

Learning **Score-based Grasping Primitive** for **Human-assisting Dexterous Grasping**

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* Equal Contribution

Motivation

- Human hand plays a fundamental role in our daily lives, enabling us to interact with and manipulate objects in a versatile and precise manner.
- Hand loss limiting the capability of performing working, social, and daily living activities^[1].



[1] Cordella F, Ciancio A L, Sacchetti R, et al. Literature review on needs of upper limb prosthesis users[J]. Frontiers in neuroscience, 2016, 10: 209.

Motivation

- The current prosthetic hand usually controls the fingers by mapping EMG or EEG signals, which can be affected by electrode shifting, muscle fatigue, etc^[1].
- Some methods predict the grasp type according to image contains the object, which is not closed-loop and only has limited grasp type^[2].



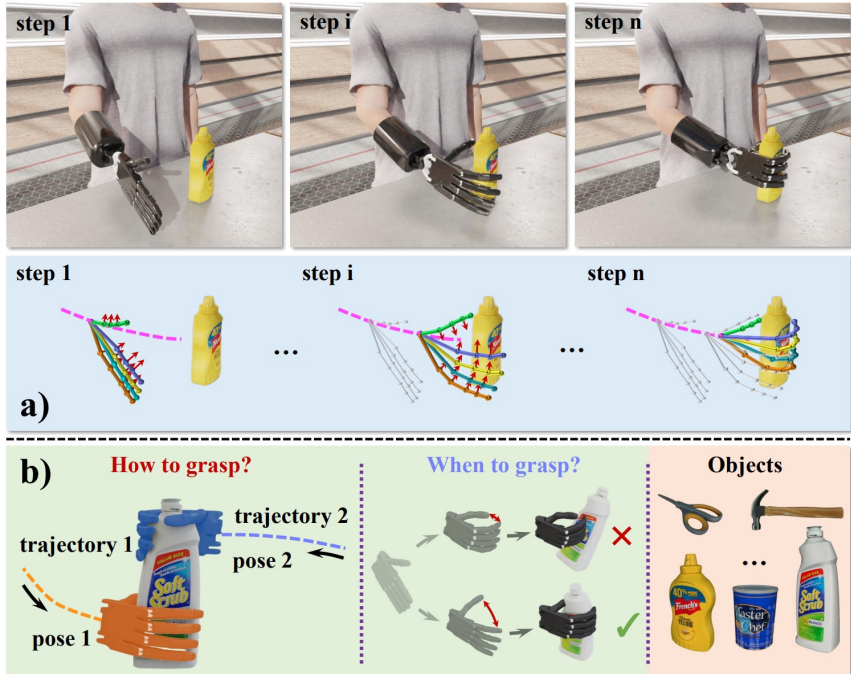
- **Human-assisting Dexterous Grasping**: train a policy to control the robotic hand's finger **autonomously in a closed-loop manner**, to assist human in grasping **diverse objects** with **diverse grasp poses** under **diverse human movement trajectories**.

[1] Zandigohar, Mehrshad, et al. "Multimodal fusion of emg and vision for human grasp intent inference in prosthetic hand control." *arXiv preprint arXiv:2104.03893* (2021).

[2] Ghazaei, Ghazal, et al. "Deep learning-based artificial vision for grasp classification in myoelectric hands." *Journal of neural engineering* 14.3 (2017): 036025.

Motivation

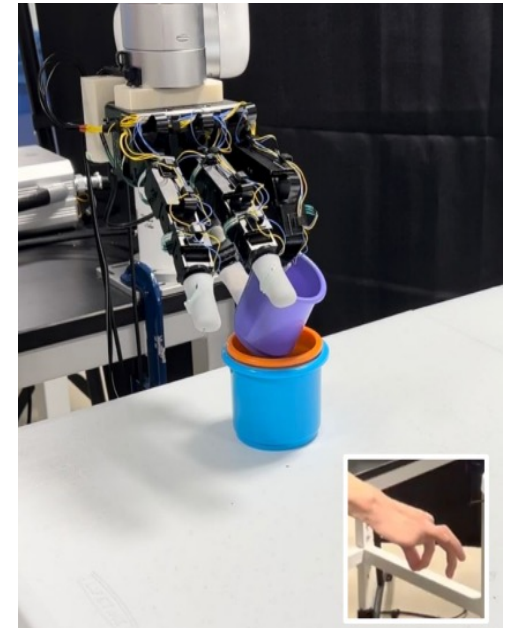
Human-assisting Dexterous Grasping Agent Centric



Conventional Dexterous Grasping Object Centric



Teleoperation^[1]



