Learning Robotic Manipulation from Human Demonstration Videos

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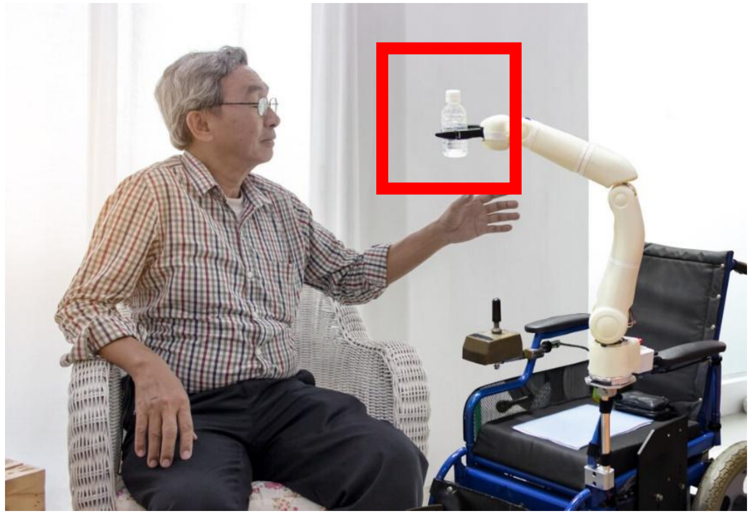
10/15/2025

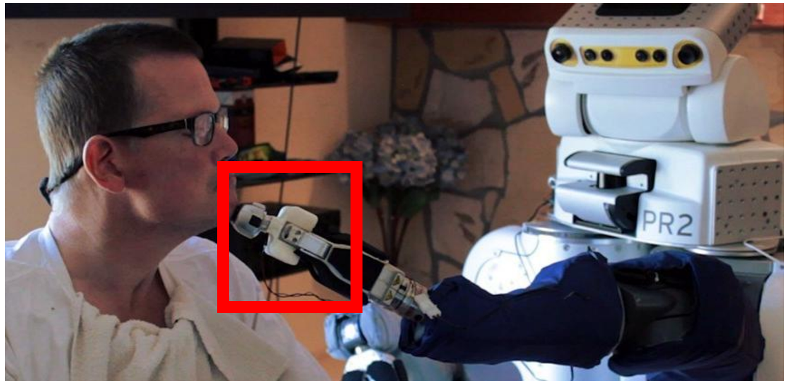
UNC Guest Lecture

Future Intelligent Robots in Human Environments

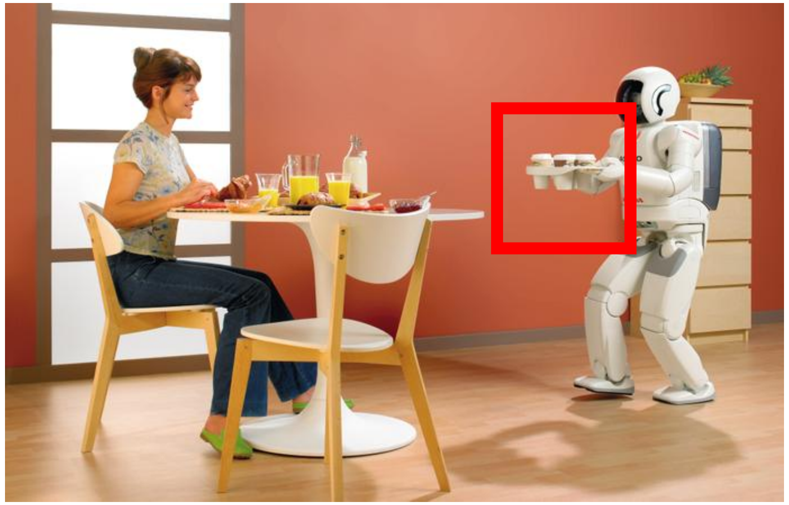
Manipulation



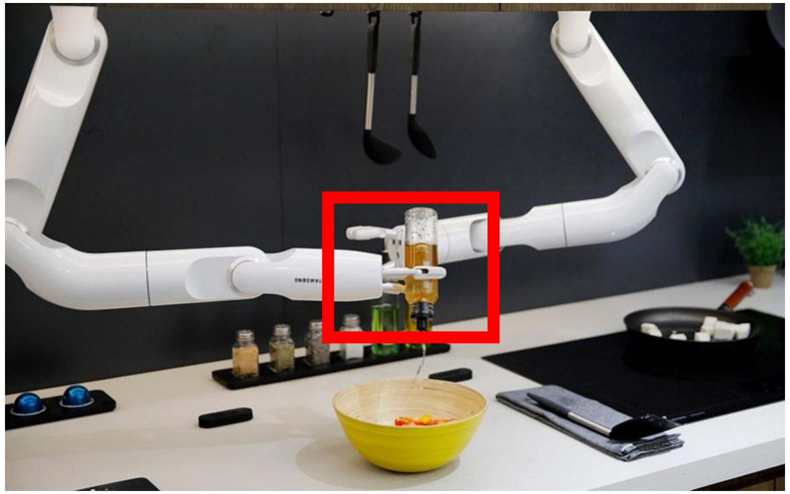
Senior Care



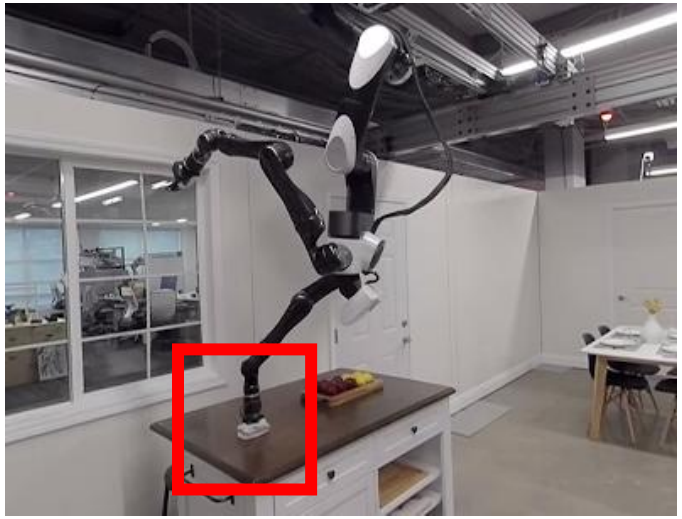
Assisting



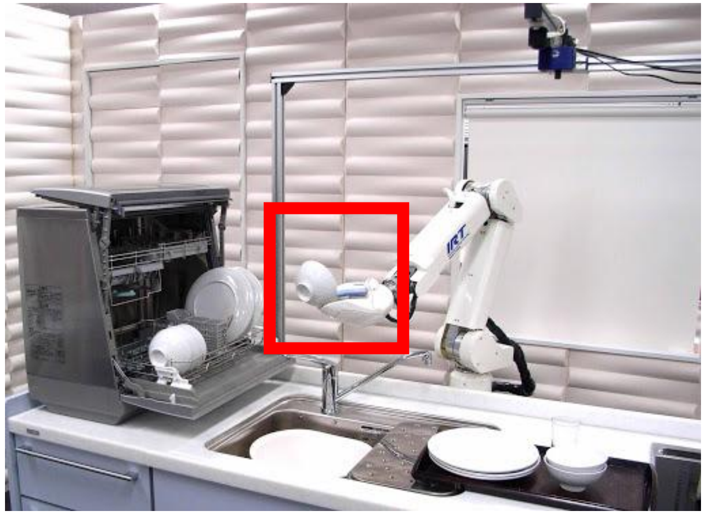
Serving



Cooking



Cleaning

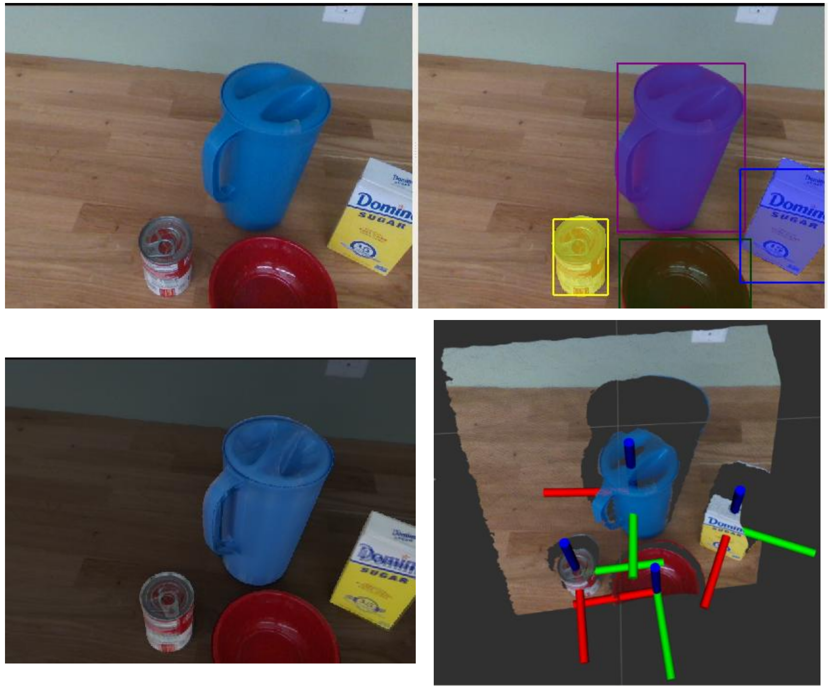


Dish washing

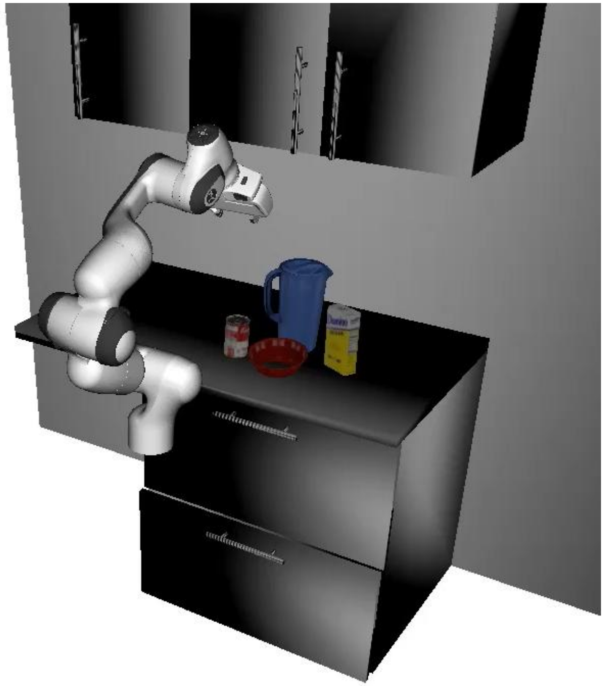
“Traditional” Approach for Robot Manipulation

Perception → Planning → Control

6D object pose estimation



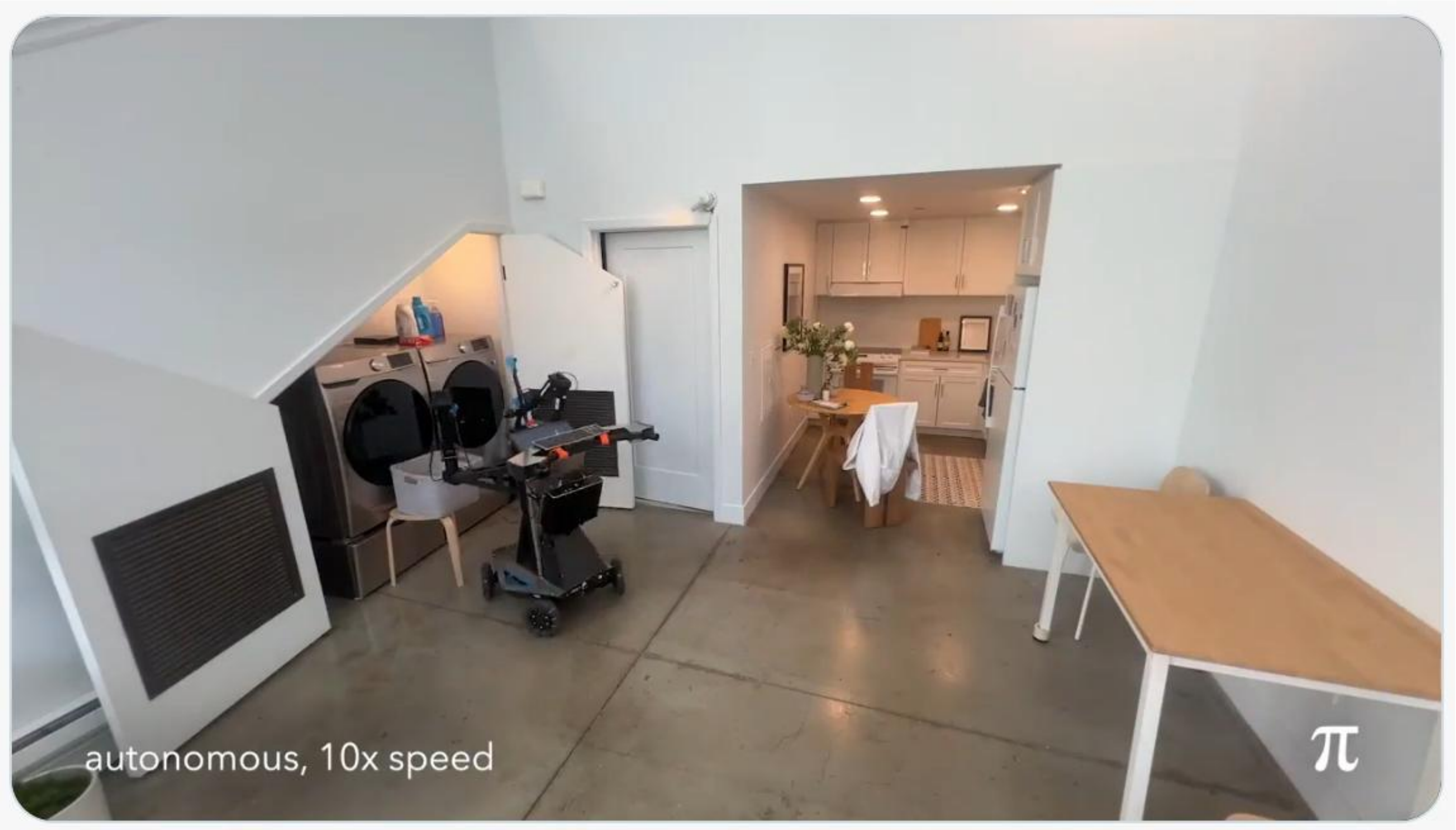
Grasp planning and motion planning



Manipulation trajectory following

Hard code the logics for manipulation based on perception and planning

Some Recent Breakthroughs



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

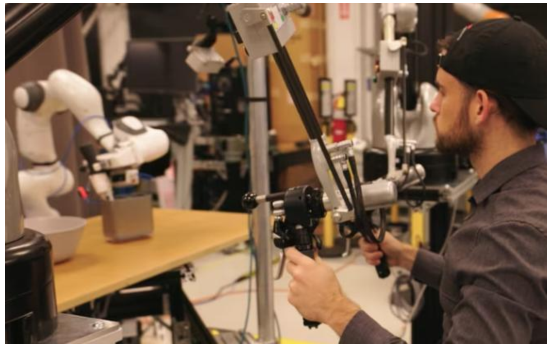
Some Recent Breakthroughs

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

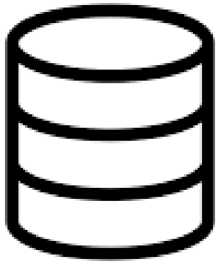
Key Ingredient: Imitation Learning

Kinesthetic Teaching

Teleoperation

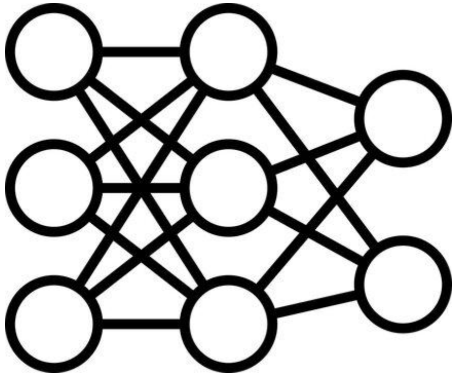


Collect Demonstrations



(state, action)

