Perceive, Plan and Act: Building Intelligent Robots in Human Environments

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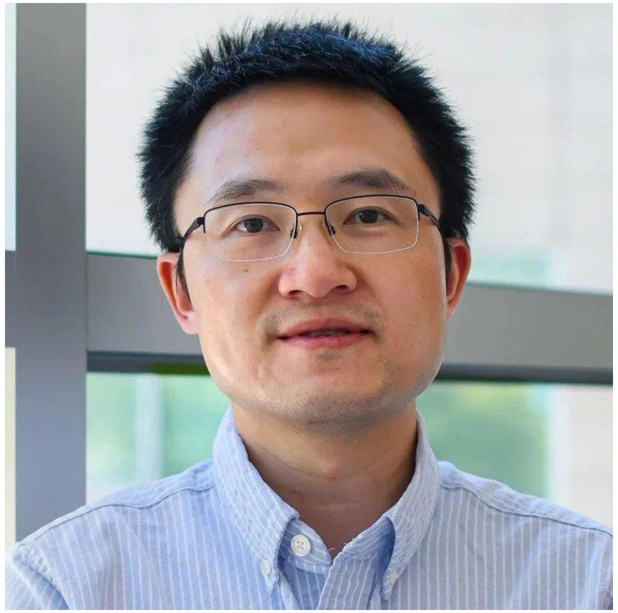
2/12/2025

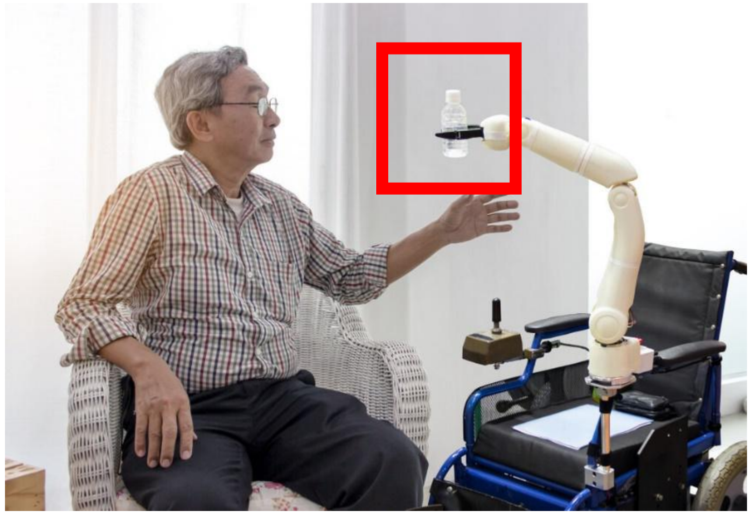
Who am I?



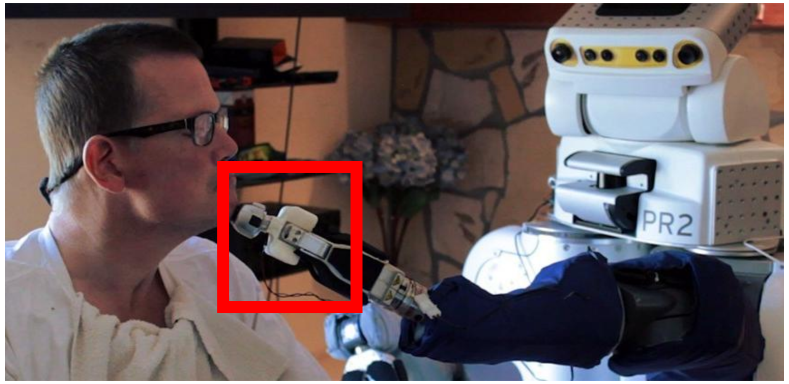
- Assistant Professor in CS at UTD (joined Fall 2021)
- Intelligent Robotics and Vision Lab at UTD
https://labs.utdallas.edu/irvl/
- Senior Research Scientist at NVIDIA (2018 – 2021) Robotics
- Ph.D. University of Michigan at Ann Arbor 2016

Future Intelligent Robots in Human Environments

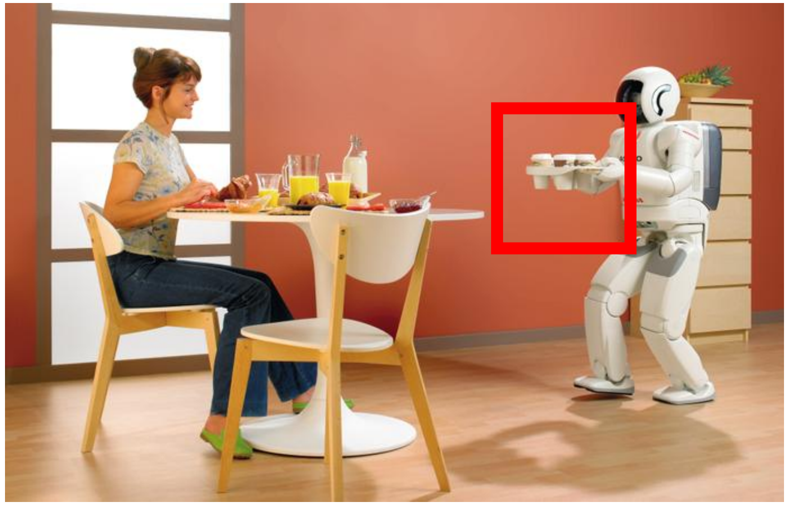
Manipulation



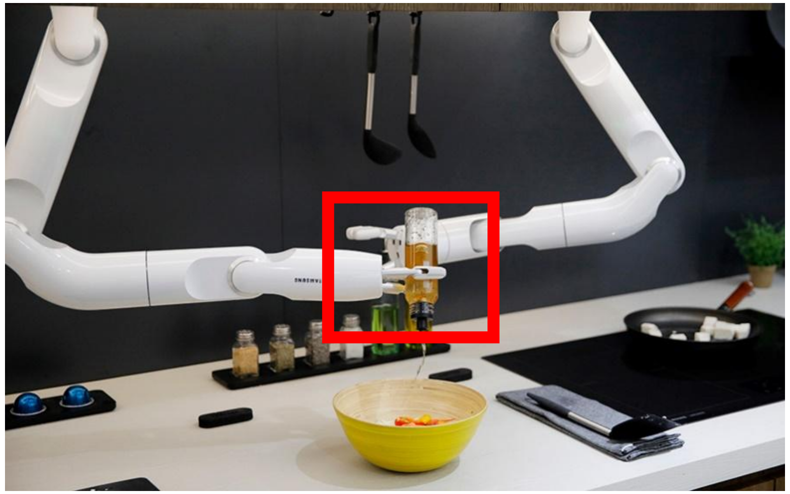
Senior Care



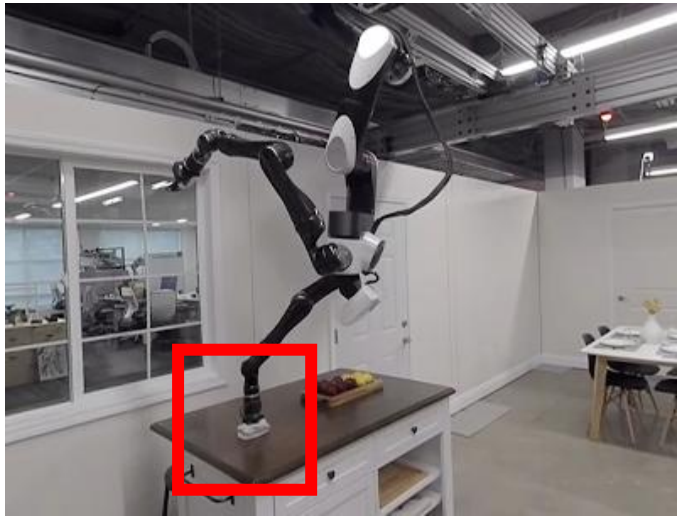
Assisting



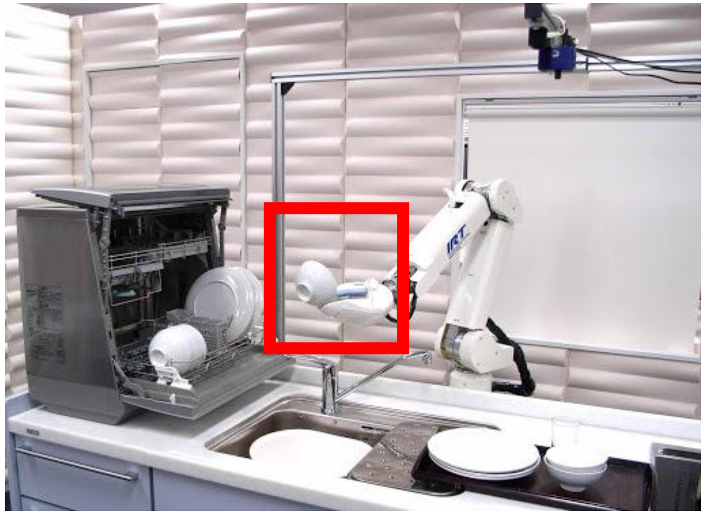
Serving



Cooking

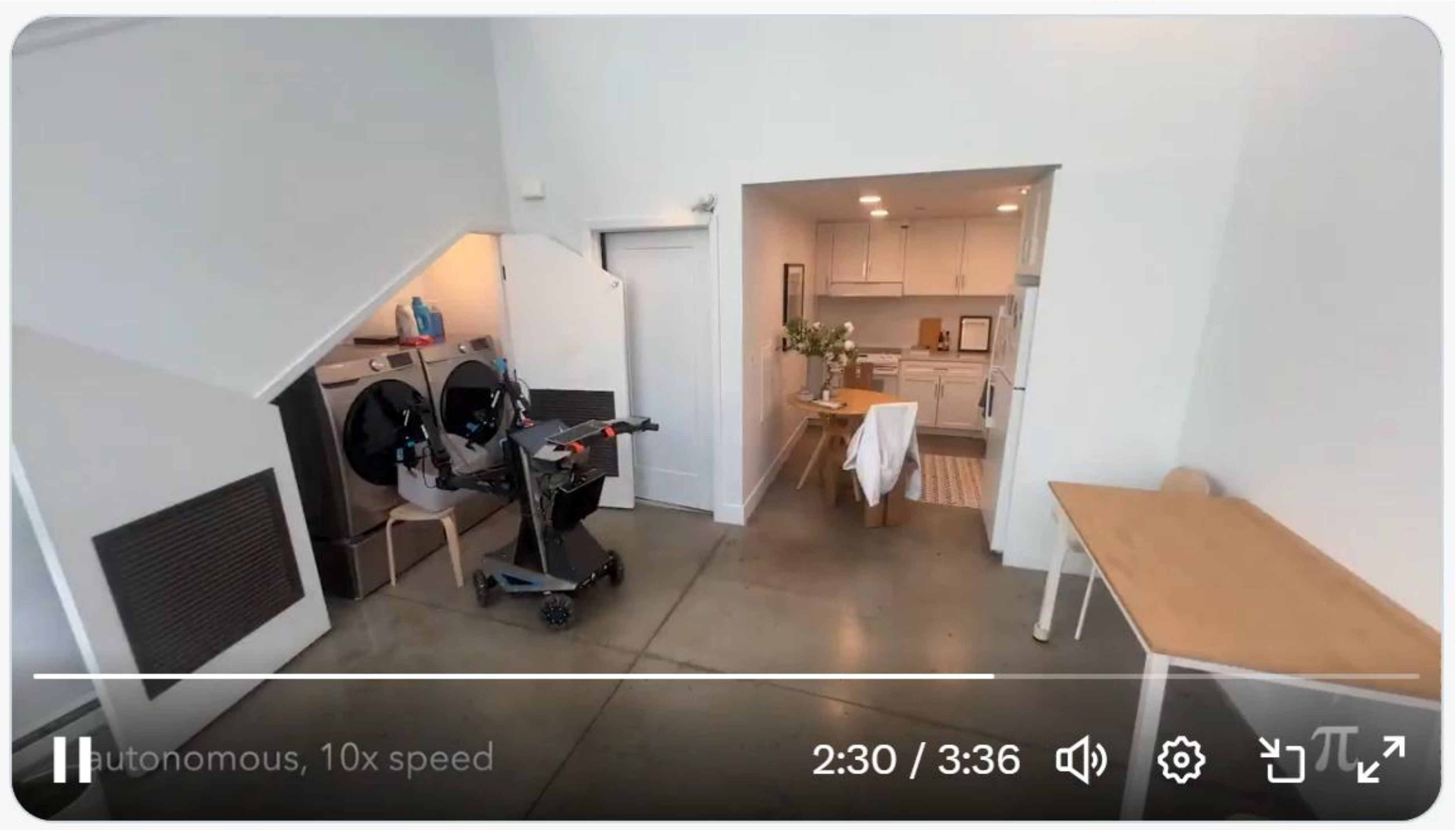


Cleaning



Dish washing

Some Recent Breakthroughs



https://www.physicalintelligence.company/blog/pi0

Physical Intelligence: a startup with people from Berkeley, Stanford, etc.

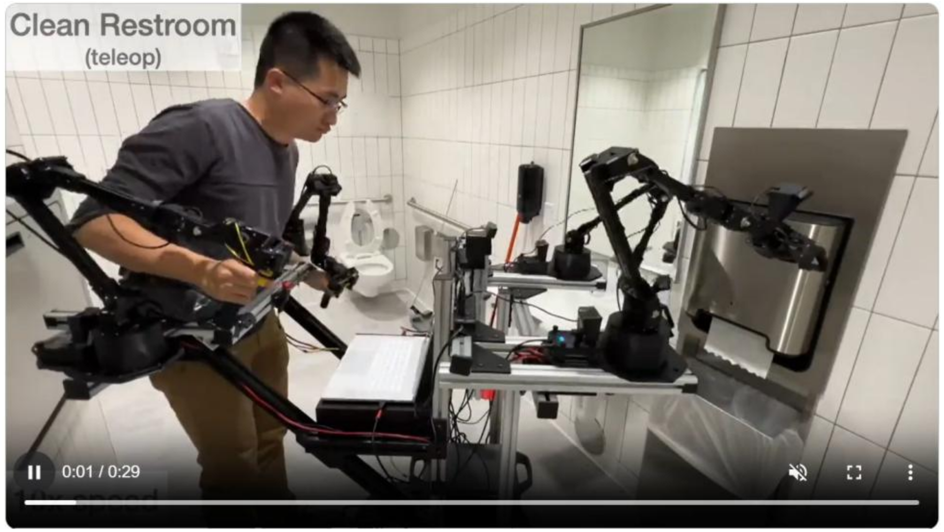
Some Recent Breakthroughs

Mobile ALOHA, Stanford, Zipeng Fu, Tony Zhao, Chelsea Finn https://mobile-aloha.github.io/

There are always Failures

Mobile ALOHA, Stanford, Zipeng Fu, Tony Zhao, Chelsea Finn https://mobile-aloha.github.io/

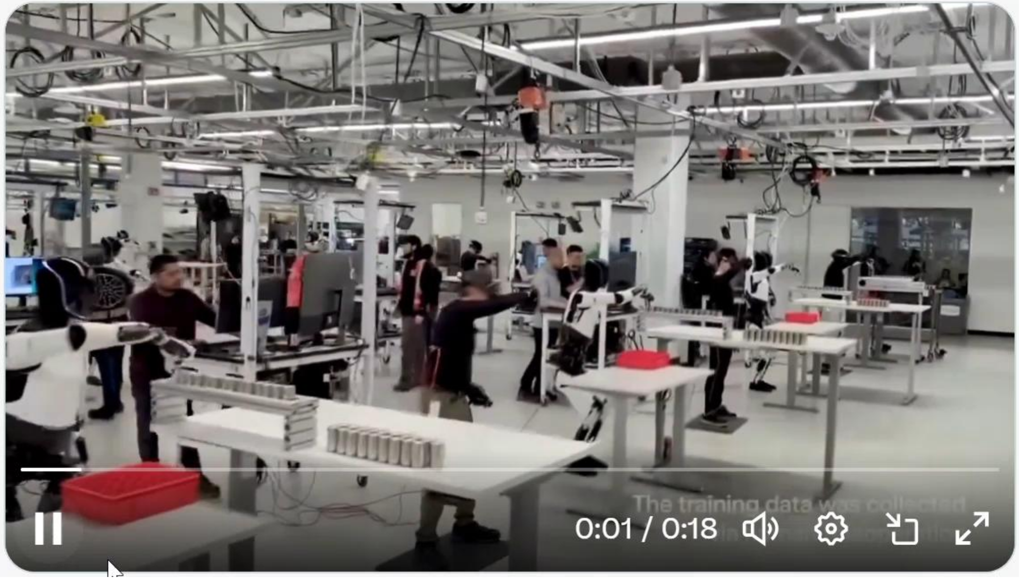
Key Ingredient: Teleoperation for Data Collection



https://mobile-aloha.github.io/

https://mobile-tv.github.io/

https://bidex-teleop.github.io/



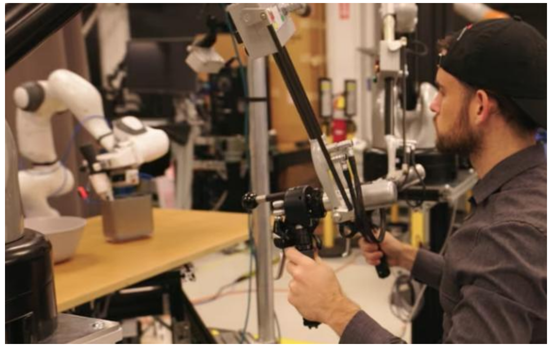
Tesla

Image-based Imitation Learning

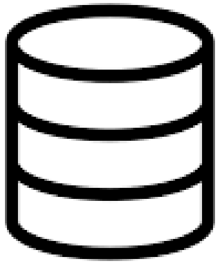
Will end-to-end imitation learning be the solution?