Robot
hand finger

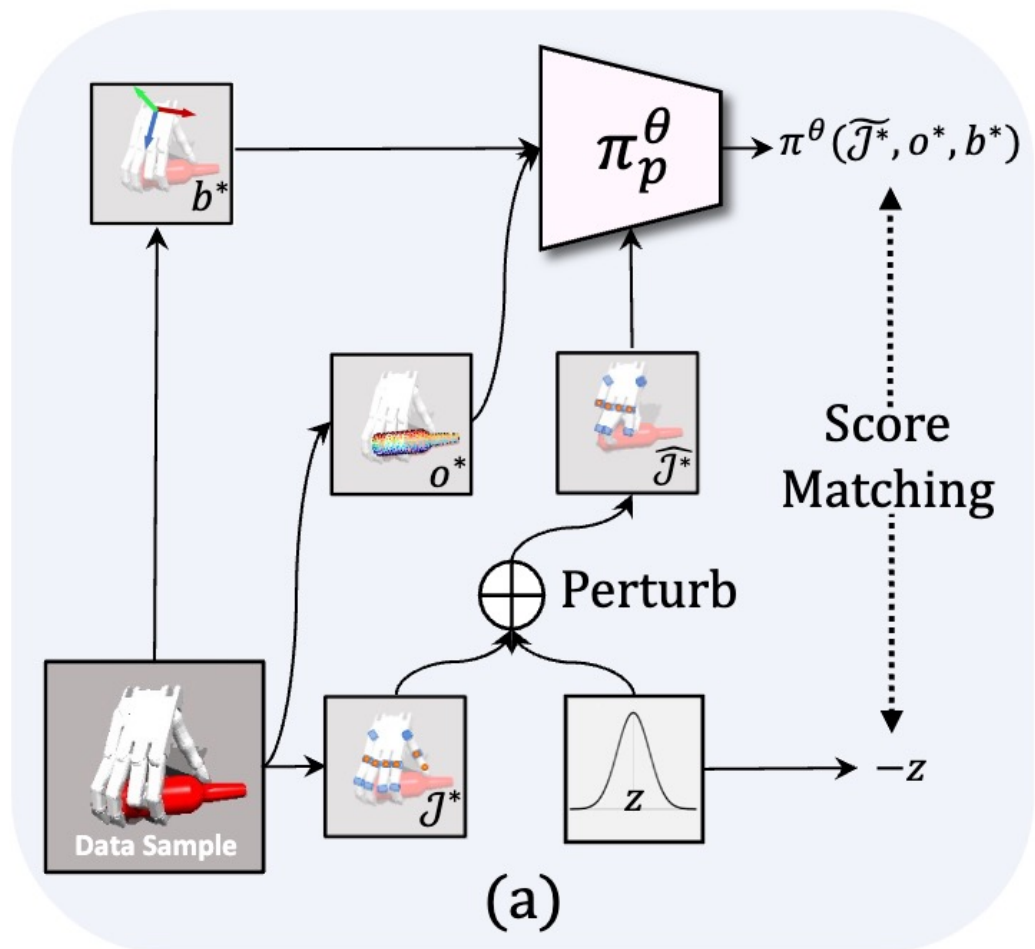
Robot
wrist

Human
hand finger

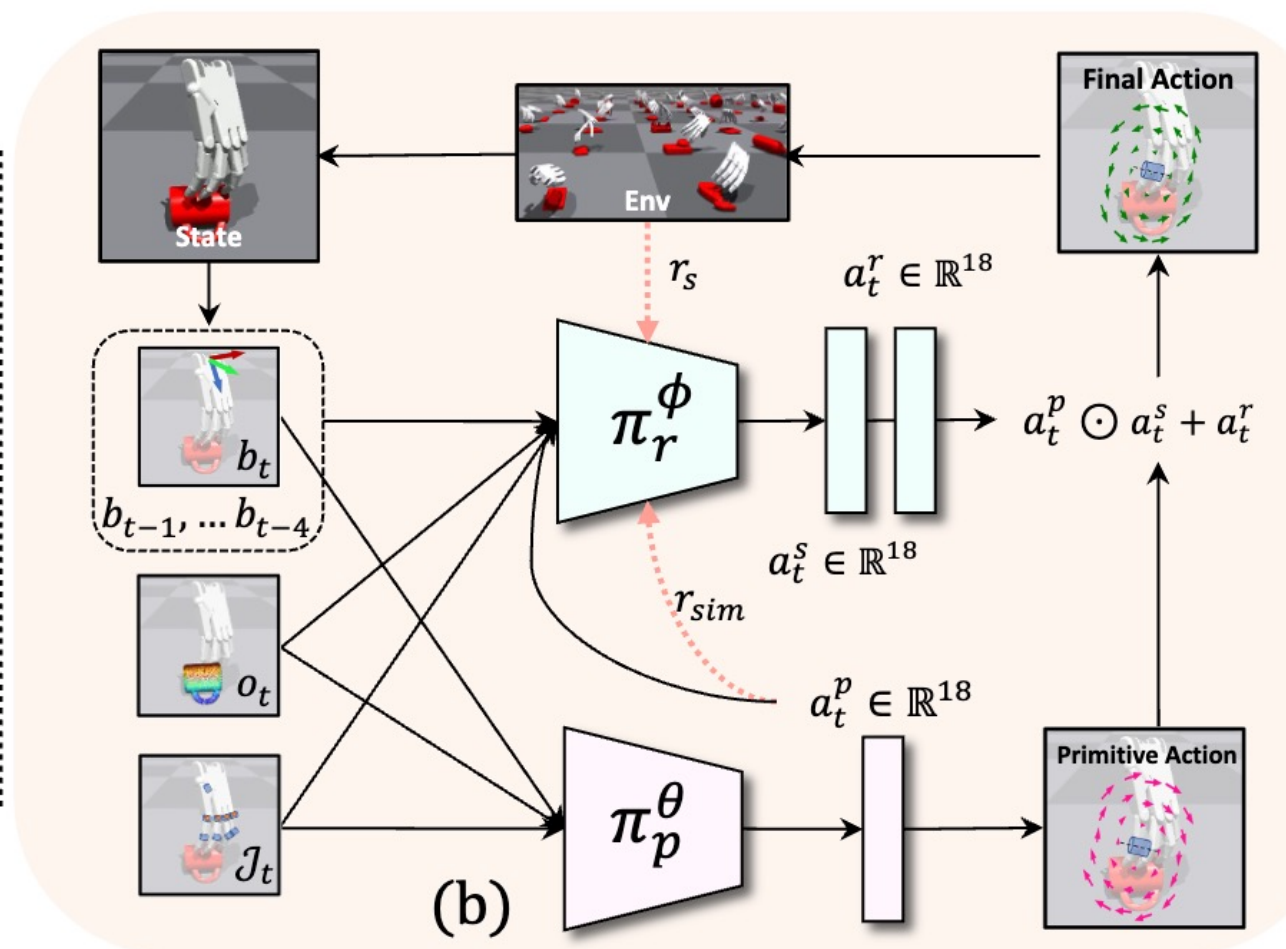
Human
wrist

[1] Qin, Yuzhe, et al. "Anyteleop: A general vision-based dexterous robot arm-hand teleoperation system." *arXiv preprint arXiv:2307.04577* (2023).

