



SpatialActor: Exploring Disentangled Spatial Representations for Robust Robotic Manipulation

AAAI 26 Oral

Hao Shi
(石昊)
@THU

<https://shihao1895.github.io>

Hao Shi¹, Bin Xie², Yingfei Liu², Yang Yue¹, Tiancai Wang²,
Haoqiang Fan², Xiangyu Zhang^{3,4}, Gao Huang^{1✉}

¹LeapLab, Tsinghua University, ²Dexmal, ³MEGVII, ⁴StepFun

shi-h23@mails.tsinghua.edu.cn

X DEXMAL

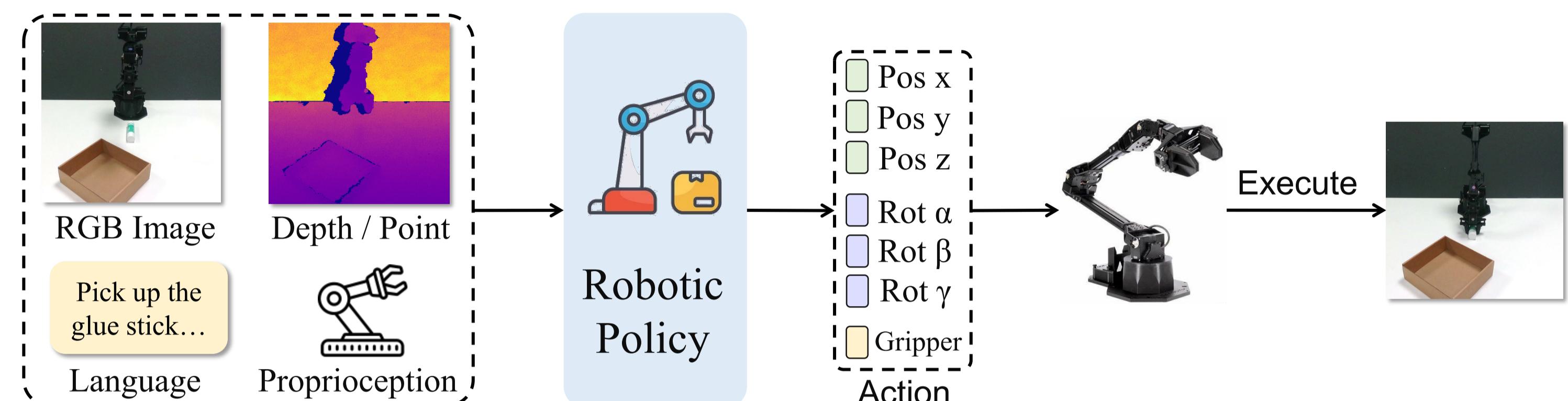


Page

Code

1 Introduction

① What is Robotic Manipulation Task?