Kinesthetic Teaching

Teleoperation

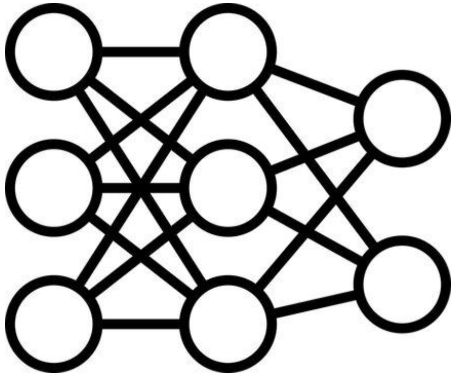


Collect Demonstrations



(state, action)

A Dataset of State-Action Pairs



Train a Policy Network

Deploy the Policy Network

Why Imitation Learning Works?

- The robot mostly replays the actions collected during teleoperation
  - It can show very cool tasks
- Due to limited data collection, it is very difficult to generalize
  - Object variations in position, shape, lighting, etc.
  - New environments
  - New tasks
  - New robots

Robot Autonomy

Intelligent Robots

- Navigation
- Manipulation
- Long-horizon tasks

Multiple Tasks

Task Diversity

Single Task

Current End-to-end Policy Learning

?

- Collect more data in many environments for many tasks for learning?
- Use simulators for learning with sim-to-real transfer?
- Enable robots to understand the 3D physical world with planning and control?

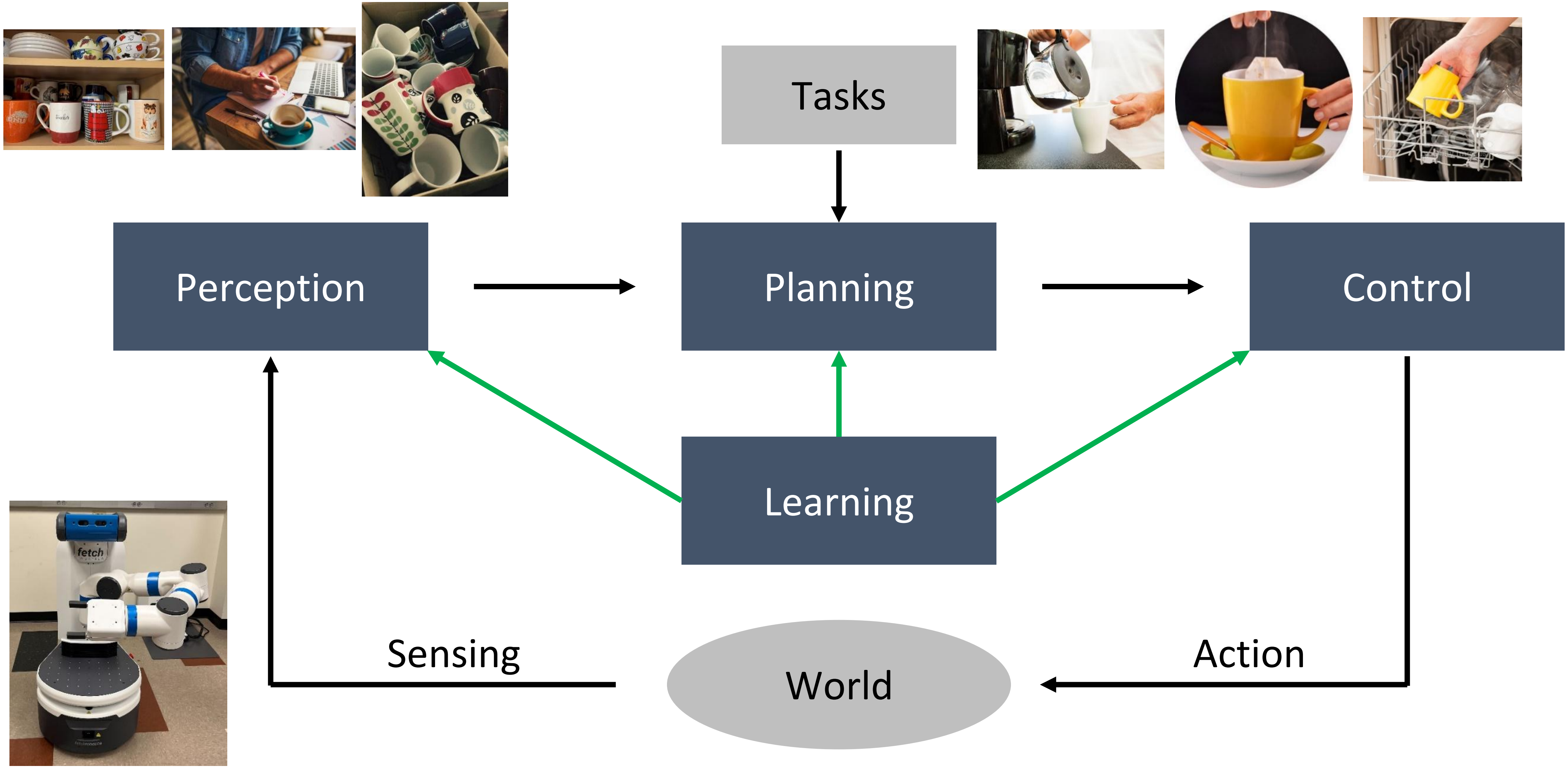
Etc. (open question)

Single Environment

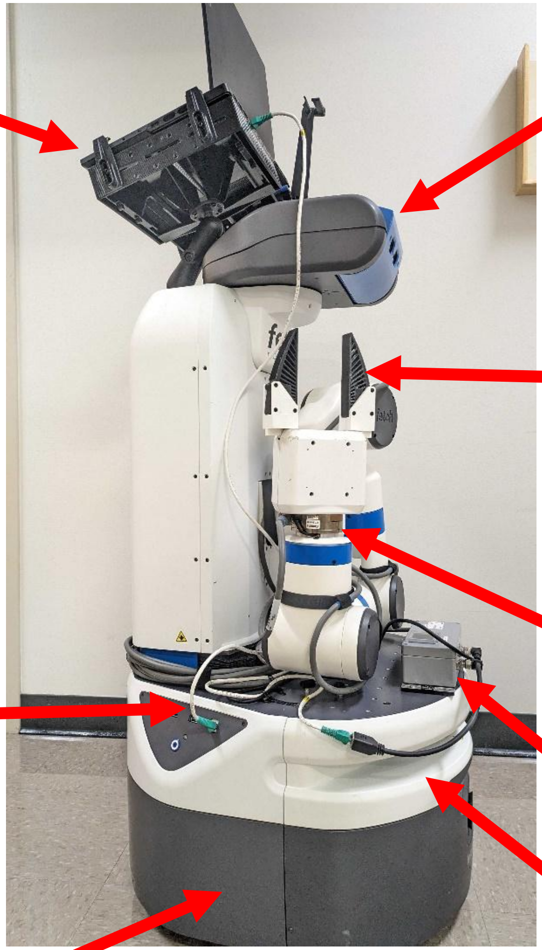
Environment Diversity

Multiple Environments

The Perception, Planning and Control Loop



Our Robot: a Fetch Mobile Manipulator



How to Represent Objects for Manipulation?

- 3D CAD models (Model-based)

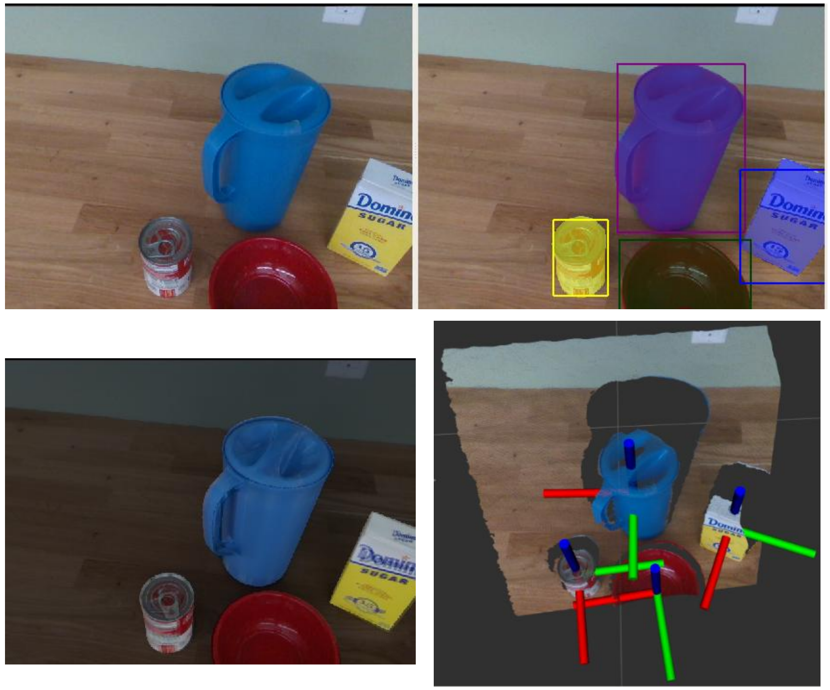
- Point clouds (Model-free)

Using 3D Object Models

Perception → Planning → Control

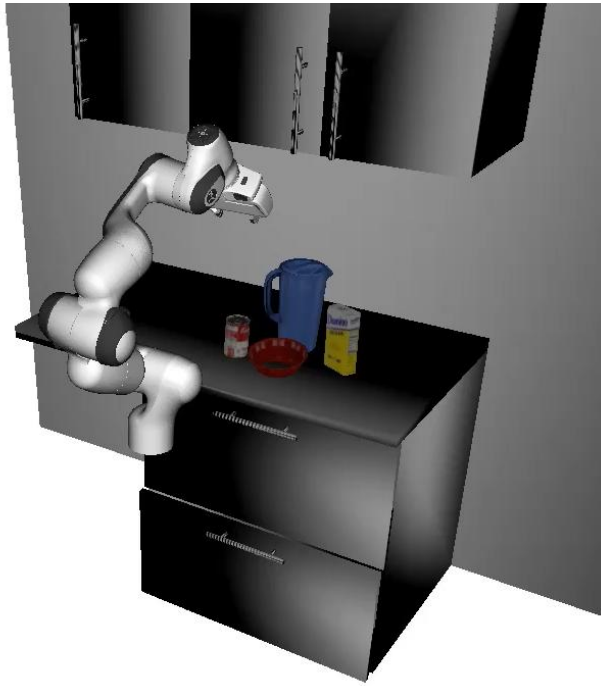
Perception

6D object pose estimation



Planning

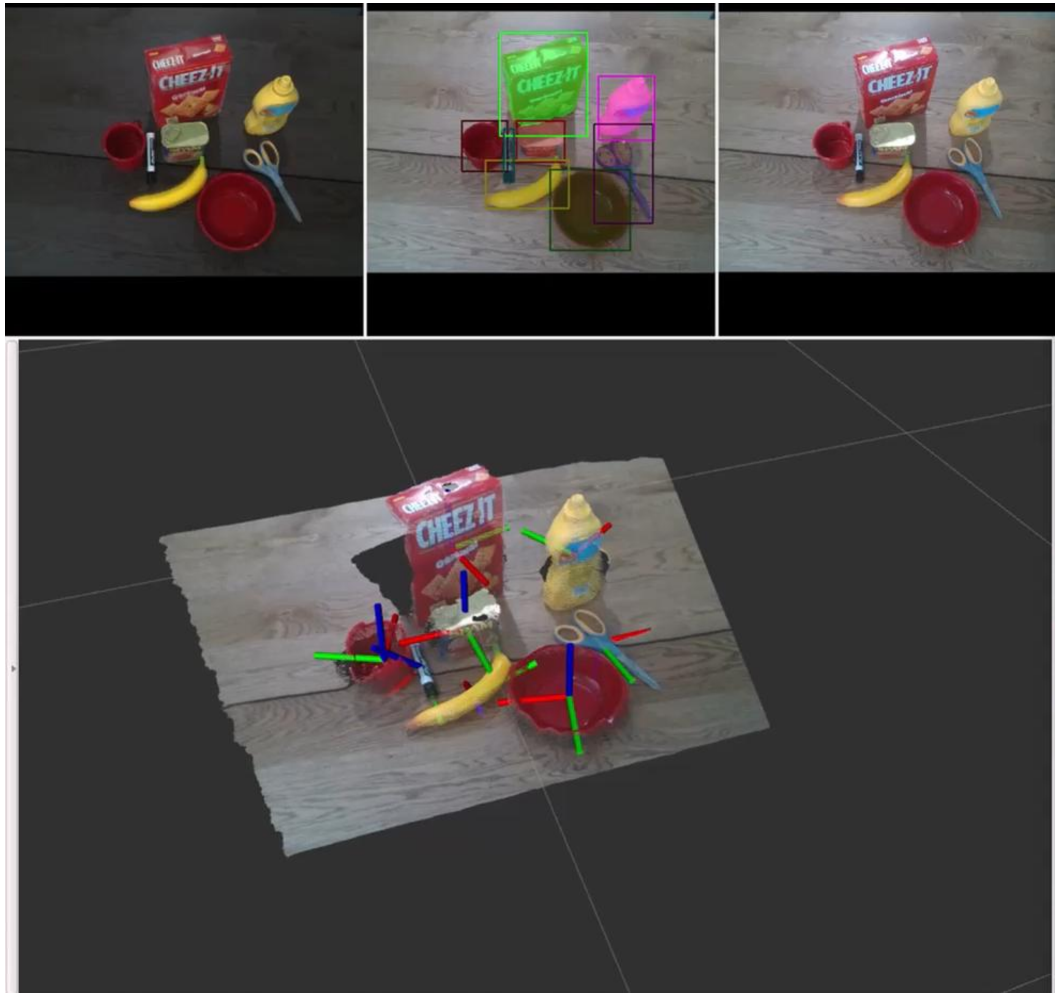
Grasp planning and motion planning



Control

Manipulation trajectory following

6D Object Pose Estimation



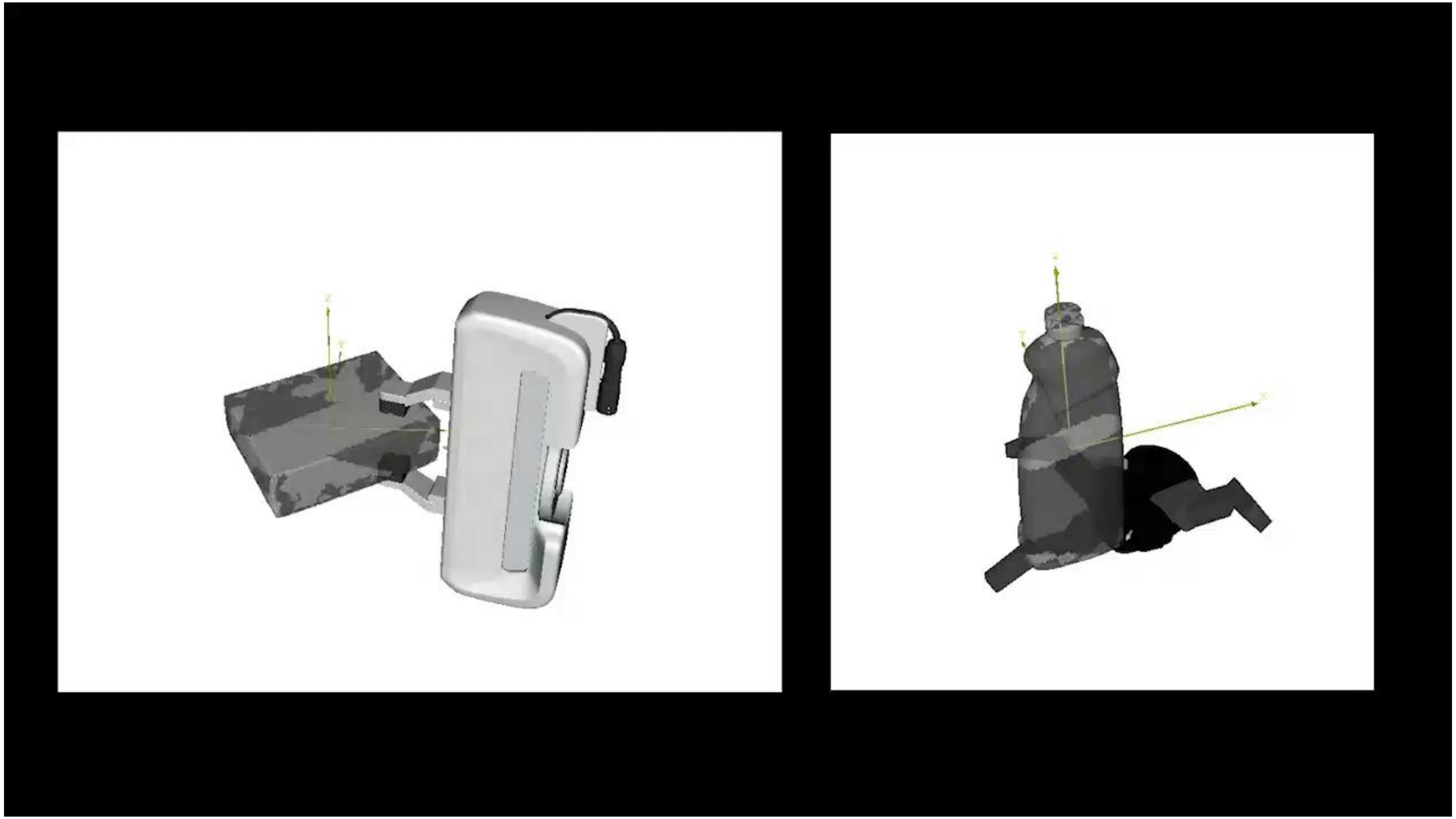
FoundationPose: Unified 6D Pose Estimation and Tracking of Novel Objects

Bowen Wen, Wei Yang, Jan Kautz, Stan Birchfield

NVIDIA

- **Xiang**-Schmidt-Narayanan-Fox, PoseCNN, RSS'18
- Li-Wang-Ji-**Xiang**-Fox, DeepIM, ECCV'18
- Tremblay-To-Sundaralingam-**Xiang**-Fox-Birchfield, DOPE, CoRL'18
- Deng-Mousavian-**Xiang**-Xia-Bretl-Fox, PoseRBPF, RSS'19, T-TO'21
- Deng-**Xiang**-Mousavian-Eppner-Bretl-Fox, Self-supervised 6D Pose, ICRA'20
- Park-Mousavian-**Xiang**-Fox, LatentFusion, CVPR'20