Method

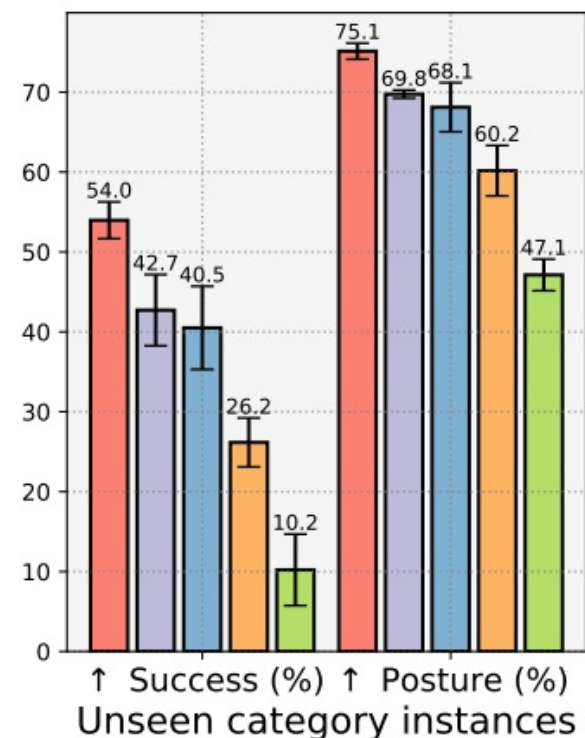
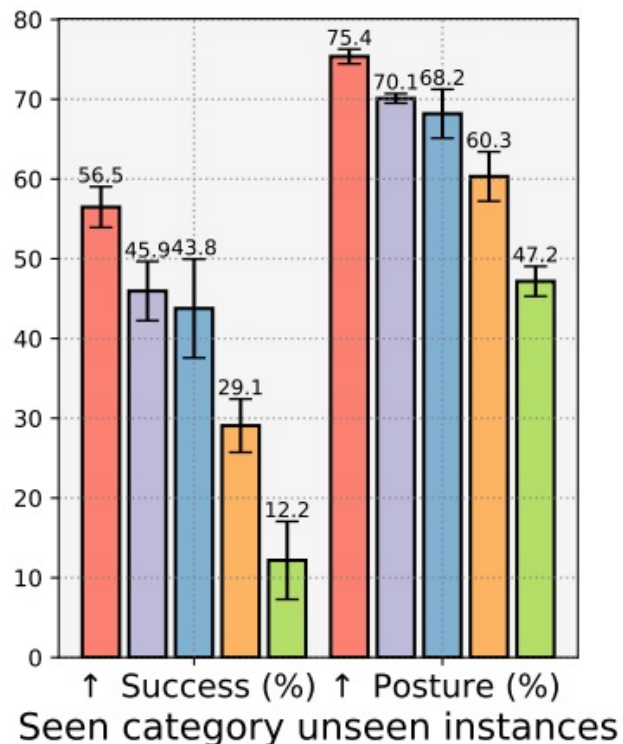
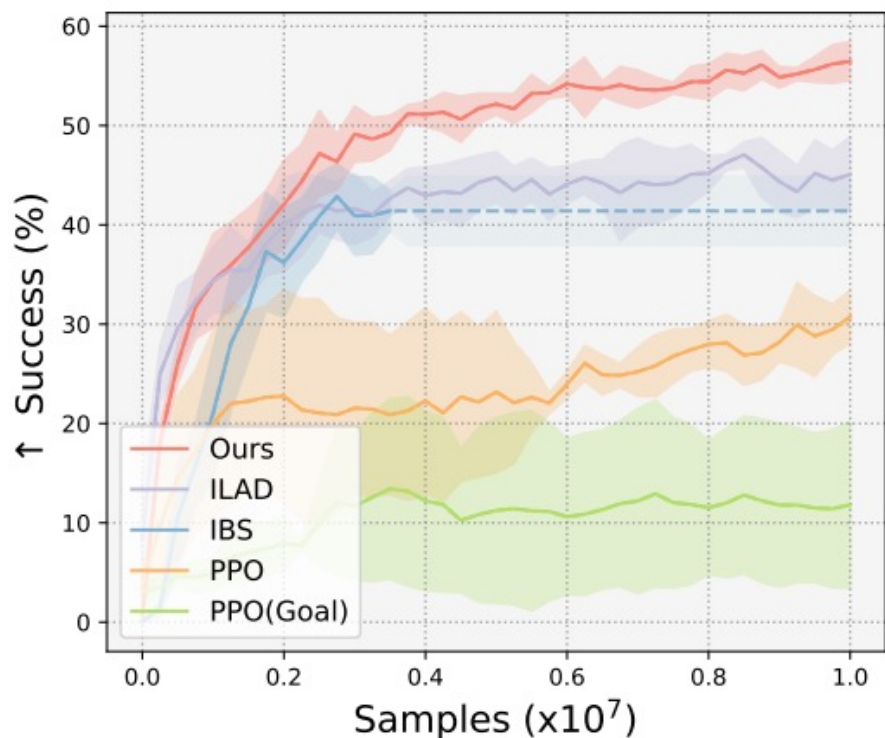


