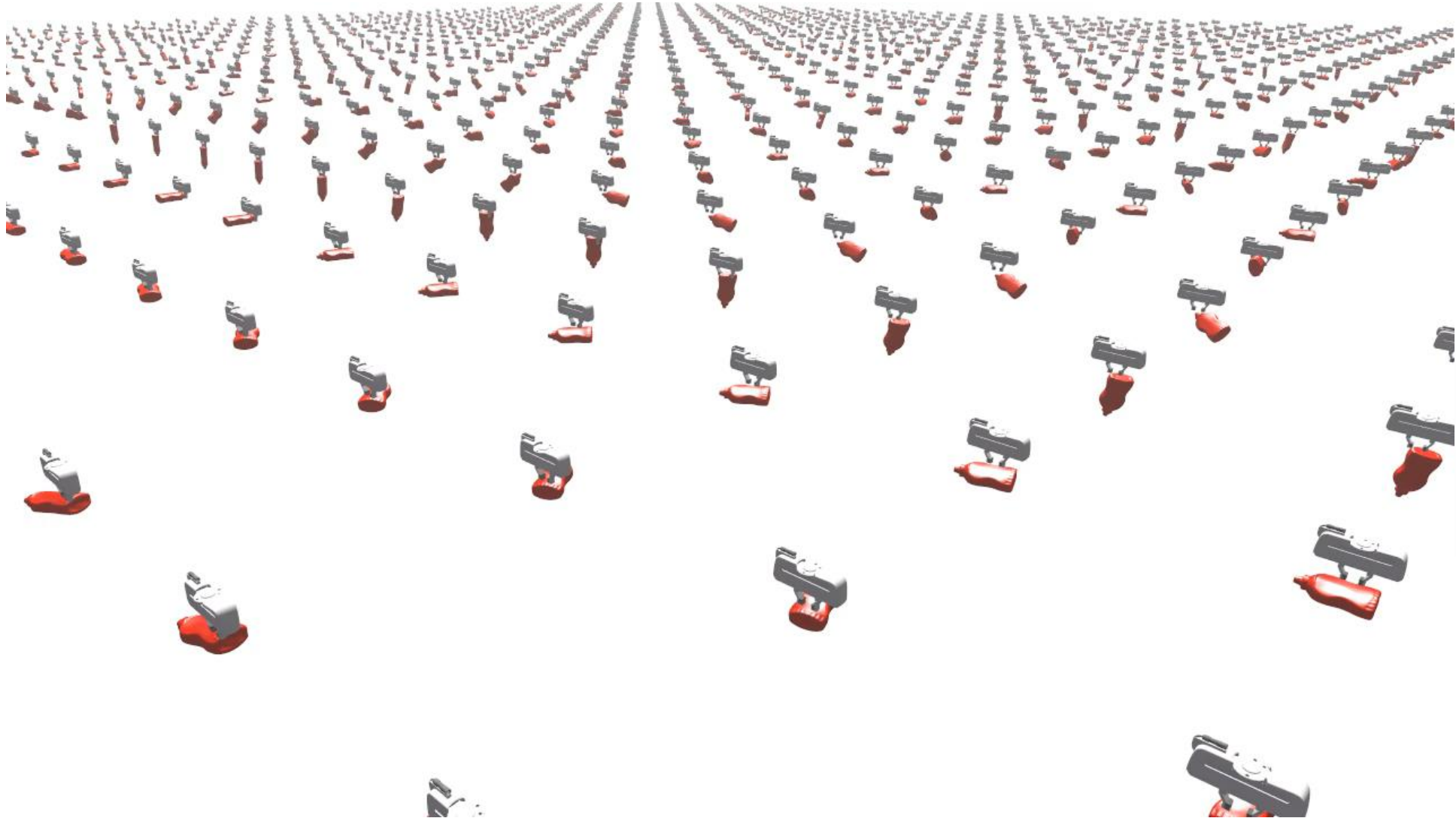
# Grasp Planning: GraspIt!



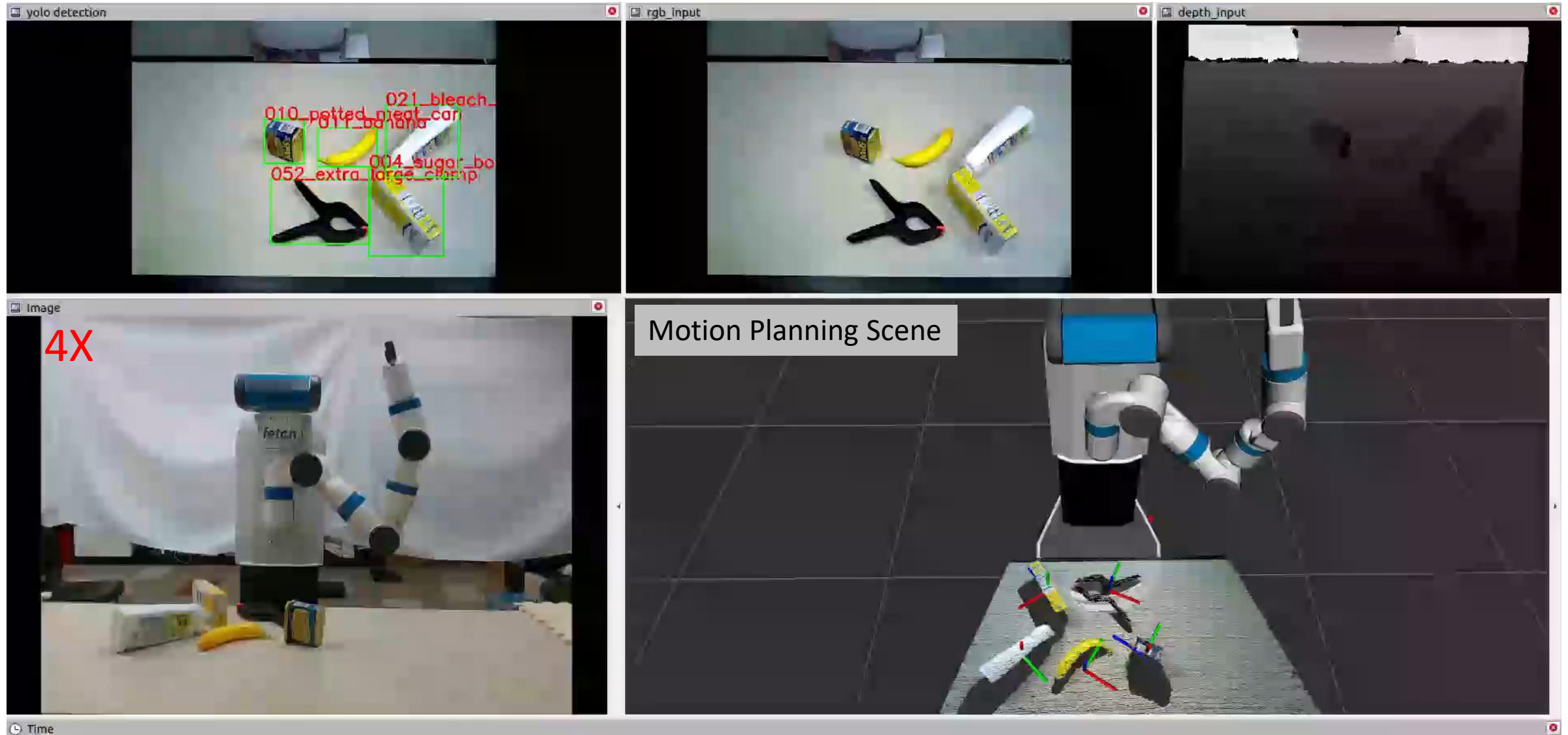
GraspIt! <https://graspit-simulator.github.io/>