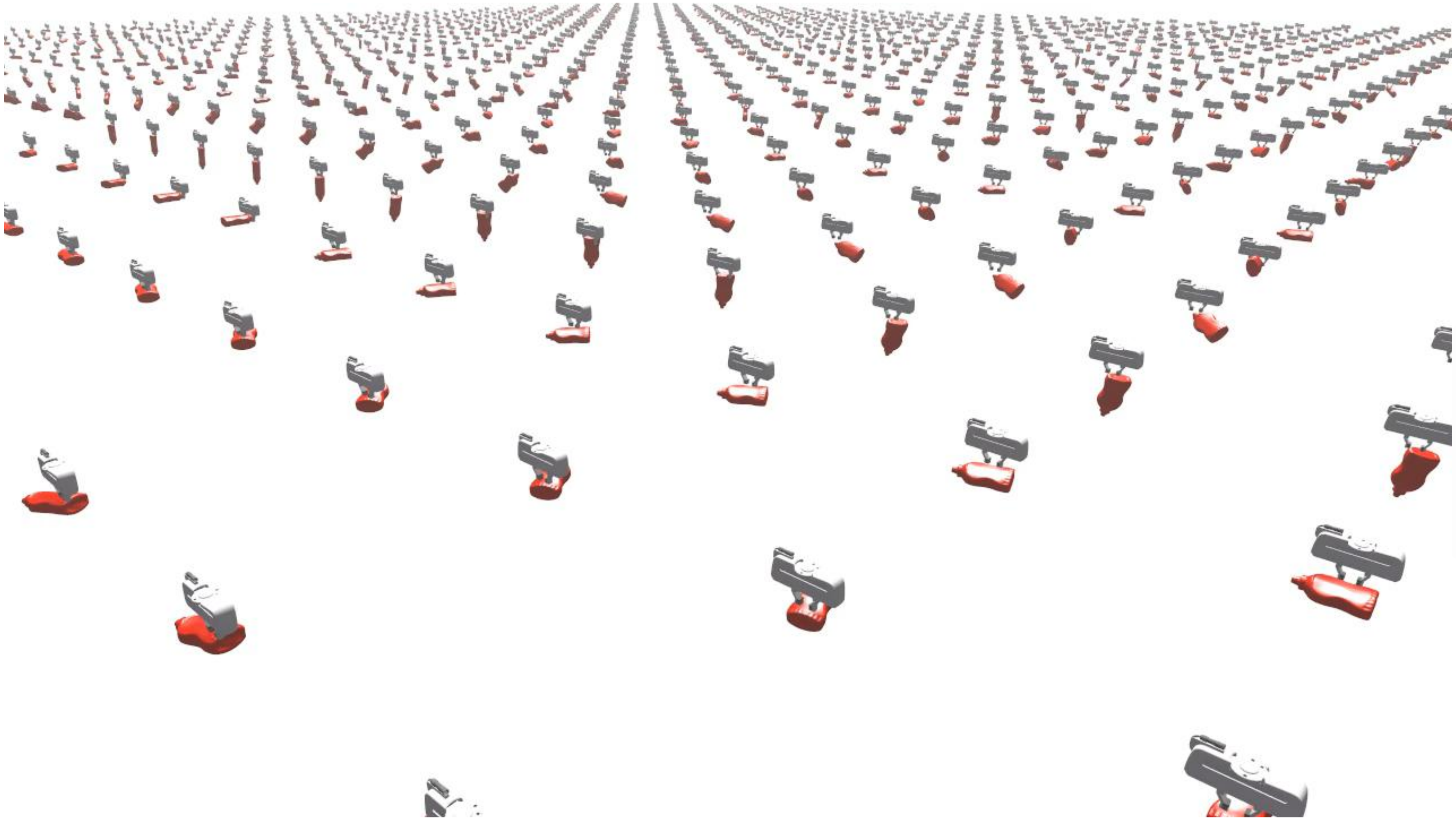
Grasp Planning: GraspIt!



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

Andrew Miller and Peter K. Allen. "Graspit!: A Versatile Simulator for Robotic Grasping". IEEE Robotics and Automation Magazine, V. 11, No.4, Dec. 2004, pp. 110-122.

Grasp Planning: A Physics-based Approach



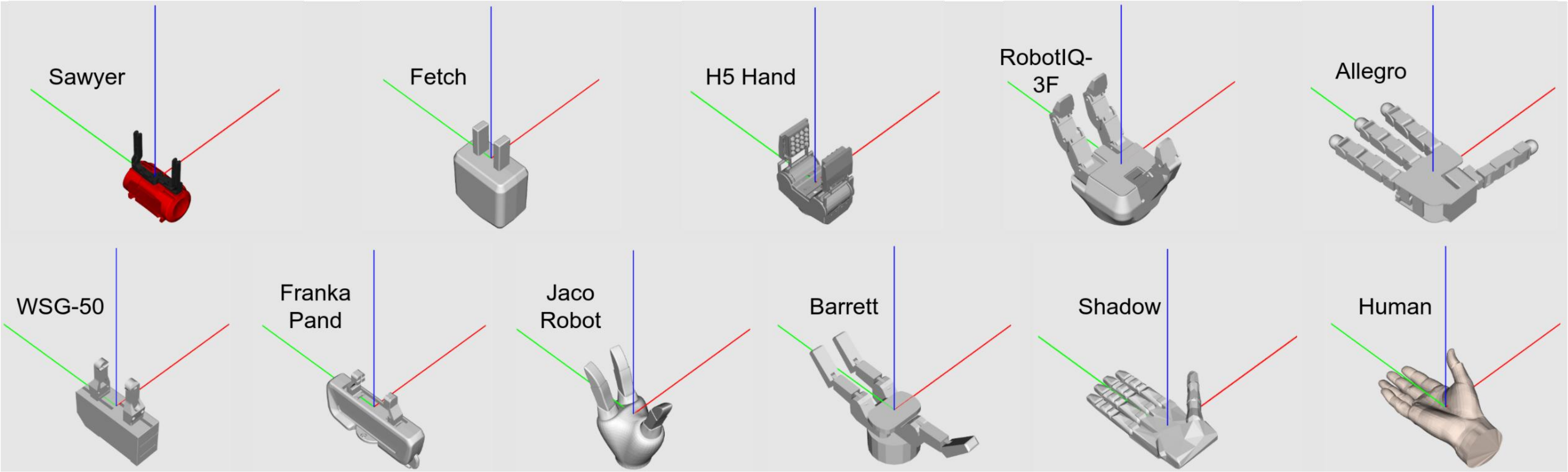
Eppner-Mousavian-Fox, ISRR'19

MultiGripperGrasp

- A large-scale dataset for robotic grasping
  - 11 grippers, 345 objects, 30M grasps

MultiGripperGrasp: A Dataset for Robotic Grasping from Parallel Jaw Grippers to Dexterous Hands
Luis Felipe Casas Murrilo*, Ninad Khargonkar*, Balakrishnan Prabhakaran, **Yu Xiang** (*equal contribution)
In IROS, 2024.

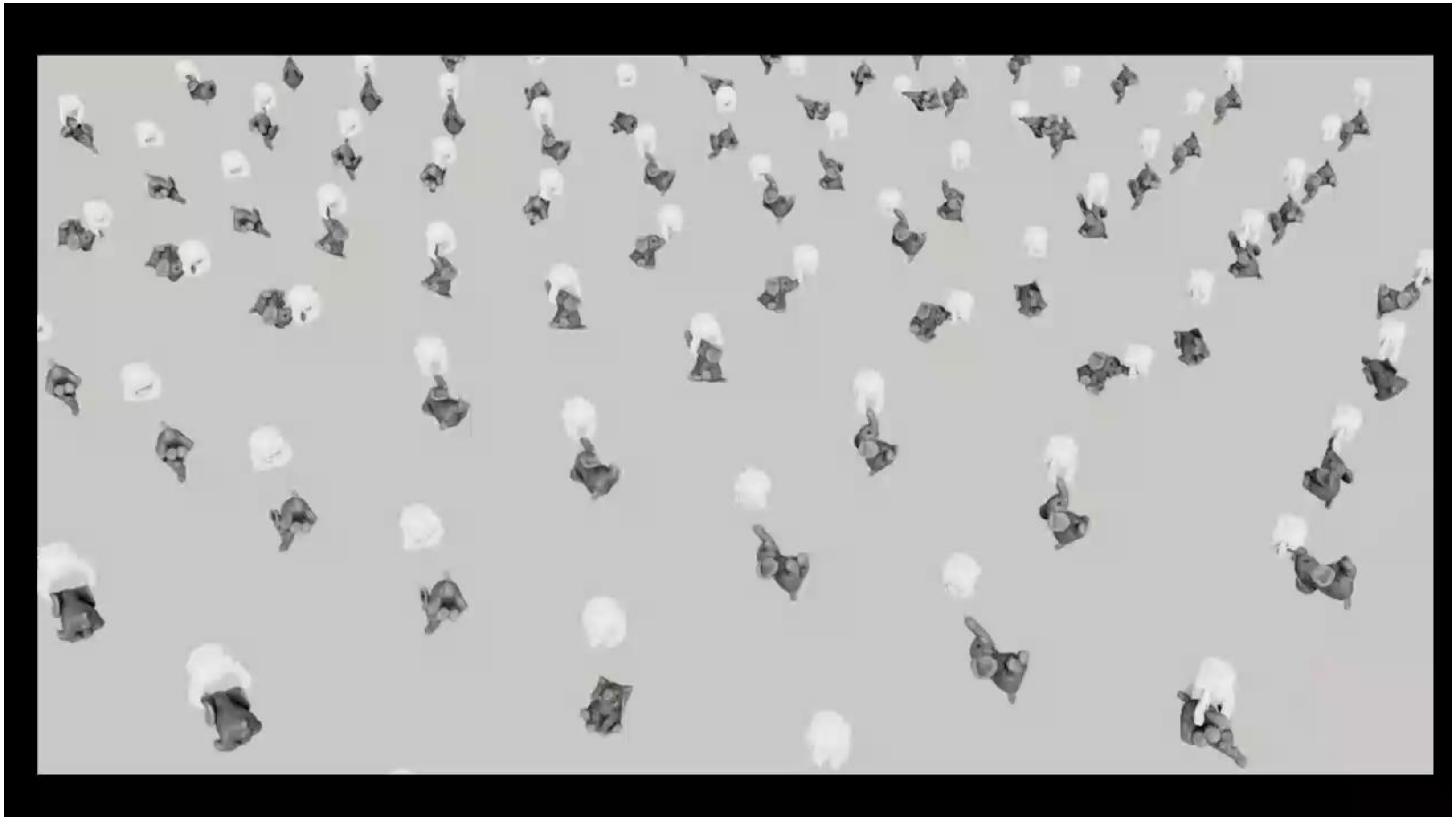
MultiGripperGrasp



- 11 grippers (aligned with palm directions)
  - 2-finger grippers: Fetch, Franka Panda, WSG50, Sawyer, H5 Hand
  - 3-finger grippers: Barrett, Robotiq-3F, Jaco Robot
  - 4-finger grippers: Allegro
  - 5 finger grippers: Shadow, Human Hand

MultiGripperGrasp

- Generate initial grasps using GraspIt!
- Ranking grasps in Isaac Sim

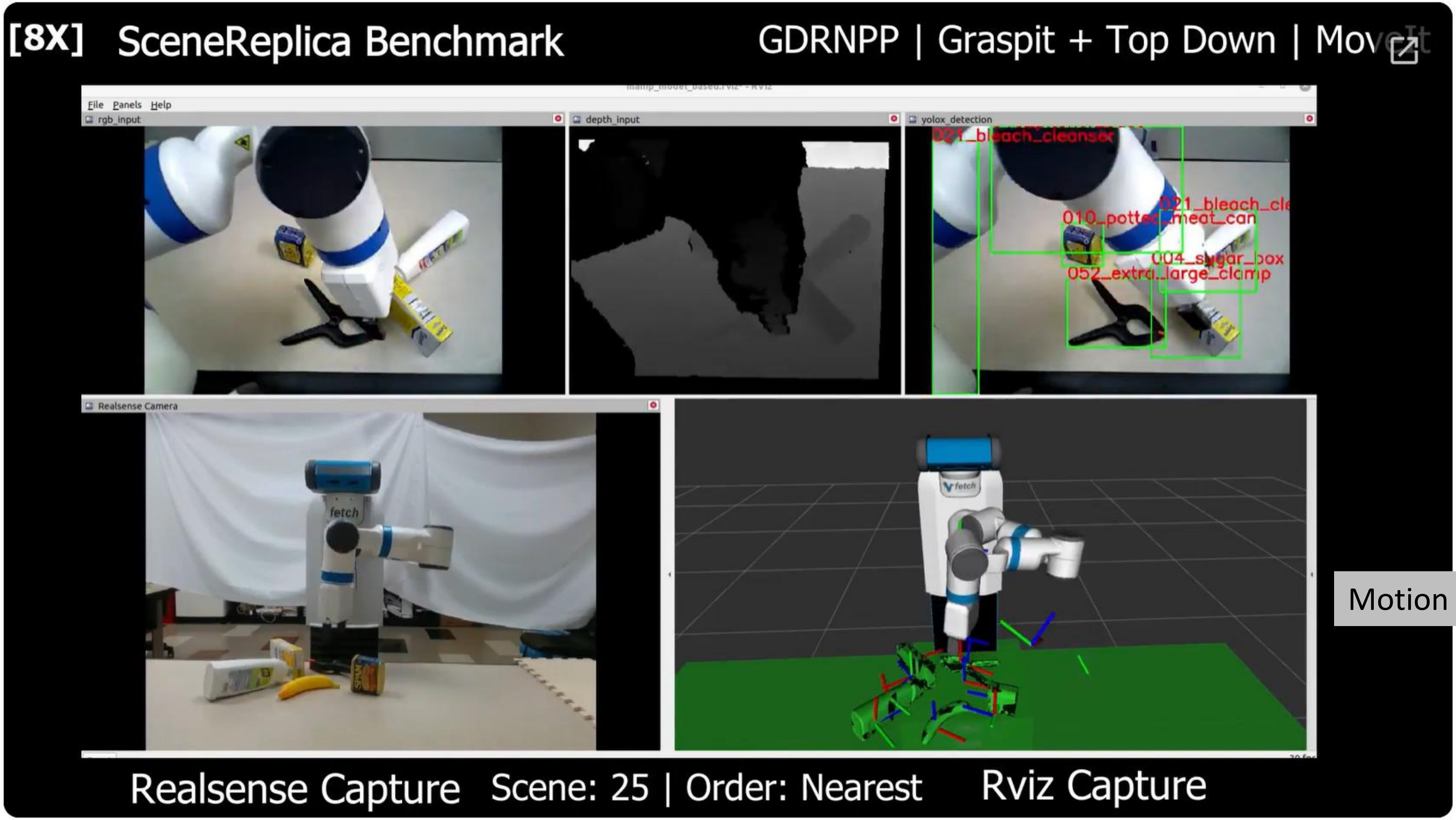


MultiGripperGrasp

- Grasp Transfer in Isaac Sim

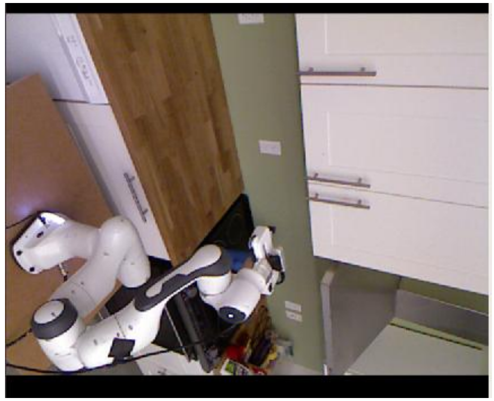
https://irvlutd.github.io/MultiGripperGrasp/