How to grasp: Primitive Policy



When to grasp: Residual Policy

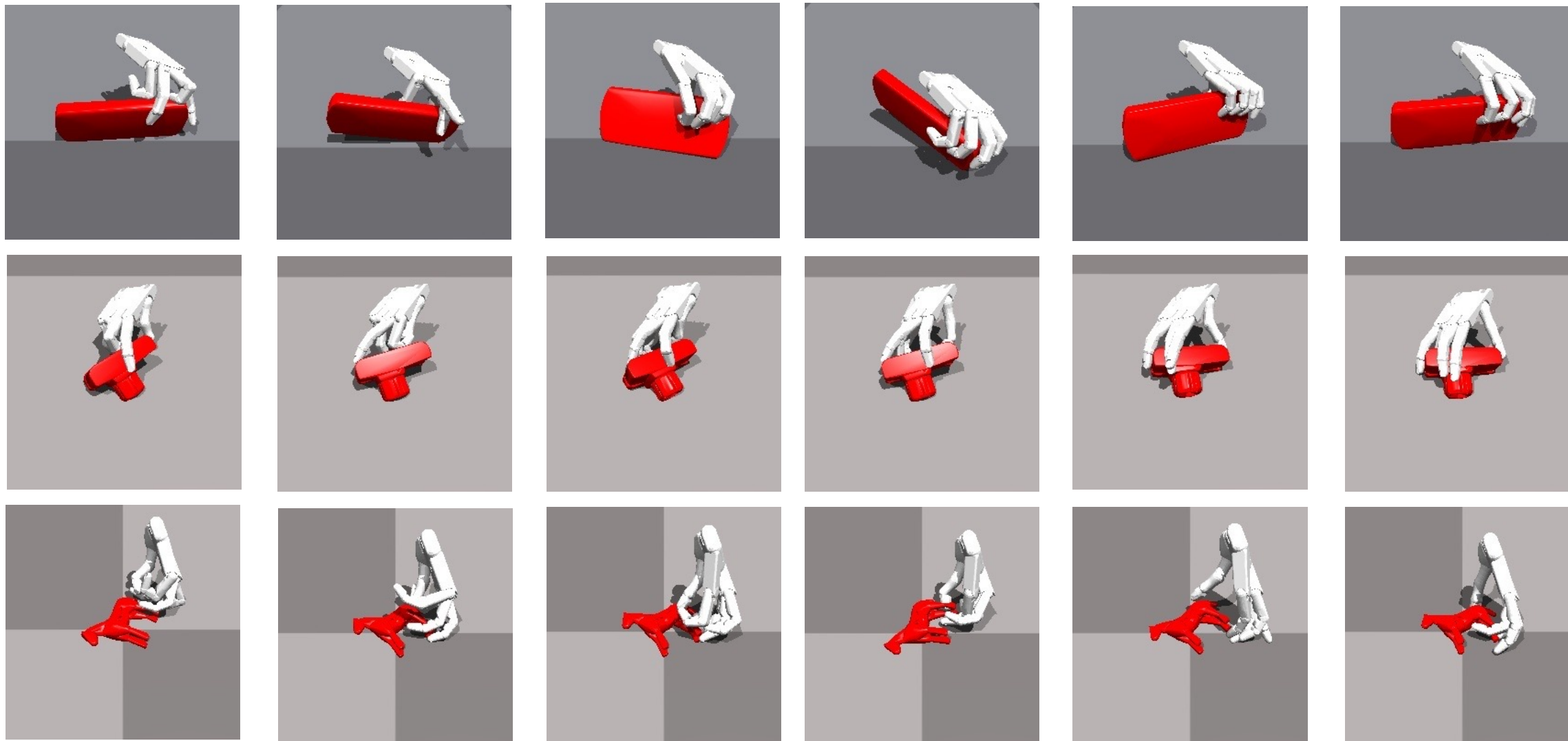
Comparative Results



	Seen Category		Unseen Category	
	Tran(cm) ↓	Rot (rad) ↓	Tran(cm) ↓	Rot (rad) ↓
PPO(Goal)	2.621 ± 0.415	0.589 ± 0.038	2.537 ± 0.296	0.543 ± 0.040
PPO	2.745 ± 0.168	0.594 ± 0.045	2.771 ± 0.254	0.563 ± 0.039
IBS	2.653 ± 0.030	0.572 ± 0.002	2.596 ± 0.119	0.520 ± 0.011
ILAD	2.443 ± 0.042	0.548 ± 0.027	2.534 ± 0.101	0.515 ± 0.022
Ours	2.131 ± 0.138	0.449 ± 0.020	2.127 ± 0.165	0.428 ± 0.029

Stability on seen category unseen instances and unseen category instances

Qualitative Results – Comparison with Baselines



PPO

PPO(Goal)