# Grasp Planning: A Physics-based Approach



# Motion Planning



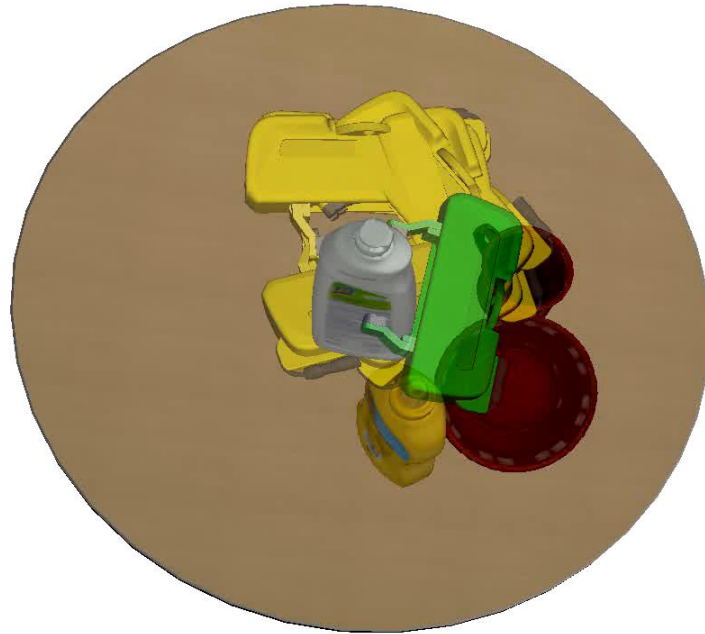
The Open Motion Planning Library in MoveIt

<https://ompl.kavrakilab.org/index.html>

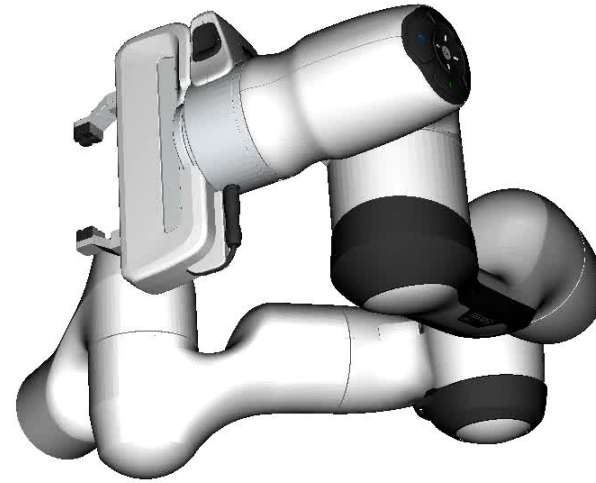
# OMG Planner: Trajectory Optimization and Grasp Selection

OMG Iter: 50

100 grasps



Modeling the goal set distribution



[Code available online](#)

