UniDoorManip: Learning Universal Door Manipulation Policy Over Large-scale and Diverse Door Manipulation Environments

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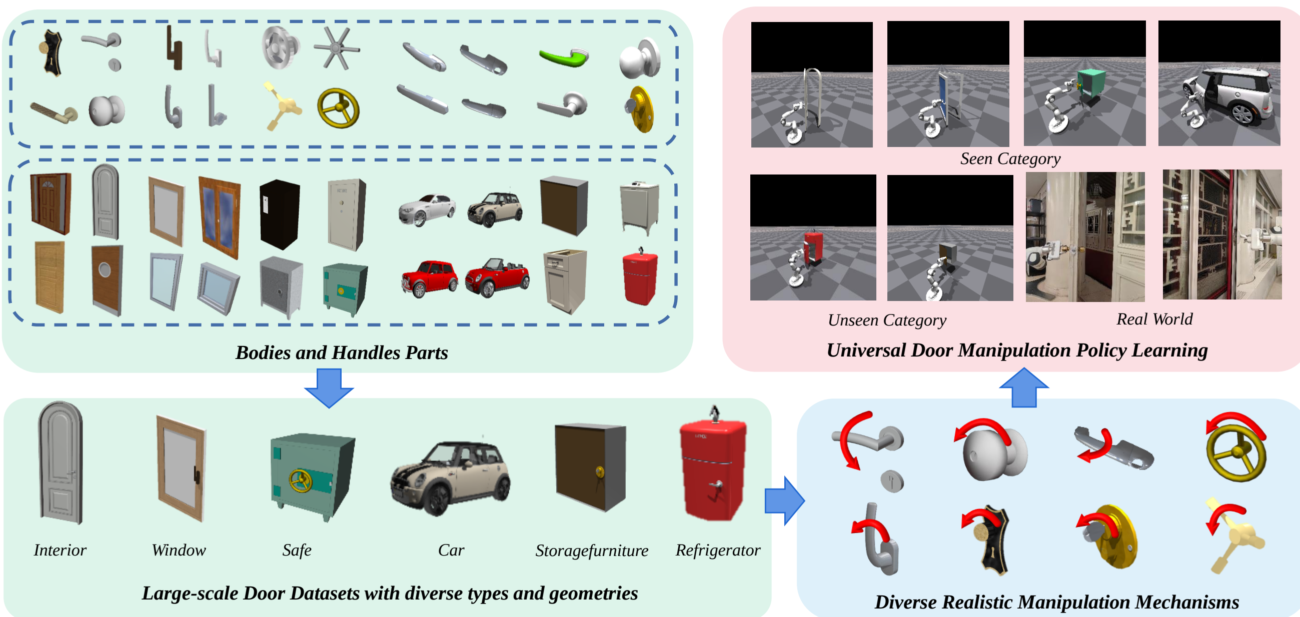

Figure 1. **Our Proposed Environment, Dataset and Universal Manipulation Policy.**

1. INTRODUCTION

Door manipulation holds significant importance due to the frequent need to open or close doors in various scenarios. While previous works have focused primarily on interior doors [10, 11], we aim to extend doors to a more general setting, *e.g.*, doors in windows, cars, safes, as illustrated in Figure 1. In the above broad scenarios, the door manipulation task covers doors with diverse types, geometries and manipulation mechanisms, which poses a great challenge to learn a universal door manipulation policy.

Due to the limited datasets and unrealistic simulation environments, previous works[1–3, 8, 13, 16] fail to achieve good performance across various doors. In this work, we **build a novel door manipulation environment** reflecting different realistic door manipulation mechanisms, and further equip this environment with **a large-scale door dataset** covering 6 door categories with hundreds of door bodies and handles, making up thousands of different door instances as shown in Figure 1. Additionally, to better emulate real-world scenarios, we introduce a mobile robot as the agent and use the partial and occluded point cloud as the observation, which are not considered in previous works while possessing significance for real-world implementations. We conduct detailed comparisons between our proposed environment and dataset and others in Table 1, 2.

To learn a universal policy over diverse doors, we **propose a novel framework disentangling** the whole manipulation process into three stages, and integrating them by training in the reversed order of inference. Extensive experiments validate the effectiveness of our designs and demonstrate our framework's strong performance. Code, data and

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Datasets	Int.			Win.			Car.			Saf.			Sto.			Ref.		
	B	**H**	**CO**	**B**	**H**	**CO**	**B**	**H**	**CO**	**B**	**H**	**CO**	**B**	**H**	**CO**	**B**	**H**	**CO**
AKB-48 [7]	-	9	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
PartNet-Mobility [15]	26	22	26	3	1	3	-	-	-	30	14	30	155	-	-	4	-	-
GAPartNet [3]	14	11	14	-	-	-	-	-	-	29	1	29	133	-	-	4	-	-
DoorGym [10]	-	20	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Ours	**57**	**96**	**5472**	**18**	**37**	**666**	**22**	**15**	**330**	**61**	**39**	**2379**	**160**	**8**	**1280**	**10**	**9**	**90**

Table 1. **Statistic Comparisons Between Previous Dataset and Ours.** For category, **Int.**, **Win.**, **Car.**, **Saf.**, **Sto.**, **Ref.** respectively denote doors from Interior, Window, Car, Safe, StorageFurniture, Refrigerator. For asset number, **B**, **H**, **CO** indicate numbers of body, handle and composited object assets with the two parts.