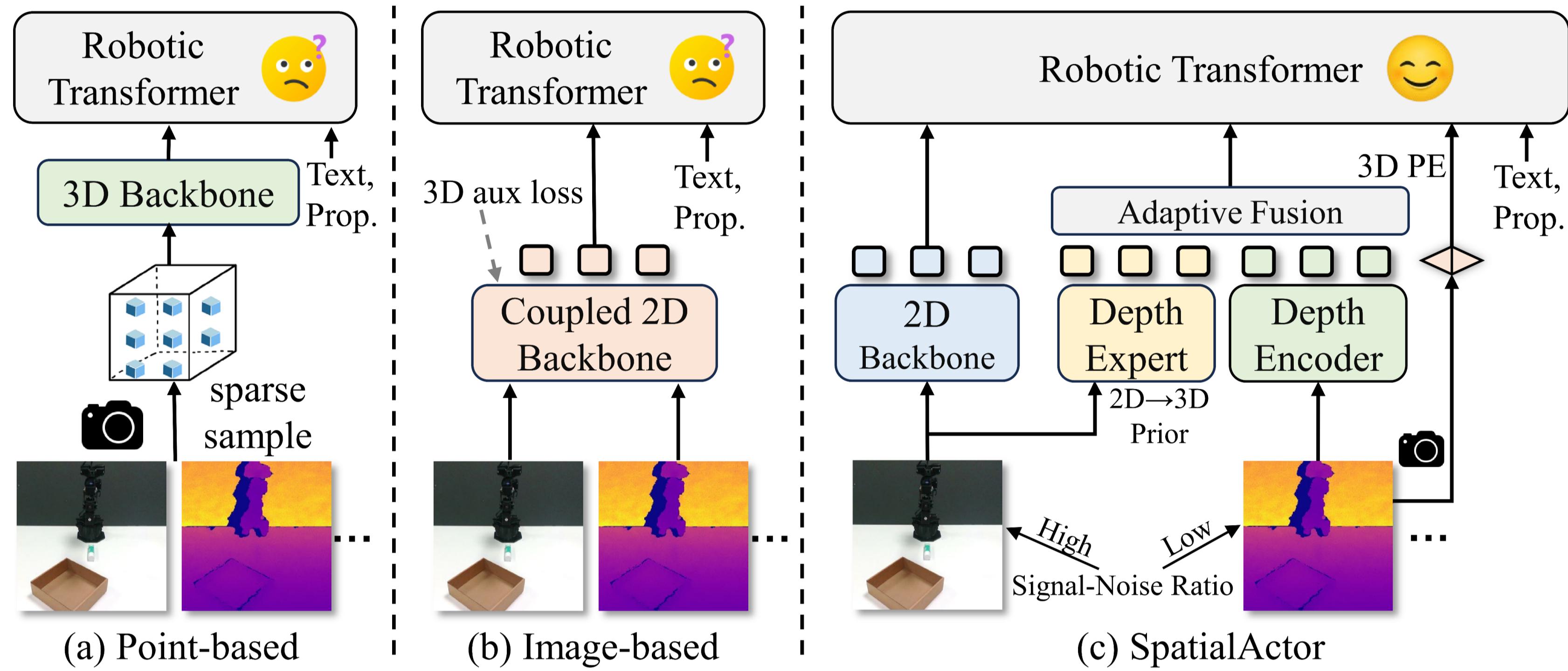
② Some Challenges in Robotic Manipulation

- ✓ Fine-grained spatial semantic understanding.
- ✓ Robustness to sensor noise.
- ✓ Low-level spatial structure inductive bias.



How to build robust spatial representations for robotic manipulation?

③ Comparison of Robotic Spatial Representations Solution



✓ Point-based

Sparse fusion → Loss fine-grained semantics.

✓ Image-based (e.g., RVT)

Coupled encode → Noisy depth interfere semantics.

