End-to-End Affordance Learning for Robotic Manipulation

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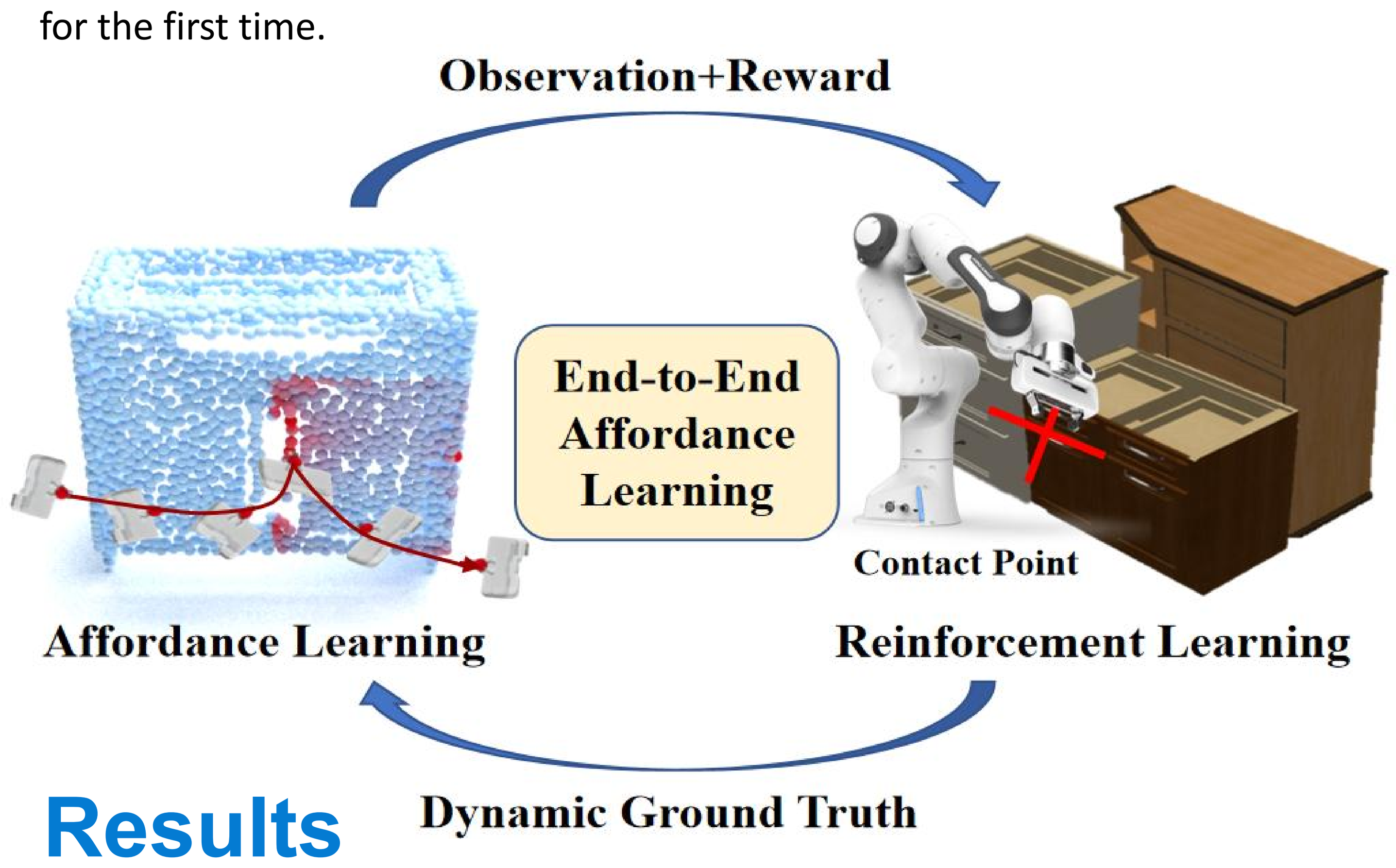
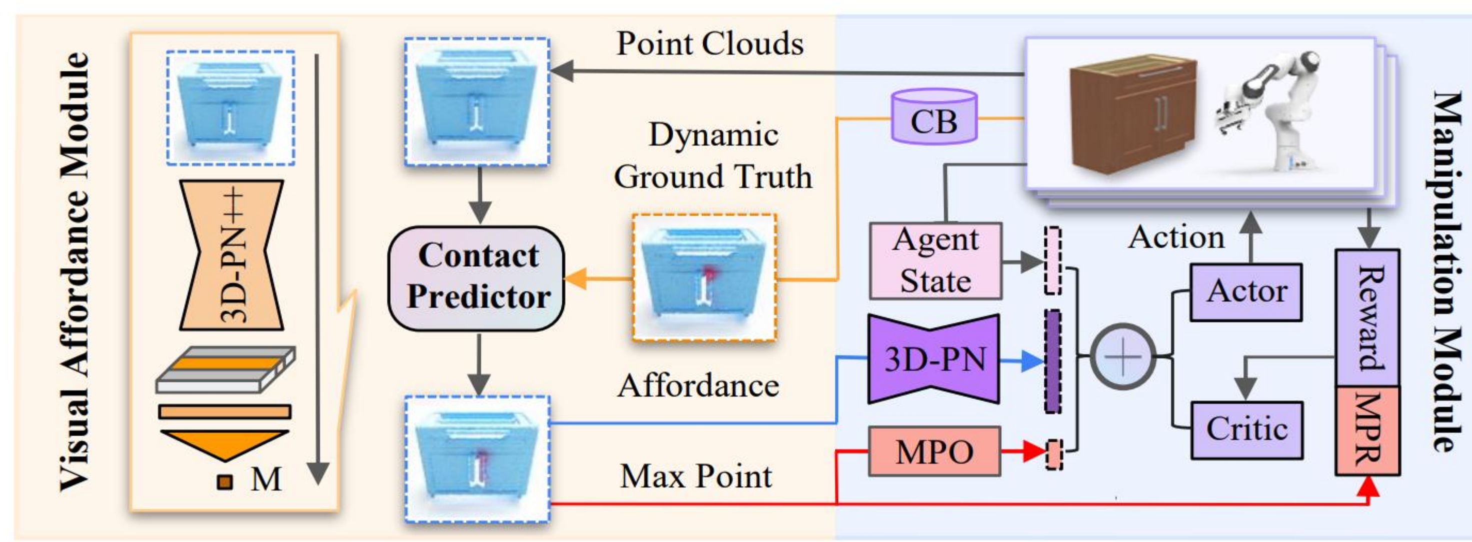
Introduction