A Dataset of State-Action Pairs



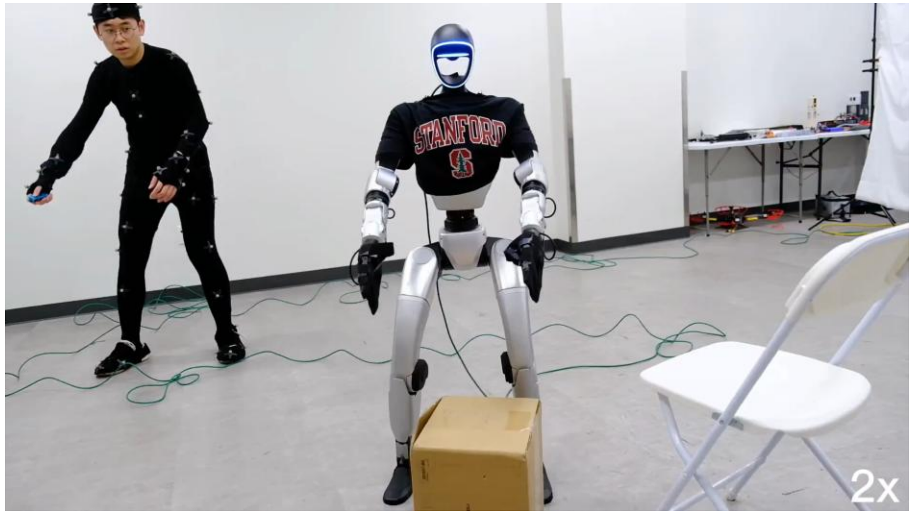
Train a Policy Network

Deploy the Policy Network

Key Ingredient: Teleoperation for Data Collection

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

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



https://yanjieze.com/TWIST/

Tesla

Key Ingredient: Teleoperation for Data Collection

- Requires specific hardware

- Requires human expertise

- Difficult to scale up

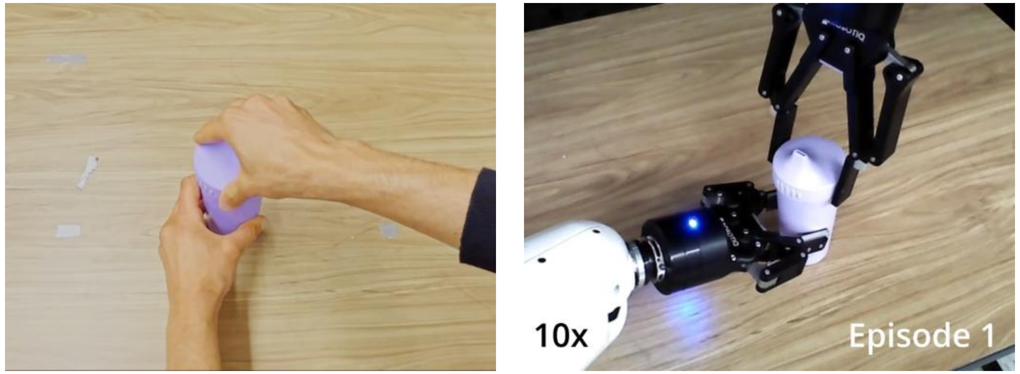
Learning Manipulation from Human Videos

Image generated by ChatGPT

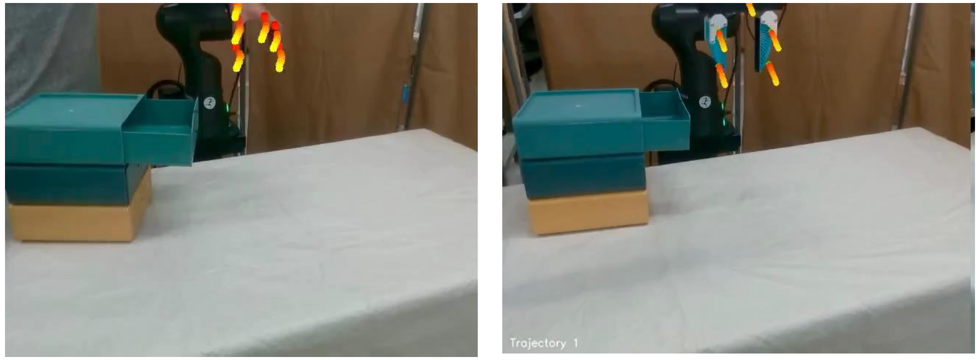
Learning Manipulation from Human Videos

- Imitation learning: convert human → robot actions, then imitate

DexMV, Qin et al. UCSD, ECCV 2022



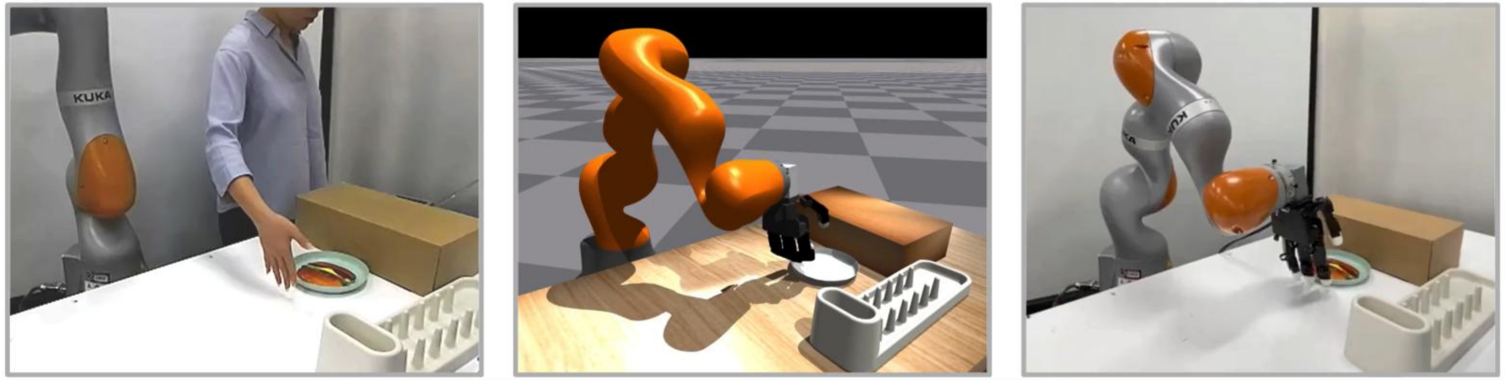
ScrewMimic, Bahety et al. UT Austin, RSS 2024



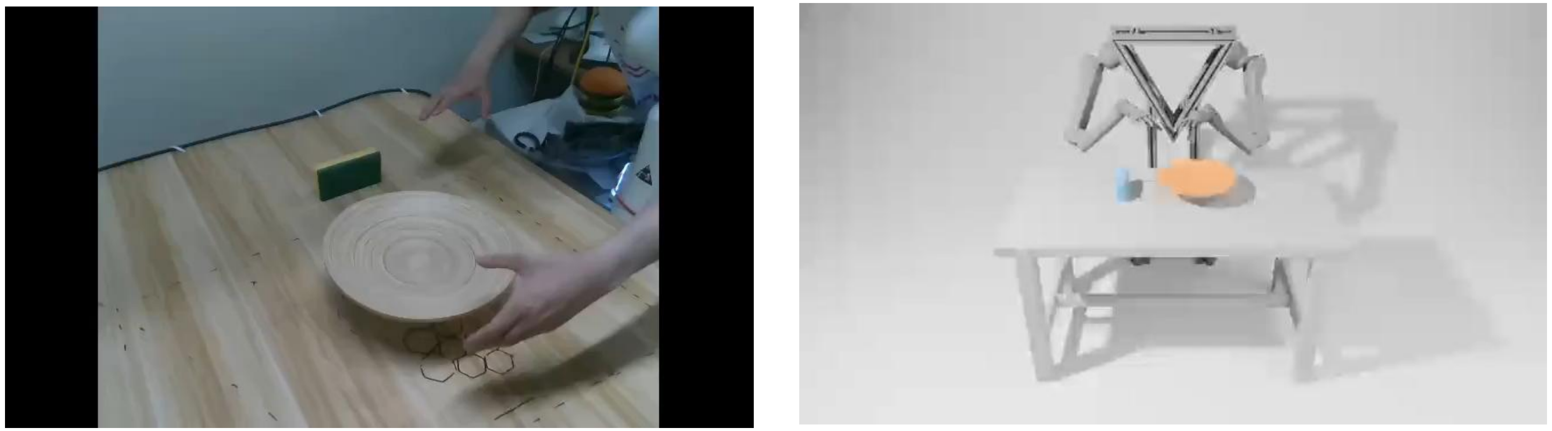
Motion Tracks, Ren et al. Cornell & Stanford, 2025

Learning Manipulation from Human Videos

- RL: replicate the environment in simulation, then train a policy



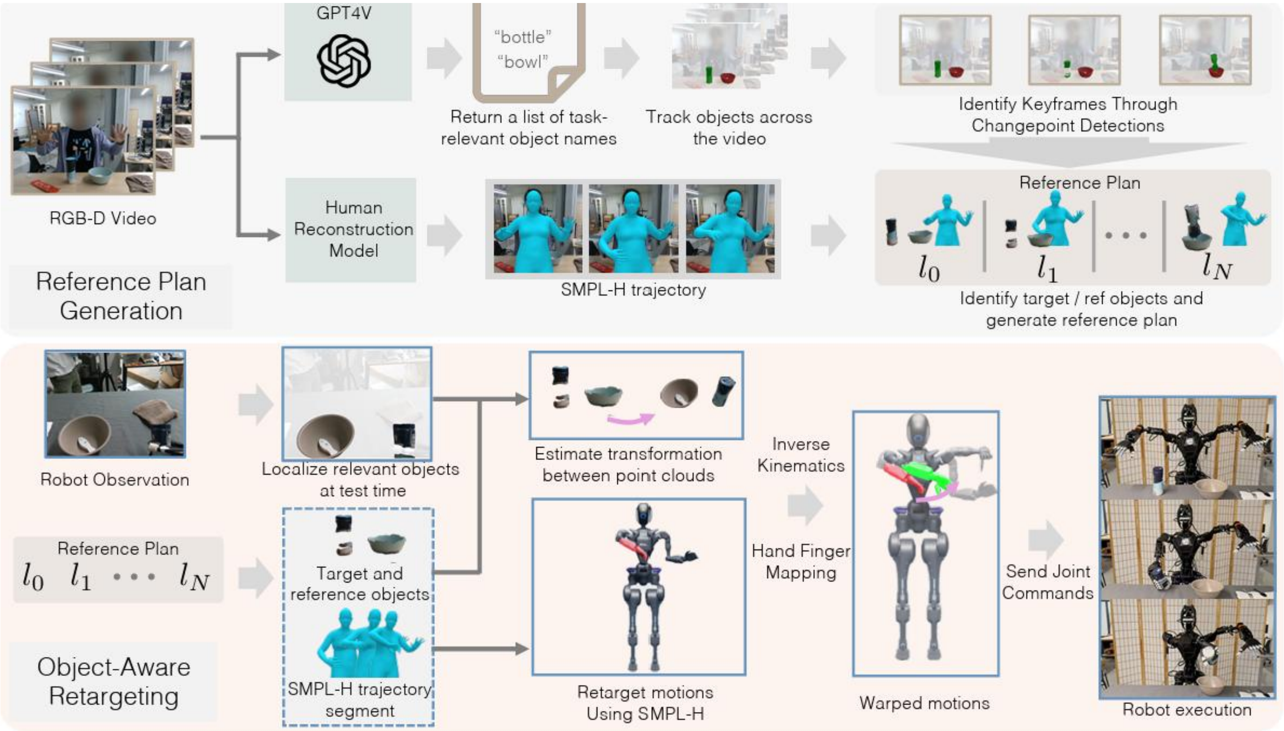
HUMAN2SIM2ROBOT, Lum et al. Stanford, 2025