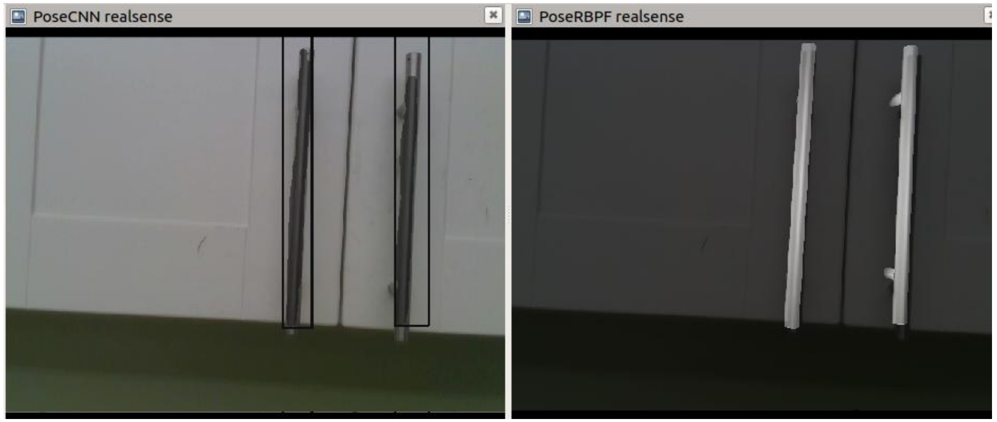
Motion Planning

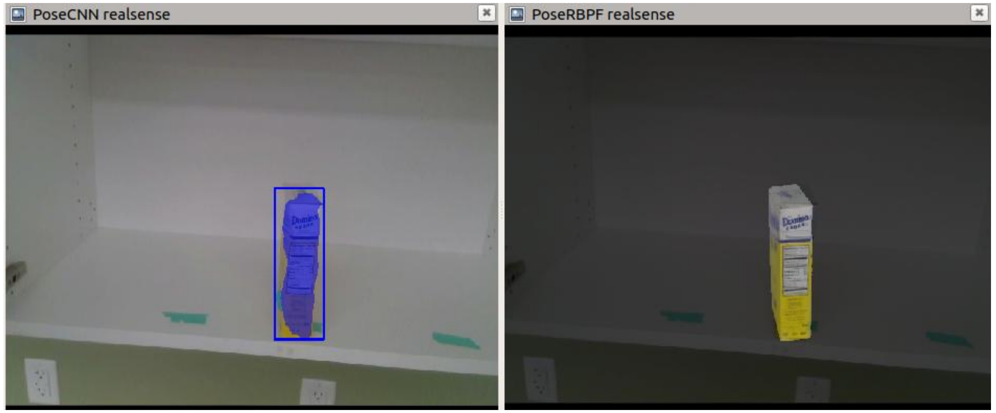


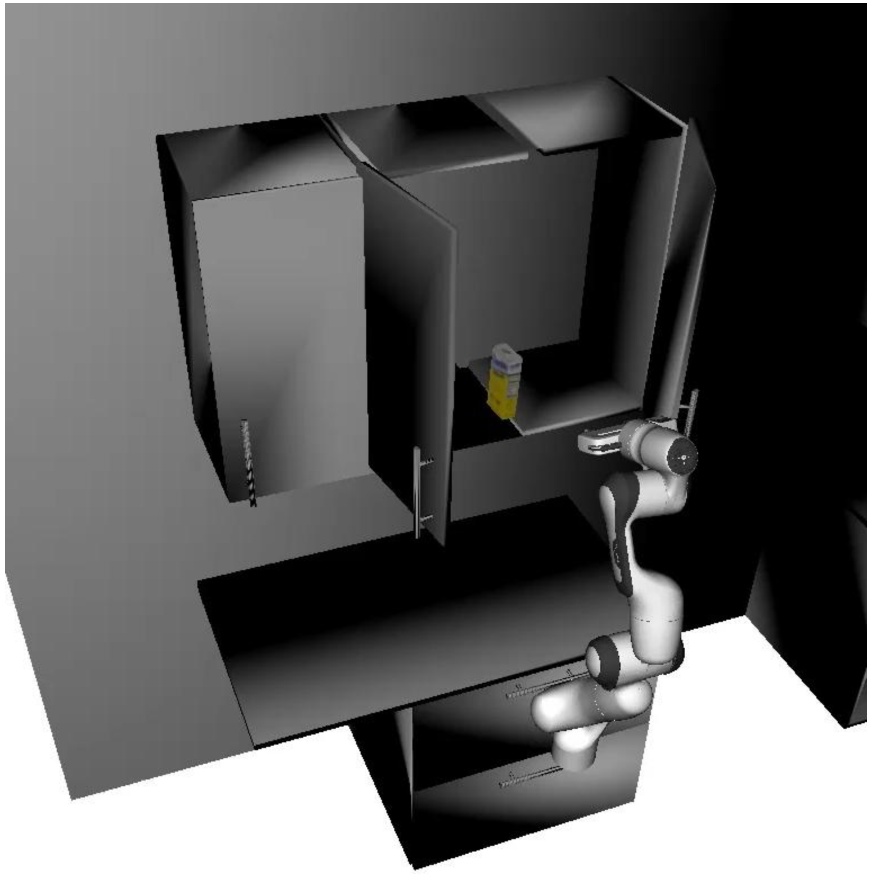
Motion Planning Scene

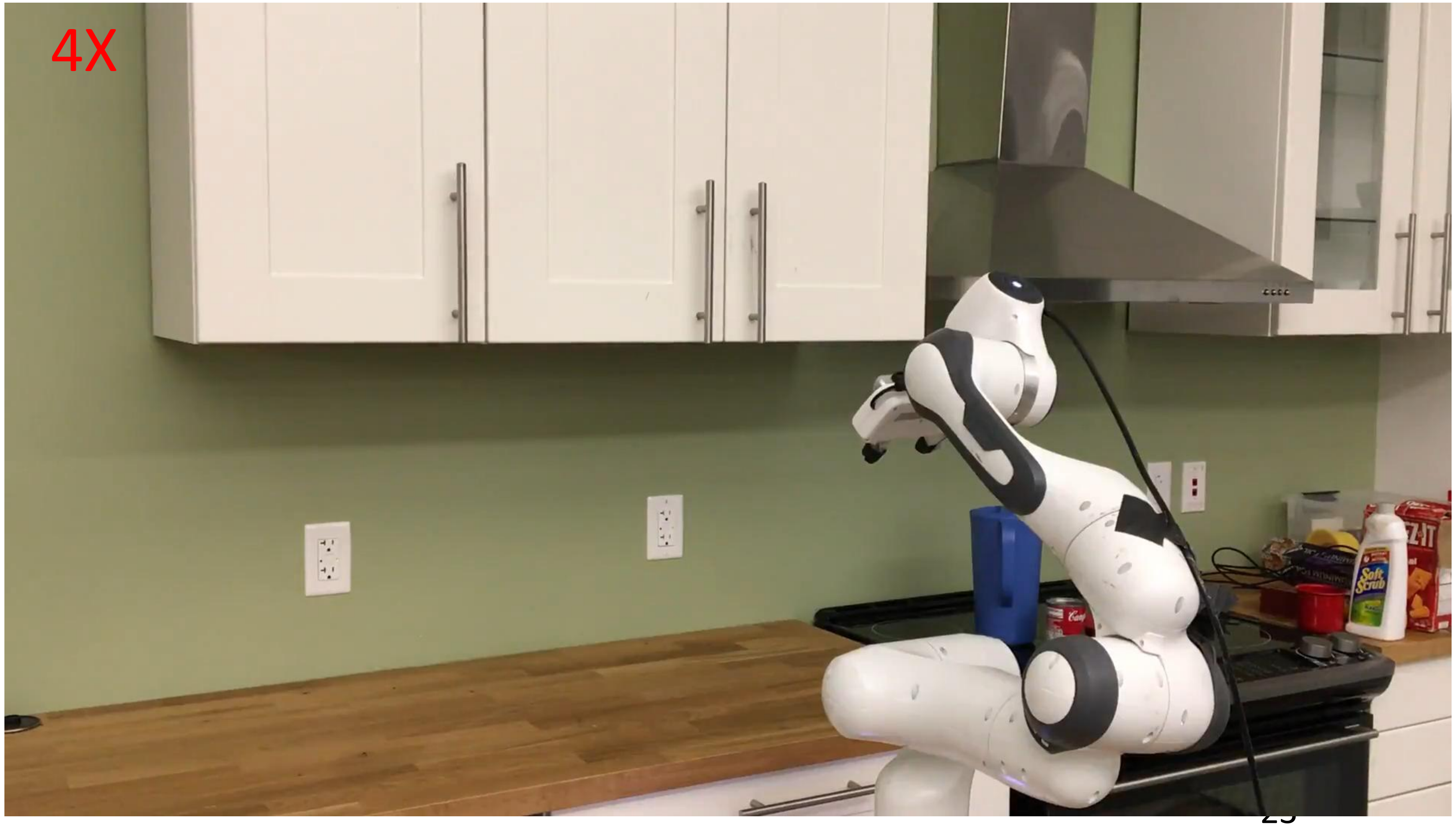
The Open Motion Planning Library in MoveIt https://ompl.kavrakilab.org/index.html




PoseCNN realsense
PoseRBPF realsense


PoseCNN realsense
PoseRBPF realsense

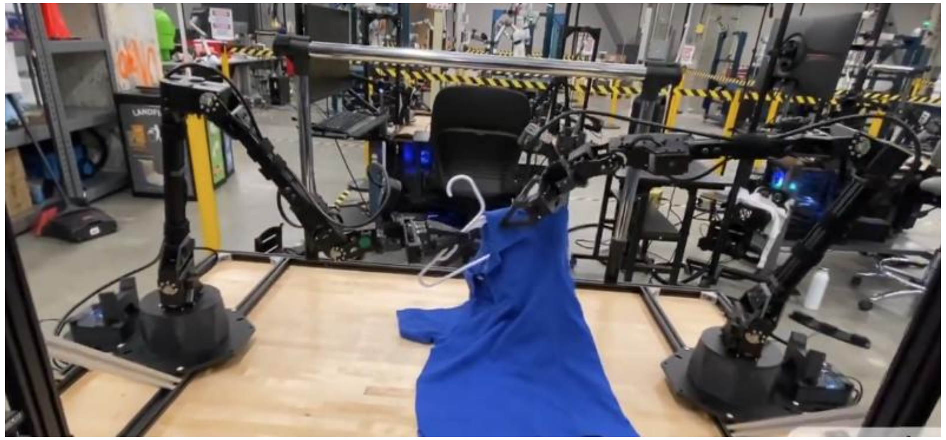



4X

Using 3D Object Models

- Pros
  - Encodes appearance, 3D shape, affordance, physical properties for perception, planning and simulation

- Cons
  - We cannot build 3D models for all objects

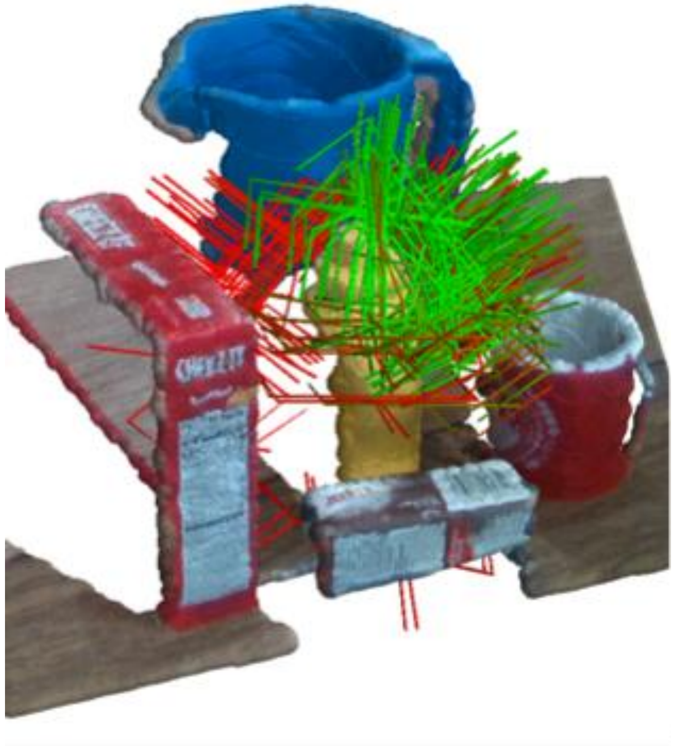


ALOHA Unleashed
Google DeepMind

Using 3D Point Clouds

Perception → Planning → Control

object instance segmentation



Grasp planning from point clouds

Control to reach grasp

Figure Credit: Murali-Mousavian-Eppner-Paxton-Fox, ICRA'20

Segmenting Unseen Objects

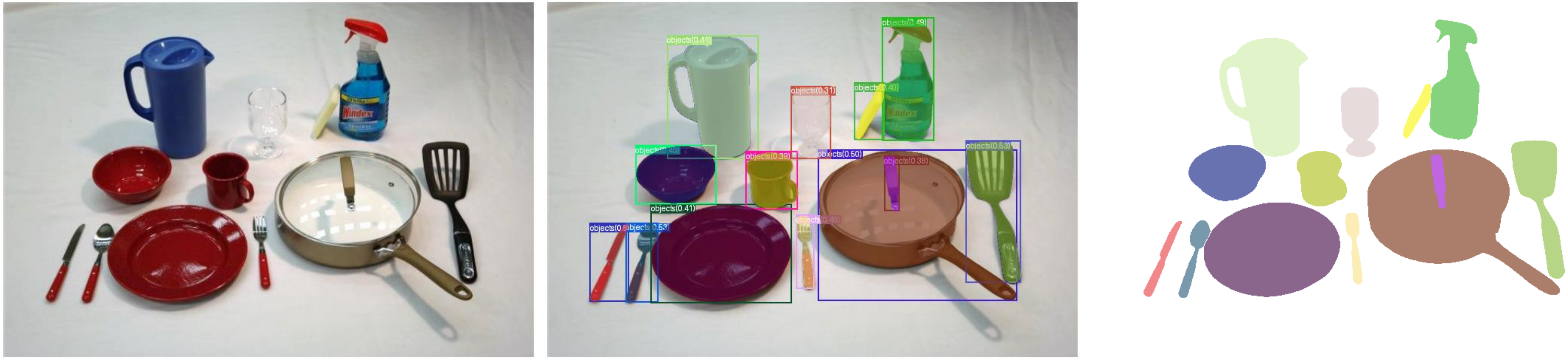
Input Image

Output Label

Xie-**Xiang**-Mousavian-Fox, CoRL'19, T-RO'21, CoRL'21
Xiang-Xie-Mousavian-Fox, CoRL'20
Lu-Khargonkar-Xu-Averill-Palanisamy-Hang-Guo-Ruozzi-**Xiang**, RSS'23
Lu-Chen-Ruozzi-**Xiang**, ICRA'24
Qian-Lu-Ren-Wang-Khargonkar-**Xiang**-Hang, ICRA'24

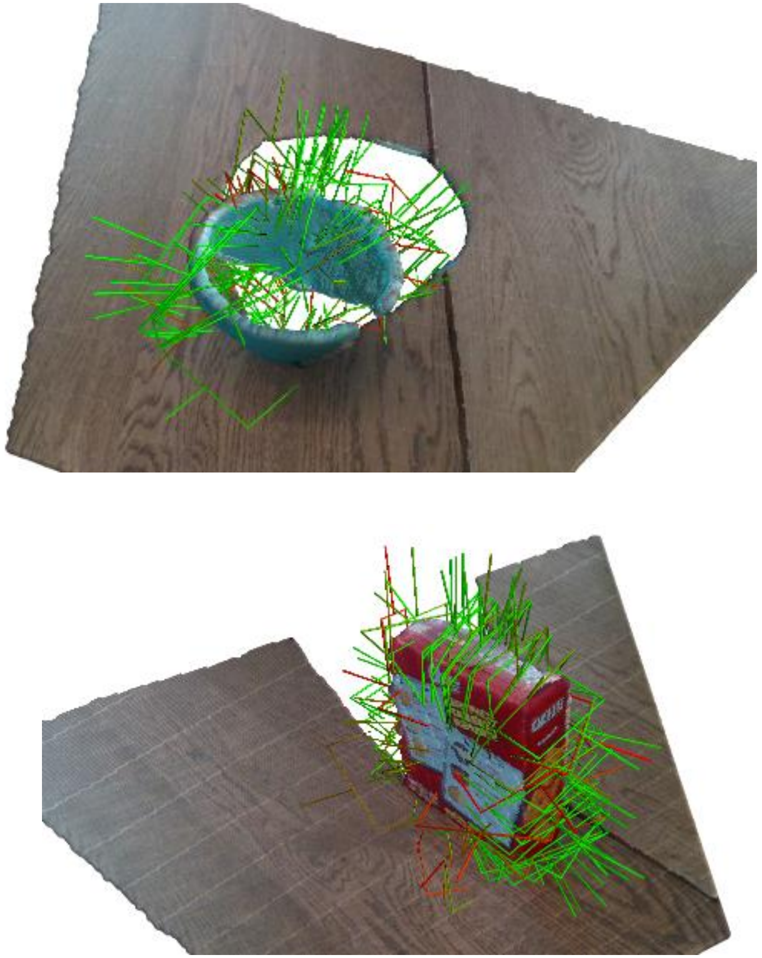
Leveraging Large Models from the Vision Community

- Gounding Dino (object detection)
- SAM (object segmentation)



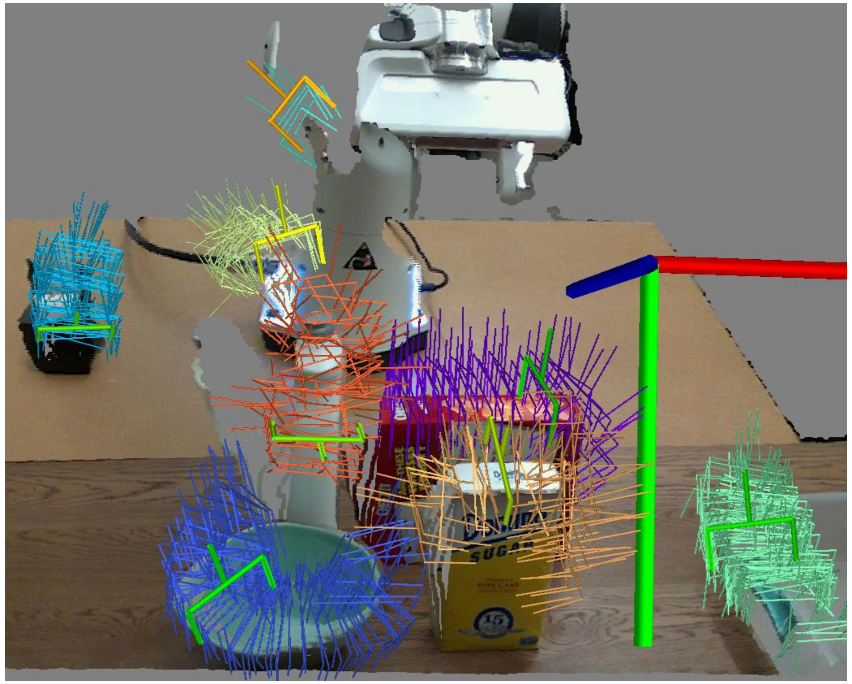
- Grounding DINO: Marrying DINO with Grounded Pre-Training for Open-Set Object Detection. Liu et al., 2023
- Segment Anything. Kirillov et al., 2023

Grasp Planning with Point Clouds



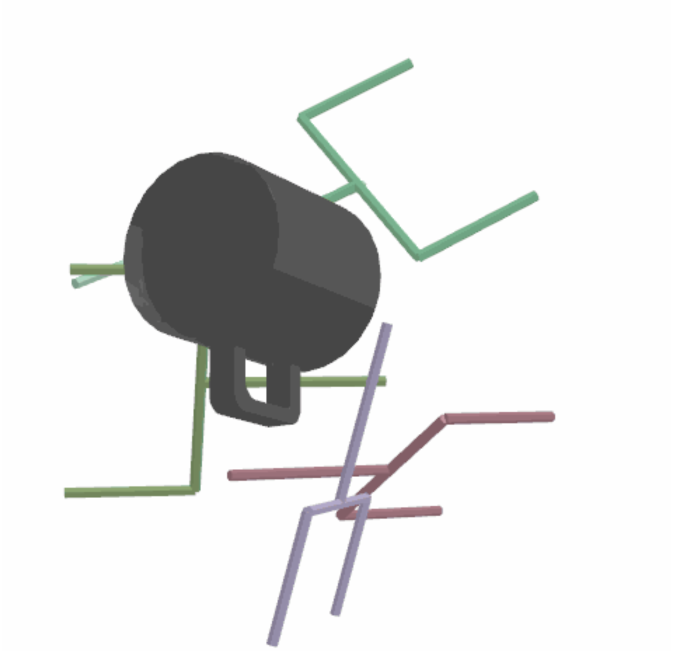
6D GraspNet

6-DOF GraspNet: Variational Grasp Generation for Object Manipulation. Mousavian et al., ICCV’19