In this study, we take advantage of the **contact information** generated during the RL training process and employ it as **unified visual representation** to predict contact map of interest. Such representation leads to an **end-to-end** learning framework that combined affordance based and RL based methods for the first time.

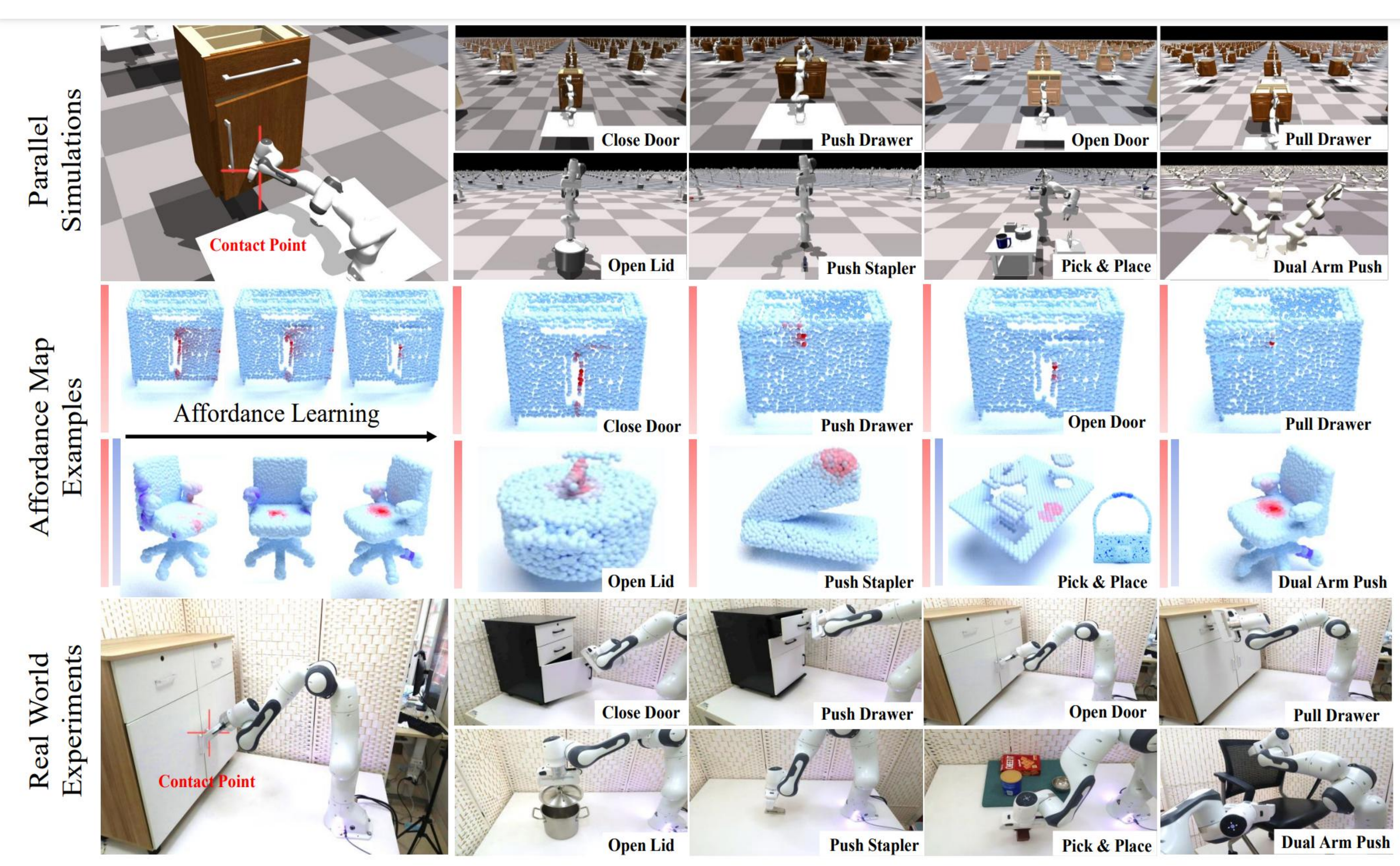


Methods



Our pipeline contains two main modules: **Manipulation Module (MA Module)** generating interaction trajectories and **Visual Affordance Module (VA Module)** learning to generate per-point affordance map M based on the real-time point cloud. The **Contact Predictor (CP)**, shared across two modules, serves as a bridge between them: 1) MA Module uses the **Affordance Map** (indicated by the blue arrow) and **Max-affordance Point Observation (MPO)** (indicated by the upper red arrow) predicted by the CP as a part of the input observation. A **Max-affordance Point Reward (MPR)** feedback (indicated by the lower red arrow) is also incorporated in training MA Module; 2) MA Module maintains a **Contact Buffer (CB)** by collecting collision information and generating **Dynamic Ground Truth (DGT)** (indicated by the orange arrow), where VA Module uses the DGT as the target for training CP.

Results



QUANTITATIVE RESULTS OF SINGLE-STAGE TASKS. (MORE RESULTS ON OUR WEBSITE.)