# Model-Based Robot Manipulation

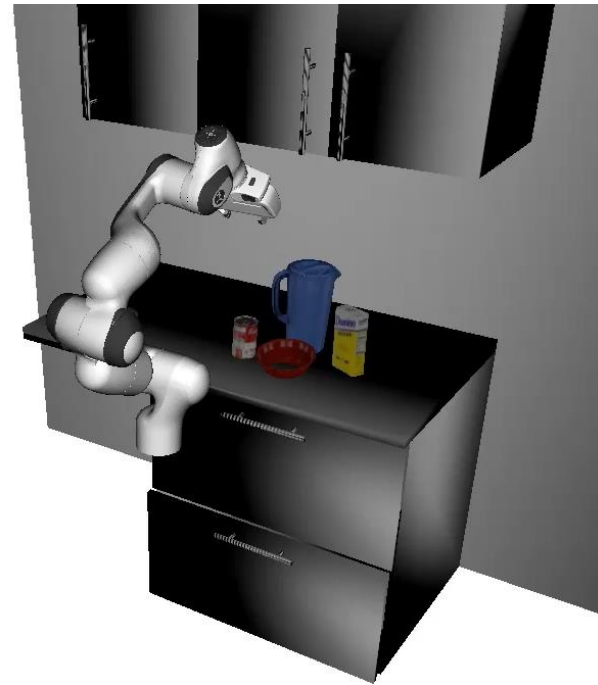
Perception

6D object pose estimation



Planning

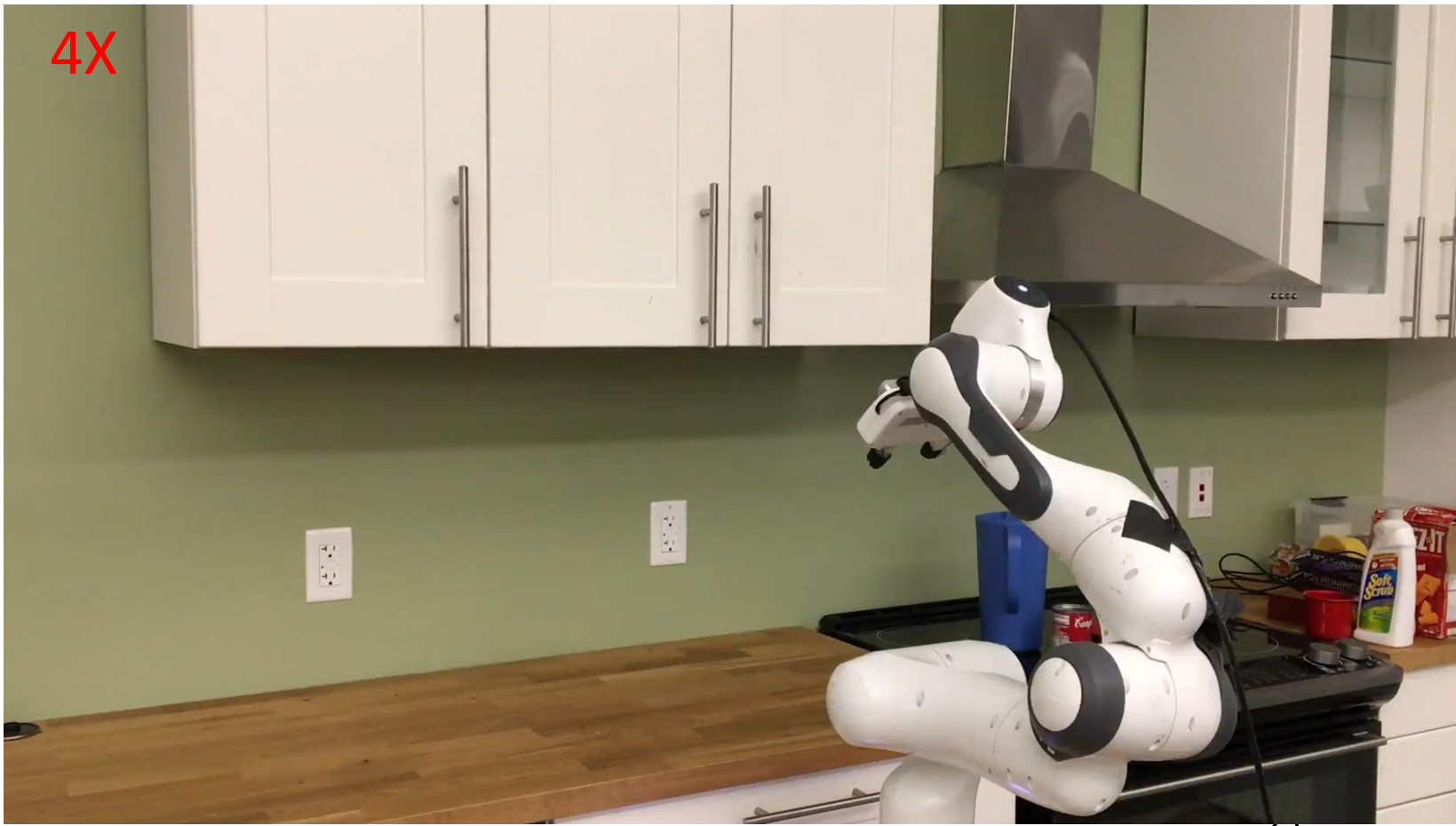
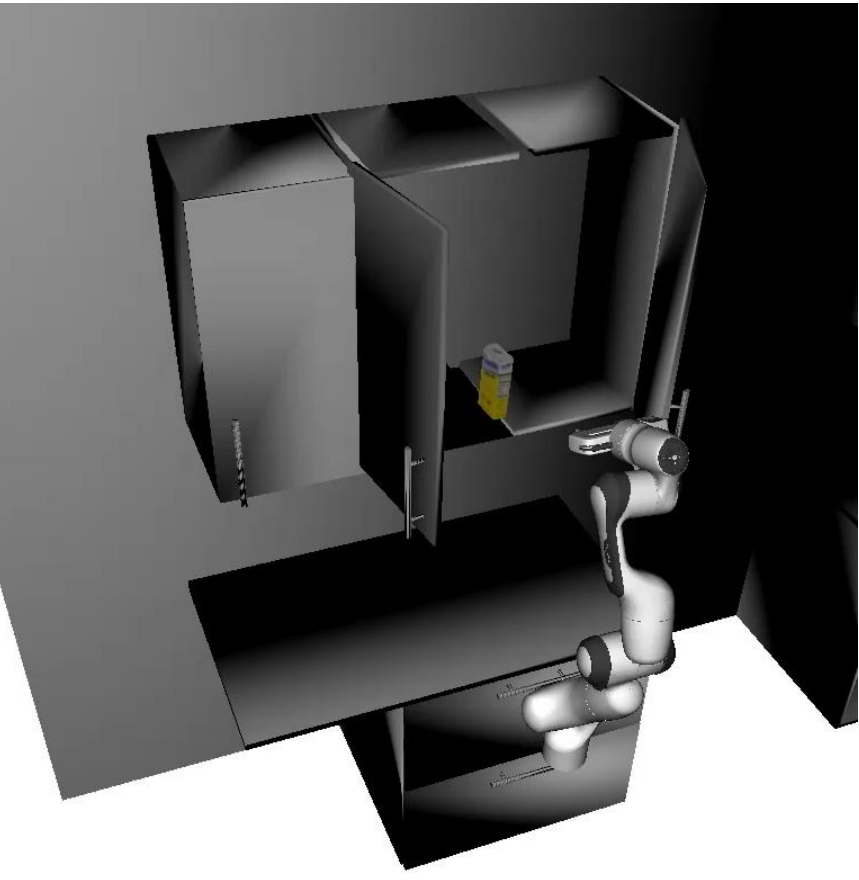
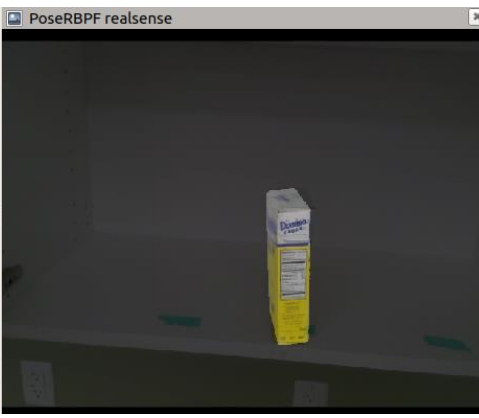
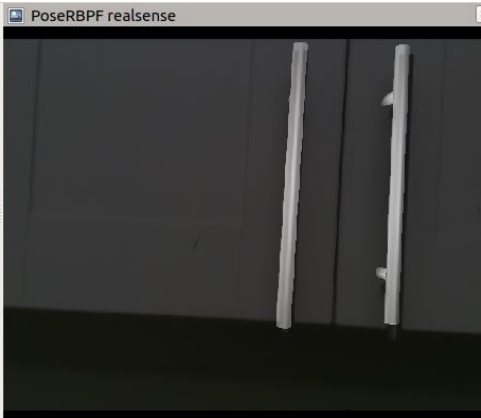
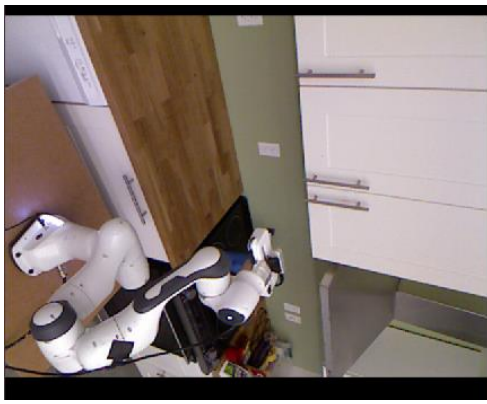
Grasp planning and motion planning