Contact-GraspNet

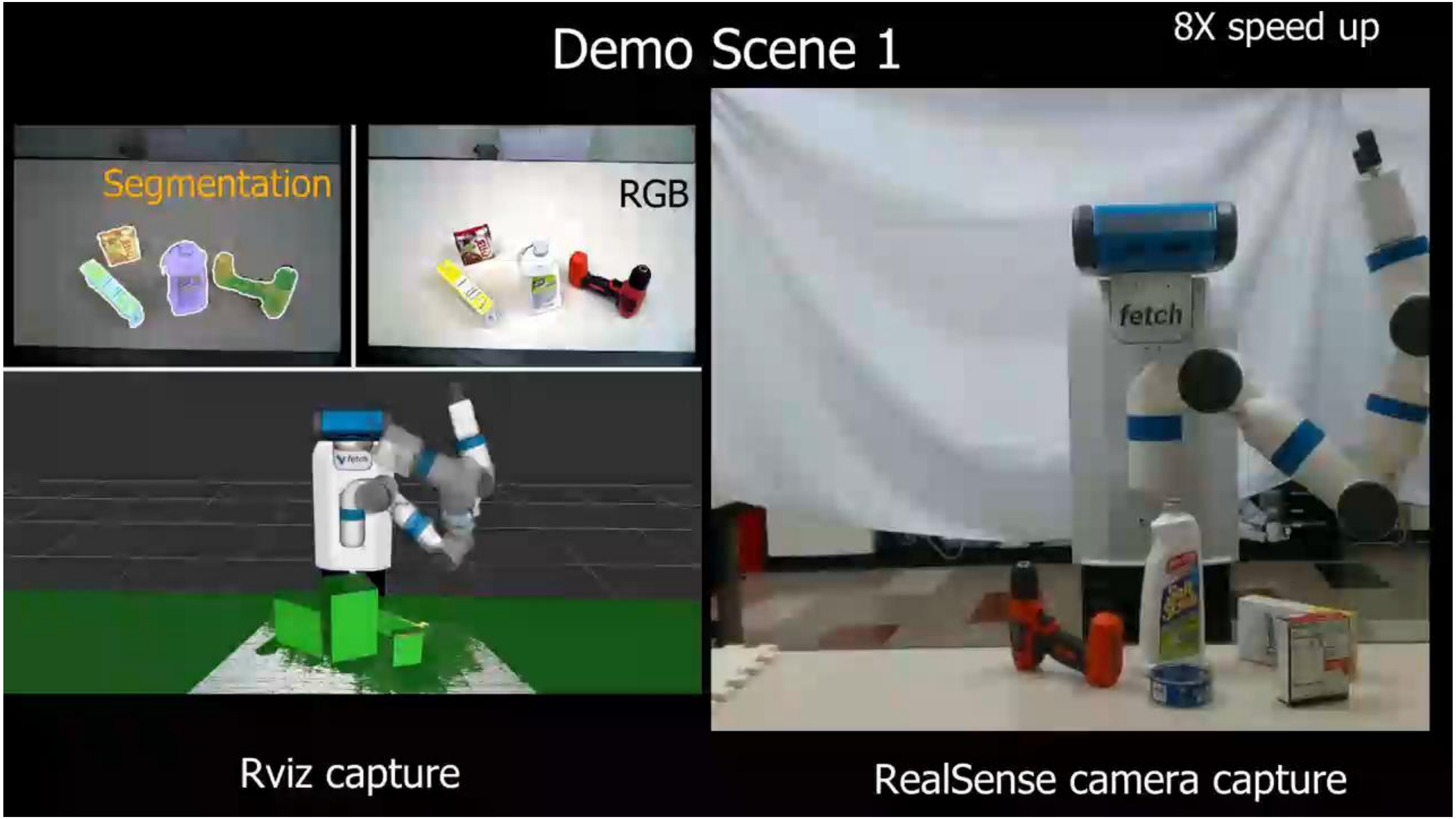
Contact-GraspNet: Efficient 6-DoF Grasp Generation in Cluttered Scenes. Sundermeyer, et al., ICRA’21



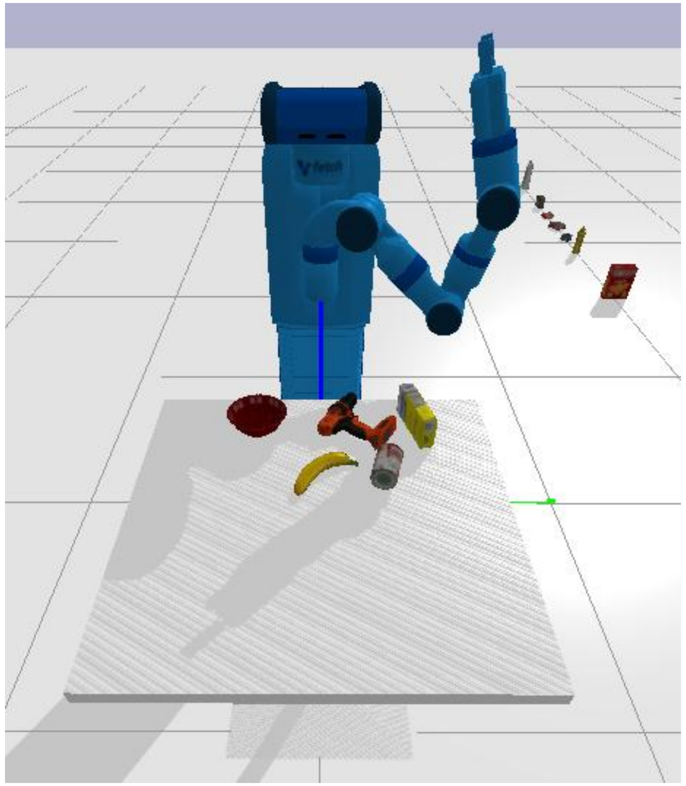
SE(3)-DiffusionFields

SE(3)-DiffusionFields: Learning smooth cost functions for joint grasp and motion optimization through diffusion. Urain et al., 2023

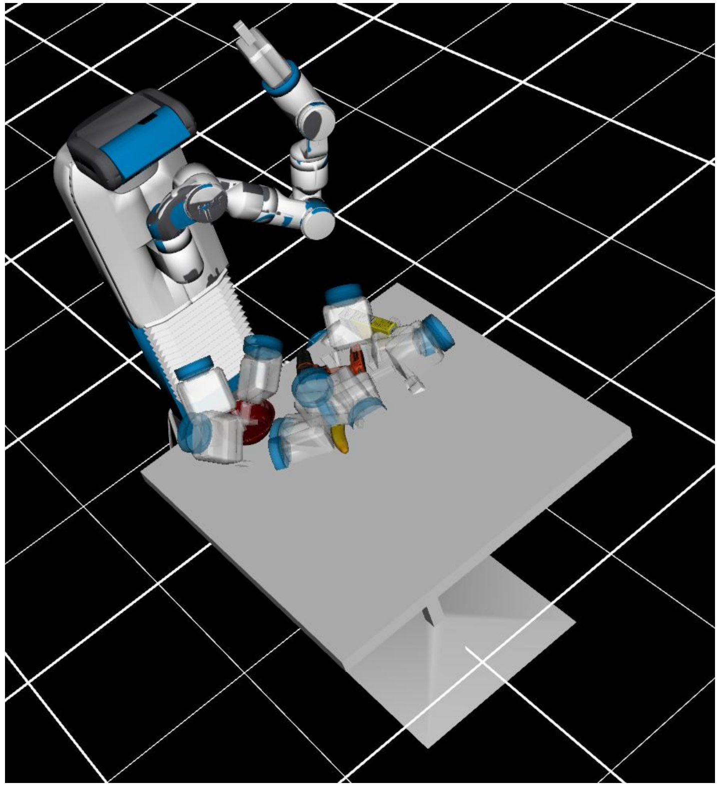
Model-free Grasping Example



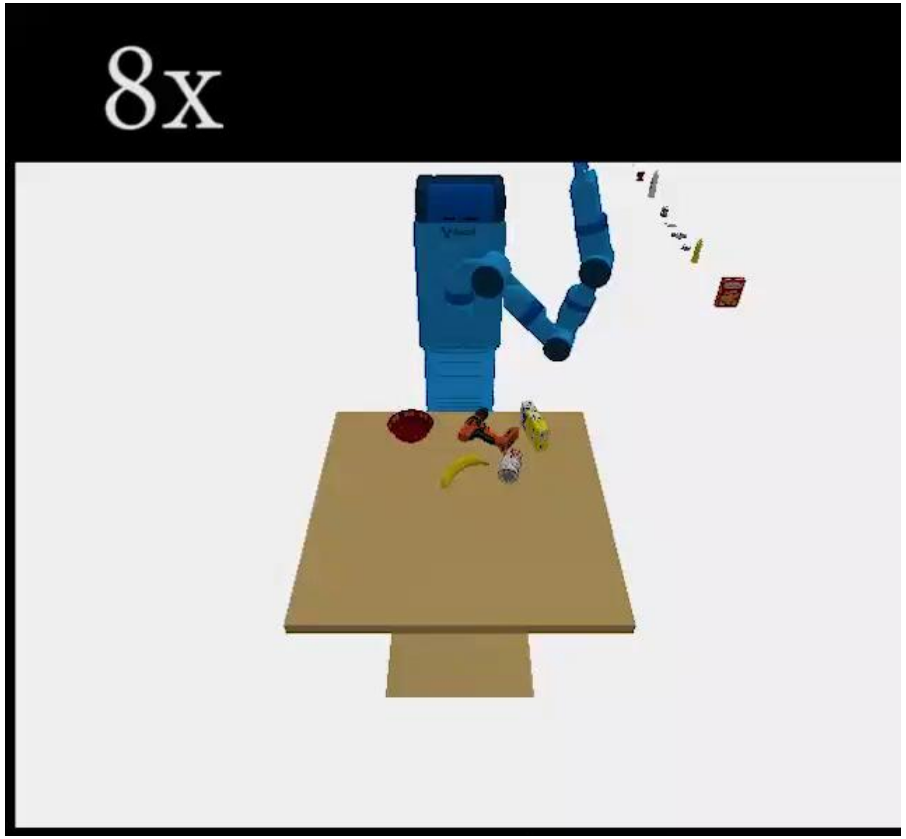
Grasping Trajectory Optimization with Point Clouds



(a) Task Space



(b) Grasp Planning

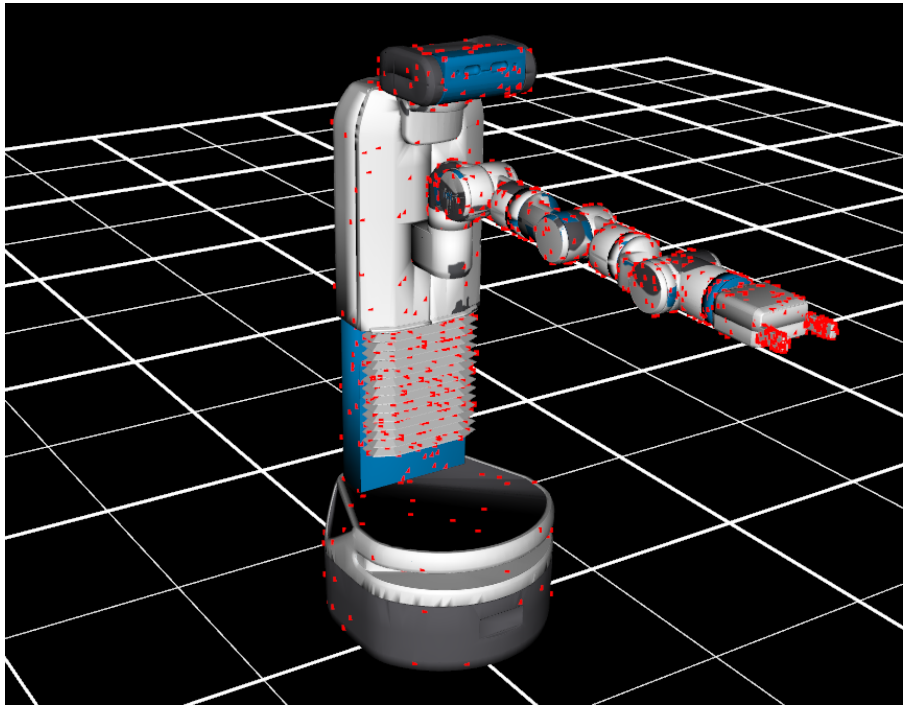


(c) Grasp Trajectory Optimization

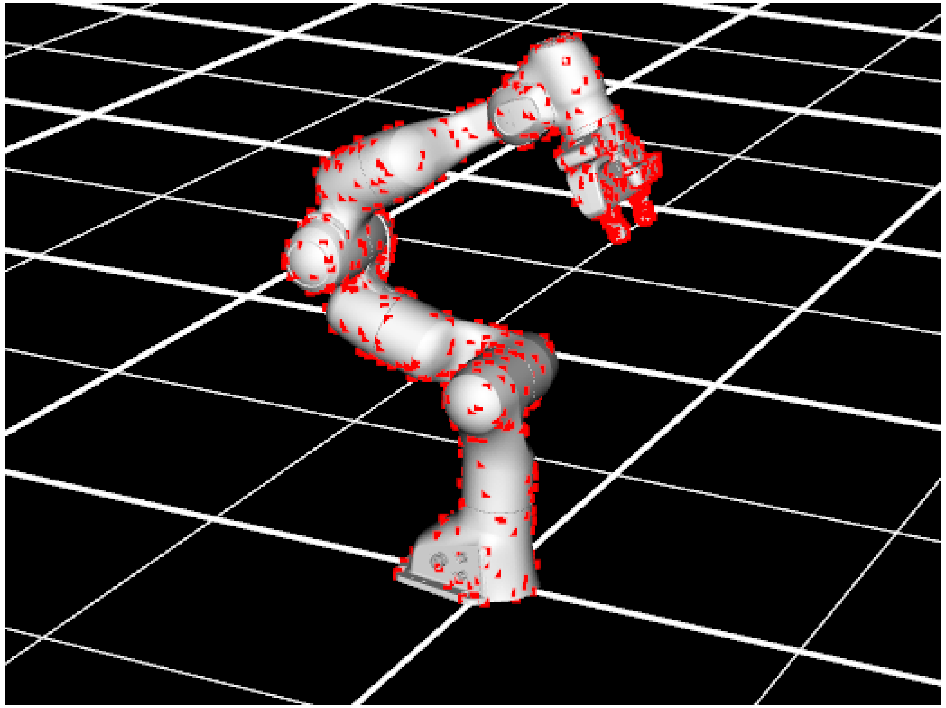
Grasping Trajectory Optimization with Point Clouds. **Yu Xiang**, Sai Haneesh Allu, Rohith Peddi, Tyler Summers, Vibhav Gogate In IROS, 2024.

Grasping Trajectory Optimization with Point Clouds

- Represent robots as point clouds (can be used for any robot)