ILAD

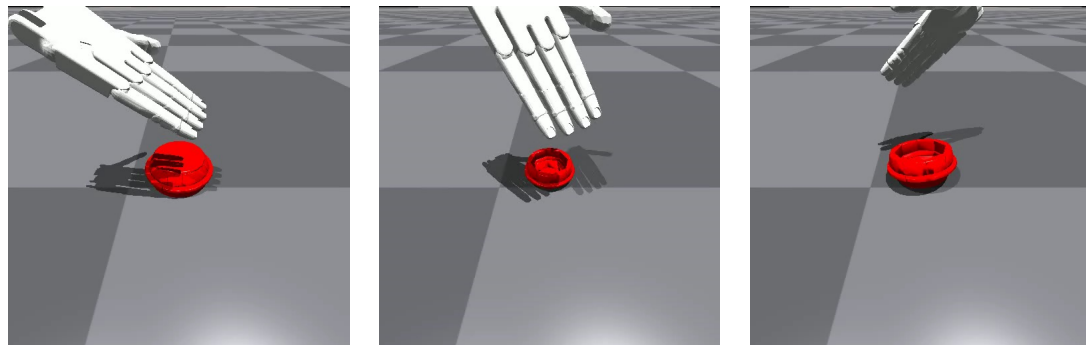
IBS

Ours

GT

Qualitative Results – User-Awareness of Our Method

Bowl



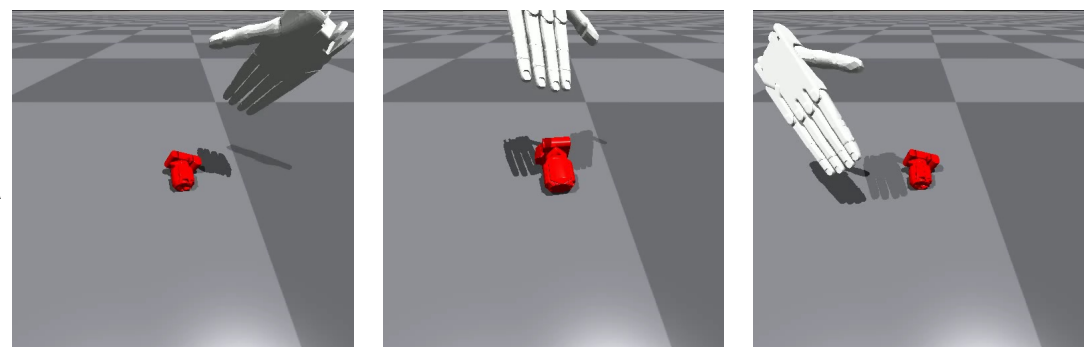
Vase



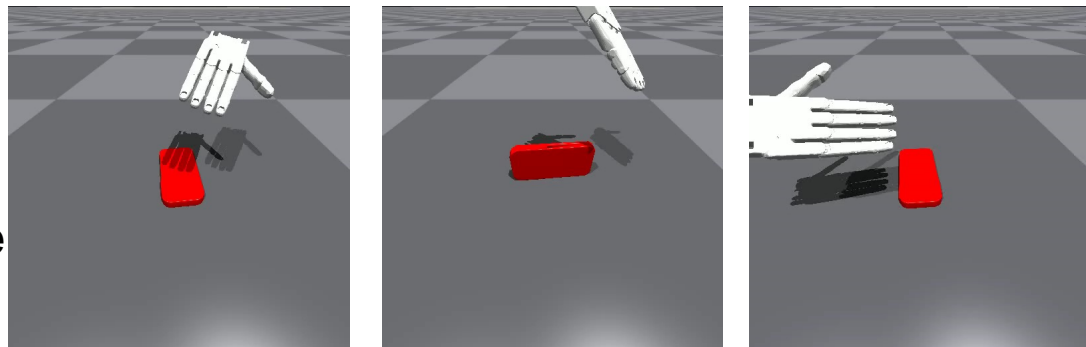
Bottle



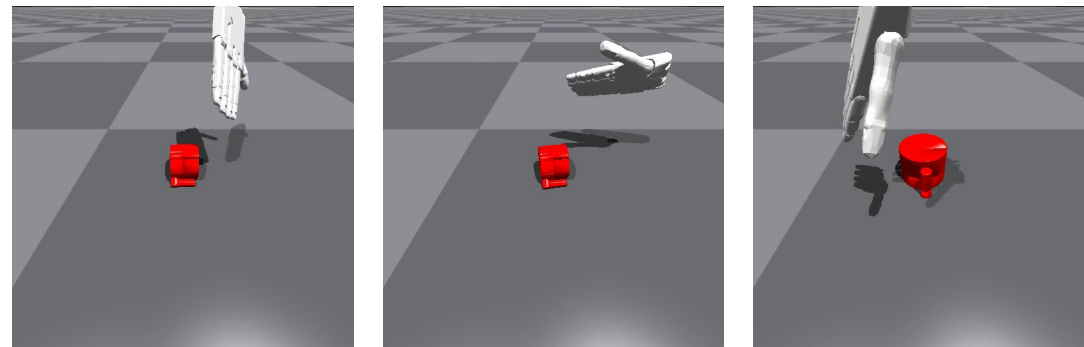
Camera