Control

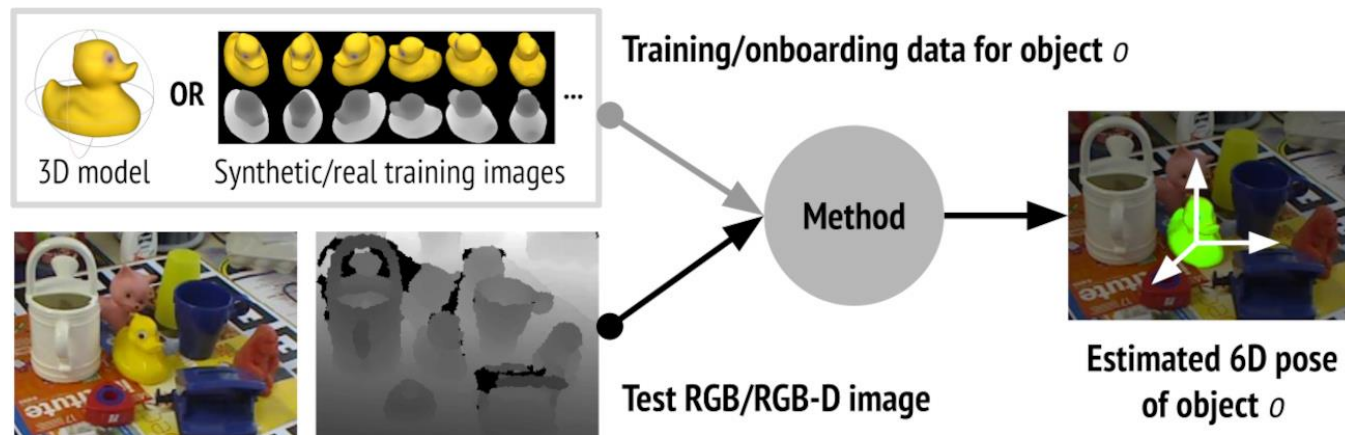
Manipulation trajectory following





# Benchmarking

- 6D object pose
  - BOP: Benchmark for 6D object pose estimation <https://bop.felk.cvut.cz/home/>



Datasets: [Core datasets](#) [LM](#) [LM-O](#) [T-LESS](#) [ITODD](#) [HB](#) [HOPE](#) [YCB-V](#) [RU-APC](#) [IC-BIN](#) [IC-MI](#) [TUD-L](#) [TYO-L](#)

## 6D localization of seen objects – Core datasets

This leaderbord shows the overall ranking for [Task 1](#) on the [core datasets](#) (LM-O, T-LESS, TUD-L, IC-BIN, ITODD, HB, YCB-V). For each method, the date of the latest considered submission is reported. If more submissions of a method are available for a dataset, the submission with the highest  $AR_{Core}$  score is considered. The reported time is the average image processing time averaged over the core datasets.

Show  entries

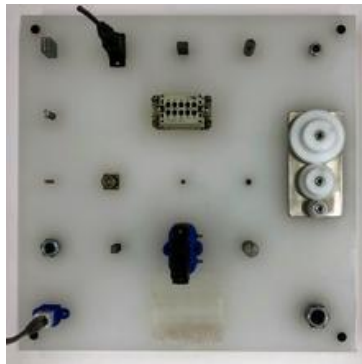
Search:

	Date (UTC) ⚡	Method	Test image ⚡	$AR_{Core}$ ⚡	$AR_{LM-O}$ ⚡	$AR_{T-LESS}$ ⚡	$AR_{TUD-L}$ ⚡	$AR_{IC-BIN}$ ⚡	$AR_{ITODD}$ ⚡	$AR_{HB}$ ⚡	$AR_{YCB-V}$ ⚡	Time (s) ⚡
1	2023-09-24	<a href="#">GPose2023-OfficialDet</a>	RGB-D	0.851	0.805	0.895	0.966	0.734	0.687	0.944	0.929	4.575
2	2022-10-15	<a href="#">GDRNPP-PBRReal-RGBD-MModel</a>	RGB-D	0.837	0.775	0.874	0.966	0.722	0.679	0.926	0.921	6.263

# Benchmarking

- Robot manipulation

Benchmark	Type	Task	Objects	AR Tag-Free	Scene Reproducibility
Meta-World [11]	Simulation	50 tasks	Synthetic	✓	✓
RLBench [12]	Simulation	100 Tasks	Synthetic	✓	✓
robosuite [13]	Simulation	9 Tasks	Synthetic	✓	✓
Grasp Planning Protocol [10]	Real	Grasp Planning	YCB (single)	✓	✗
NIST Assembly [7]	Real	Assembly	Task Boards	✓	✓
FurnitureBench [14]	Real	Assembly	3D Printing	✗	✓
GRASPA [8]	Real	Grasping	YCB (clutter)	✗	✓
OCRTOC [15]	Real	Rearrangement	YCB + Others	✓	✗
RB2 [16]	Real	Pouring, Scooping, Zipping, Insertion	Others	✓	✗
Box and Blocks Test [17]	Real	Pick-and-Place	Blocks	✓	✗
<b>SceneReplica (Ours)</b>	Real	Pick-and-Place	YCB (clutter)	✓	✓