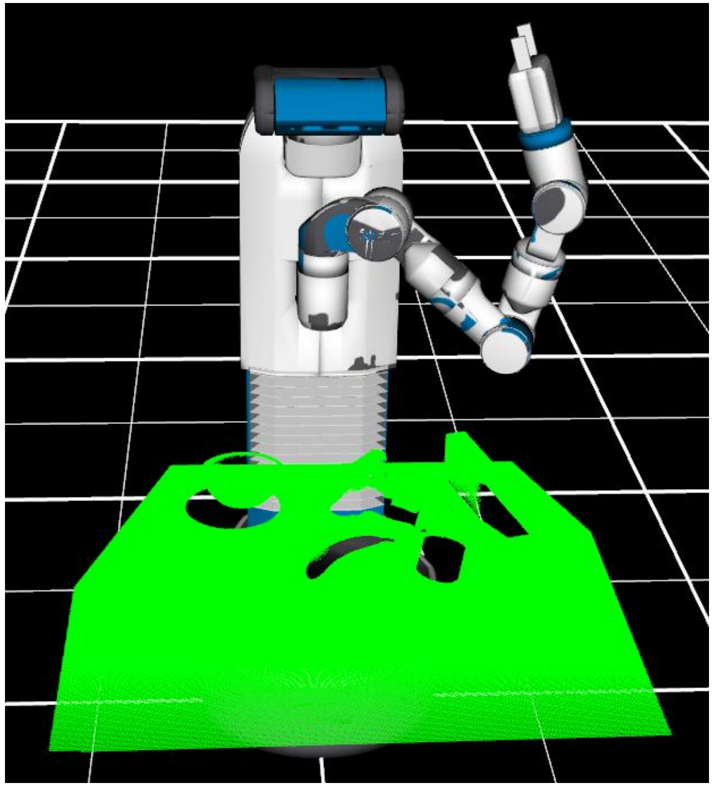
(a) A Fetch Mobile Manipulator



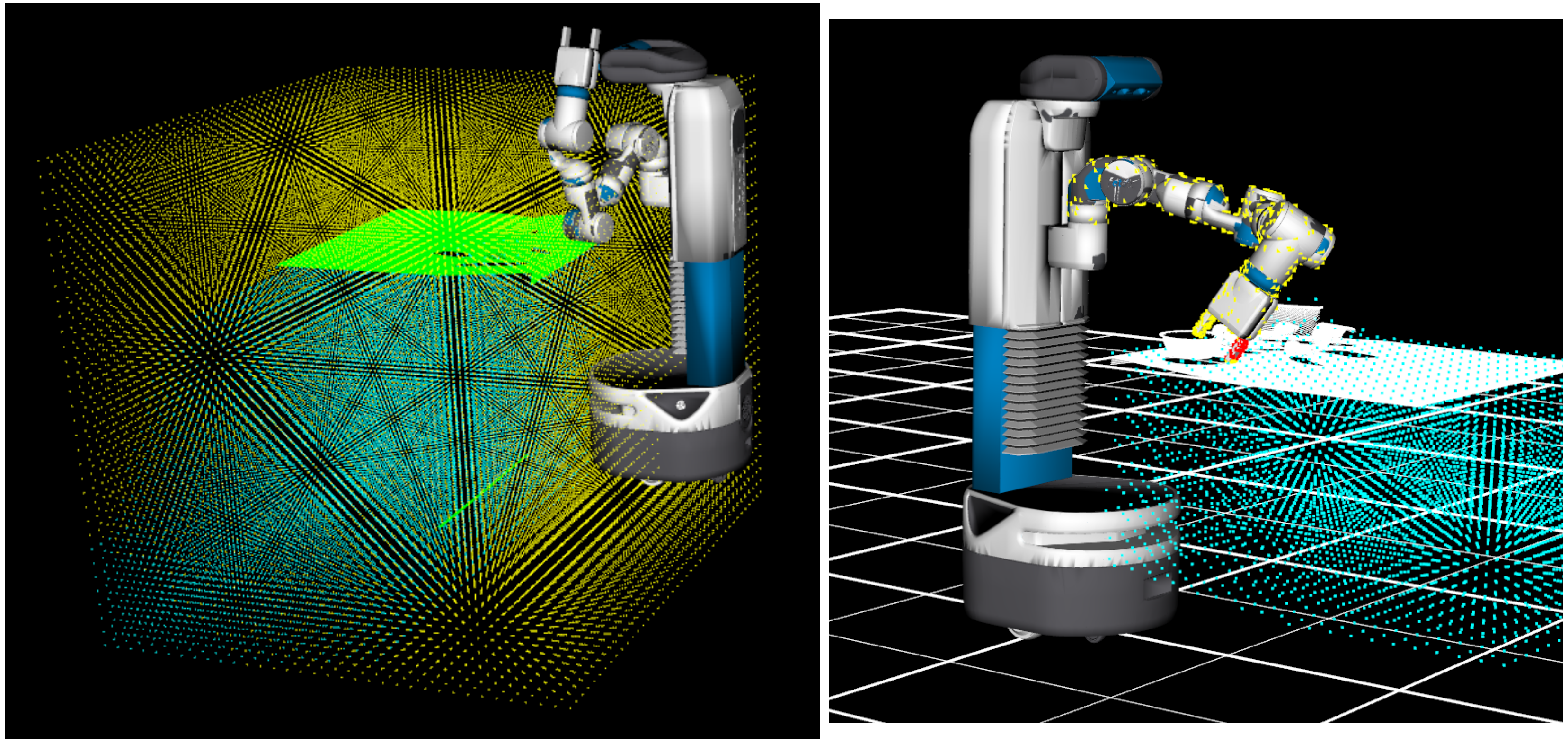
(b) A Franka Panda Arm

Grasping Trajectory Optimization with Point Clouds

- Represent task spaces as point clouds (can be used for any task)
- Build signed distance fields using point clouds for collision avoidance



(a) 3D Scene Points from a Depth Image



(b) Signed Distance Field of the Task Space

Grasping Trajectory Optimization with Point Clouds

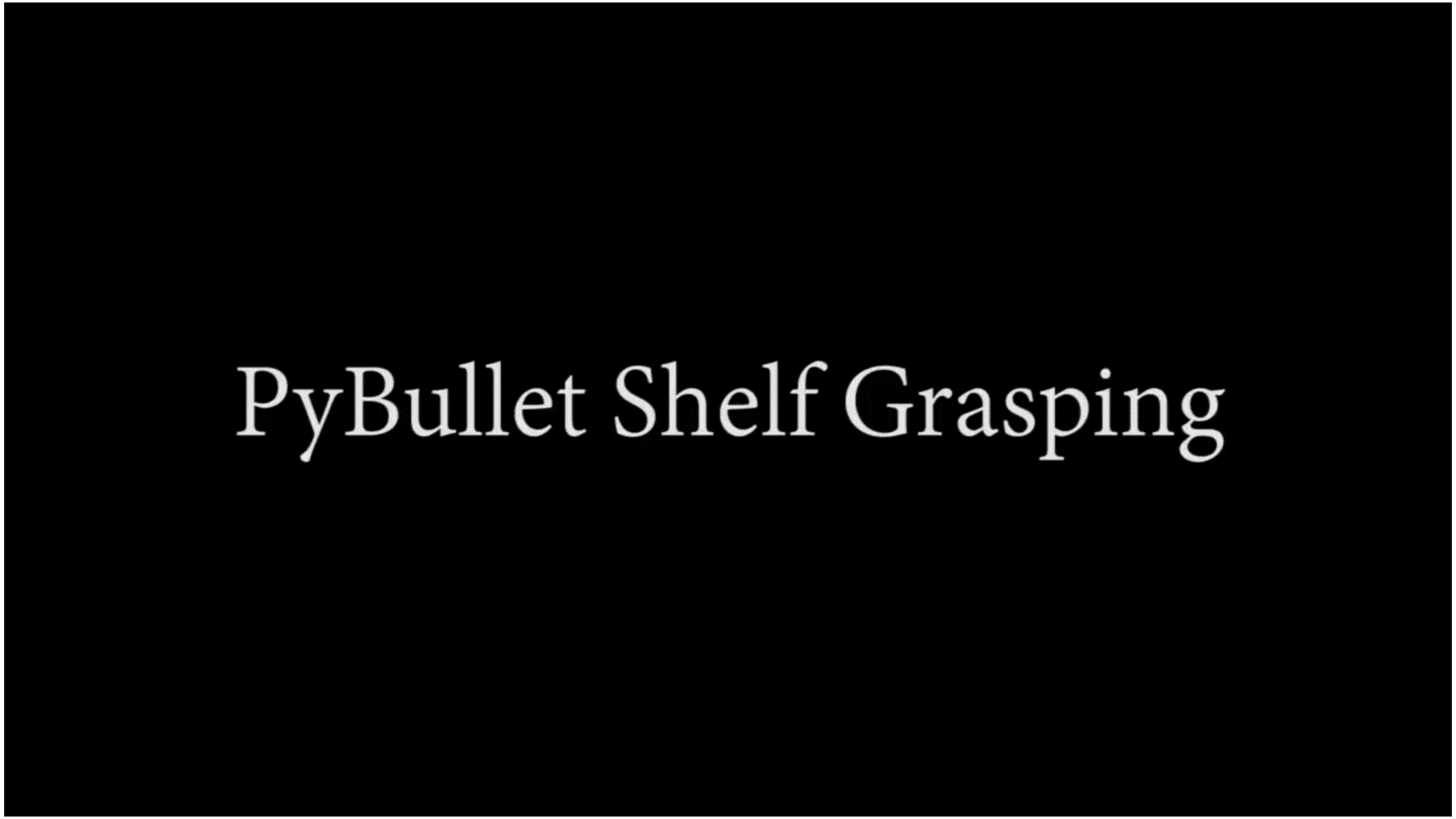
- Solve a trajectory with joint positions and joint velocities

$$\mathcal{Q} = (\mathbf{q}_1, \dots, \mathbf{q}_T) \qquad \dot{\mathcal{Q}} = (\dot{\mathbf{q}}_1, \dots, \dot{\mathbf{q}}_T)$$

$$\begin{aligned}
\underset{\mathcal{Q}, \dot{\mathcal{Q}}}{\arg\min} \quad & \Big(\min_{i=1}^{K} \left(c_{\text{goal}}(\mathbf{T}(\mathbf{q}_T), \mathbf{T}_i) + c_{\text{standoff}}(\mathbf{T}(\mathbf{q}_{T-\delta}), \mathbf{T}_i \mathbf{T}_\Delta) \right) \\
& \quad + \lambda_1 \textstyle\sum_{t=1}^{T} c_{\text{collision}}(\mathbf{q}_t) + \lambda_2 \sum_{t=1}^{T} \|\dot{\mathbf{q}}_t\|^2 \Big) \\
\text{s.t.,} \quad & \mathbf{q}_1 = \mathbf{q}_0 \\
& \dot{\mathbf{q}}_1 = \mathbf{0}, \dot{\mathbf{q}}_T = \mathbf{0} \\
& \mathbf{q}_{t+1} = \mathbf{q}_t + \dot{\mathbf{q}}_t dt, t = 1, \dots, T-1 \\
& \mathbf{q}_l \leq \mathbf{q}_t \leq \mathbf{q}_u, t = 1, \dots, T \\
& \dot{\mathbf{q}}_l \leq \dot{\mathbf{q}}_t \leq \dot{\mathbf{q}}_u, t = 1, \dots, T,
\end{aligned}$$

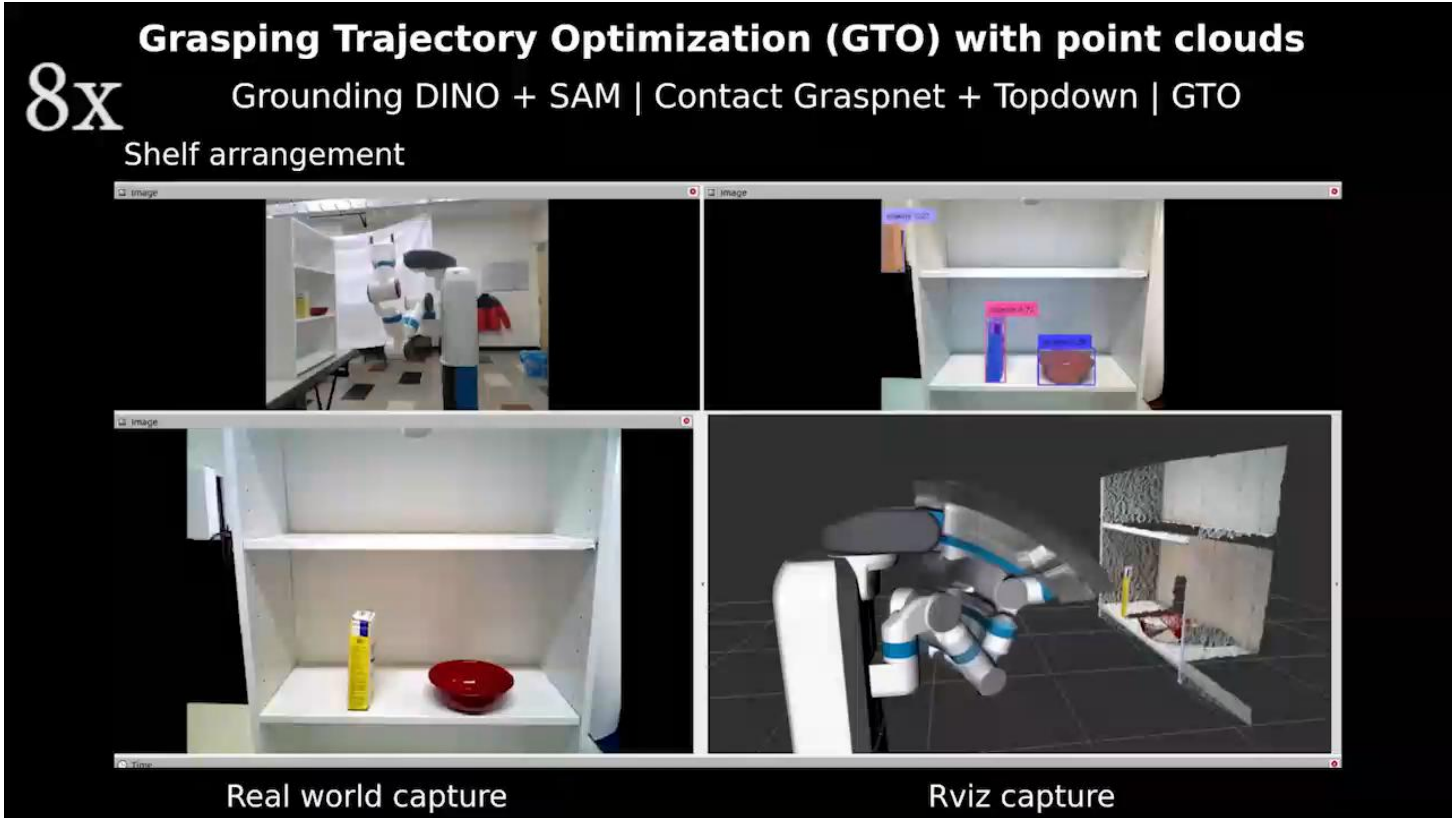
Grasping Trajectory Optimization with Point Clouds

- Simulation results



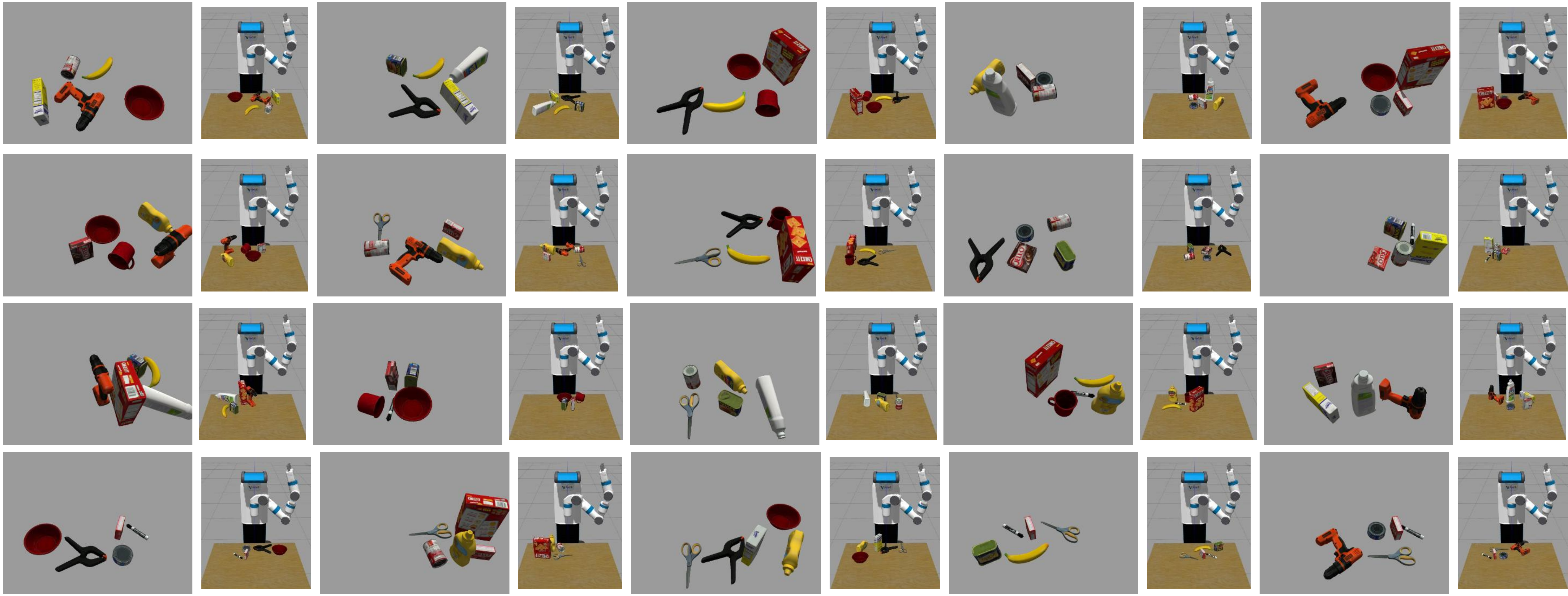
Grasping Trajectory Optimization with Point Clouds

- Real-world results



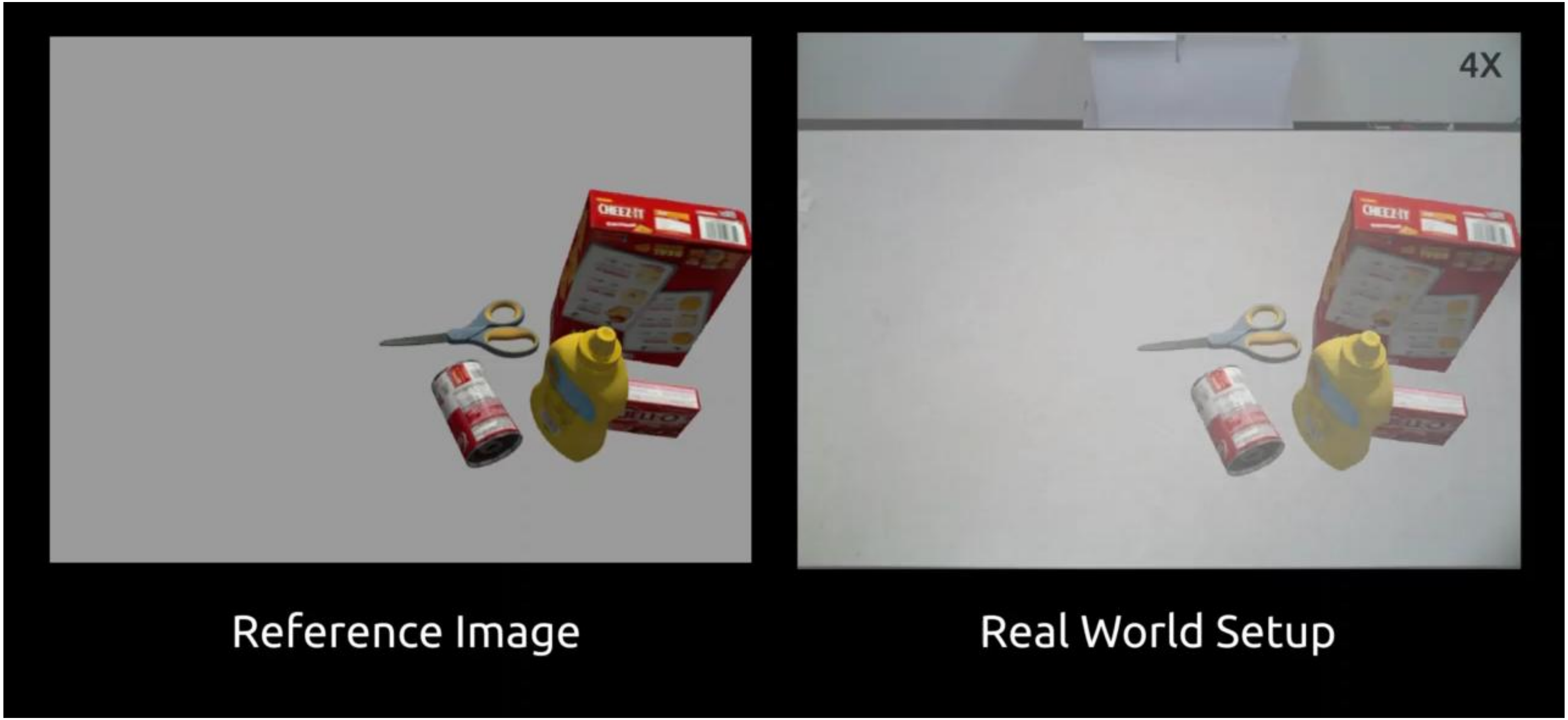
SceneReplica Benchmark

20 Scenes



SceneReplica, Khargonkar-Allu-Lu-P-Prabhakaran-**Xiang**, ICRA'24: https://irvlutd.github.io/SceneReplica/