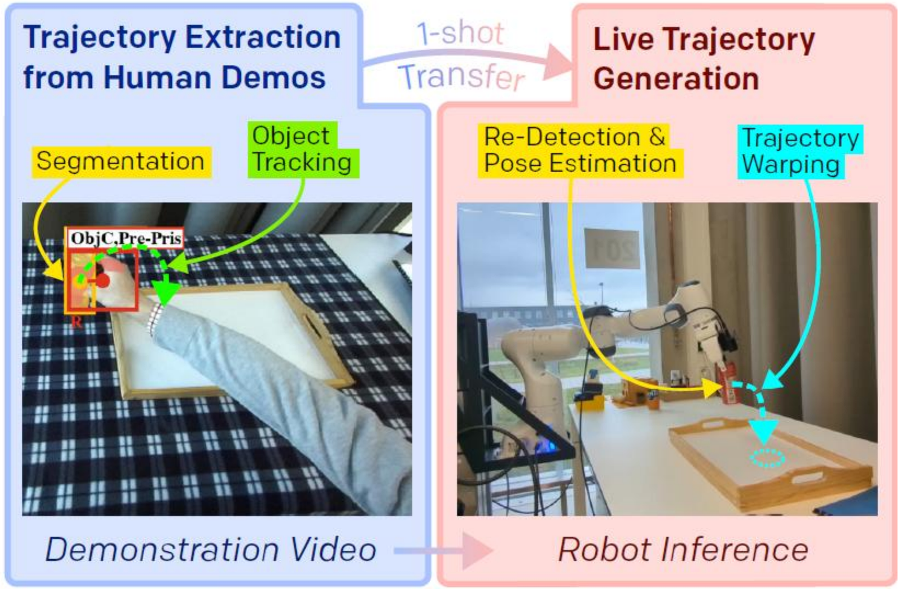
HERMES, Yuan et al., Tshinghua, 2025

Learning Manipulation from Human Videos

- Training-free: use perception + geometry to transfer trajectories



OKAMI, Li et al. UT Austin, CoRL 2024

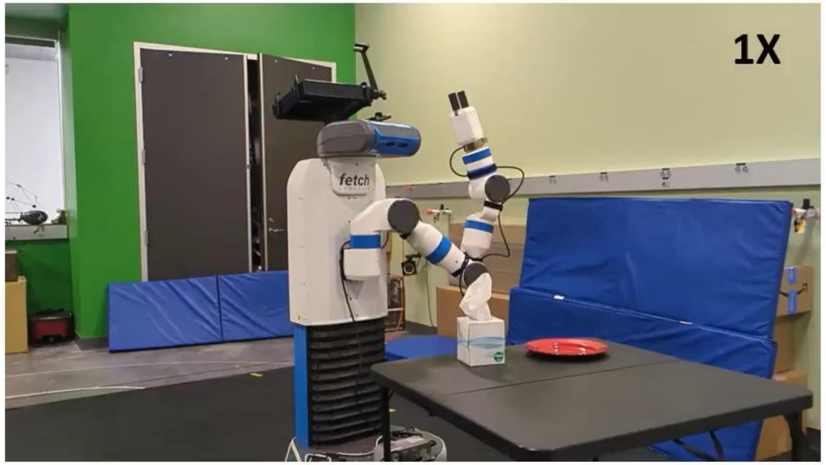


Trajectory Transfer, Heppert et al. University of Freiburg, IROS 2024

Our Work: One-Shot Human-to-Robot Trajectory Transfer

One-shot Human Demonstration

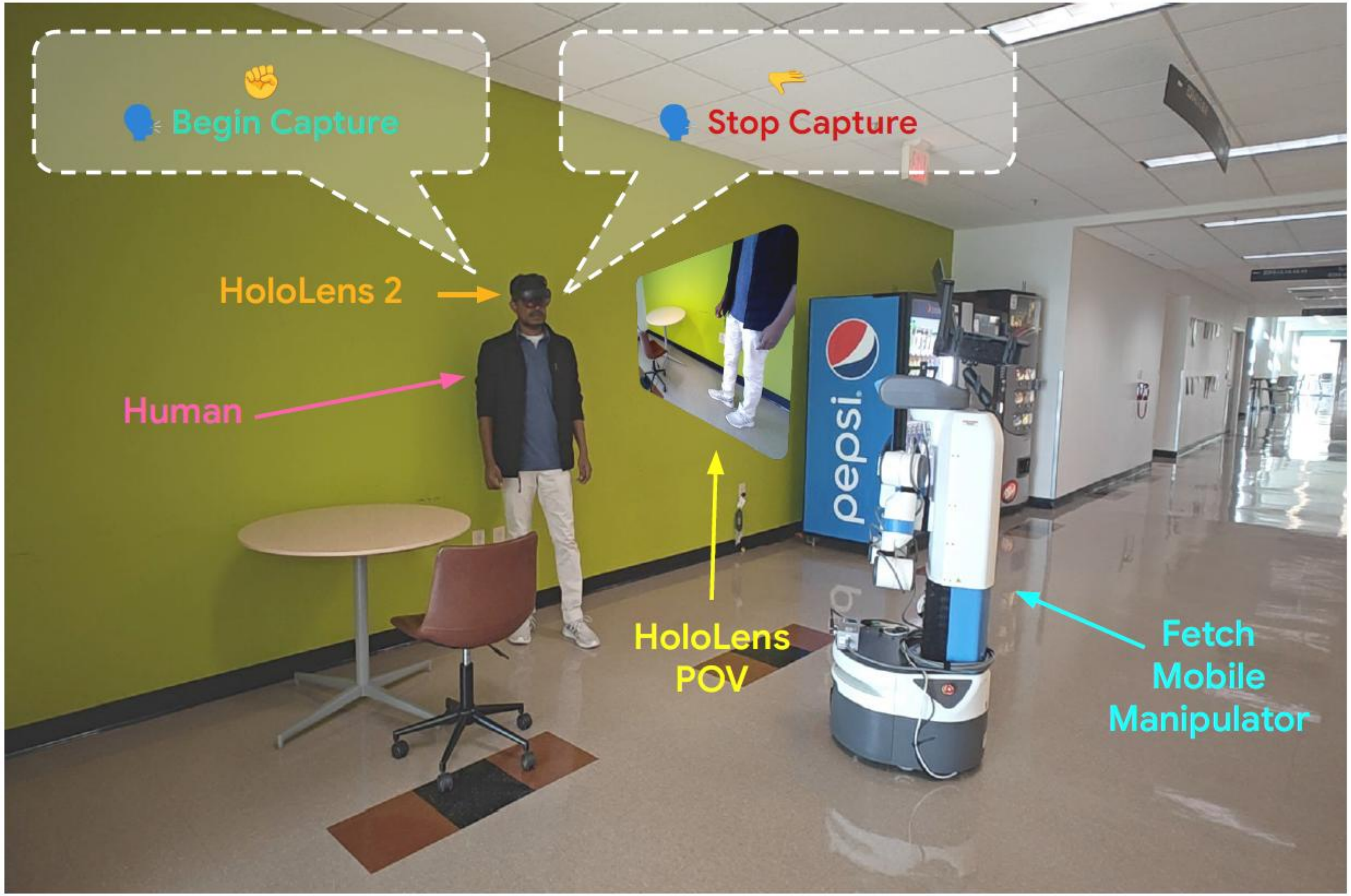
Robot Execution in Different Environments



Sai Haneesh Allu

Jishnu Jaykumar P

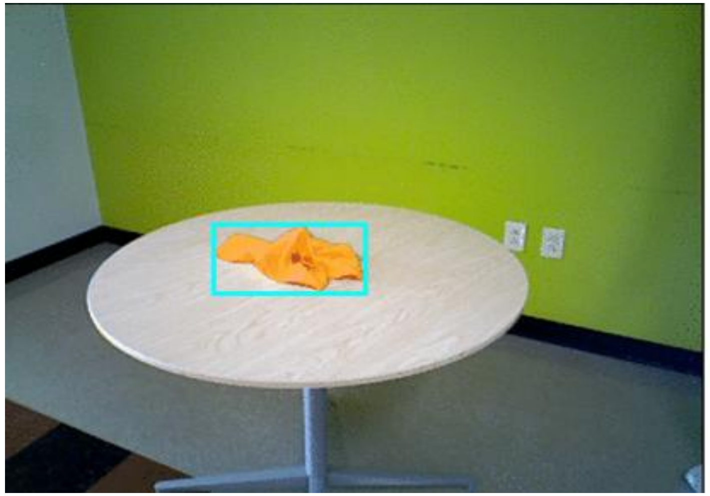
Human Demonstration Collection



Human Demonstration Collection

Human Demonstration Collection

Human Demonstration Collection



Clean table using Towel

Close jar with Red Lid

Pour Tumbler

Understanding of the Human Demonstrations

Text Prompt:
"Brown Chair"

Grounding
DINO

SAM2

Understanding of the Human Demonstrations

HaMeR

Optimization using Depth

Human-to-Robot Grasp Transfer

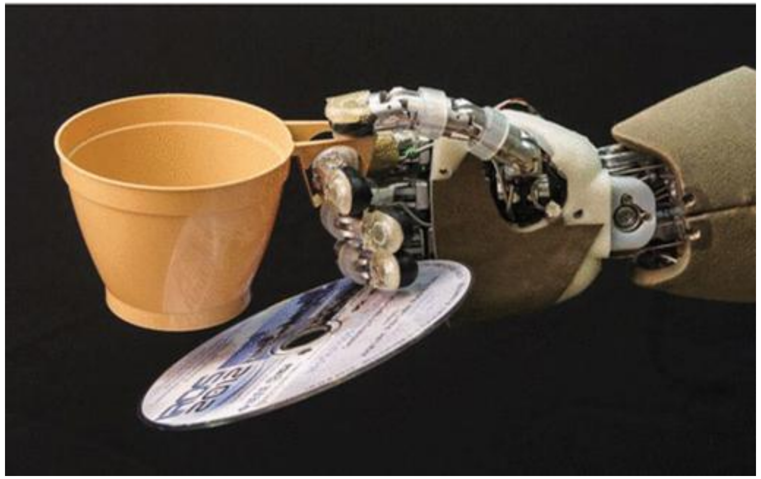
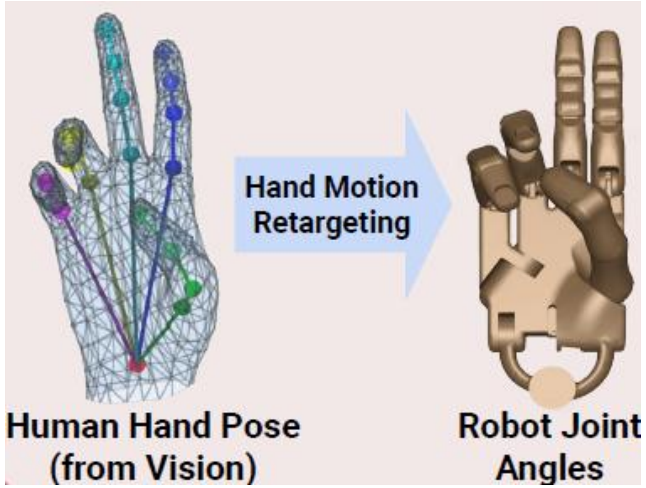