NIST Assembly board



FurnitureBench



GRASPA



SceneReplica

# SceneReplica for Real-World Robot Manipulation

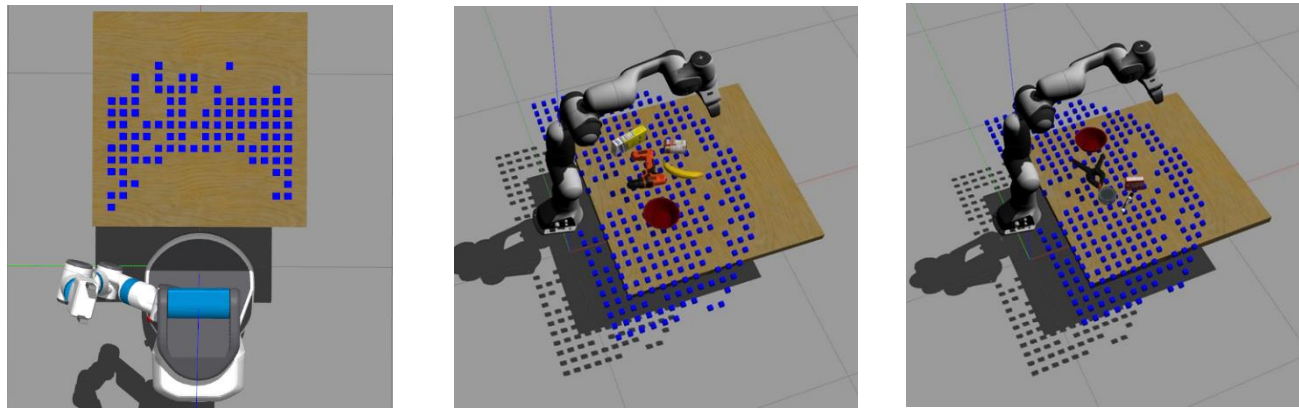
- 16 YCB objects



- Stable poses



- Reachability testing in simulation







# Real-World Scene Setup



Reference Image

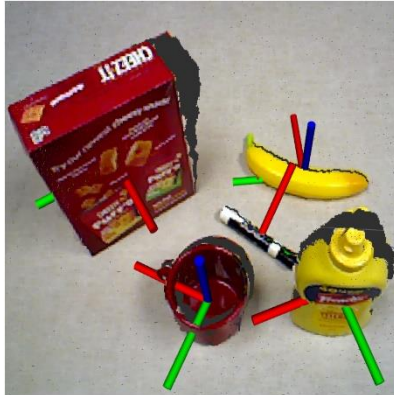


Real World Setup

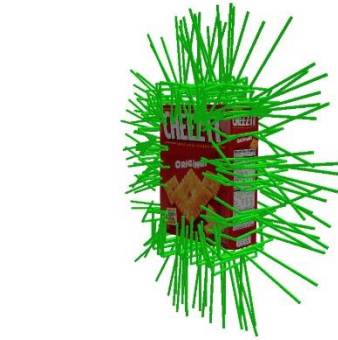
# Model-based Grasping vs Model-free Grasping