Methods \ Datasets	Open Door				Pull Drawer				Push Stapler				Open Pot Lid			
	ASR		MP		ASR		MP		ASR		MP		ASR		MP	
	train	test	train	test	train	test	train	test	train	test	train	test	train	test	train	test
Where2act	22.8	14.1	6.8	8.3	19.0	12.9	2.3	0.0	16.4	14.4	13.0	13.0	10.5	5.4	8.7	4.3
VAT-Mart	23.2	21.9	31.8	33.3	5.5	5.1	0.0	0.0	21.9	20.9	17.4	13.0	27.4	21.5	17.4	17.4
Multi-task RL	18.8	9.2	11.4	5.0	0.1	2.4	0.0	2.8	34.9	30.2	30.4	26.1	35.2	32.6	21.7	17.4
RL	21.5	5.5	22.7	0.0	23.1	22.4	19.6	19.5	45.5	40.6	34.8	30.4	32.5	28.6	21.7	21.7
RL+Where2act	20.5	8.0	19.3	9.4	25.2	22.2	24.4	21.9	48.9	45.2	39.1	34.8	38.2	30.6	26.1	21.7
Ours	**52.9**	**32.6**	**61.4**	**41.7**	59.7	**58.6**	62.8	**63.3**	**69.5**	**53.2**	**47.8**	**39.1**	**49.5**	**44.6**	**34.8**	**30.4**
Ours w/o MPO	48.0	23.8	50.0	16.7	41.9	42.5	38.6	43.8	60.6	52.5	43.5	**39.1**	44.2	40.7	**34.8**	**30.4**
Ours w/o MPR	28.2	8.4	29.5	8.3	**62.3**	44.0	**65.9**	43.8	50.8	39.9	39.1	30.4	44.8	40.1	30.4	26.1
Ours w/o E2E	21.2	12.4	20.5	8.3	57.7	57.3	61.1	61.7	40.2	36.6	39.1	34.8	32.1	30.6	30.4	26.1

QUANTITATIVE RESULTS OF PICK-AND-PLACE.

Methods \ Metrics	ASR		MP	
	train	test	train	test
RL	25.2	22.1	19.2	11.5
RL+O2OAfford	26.1	22.2	19.2	11.5
RL+Where2act	28.6	23.5	23.1	15.4
RL+O2OAfford+Where2act	30.5	26.2	23.1	15.4
Ours	**46.5**	**39.2**	**30.7**	**26.9**
Ours w/o A2O Map	26.7	22.3	23.1	19.2
Ours w/o O2O Map	31.9	26.2	23.1	15.4
Ours w/o MPO	40.1	30.2	19.2	15.4
Ours w/o MPR	36.2	33.5	**30.7**	23.1
Ours w/o E2E	30.2	21.4	26.9	19.2

QUANTITATIVE RESULTS OF DUAL-ARM-PUSH.

Methods \ Metrics	ASR		MP	
	train	test	train	test
MAPPO	7.8	9.0	0.0	0.0
RL	37.2	36.1	36.4	31.3
Multi-task RL	51.6	52.9	54.5	56.3
Ours	83.9	78.5	90.9	93.8
Ours w/o MPO	**95.9**	**96.3**	**100.0**	**100.0**
Ours w/o MPR	63.9	55.3	63.6	56.3
Ours w/o E2E	53.5	55.9	56.8	50.0

- **Average Success Rate (ASR)**: The ASR is the average of the algorithm's success rate on all objects in the training / testing dataset.
- **Master Percentage (MP)**: The master percentage is the percentage of objects which the algorithm can success with a probability greater than or equal to 50%.

Affrodance Maps

Conclusion

To the best of our knowledge, this the first work that proposes an end-to-end affordance RL framework for robotic manipulation tasks. In RL training, affordance can improve the policy learning by providing additional observation and reward signals. Our framework automatically learns affordance semantics through RL training without human demonstration or other artificial designs dedicated to data collection. The simplicity of our method, together with the superior performance over strong baselines and the wide range of applicable tasks, has demonstrated the effectiveness of learning from contact information. We believe our work could potentially open a new way for future RL-based manipulation developments

Reference

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