Image generated by ChatGPT

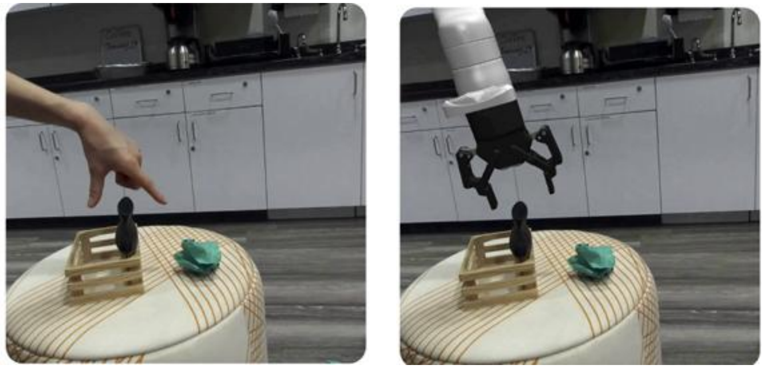
Human-to-Robot Grasp Transfer

- Retargeting



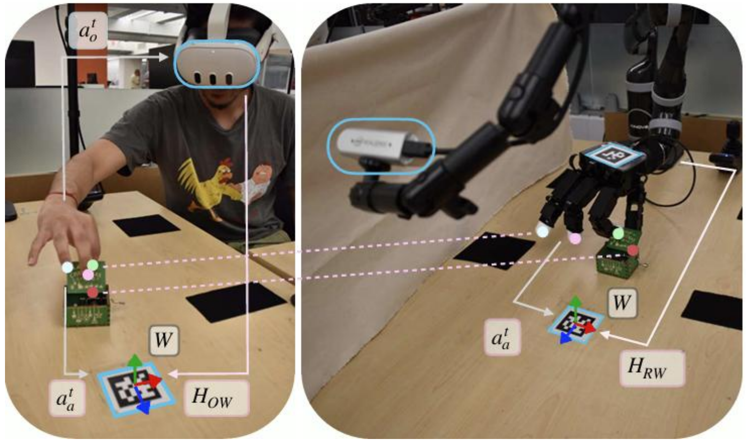
DexMV, Qin et al. UCSD, ECCV 2022

https://yzqin.github.io/dexmv/



Phantom, Lepert et al. Stanford 2025

https://phantom-human-videos.github.io/

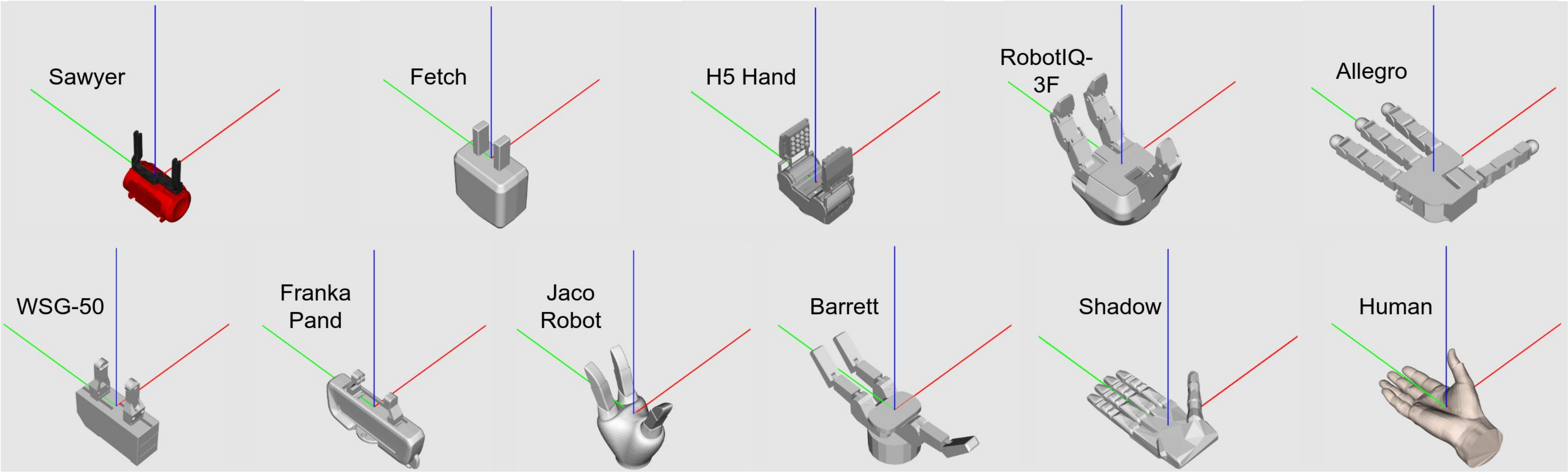


HuDOR, Guzey et al. NYU 2025

https://object-rewards.github.io/

A Common Grasping Space

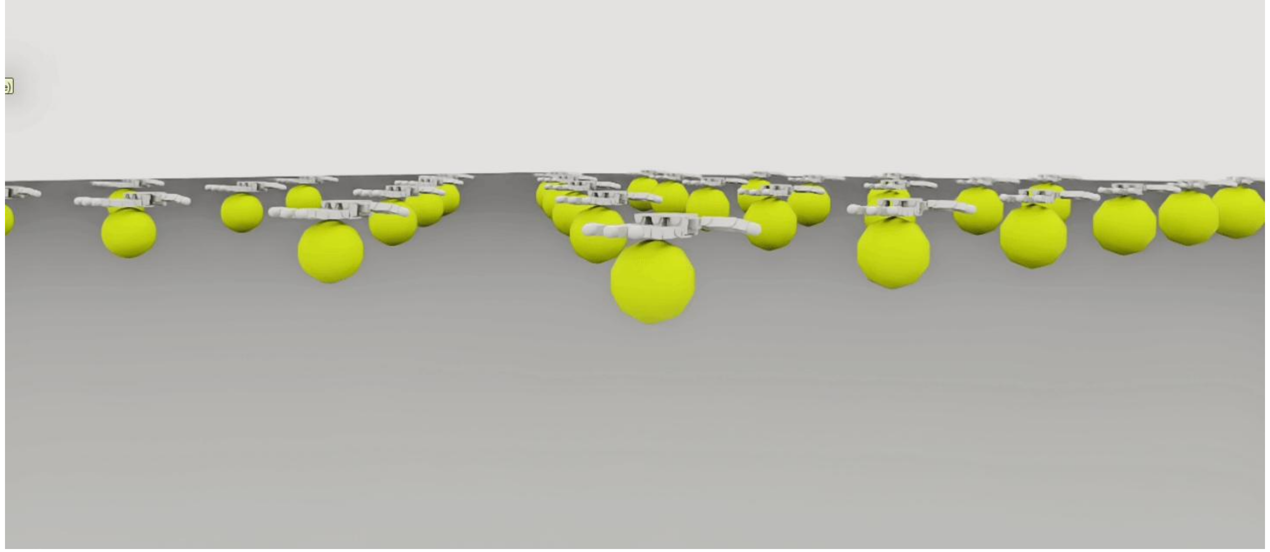
- Can we find a common grasping space for all the grippers?

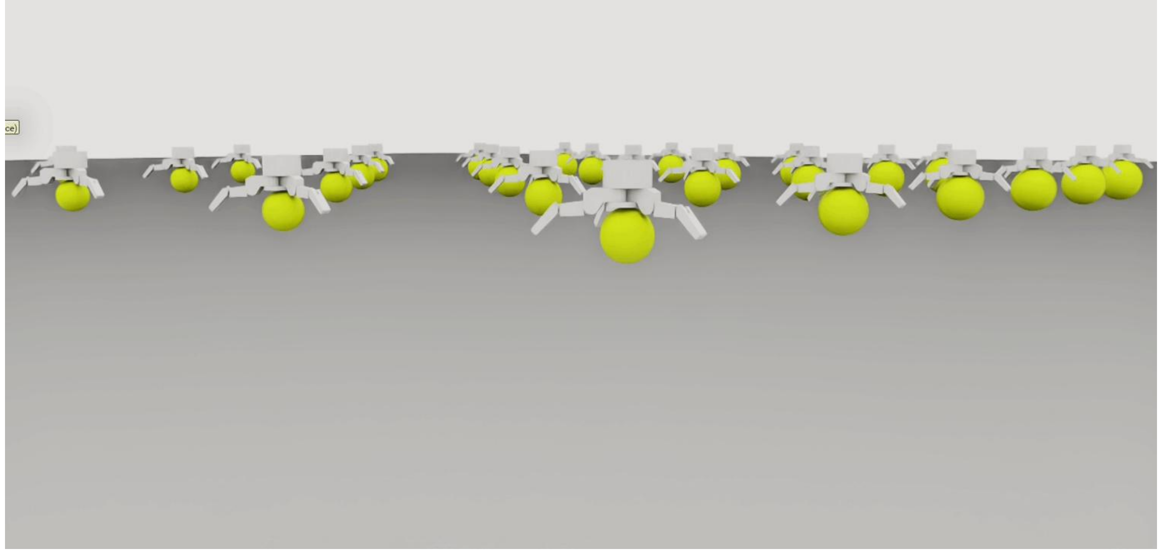


- We can align the palm orientations
- How to map fingers?

A Common Grasping Space

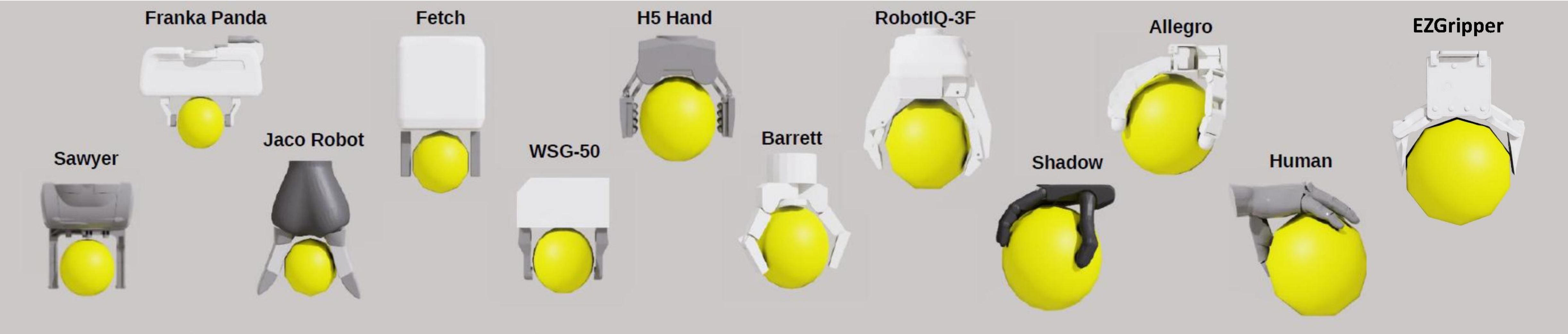
- Having the hands to grasp a common sphere
- Using contact maps on the sphere for retargeting
- Maximal sphere test in simulation





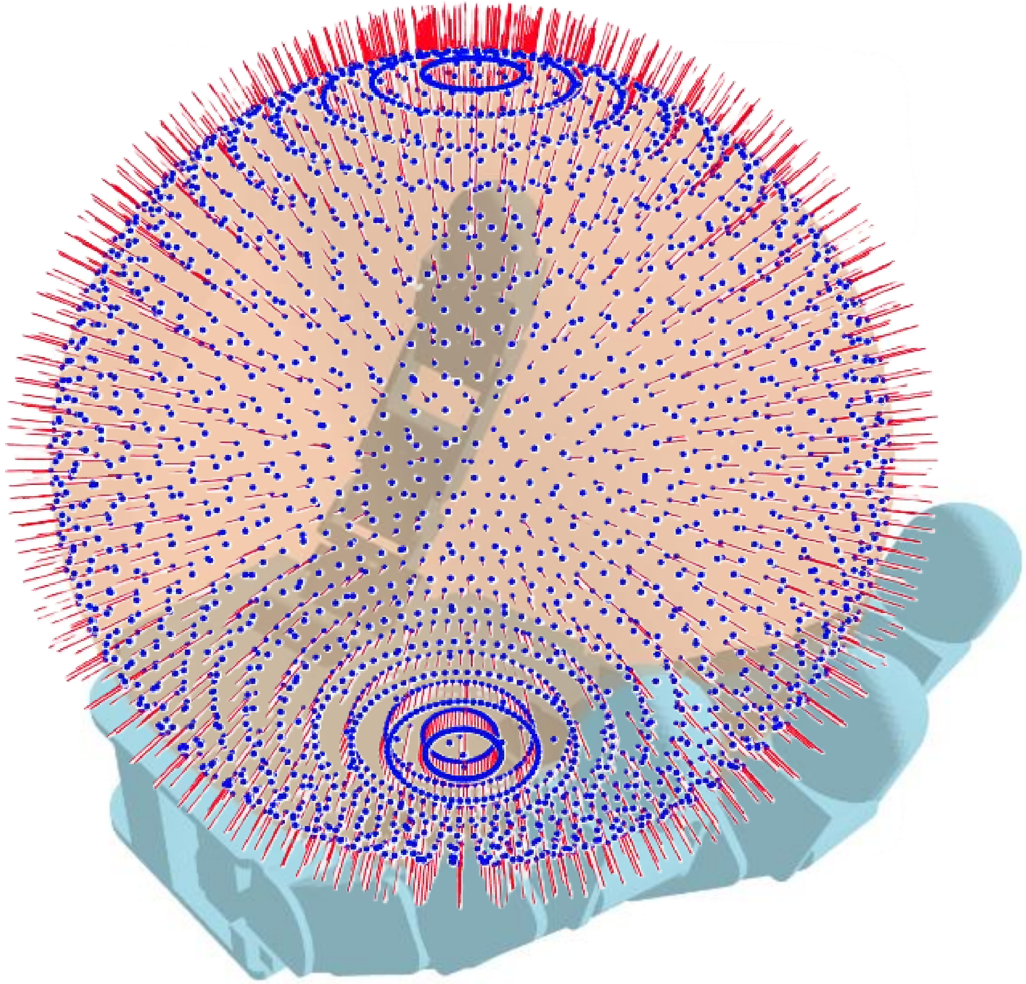
A Common Grasping Space

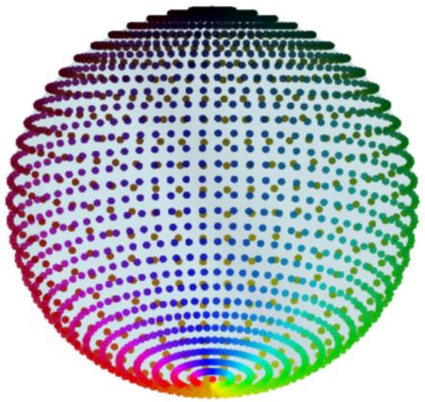
- Maximal spheres for each gripper



A Unified Gripper Coordinate Space

- Map spherical coordinates to the gripper

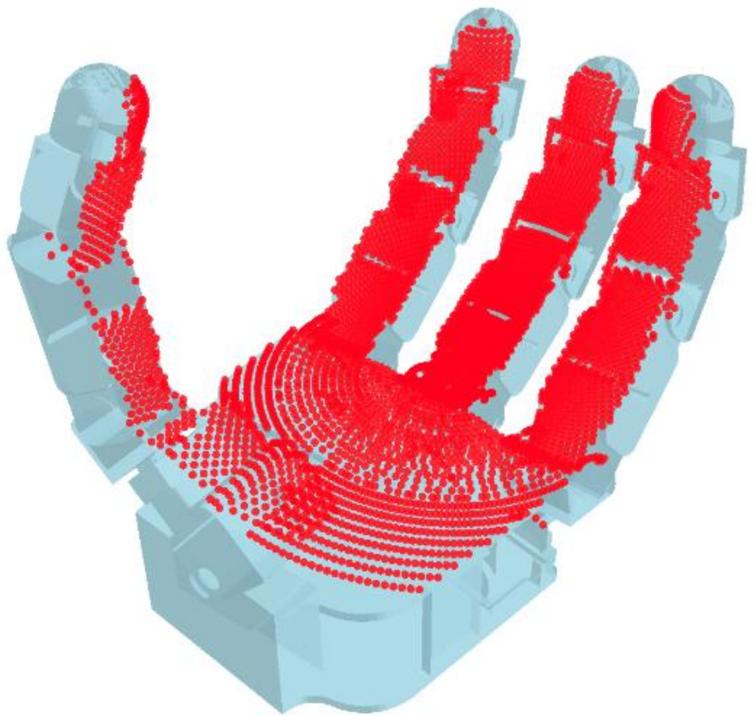


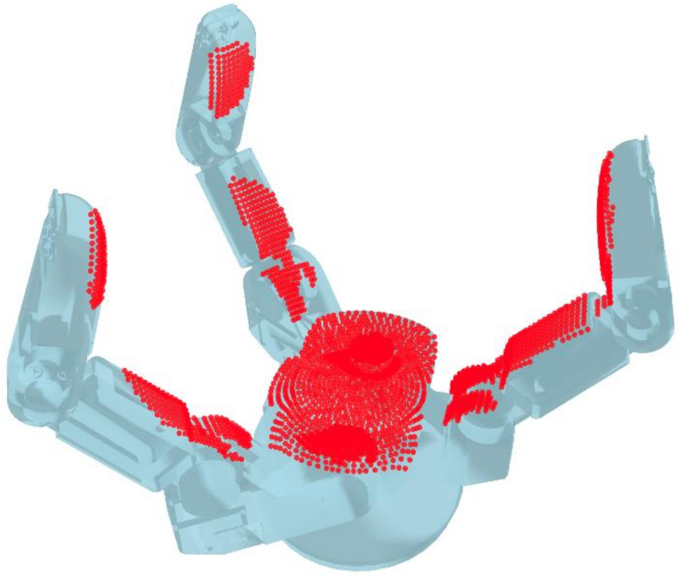


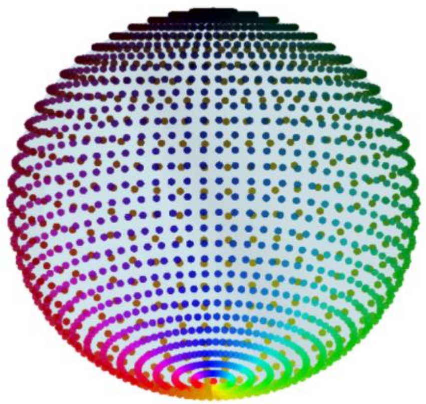
(λ, ϕ)