✓ Ours: Disentangled framework

① Visual semantics

② Complementary high-level geometry

□ Fine-grained yet noisy: from real sensor depth

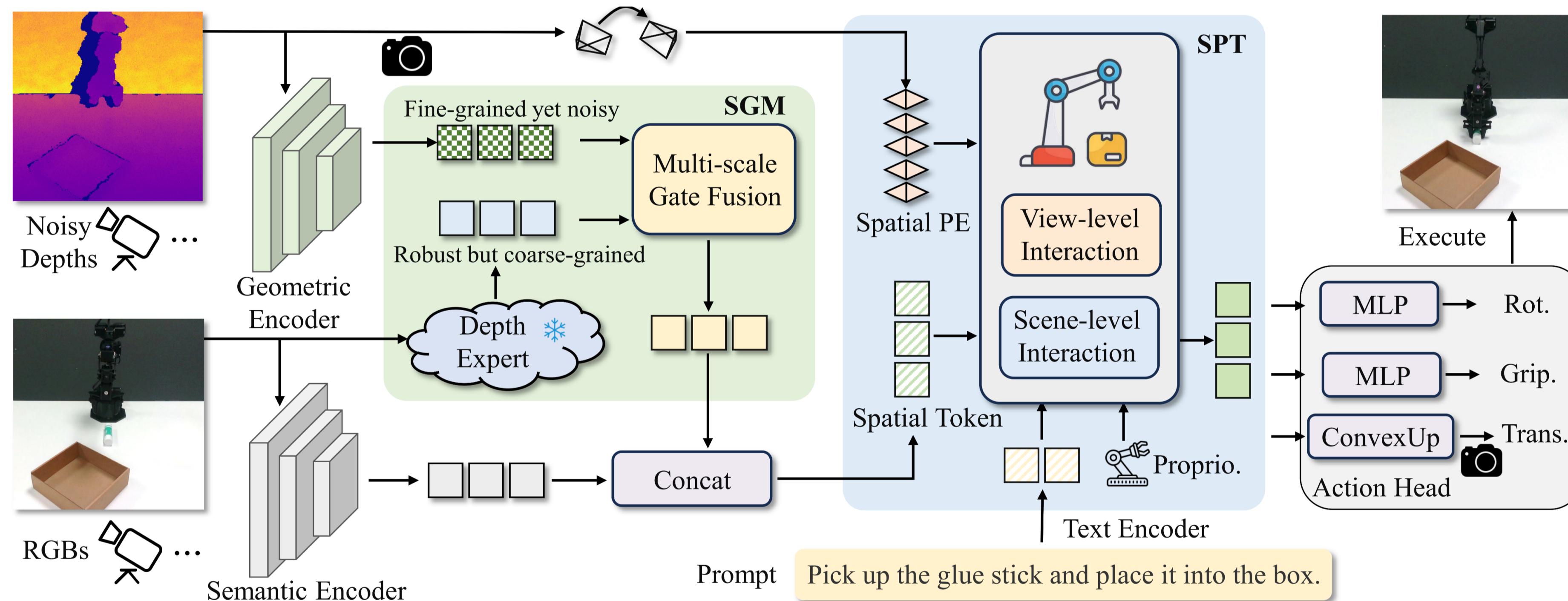
□ Robust but coarse-grained: from depth expert

(High-SNR semantics + 2D-to-3D priors help smooth noisy depth)