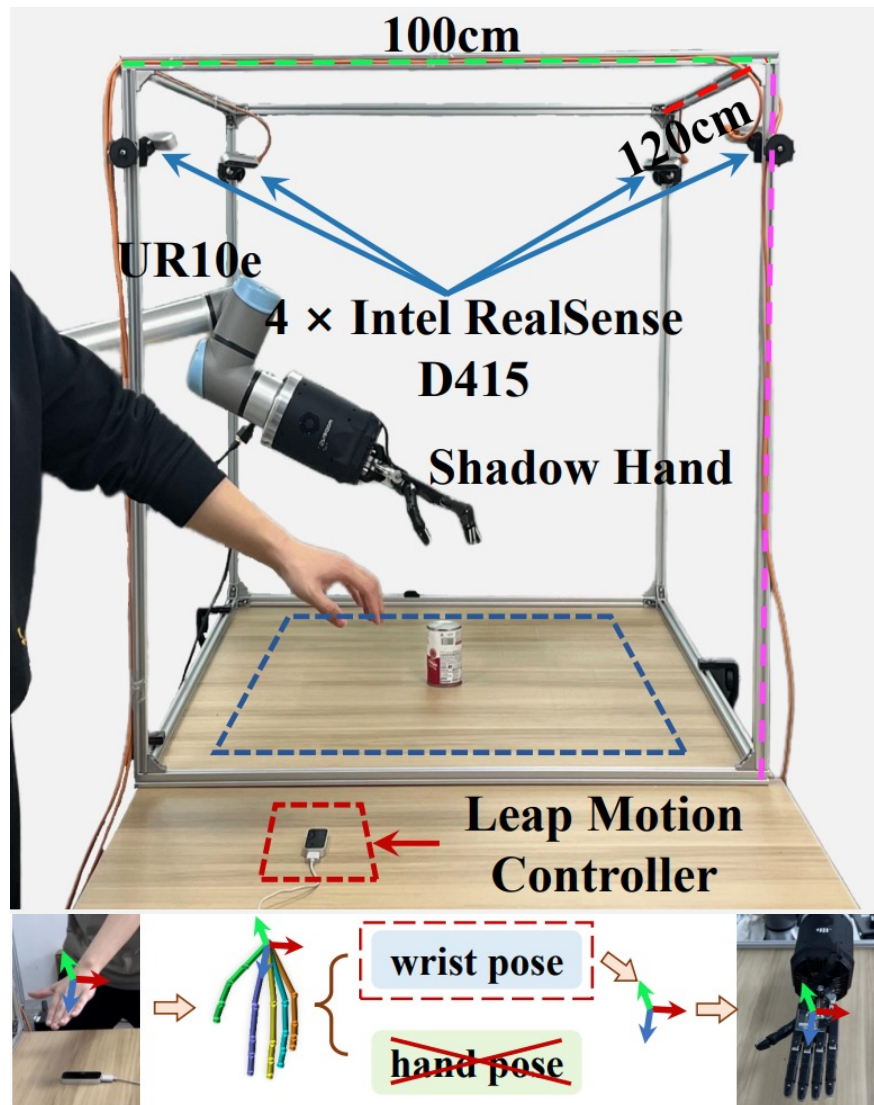
Cell-Phone



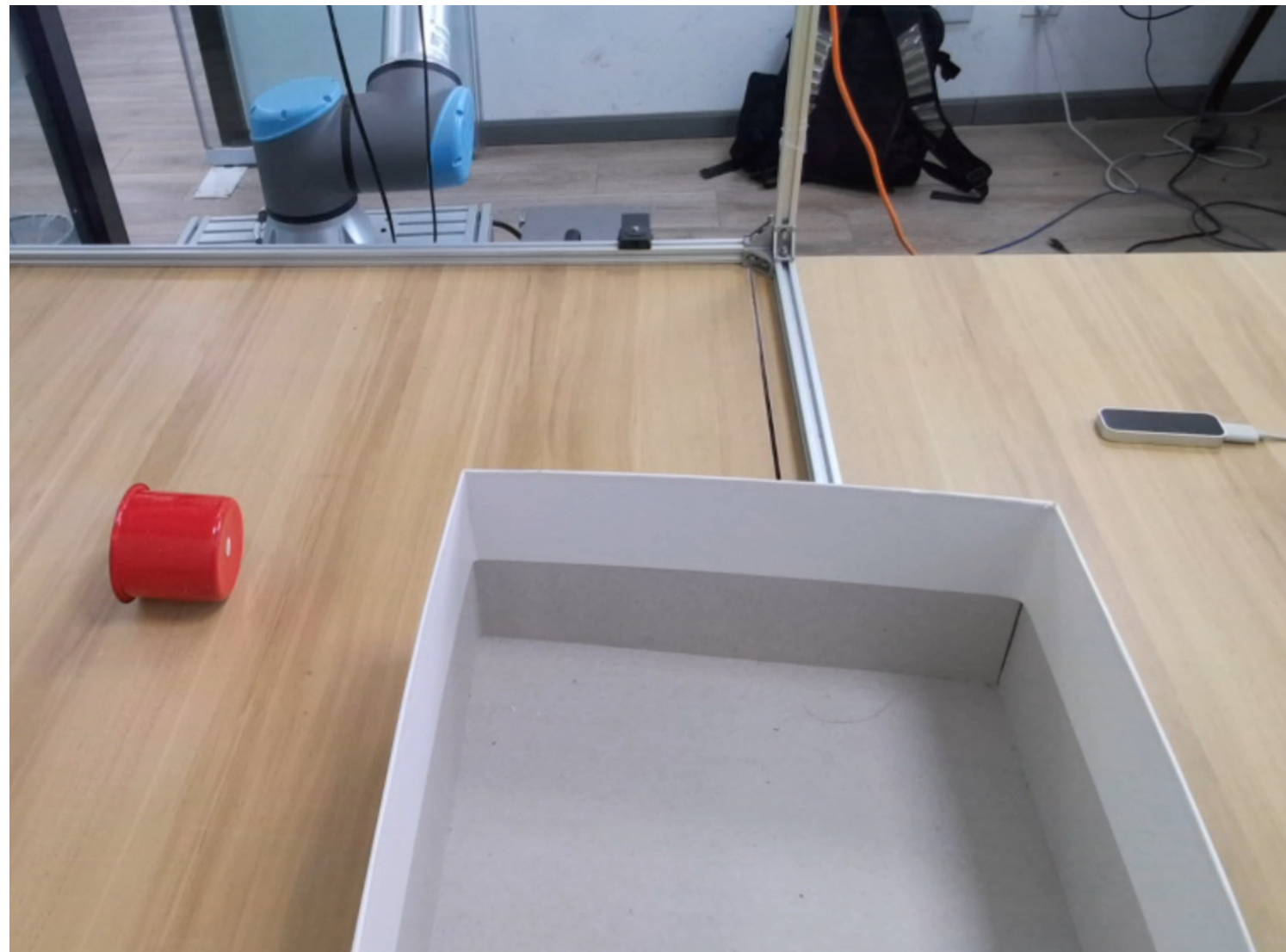
Mug



Real-World Experiment

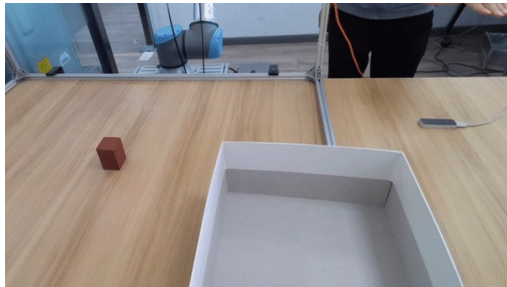


a) real-world setup

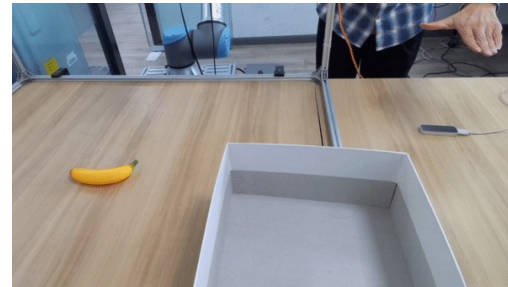


b) real-world experiment demonstration

Foam Brick



Banana