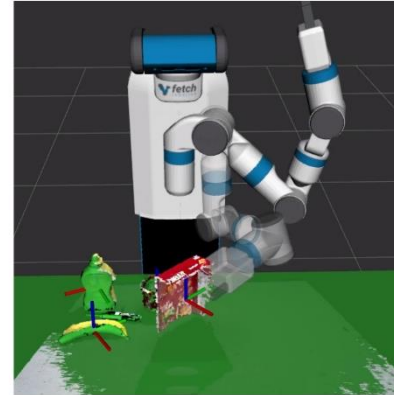
Input real world scene



6D Pose Estimation



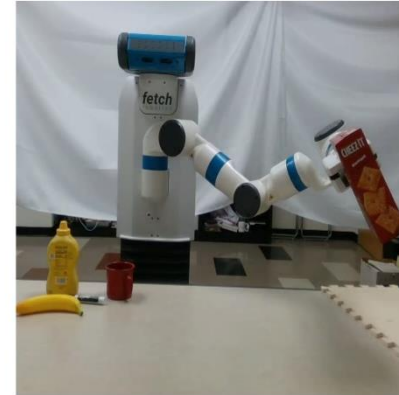
Offline Grasp Database



Motion Planning Setup



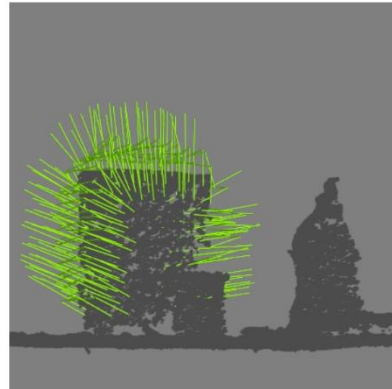
Grasping & Lifting



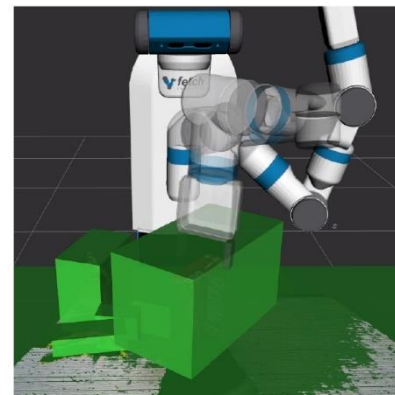
Moving arm for Dropoff



Unseen Object Segmentation



Model-free Grasp Planning



Motion Planning Setup



Grasping & Lifting

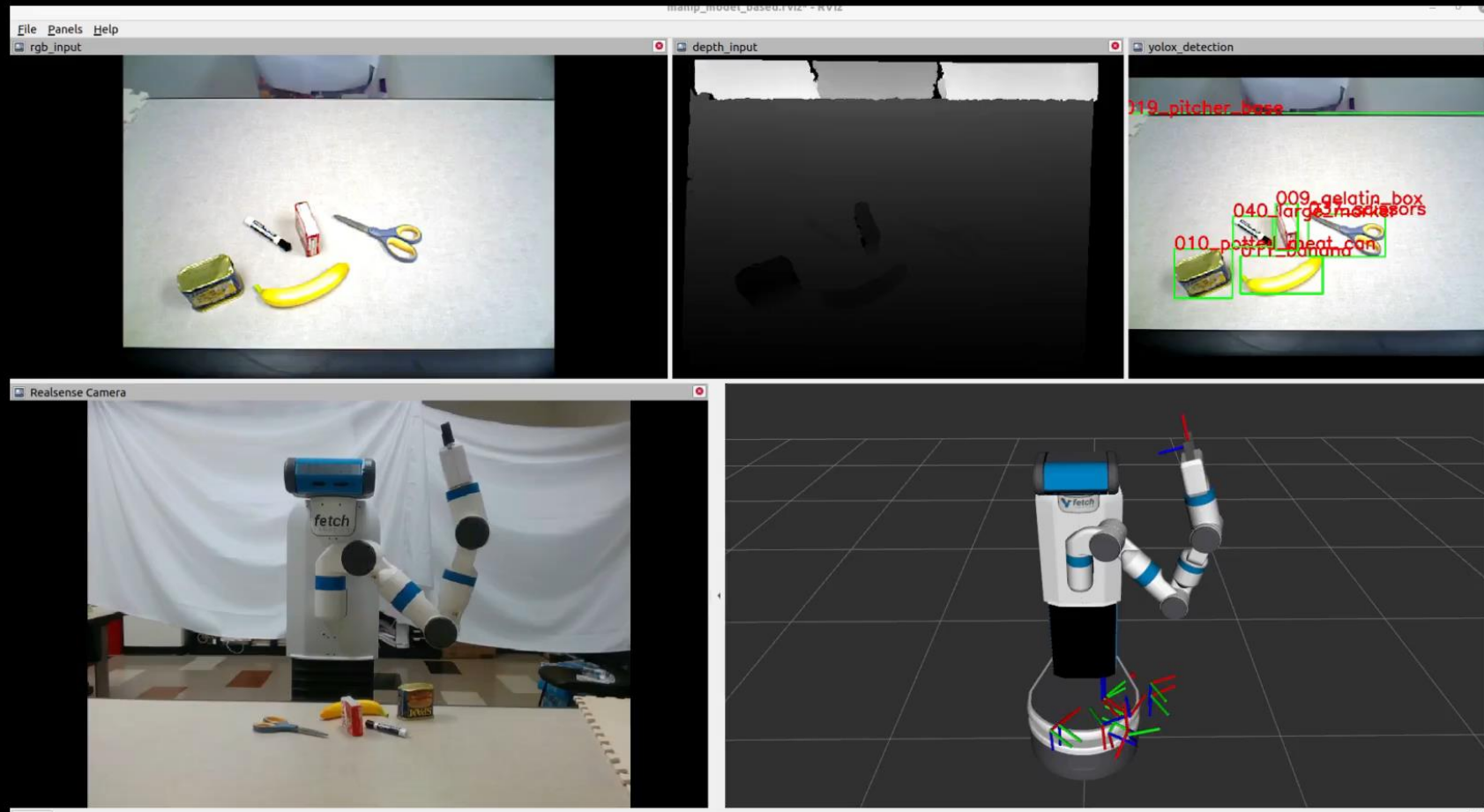


Moving arm for Dropoff

# Model-based Grasping Example

[8X] SceneReplica Benchmark

GDRNPP | Graspit + Top Down | MoveIt



Realsense Capture Scene: 148 | Order: Random Rviz Capture

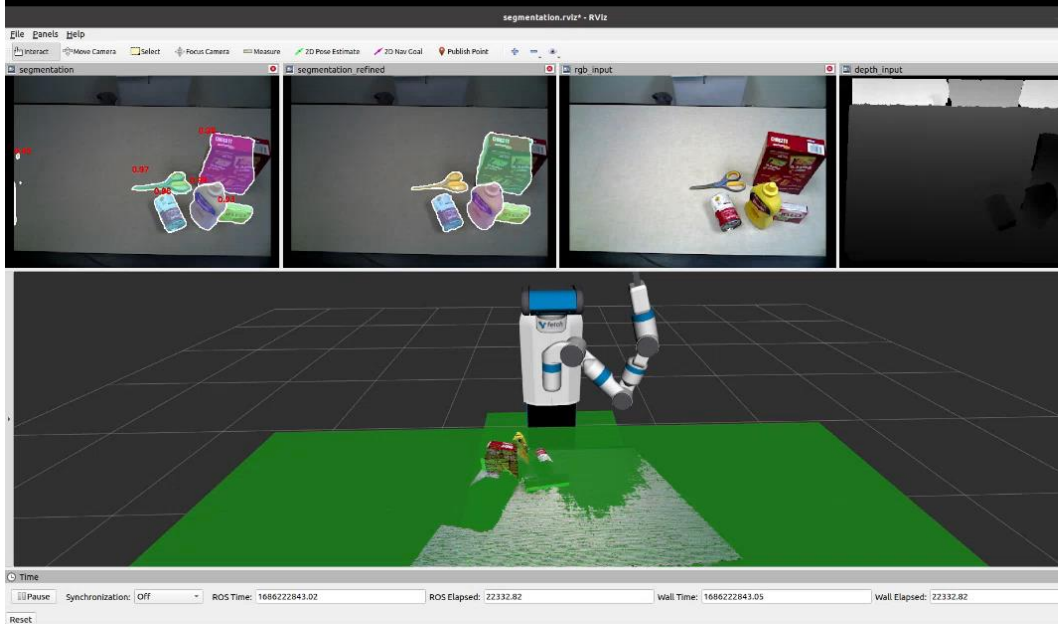
# Model-free Grasping Example

8X

SceneReplica Benchmark

MSMFormer | Contact GraspNet + Top Down | MoveIt

Scene: 130 | Order: Random

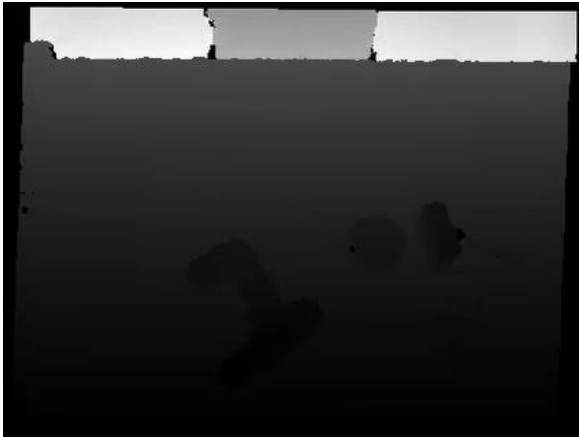


Rviz Capture

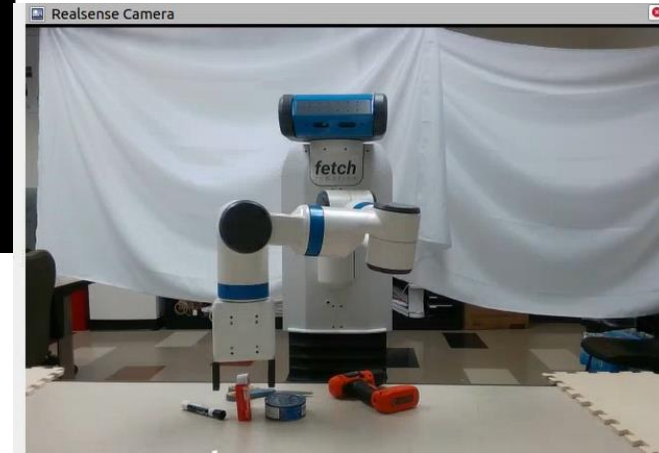
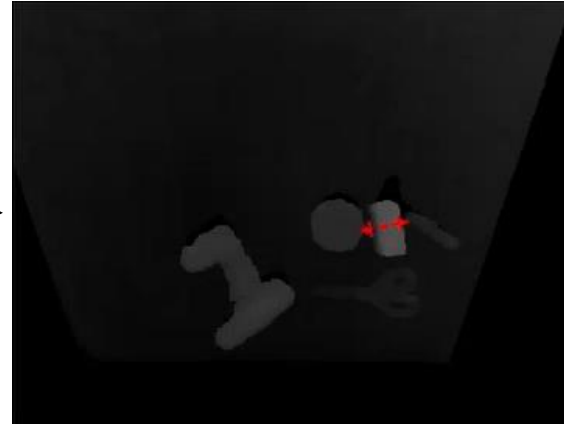