A Unified Gripper Coordinate Space

- Map spherical coordinates to the gripper







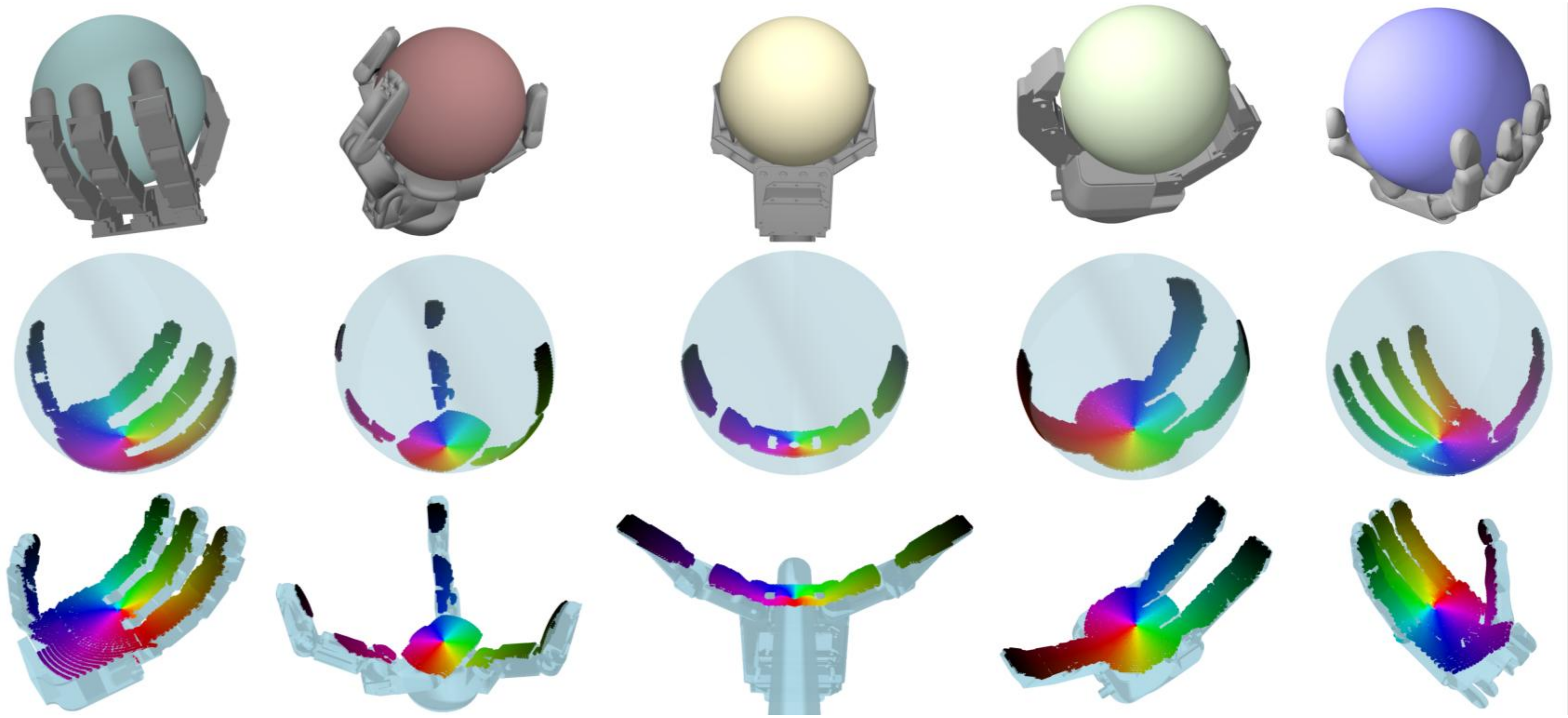
(λ, ϕ)

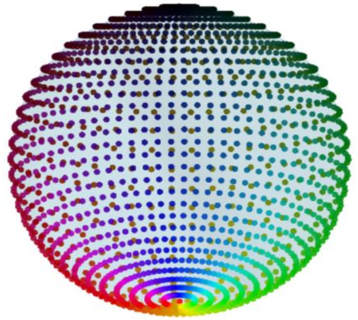
A Gripper is represented by a set of interior points $P_G = \{\mathbf{v}_g \mid \mathbf{v}_g \in \mathbb{R}^3\}$

Grasp configuration $\mathbf{q}$ changes the location of $\mathbf{v}_g$ $P_G(\mathbf{q})$

A Unified Gripper Coordinate Space

- Finger print: map spherical coordinates to the gripper



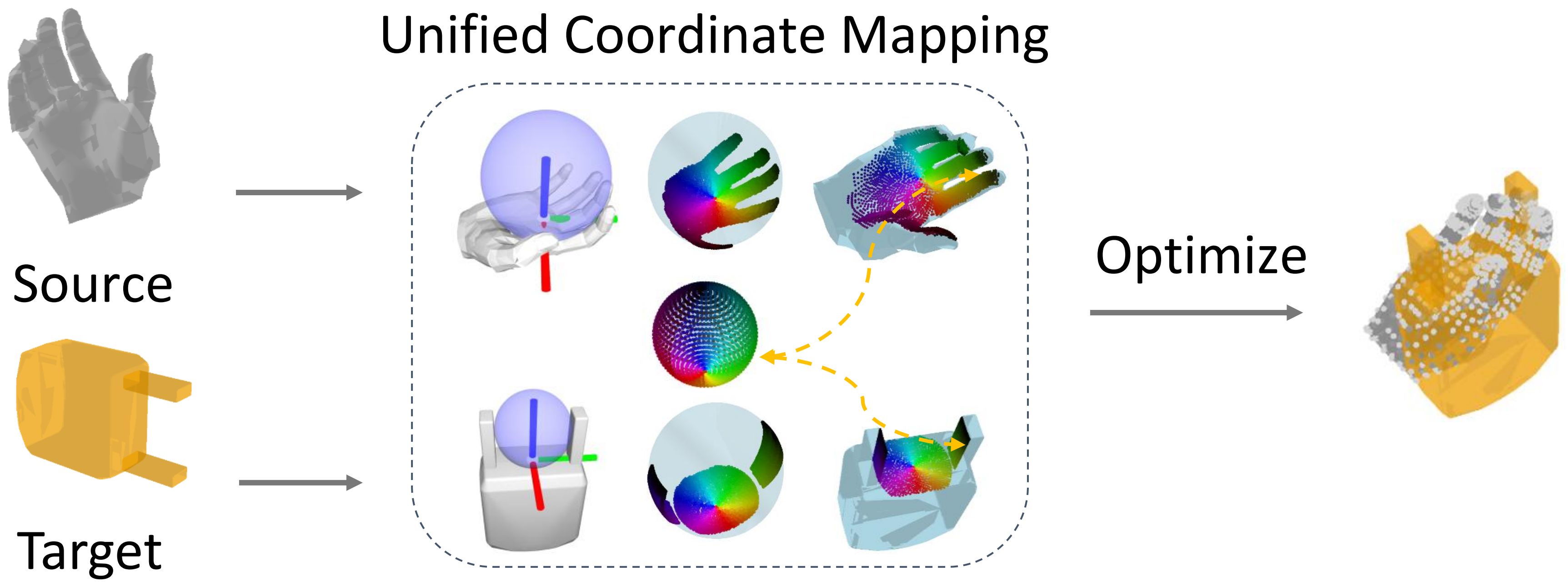


(λ, ϕ)

A UGCS coordinate is assigned to each point (fixed after assignment, independent of grasp)

$$\Phi_G = \{(\lambda_{\mathbf{v}_g}, \varphi_{\mathbf{v}_g}) \mid \mathbf{v}_g \in P_G \; ; \; \lambda_{\mathbf{v}_g}, \varphi_{\mathbf{v}_g} \in [0, 1]\}$$

Grasp Transfer



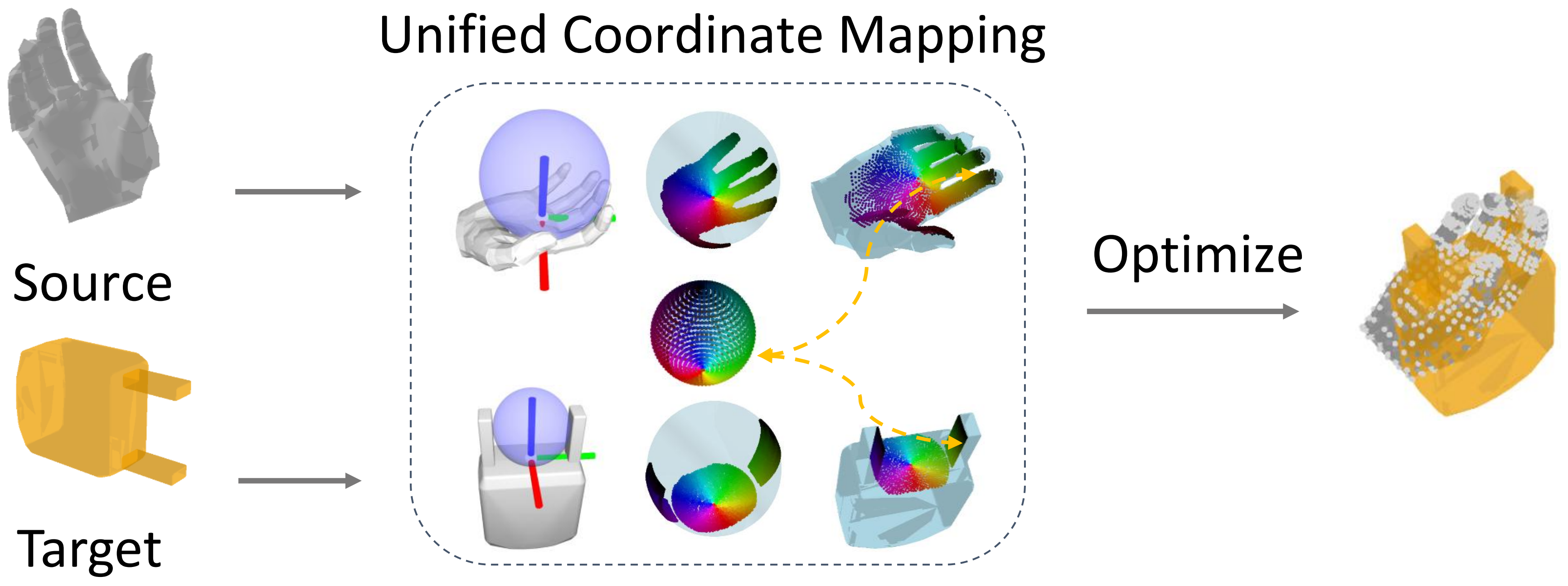
Two UGCS coordinate maps for two grippers

$$\Phi_{G_1} = \{(\lambda_{\mathbf{v}_g}, \varphi_{\mathbf{v}_g}) \mid \mathbf{v}_g \in P_{G_1} \; ; \; \lambda_{\mathbf{v}_g}, \varphi_{\mathbf{v}_g} \in [0,1]\}$$
$$\Phi_{G_2} = \{(\lambda_{\mathbf{v}_g}, \varphi_{\mathbf{v}_g}) \mid \mathbf{v}_g \in P_{G_2} \; ; \; \lambda_{\mathbf{v}_g}, \varphi_{\mathbf{v}_g} \in [0,1]\}$$

Matching their UGCS coordinates to establish correspondences (find mutually closest pairs)

$$P^c_{G_1} \subset P_{G_1}, P^c_{G_2} \subset P_{G_2}, |P^c_{G_1}| = |P^c_{G_2}|$$

Grasp Transfer



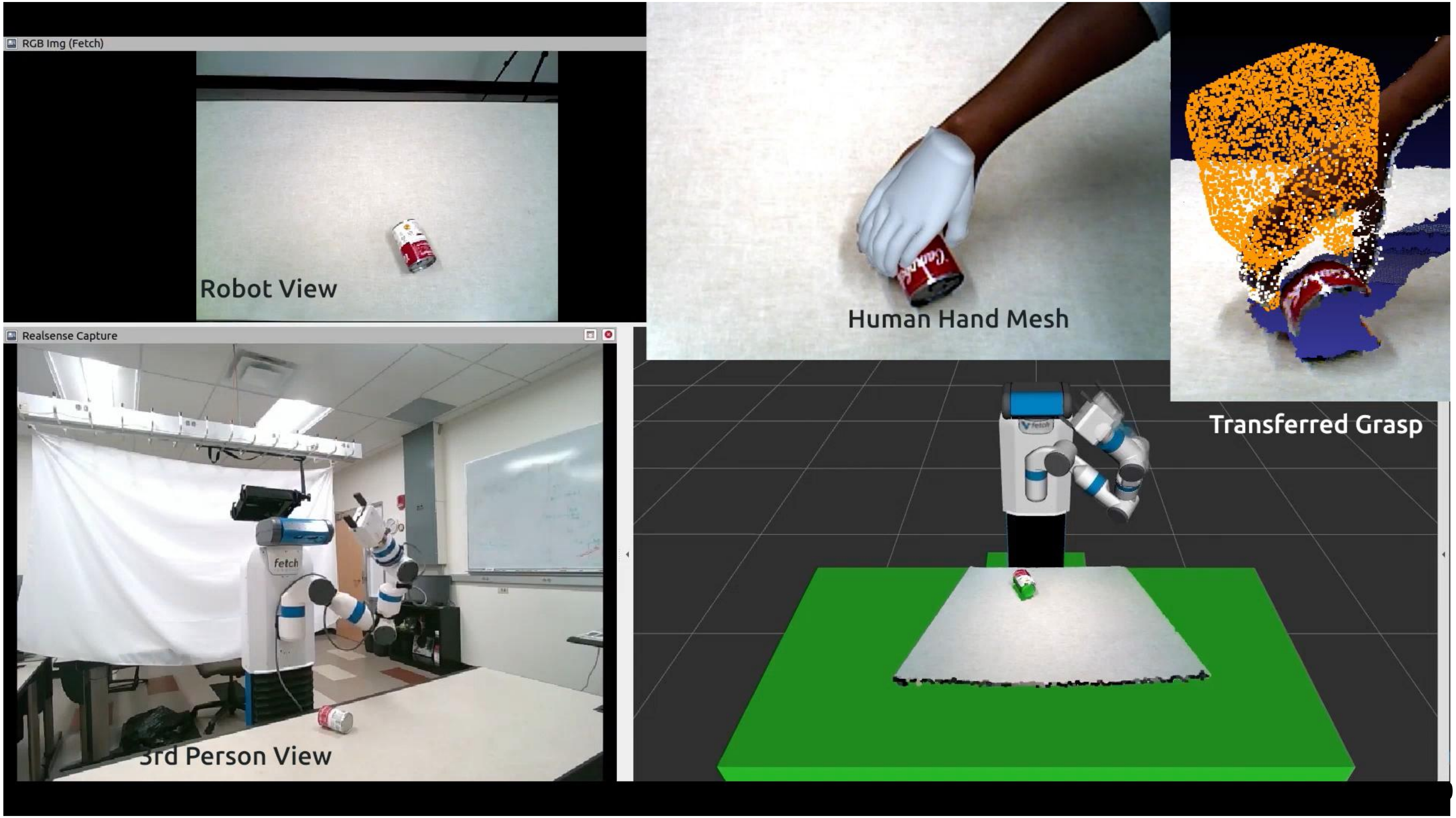
Optimize the target grasp

$$\mathbf{q}_F^* = \arg\min_{\mathbf{q}_F} \; E_{\text{dist}}(P_H^c(\mathbf{q}_H), P_F^c(\mathbf{q}_F)) + E_{\text{n}}(\mathbf{q}_F)$$