Real-World Scene Setup



SceneReplica Benchmark

Method #	Perception	Grasp Planning	Motion Planning	Control	Ordering	Pick-and-Place Success	Grasping Success
			Model-based Grasping				
1	PoseRBPF [21]	GraspIt! [22] + Top-down	OMPL [24]	MoveIt	Near-to-far	58 / 100	64 / 100
1	PoseRBPF [21]	GraspIt! [22] + Top-down	OMPL [24]	MoveIt	Fixed	59 / 100	59 / 100
2	PoseCNN [19]	GraspIt! [22] + Top-down	OMPL [24]	MoveIt	Near-to-far	47 / 100	48 / 100
2	PoseCNN [19]	GraspIt! [22] + Top-down	OMPL [24]	MoveIt	Fixed	40 / 100	45 / 100
3	GDRNPP [34], [36]	GraspIt! [22] + Top-down	OMPL [24]	MoveIt	Near-to-far	**66 / 100**	69 / 100
3	GDRNPP [34], [36]	GraspIt! [22] + Top-down	OMPL [24]	MoveIt	Fixed	62 / 100	64 / 100
			Model-free Grasping				
4	UCN [26]	GraspNet [28] + Top-down	OMPL [24]	MoveIt	Near-to-far	43 / 100	46 / 100
4	UCN [26]	GraspNet [28] + Top-down	OMPL [24]	MoveIt	Fixed	37 / 100	40 / 100
5	UCN [26]	Contact-graspnet [29] + Top-down	OMPL [24]	MoveIt	Near-to-far	60 / 100	63 / 100
5	UCN [26]	Contact-graspnet [29] + Top-down	OMPL [24]	MoveIt	Fixed	60 / 100	64 / 100
6	MSMFormer [27]	GraspNet [28] + Top-down	OMPL [24]	MoveIt	Near-to-far	38 / 100	41 / 100
6	MSMFormer [27]	GraspNet [28] + Top-down	OMPL [24]	MoveIt	Fixed	36 / 100	41 / 100
7	MSMFormer [27]	Contact-graspnet [29] + Top-down	OMPL [24]	MoveIt	Near-to-far	57 / 100	65 / 100
7	MSMFormer [27]	Contact-graspnet [29] + Top-down	OMPL [24]	MoveIt	Fixed	61 / 100	**70 / 100**
8	MSMFormer [27]	Top-down	OMPL [24]	MoveIt	Fixed	56 / 100	59 / 100
			End-to-end Learning-based Grasping				
9	Dex-Net 2.0 [37] (Top-Down Grasping)		OMPL [24]	MoveIt	Algorithmic	43 /100	51 / 100
			Ground truth pose-based Grasping				
10	Ground truth object pose	GraspIt! [22] + Top-down	OMPL [24]	MoveIt	Near-to-far	78 / 100	82 / 100
11	Ground truth object pose	GraspIt! [22] + Top-down	OMPL [24]	MoveIt	Fixed	78 / 100	87 / 100

Grasping Trajectory Optimization with Point Clouds

- Real world experiments

Method #	Perception	Grasp Planning	Motion Planning	Control
			Model-free Grasping	
1	MSMFormer [33]	Contact-graspnet [29] + Top-down	OMPL [34]	MoveIt
2	MSMFormer [33]	Contact-graspnet [29] + Top-down	**GTO (Ours)**	MoveIt

Ordering	Pick-and-Place Success	Grasping Success
Near-to-far	57 / 100	65 / 100
Near-to-far	**65 / 100**	**71 / 100**

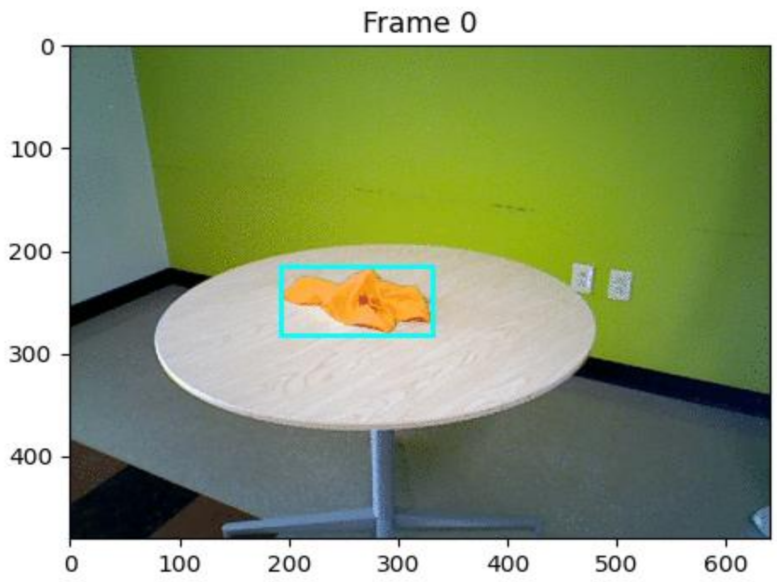
Grasping Trajectory Optimization with Point Clouds. **Yu Xiang**, Sai Haneesh Allu, Rohith Peddi, Tyler Summers, Vibhav Gogate
In IROS, 2024.

Using 3D Point Clouds

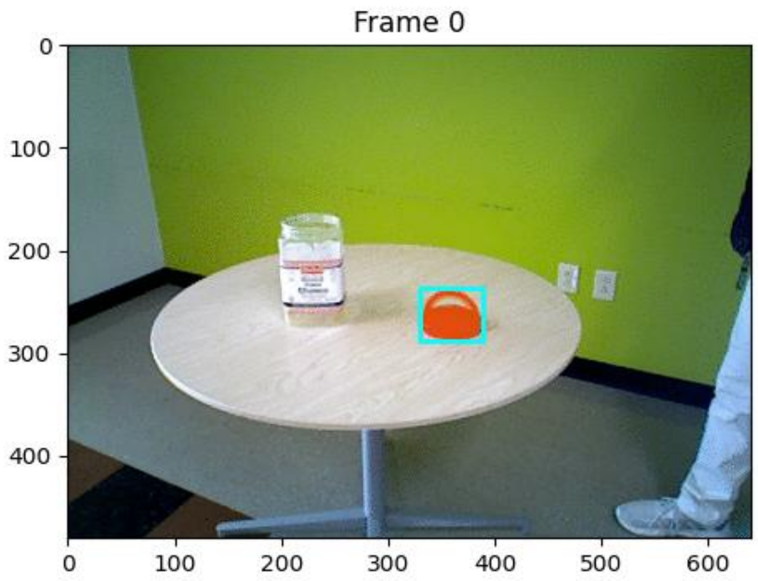
- Pros
  - No need to build 3D models
  - Direct sensor input from RGB-D cameras
  - Encode appearance and 3D geometry

- Cons
  - It is difficult to capture depth for certain objects (flat, thin, transparent, metal)
  - Planning from partial observations

Learning Manipulation Skills from Human Videos



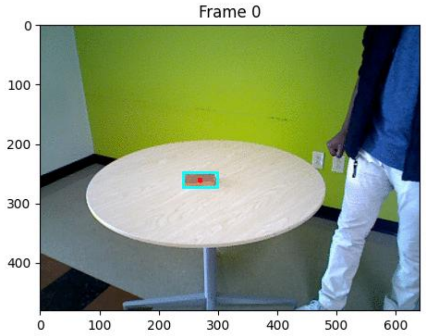
Clean table using Towel



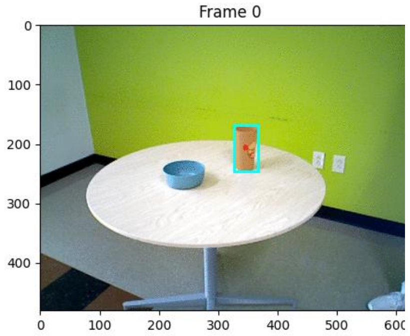
Close jar with Red Lid

On-going work

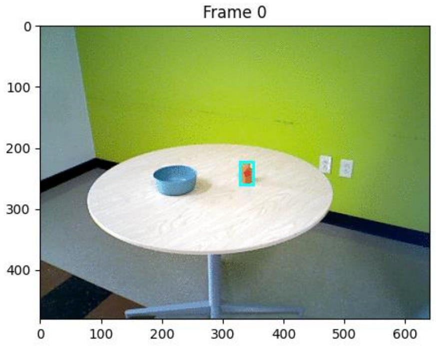
Learning Manipulation Skills from Human Videos