Realsense Capture

# End-to-end Learning-based Grasping

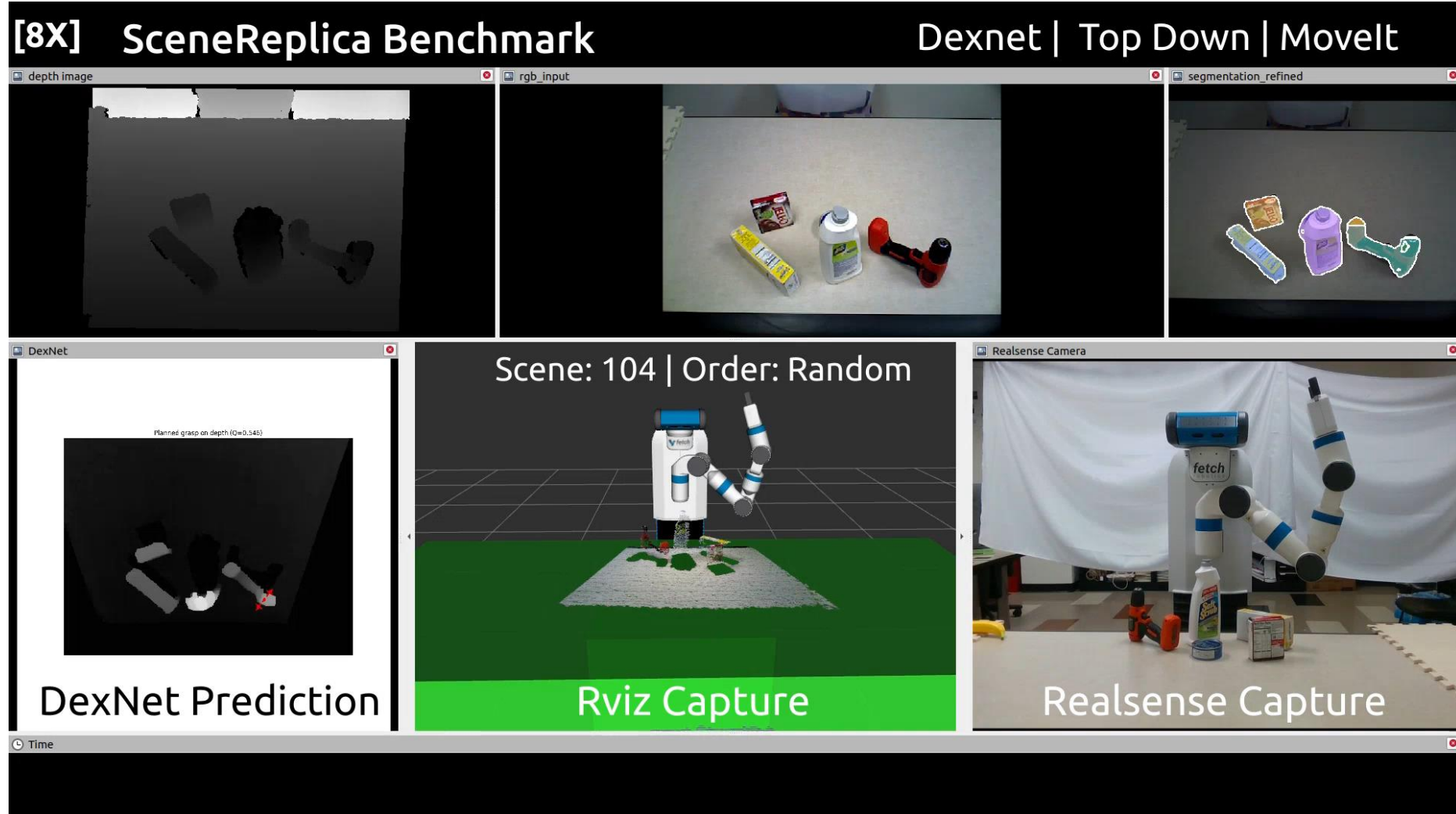


Dex-Net 2.0



J. Mahler, J. Liang, S. Niyaz, M. Laskey, R. Doan, X. Liu, J. A. Ojea, and K. Goldberg, "Dex-net 2.0: Deep learning to plan robust grasps with synthetic point clouds and analytic grasp metrics", arXiv preprint arXiv:1703.09312, 2017.

# Dex-Net 2.0 Grasping Example



# Current Leaderboard

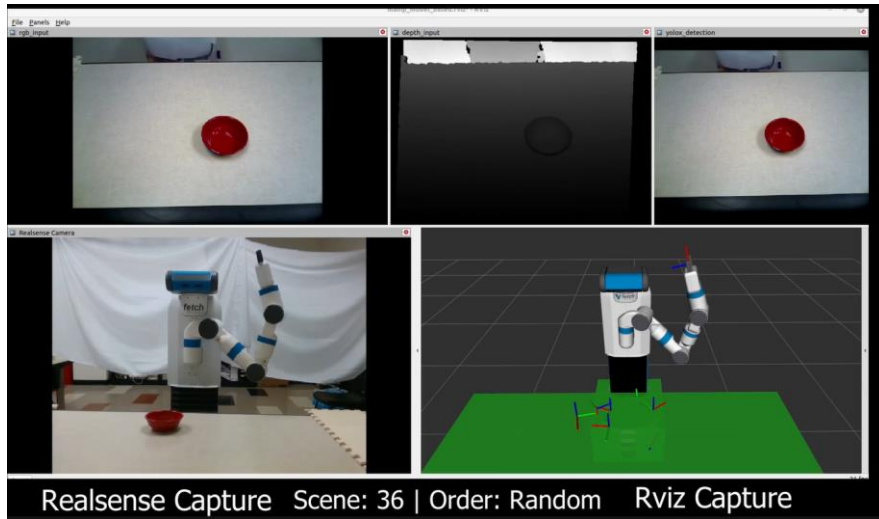
Overall best method in the BOP Challenge 2022