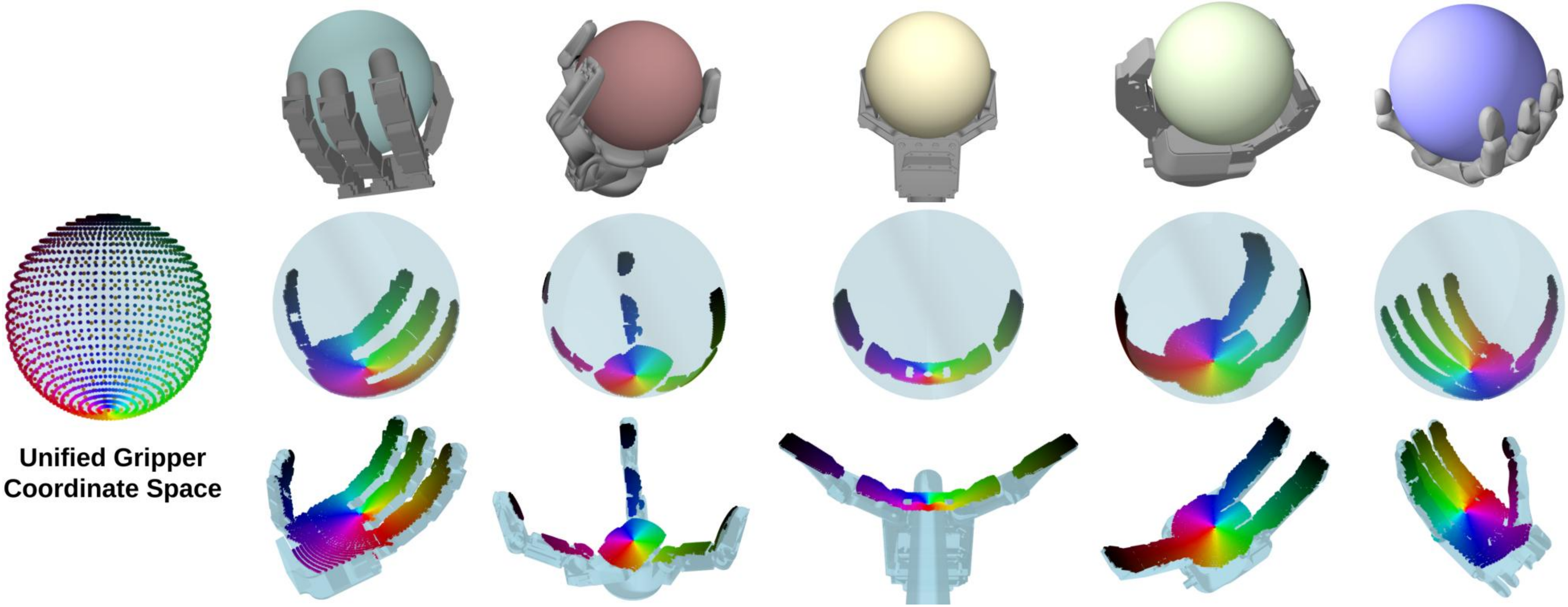
Reference grasp

Joint limits

Grasp Transfer

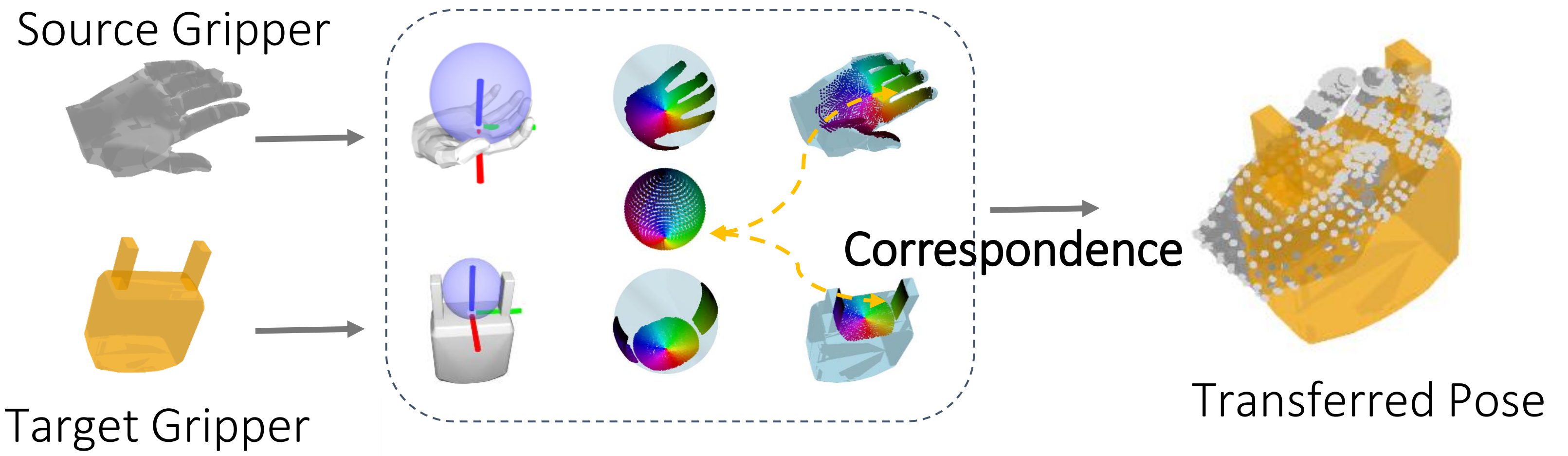


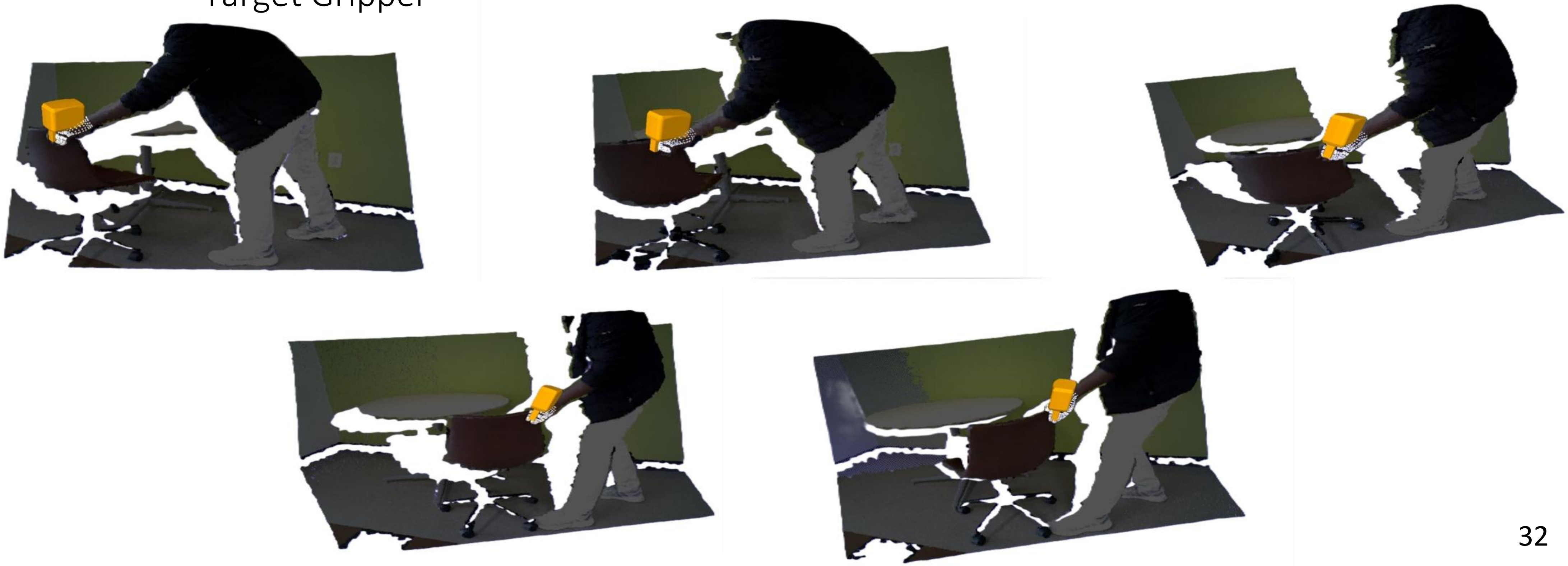
RobotFingerPrint



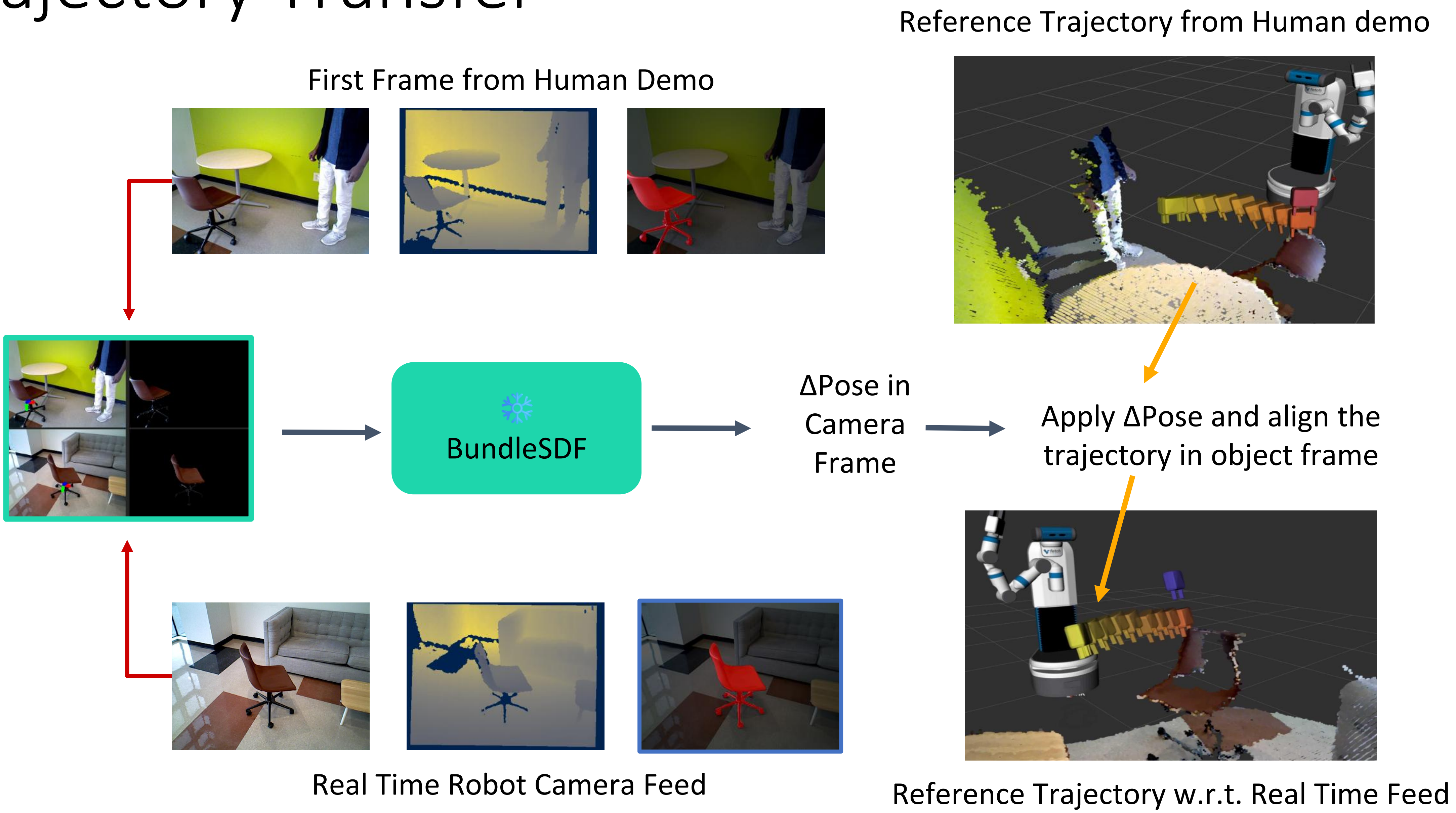
RobotFingerPrint: Unified Gripper Coordinate Space for Multi-Gripper Grasp Synthesis and Transfer.
Ninad Khargonkar, Luis Felipe Casas, Balakrishnan Prabhakaran, Yu Xiang. In IROS, 2025.

Understanding of the Human Demonstrations





Trajectory Transfer

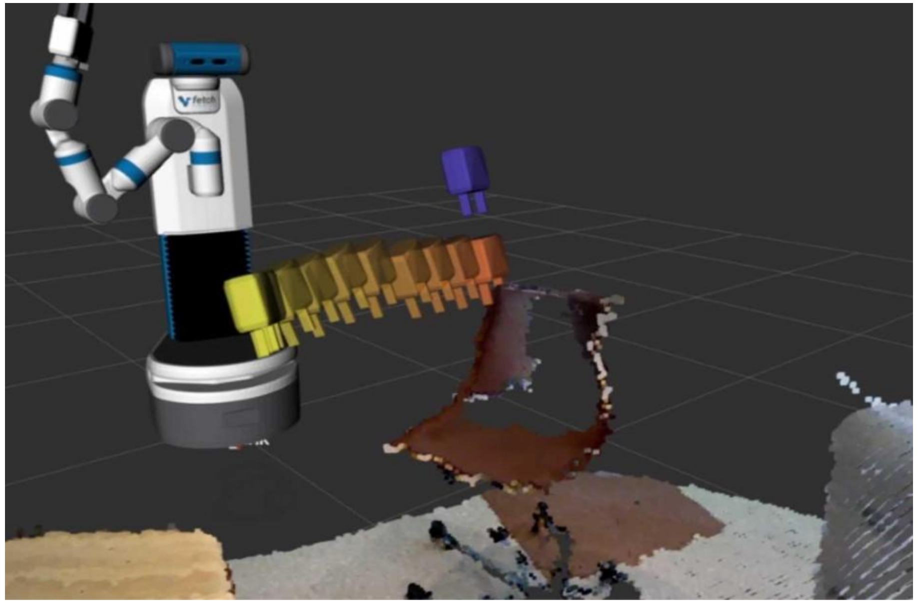


Trajectory Transfer

- How to follow the transferred gripper trajectory?