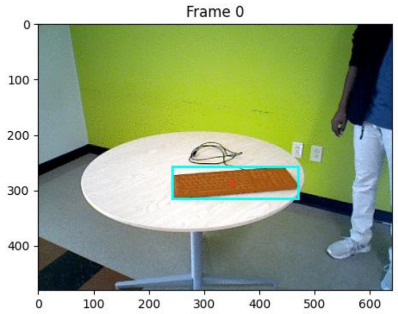
Use Scrubber



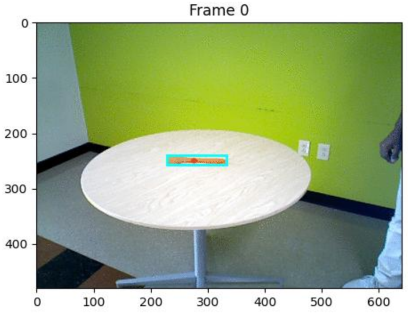
Pour Tumbler



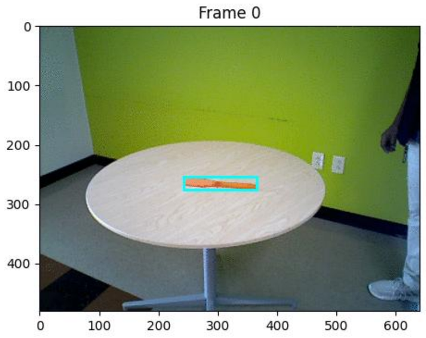
Use Salt Shaker



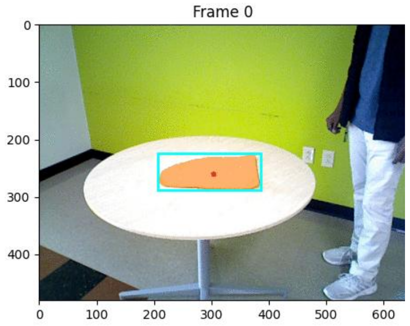
Press any key on keyboard



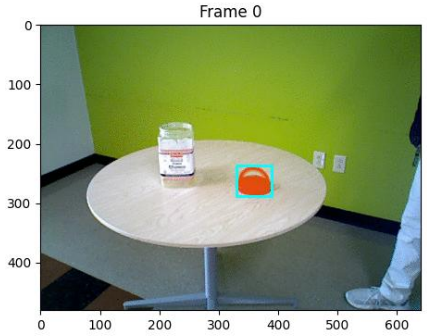
Use basting brush



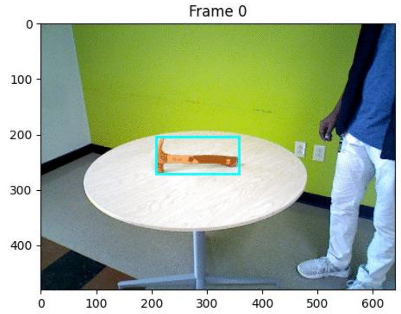
Use Spatula



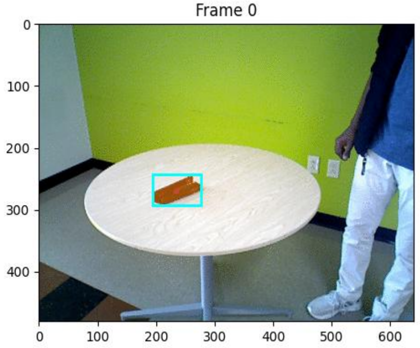
Fold Towel



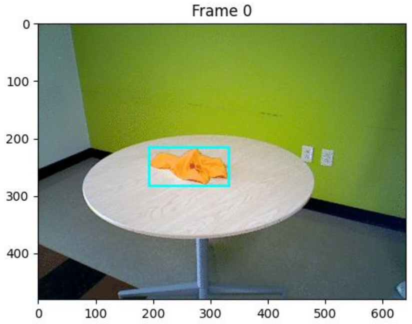
Close jar with Red Lid



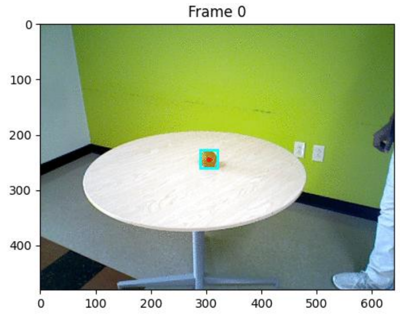
Use hammer



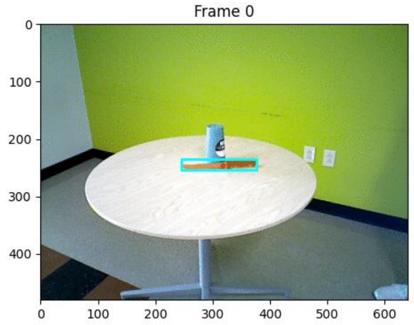
Use Stapler



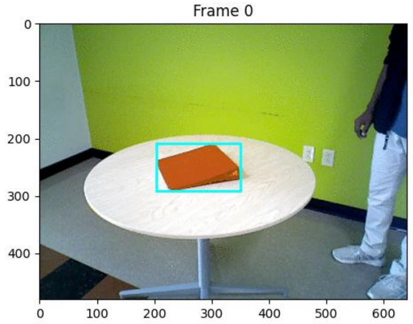
Clean table using Towel



Squeeze the Sponge ball

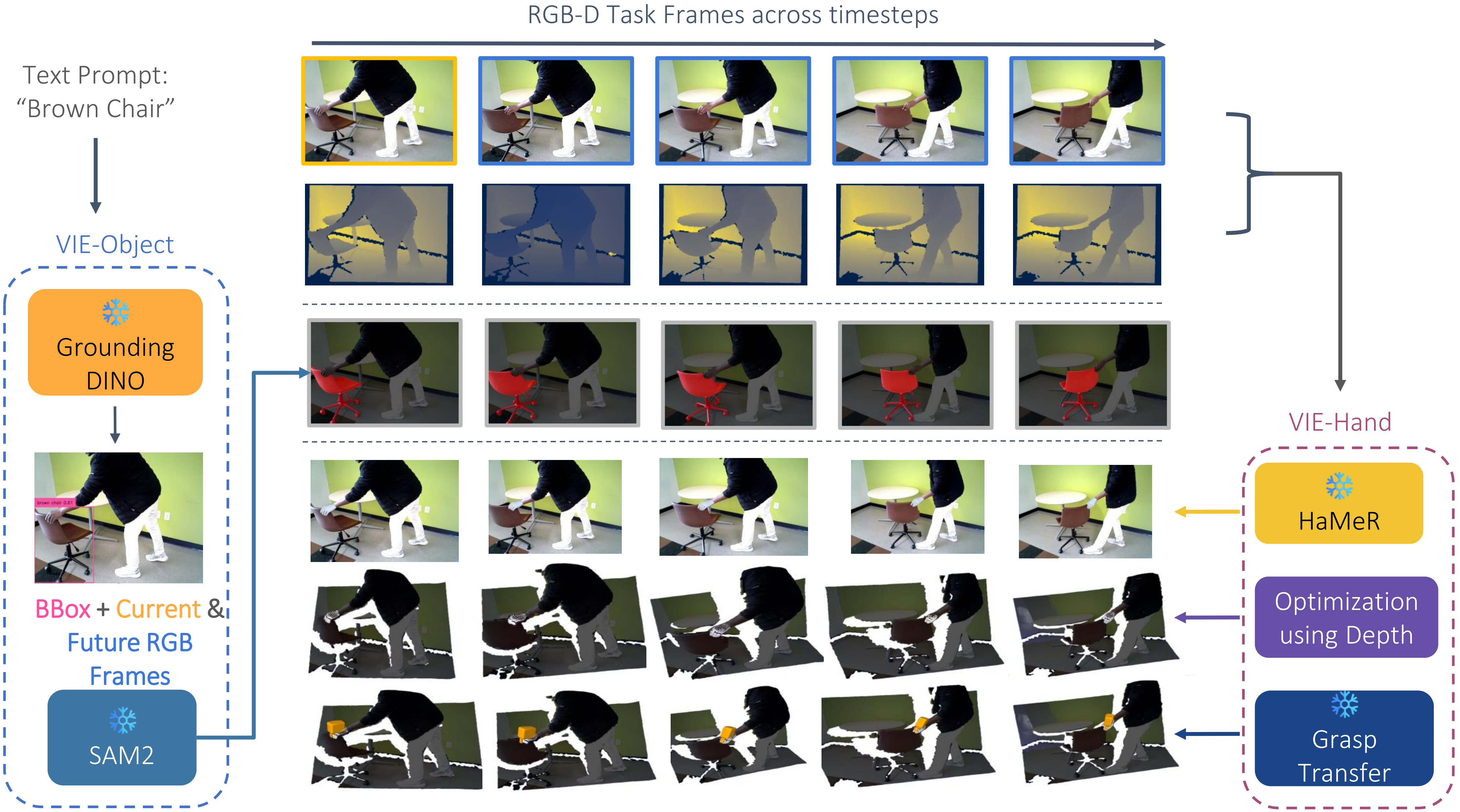


Use Knife

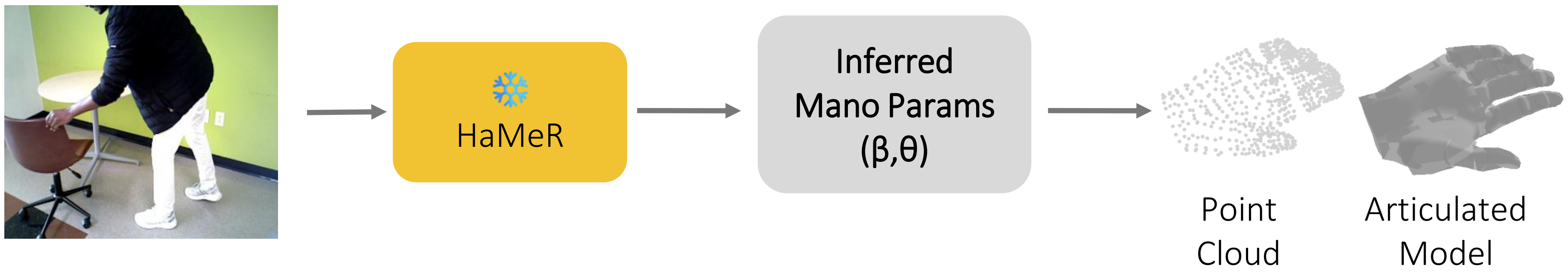


Open folder

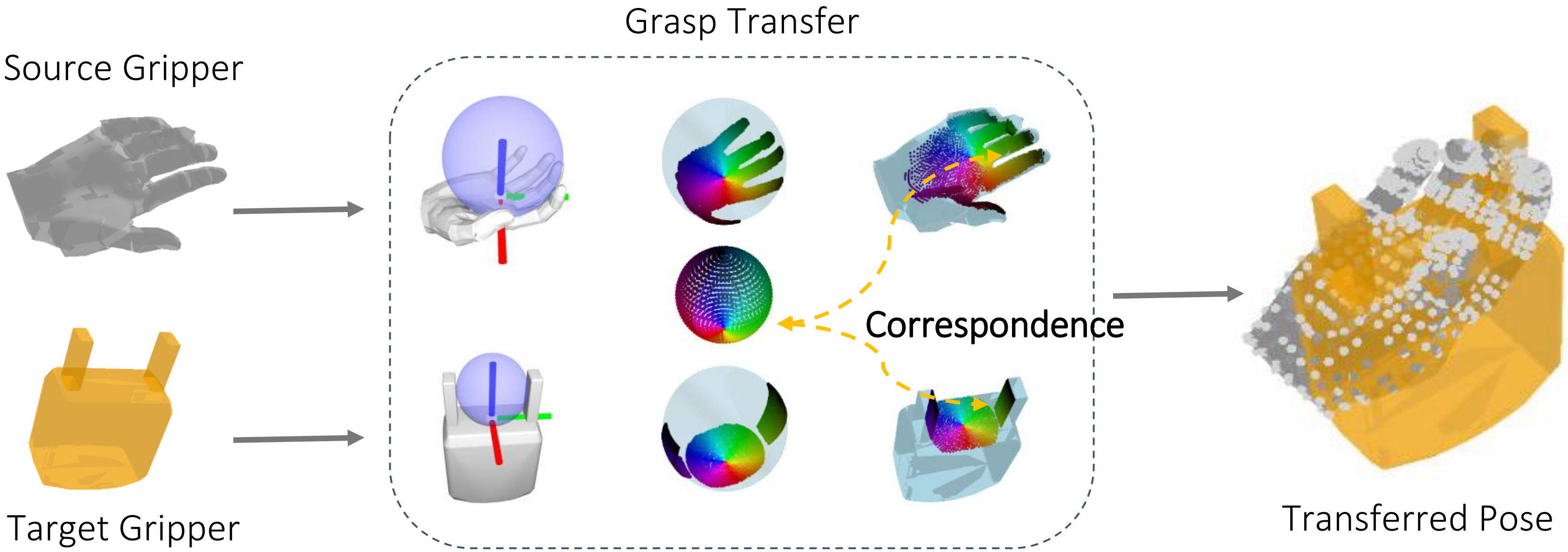
Understanding of the Human Demonstrations



Grasp Transfer from Human to Robot

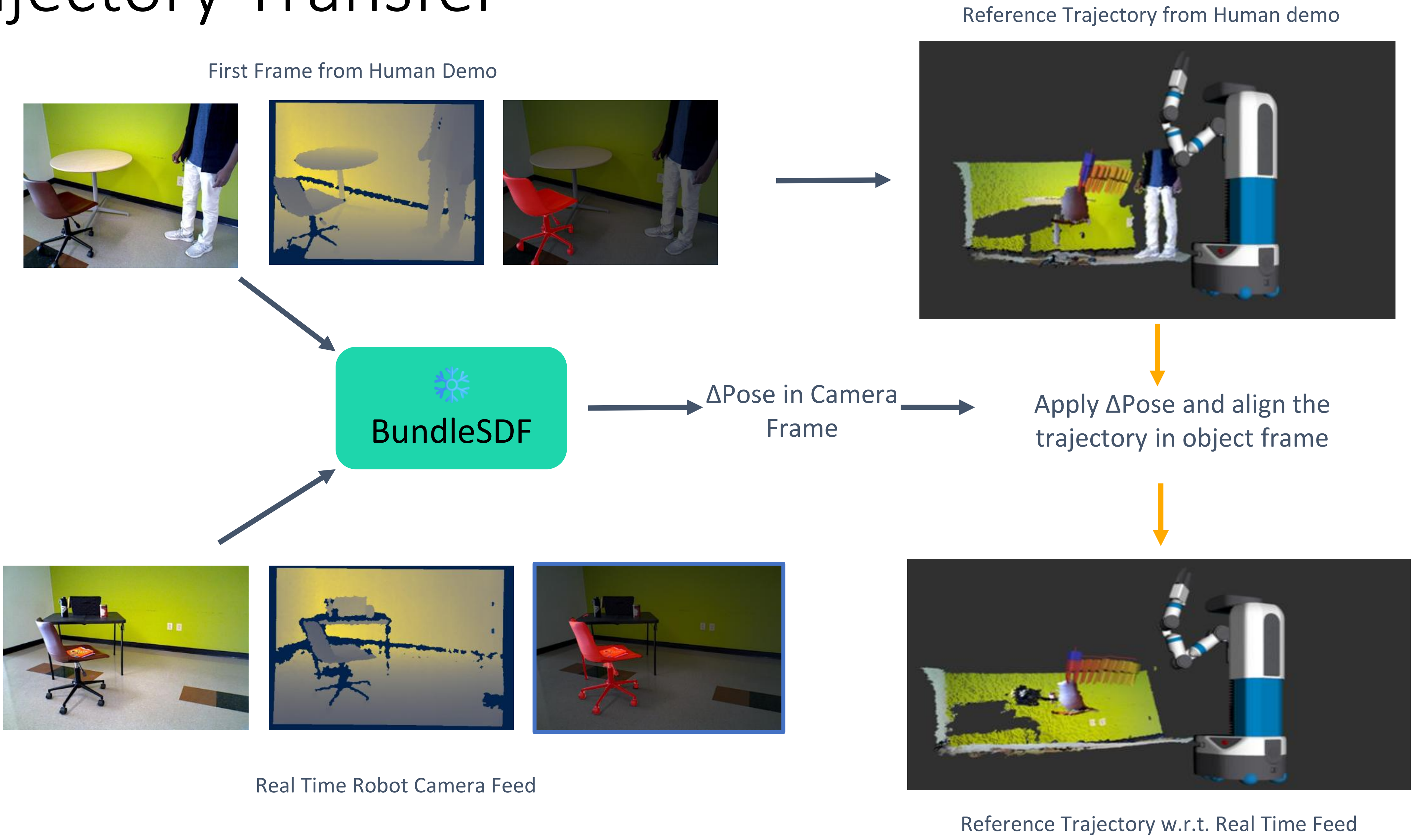


(a) 6D hand pose using HaMeR predicted Mano params

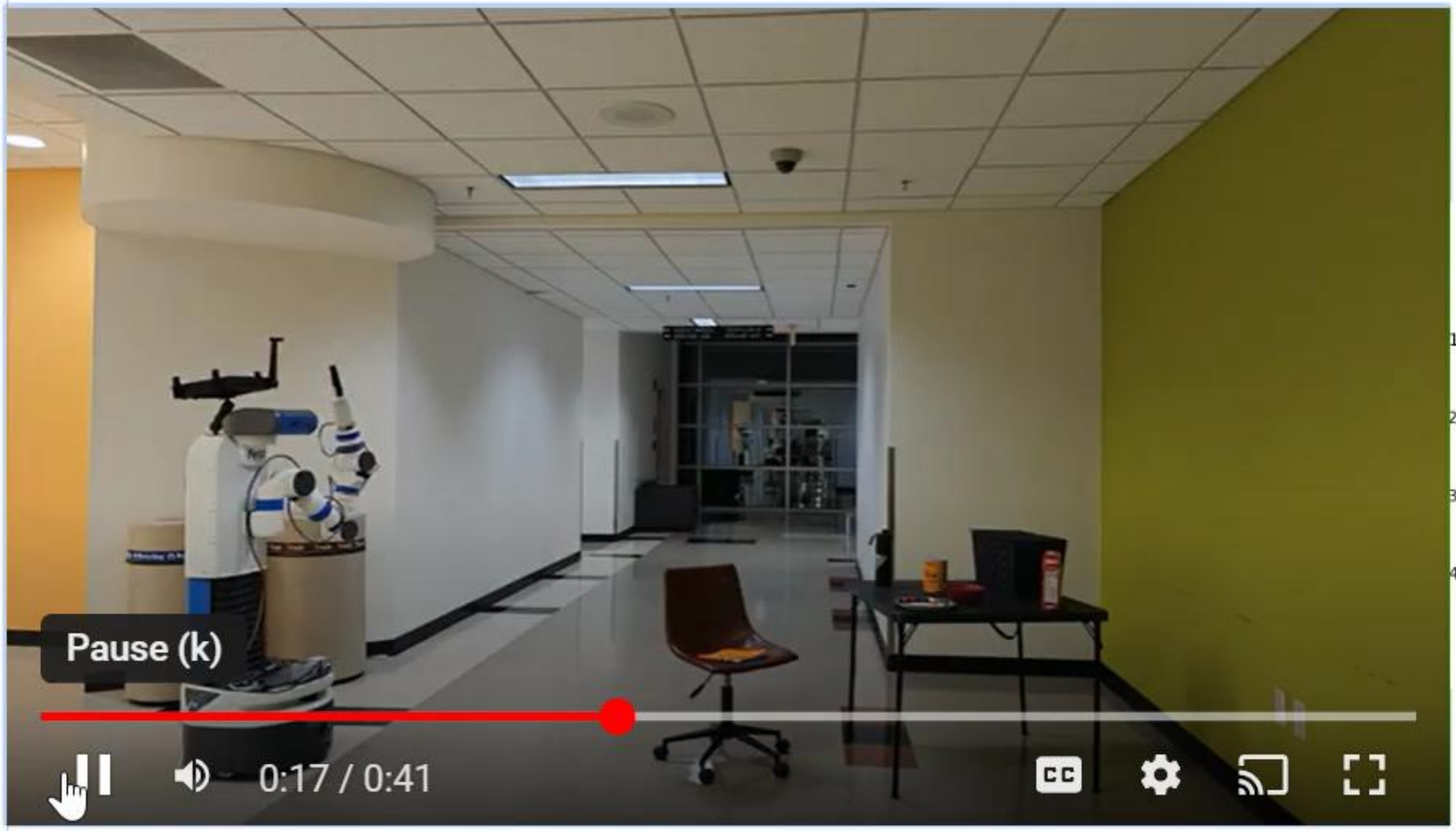


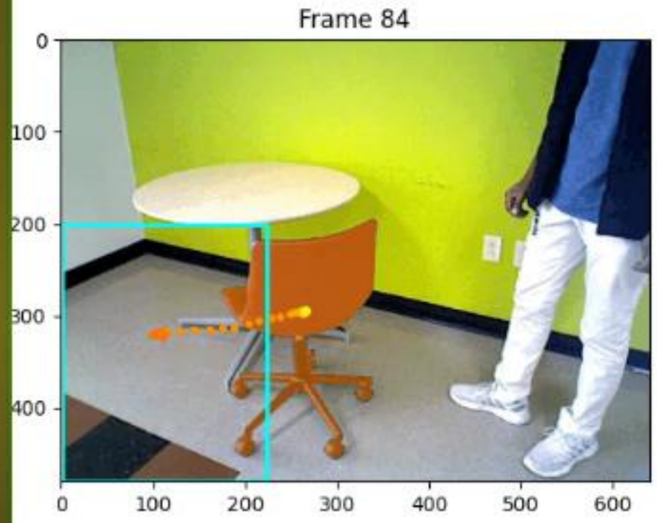
(b) Grasp Transfer using Unified Gripper Coordinate Space

Trajectory Transfer

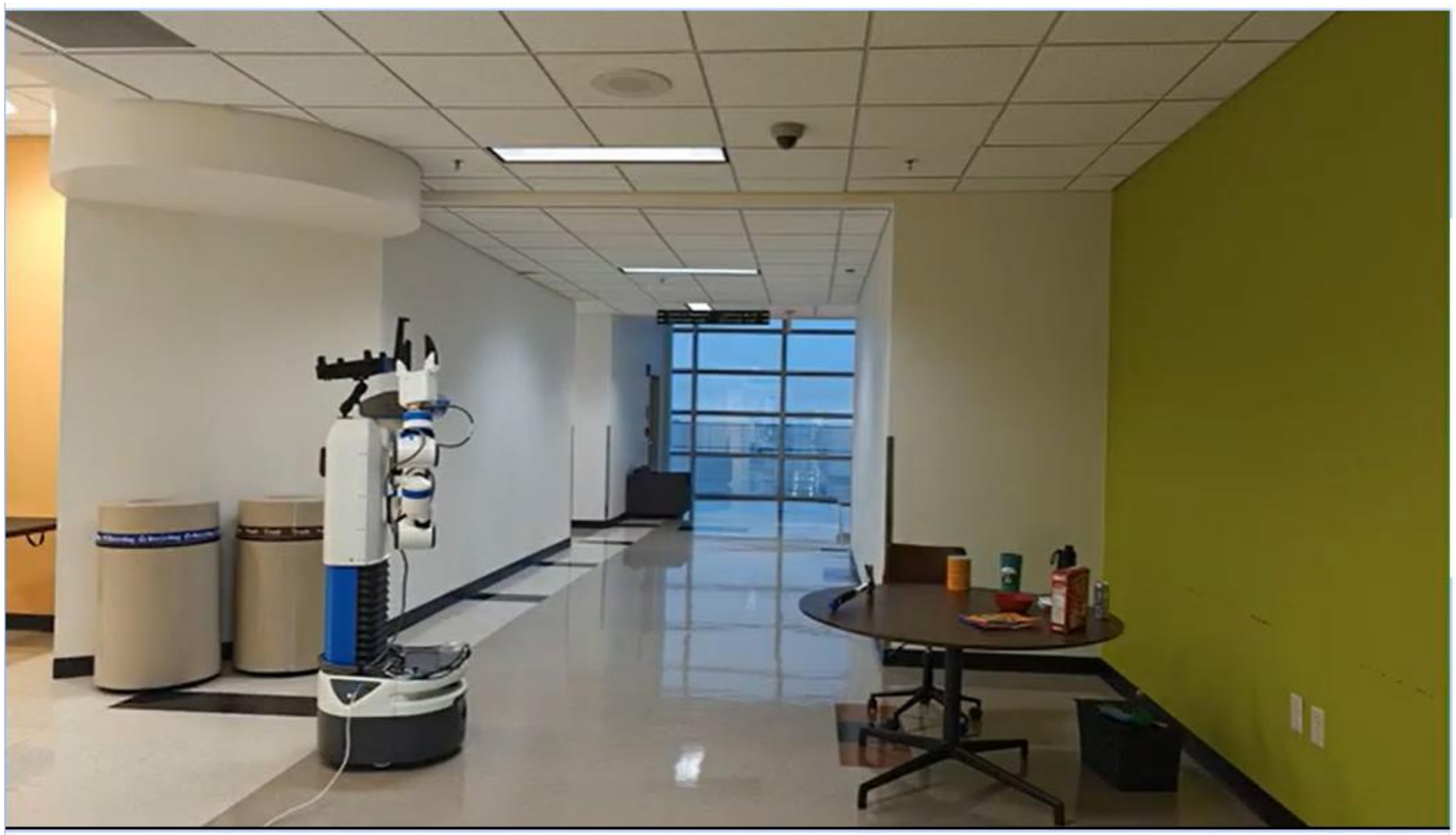


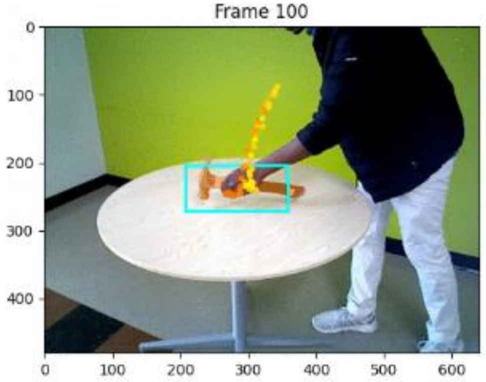
Trajectory Optimization to Follow the Reference





Trajectory Optimization to Follow the Reference





Failure Example

Frame 0

Key Ingredients for Building Intelligent Robots

- Hardware: humanoids, hands, sensors, processing units, etc.

- Perception: robots need to understand the 3D world, human-robot interaction, etc.

- Planning & Control: robots need to plan for the high-level tasks and the low-level motions, and generate control commands to achieve the motions

- Learning & Reasoning: robots need to learn and reason about how to do tasks (imitation learning, RL, learning in simulation, etc.)

Thank you!