#	Perception	Grasp Planning	Motion Planning	Control	Ordering	Grasping Type	Pick & Place Success 🚩	Grasping Success	Videos
3	GDRNPP [9]	GraspIt! [2] + Top-Down	OMPL [3]	MoveIt	Near-to-Far	Model-Based	66/100	69/100	<a href="#">🔗</a>
3	GDRNPP [9]	GraspIt! [2] + Top-Down	OMPL [3]	MoveIt	Fixed Random	Model-Based	62/100	64/100	<a href="#">🔗</a>
7	MSMFormer [8]	Contact-graspnet [7] + Top-Down	OMPL [3]	MoveIt	Fixed Random	Model-Free	61/100	70/100	<a href="#">🔗</a>
5	UCN [5]	Contact-graspnet [7] + Top-Down	OMPL [3]	MoveIt	Near-to-Far	Model-Free	60/100	63/100	<a href="#">🔗</a>
5	UCN [5]	Contact-graspnet [7] + Top-Down	OMPL [3]	MoveIt	Fixed Random	Model-Free	60/100	64/100	<a href="#">🔗</a>
1	PoseRBPF [1]	GraspIt! [2] + Top-Down	OMPL [3]	MoveIt	Fixed Random	Model-Based	59/100	59/100	<a href="#">🔗</a>
1	PoseRBPF [1]	GraspIt! [2] + Top-Down	OMPL [3]	MoveIt	Near-to-Far	Model-Based	58/100	64/100	<a href="#">🔗</a>

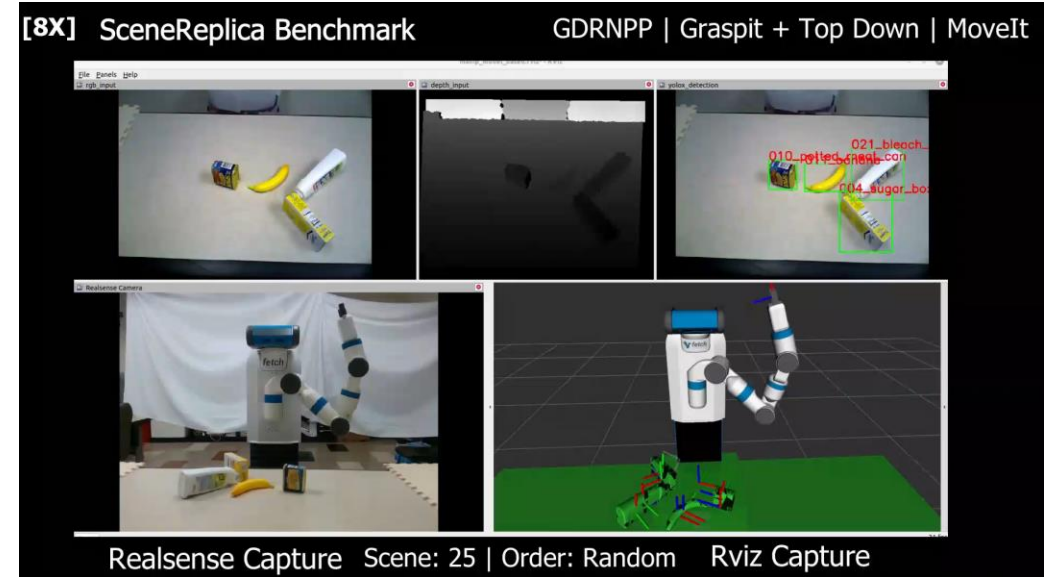
<https://irvlutd.github.io/SceneReplica/>



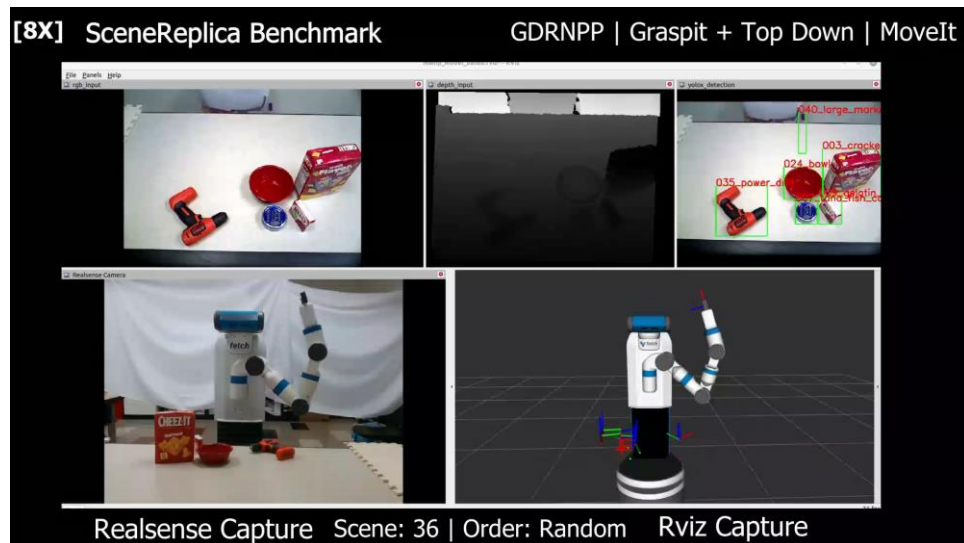
# Failure Analysis (GDRNPP + Graspl! + Top-Down)



Object Detection Error



Grasp Planning Error



Pose Estimation Error

Object	Method 3			
	S	$P_{EF}$	$P_{LF}$	EF
003 cracker box	3	2	1	-
004 sugar box	5	-	-	-
005 tomato soup can	5	1	-	1
006 mustard bottle	7	-	-	-
007 tuna fish can	1	5	-	-
008 pudding box	5	-	-	-
009 gelatin box	6	-	1	-
010 potted meat can	7	-	-	-
011 banana	6	-	1	-
021 bleach cleanser	3	1	-	1
024 bowl	2	4	1	-
025 mug	4	-	1	-
037 scissors	4	3	-	-
035 power drill	1	3	2	1
040 large marker	2	4	-	-
052 extra large clamp	5	1	-	-
ALL	66	24	7	3

$P_{EF}$ : #perception failure

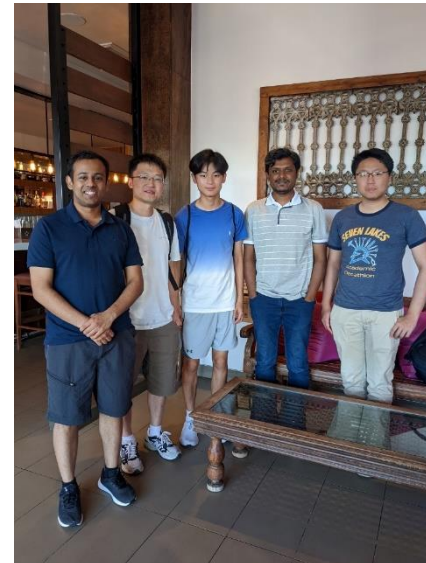
$P_{LF}$ : #planning failure

EF: #execution failure

# Conclusion



- 6D object pose estimation can facilitate robot manipulation
- The performance of 6D object pose estimation is not saturated yet
- Connecting BOP and SceneReplica to evaluate object pose estimation and robot grasping in the real world



Thank you!