Task Space

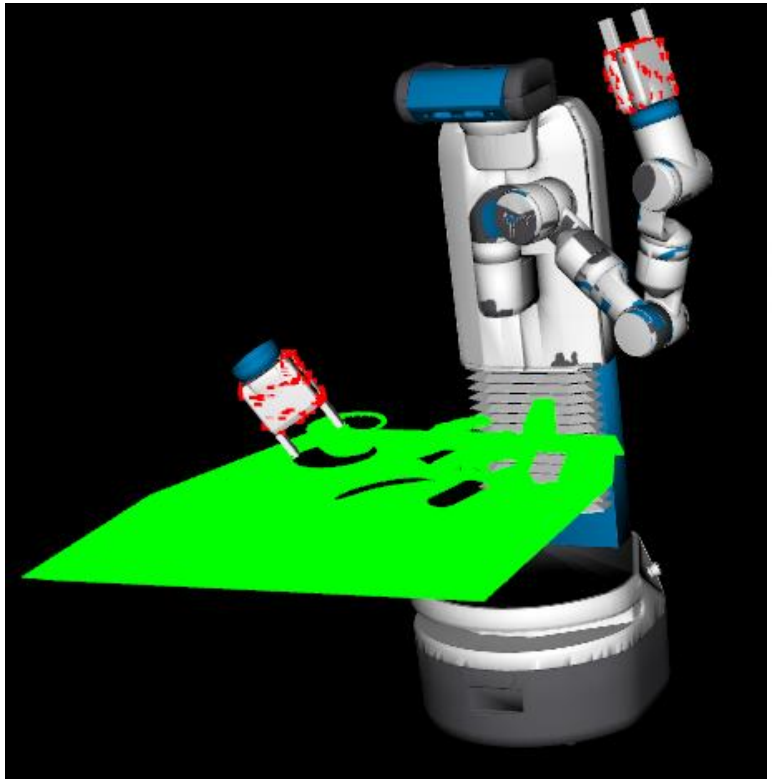
Robot View



Reference Trajectory w.r.t. Real Time Feed

Trajectory Optimization

- Point Cloud-based Cost Function for Goal Reaching



Gripper pose

Goal pose

$$c_{\text{goal}}(\mathbf{T}_T, \mathbf{T}_g)$$
$$= \sum_{i=1}^{m} \|(\mathbf{R}_T \mathbf{x}_i + \mathbf{t}_T) - (\mathbf{R}_g \mathbf{x}_i + \mathbf{t}_g)\|^2,$$

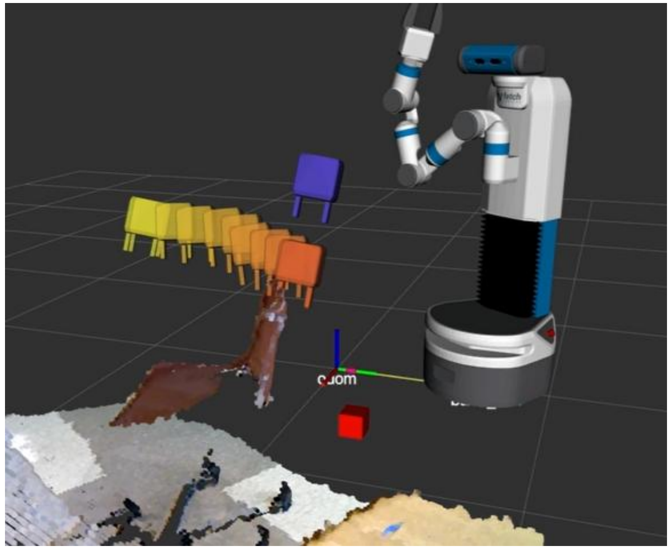
Points on the gripper

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

Optimizing the Robot Base Location

- Find the base position that can reach N gripper poses from the trajectory

Base $\mathbf{x} = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix}$ $\mathbf{T}(\mathbf{x}) = \begin{bmatrix} \cos\theta & -\sin\theta & 0 & x \\ \sin\theta & \cos\theta & 0 & y \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$ Unknown



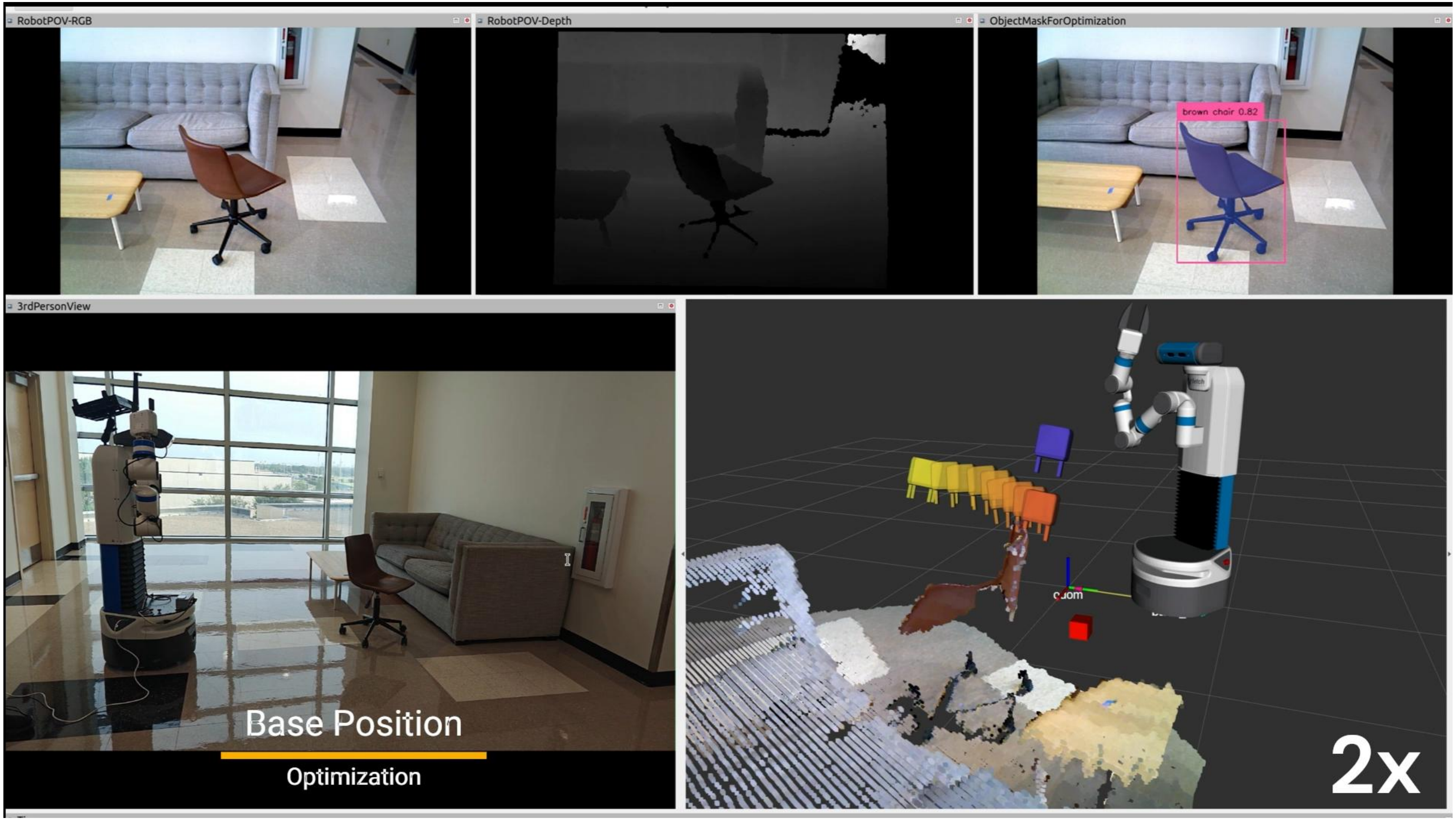
Gripper pose $\mathcal{T} = \{\mathbf{T}_1, \mathbf{T}_2 \dots, \mathbf{T}_N\}$ Known

Arm configuration $\mathcal{Q} = \{\mathbf{q}_1, \mathbf{q}_2 \dots, \mathbf{q}_N\}$ Unknown

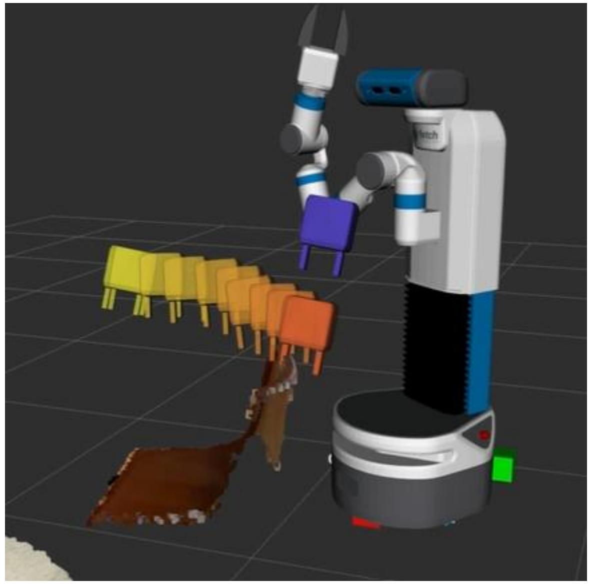
$$\begin{aligned} \arg\min_{\mathbf{x}, \mathcal{Q}} \quad & \lambda_{\text{effort}} \|\mathbf{x}\|^2 + \lambda_{\text{goal}} \textstyle\sum_{i=1}^{N} c_{\text{goal}}(\mathbf{T}(\mathbf{q}_i), \underline{\mathbf{T}(\mathbf{x}) \cdot \mathbf{T}_i}) \\ \text{s.t.,} \quad & \mathbf{x}_l \leq \mathbf{x} \leq \mathbf{x}_u \\ & \mathbf{q}_l \leq \mathbf{q}_i \leq \mathbf{q}_u, i = 1, \dots, N \end{aligned}$$

Gripper goal in new base

Optimizing the Robot Base Location



Optimizing the Robot Trajectory



- Find the trajectory to follow the gripper poses well

Unknown $\mathcal{Q} = (\mathbf{q}_1, \ldots, \mathbf{q}_T) \quad \dot{\mathcal{Q}} = (\dot{\mathbf{q}}_1, \ldots, \dot{\mathbf{q}}_T)$

Known $\mathcal{T} = \{\mathbf{T}_1, \mathbf{T}_2 \ldots, \mathbf{T}_T\}$

Gripper trajectory in new robot base

$$\arg\min_{\mathcal{Q}, \dot{\mathcal{Q}}} \sum_{t=1}^{T} c_{\text{goal}}(\mathbf{T}(\mathbf{q}_t), \mathbf{T}_t) + \lambda_1 c_{\text{collision}}(\mathbf{q}_t) + \lambda_2 \sum_{t=1}^{T} \|\dot{\mathbf{q}}_t\|^2$$

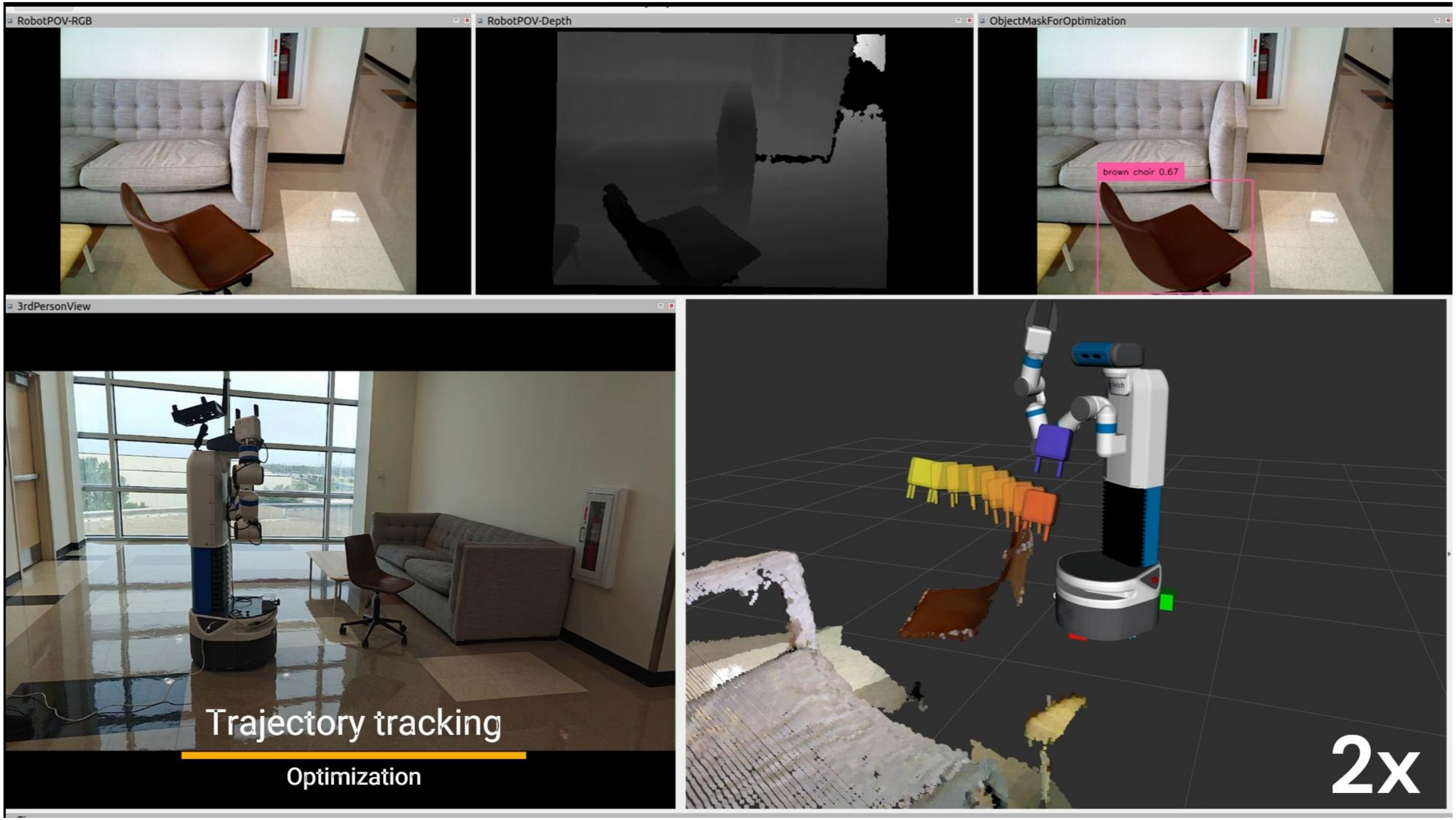
$$\dot{\mathbf{q}}_1 = \mathbf{0}, \dot{\mathbf{q}}_T = \mathbf{0}$$

$$\mathbf{q}_{t+1} = \mathbf{q}_t + \dot{\mathbf{q}}_t dt, t = 1, \ldots, T-1$$

$$\mathbf{q}_l \leq \mathbf{q}_t \leq \mathbf{q}_u, t = 1, \ldots, T$$

$$\dot{\mathbf{q}}_l \leq \dot{\mathbf{q}}_t \leq \dot{\mathbf{q}}_u, t = 1, \ldots, T$$