Env.	Data.	Mob.	Latch.	Part.	Occ.
GAPartNet [3]	P + A				
W2A [8, 12, 13]	P			✓	
RLAfford [4]	P	✓			
PartManip [2]	G	✓		✓	
DoorGym [10]	D		✓	✓	
EnvAfford [14]	P			✓	✓
Ours	**Ours**	✓	✓	✓	✓

Table 2. **Comparison between Our Environment and Others**. For simplicity, **Data.**, **Mob.**, **Latch.**, **Part.** and **Occ.** respectively denote Dataset, Mobile Robot Arm, Latching Mechanism, Partial Observation and Occlusion in Observation. Besides, **P**, **A**, **G** and **D** respectively denote PartNet-Mobility, AKB-48, GAPartNet and DoorGym in Table 1.

videos are avaible on https://unidoormanip.github.io/.

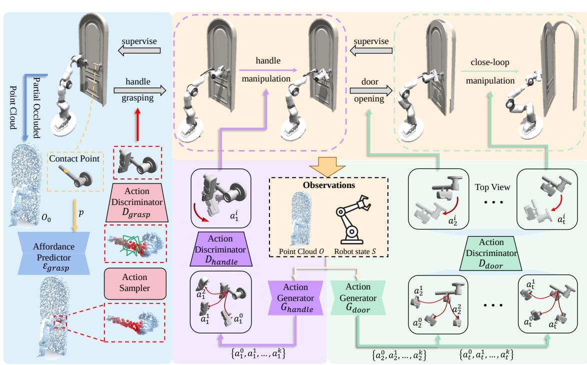

Figure 2. **Our Pipeline For The Framework**.

2. METHOD

As illustrated in Figure 2, we propose a novel framework that disentangles door manipulation into three distinct but related stages, each with a corresponding universal manipulation policy. We leverage conditioned training to train these policies, as they have inter-dependencies, and thus they can be integrated into a unified universal policy. In the first stage, we employ generalizable point-level visual affordance [5, 6, 9, 17] to propose stable grasp poses. In the second stage, we train a universal policy covering multiple handle manipulation mechanisms in our proposed realistic environment. In the third stage, we train a policy to open doors with unlocked handles.

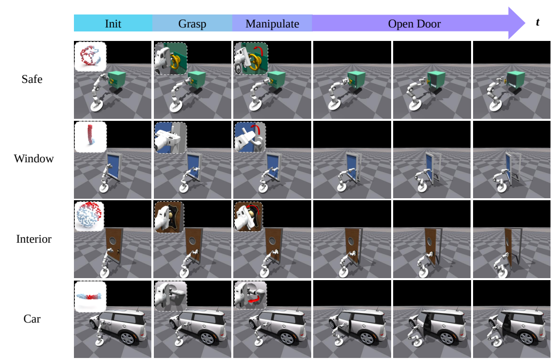

Figure 3. **Qualitative Results of Manipulation Sequence.**

Task	Pull Door					
Method	Train				Test	
GAPartNet [3]+GT	0.62	0.88	0.41	0.44	0.52	0.26
DoorGym [10]	0.56	0.72	0.61	0.41	0.19	0.23
PartManip [2]	0.47	0.61	0.54	0.34	0.42	0.19
VAT-MART [13]	0.59	0.62	0.57	0.43	0.51	0.25
Ours w/o disentangle.	0.44	0.88	0.20	0.19	0.05	0.22
Ours w/o condition.	0.77	0.31	0.58	0.51	0.54	0.33
Ours w/o state.	0.73	0.59	0.16	0.36	0.45	0.37
Ours w/o mobile.	0.87	0.60	0.00	0.43	0.50	0.81
Ours	**0.99**	**0.91**	**0.81**	**0.72**	**0.75**	**0.89**

Table 3. **Quantitative Results of the Baselines and Ablations.**

3. EXPERIMENTS

We conduct our experiments on the representative door manipulation tasks: **pull door**. The robot arm needs to pull the door until the door joint angle θ_d is larger than a threshold $thre_{door}$. Here, we set $thre_{door}$ to be $45°$.

Figure 3 shows the whole manipulation sequence of our universal manipulation. We also compare our method with baselines and conduct an ablation study as shown in Table 3. Qualitative and quantitative results demonstrate that our universal policy can generalize over diverse categories, geometries and manipulation mechanisms.

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