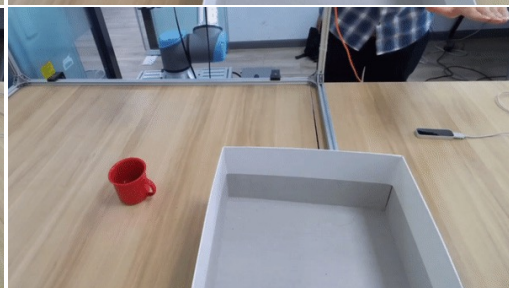
Pudding Box



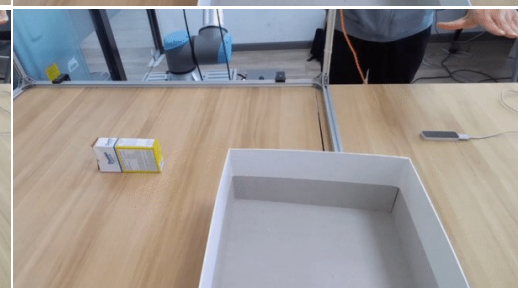
Tomato Soup Can



Mug



Sugar Box



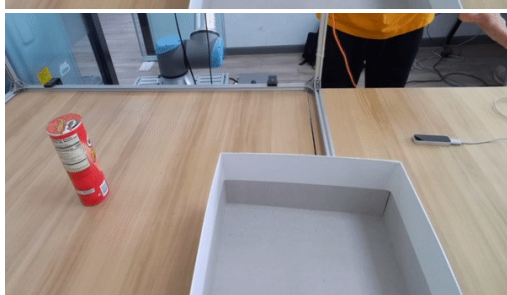
Timer



Cracker Box



Chips Can



Bleach Cleanser



Thank for your watching!

<https://sites.google.com/view/graspgf>