Optimizing the Robot Trajectory



Trajectory Optimization to Follow the Reference

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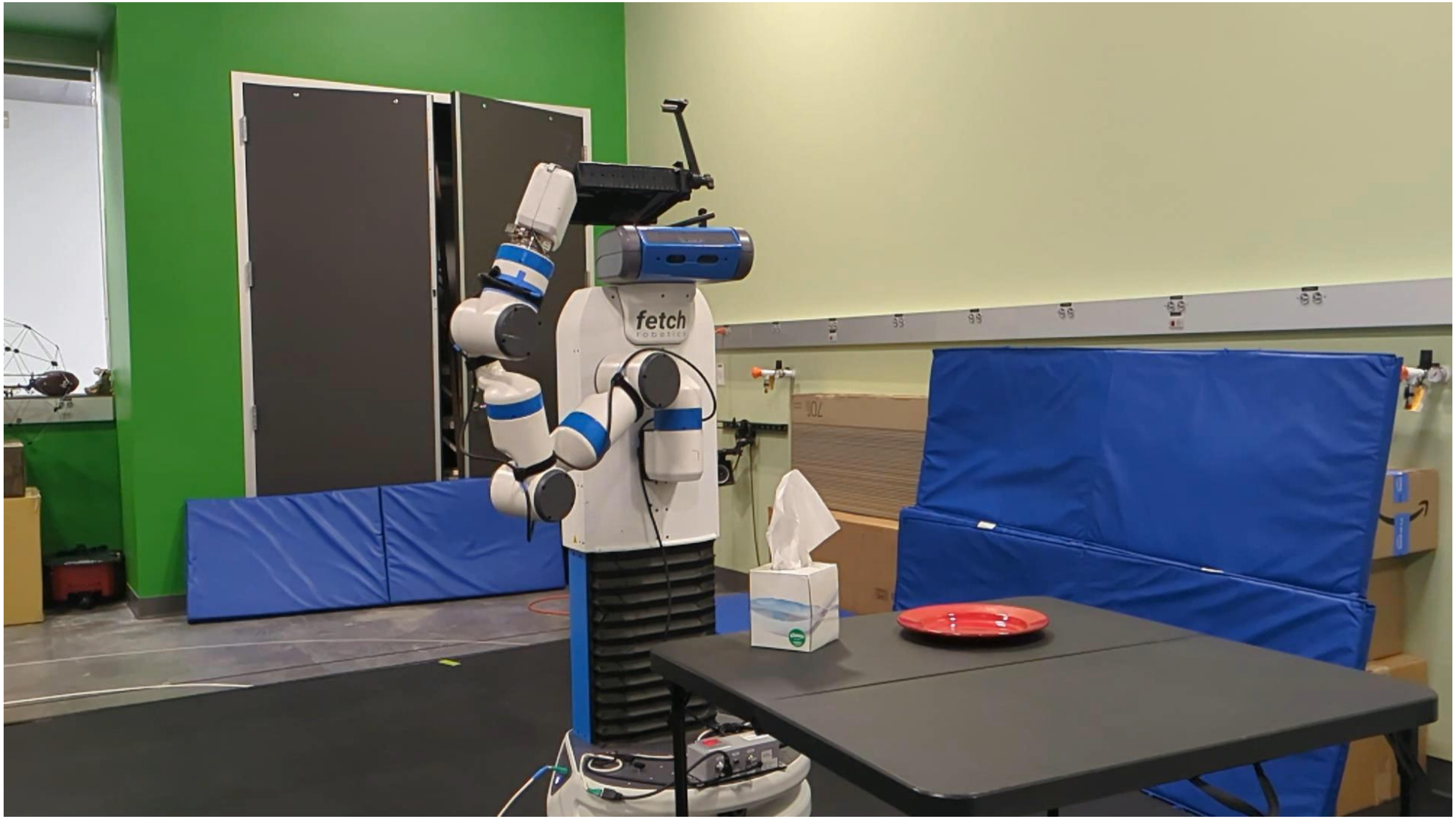
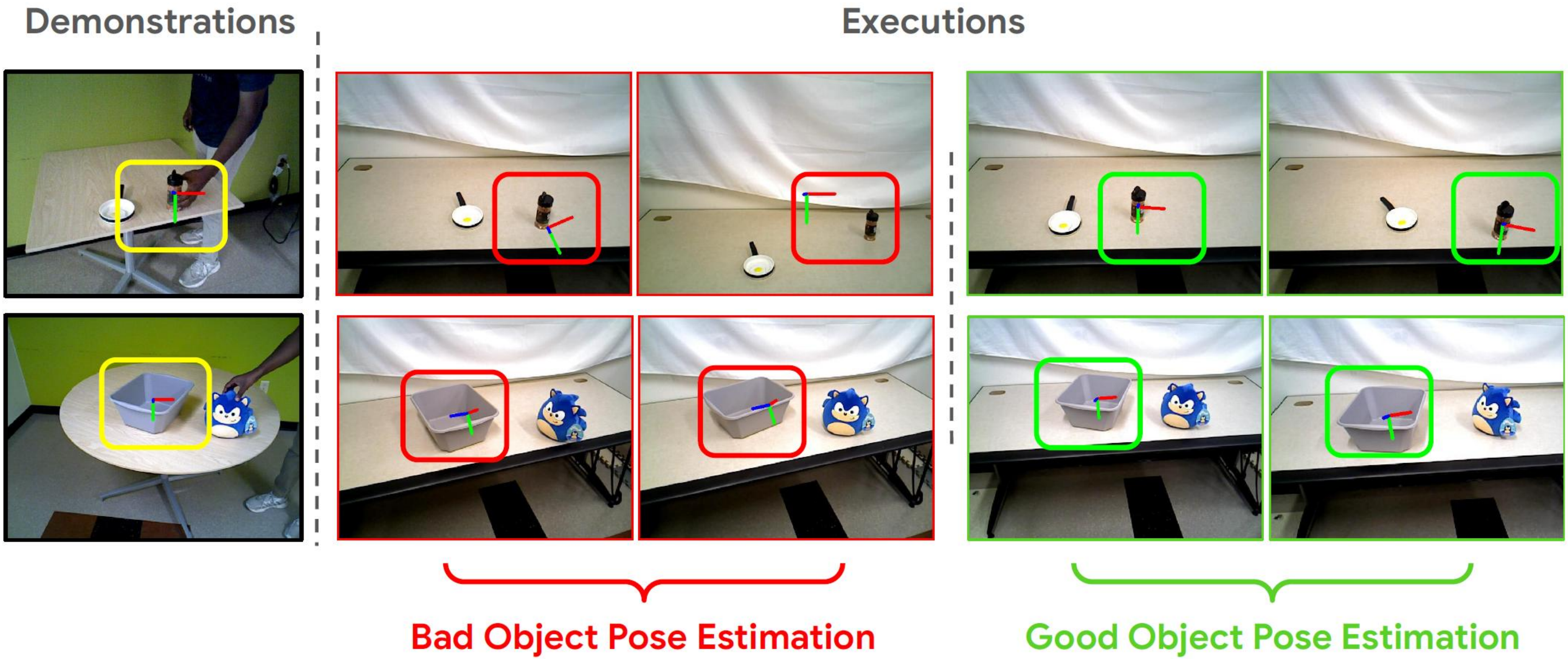
Trajectory Optimization to Follow the Reference



Failure Example

Object Pose Verification



Quantitative Evaluation

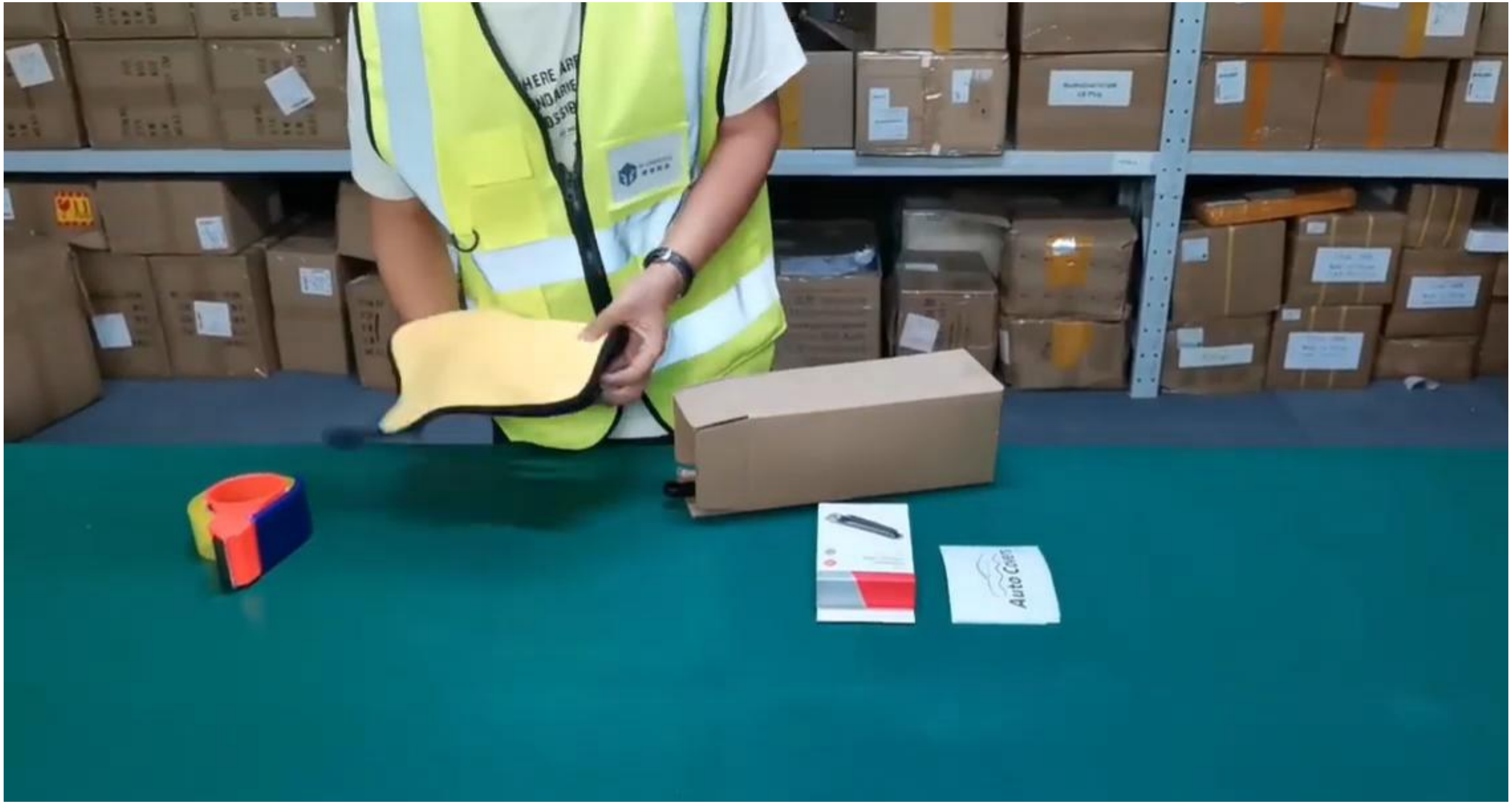
Skill	Grasp success		Task completion	
	Ours	DITTO [16]	Ours	DITTO [16]
Single object				
Move the chair	3	3	3	0
Close fire extinguisher door	3	0	3	0
Dual object				
Put toy in the bin	3	2	3	1
Put bread in the toaster	3	1	3	1
Put seasoning on the omelette	3	3	3	2
Put Lays on the red plate	2	2	2	1
Clean plate with brush	3	1	3	0
Clean plate with tissue	3	0	3	0
Clean plate with kitchen towel	3	2	3	1
Remove cap from wall hook	3	3	3	1
Hang cap onto wall hook	3	0	2	0
Take out sugar box from shelf	3	1	3	0
Rearrange sugar box in the shelf	3	2	2	0
Place bottle in the shelf	3	3	3	0
Close jar with a lid	3	2	2	0
Displace cracker box	3	3	3	3
Total	**47/48**	**28/48**	**44/48**	**10/48**

DITTO [16]:Trajectory Transfer, Heppert et al. University of Freiburg, IROS 2024

Challenges and Opportunities on Learning from Human Videos

- Understanding of human manipulation from videos is still challenging
  - 3D understanding
  - Deformable, articulated objects
  - Long-horizon tasks
- Trajectory transfer & optimization is slow
  - Better & faster optimization tools
  - Policy learning, e.g., using data from trajectory optimization
- Dexterous manipulation with multi-finger hands
  - Force feedback & tactile sensing
  - Bimanual manipulation

Robot Manipulation is still an Open Challenge



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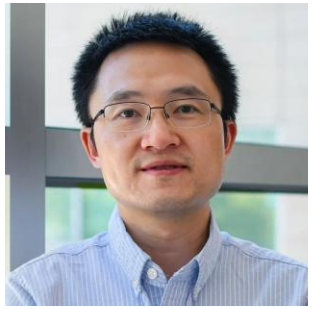


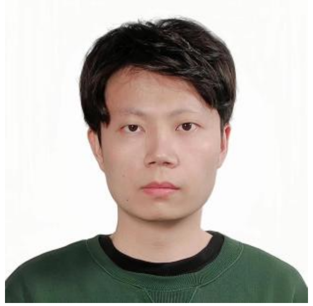














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Assisted by
Ms. Rhonda Walls

Thank you!