③ ◇ Low-level geometry: explicit 2D-3D correspondence

2 Method

① Overall Framework

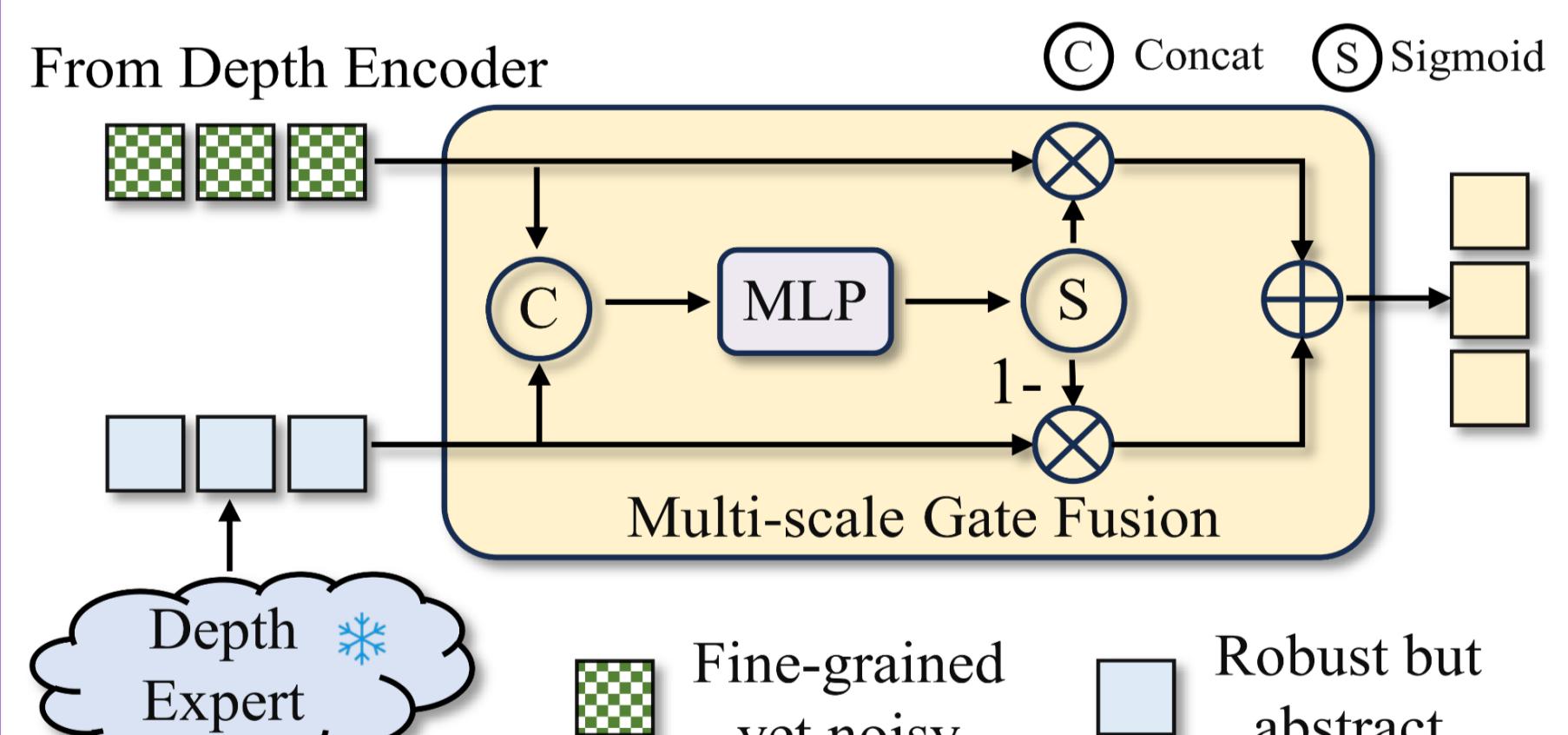


3 Experiments

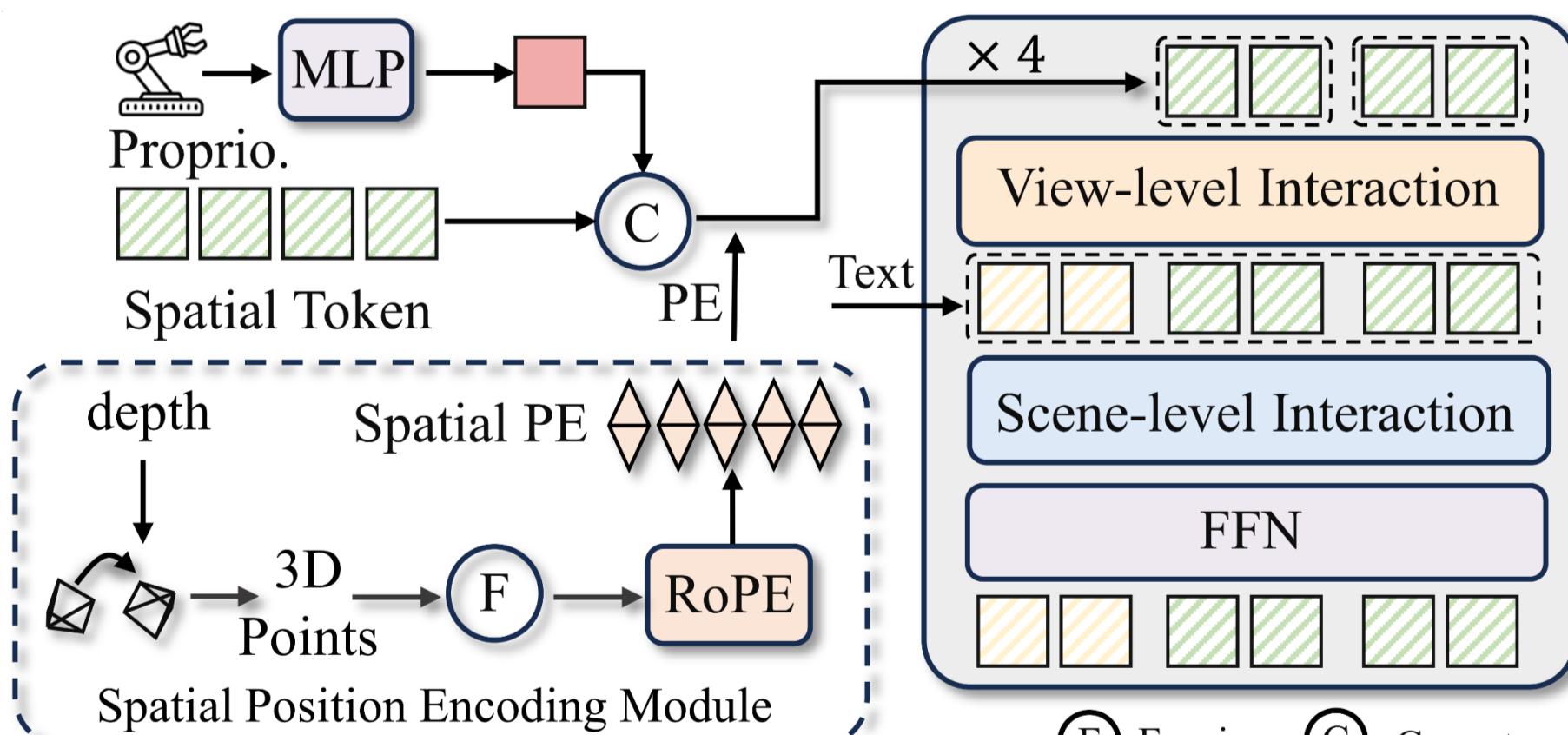
① RLBench SOTA: 87.4% Success Rate

Models	Avg. Success ↑	Avg. Rank ↓	Close Jar	Drag Stick	Insert Peg	Meat off Grill	Open Drawer	Place Cups	Place Wine	Push Buttons
C2F-ARM-BC	20.1	9.5	24.0	24.0	4.0	20.0	20.0	0.0	8.0	72.0
HiveFormer	45.3	7.8	52.0	76.0	0.0	100.0	52.0	0.0	80.0	84.0
PolarNet	46.4	7.3	36.0	92.0	4.0	100.0	84.0	0.0	40.0	96.0
PerAct	49.4	7.1	55.2 _{±4.1}	89.6 _{±4.1}	5.6 _{±4.1}	70.4 _{±5.7}	88.0 _{±5.7}	2.4 _{±3.2}	44.8 _{±7.8}	92.8 _{±3.0}
RVT	62.9	5.3	52.0 _{±4.5}	99.2 _{±1.6}	11.2 _{±3.0}	88.0 _{±2.5}	71.2 _{±6.9}	4.0 _{±2.5}	91.0 _{±5.2}	100.0 _{±0.0}
Act3D	65.0	5.3	92.0	92.0	27.0	94.0	93.0	3.0	80.0	99.0
SAM-E	70.6	2.9	82.4 _{±3.6}	100.0 _{±0.0}	18.4 _{±4.6}	95.2 _{±5.2}	0.0 _{±0.0}	94.4 _{±4.6}	100.0 _{±0.0}	
3D-Diff-Actor	81.3	2.8	96.0 _{±2.5}	100.0 _{±0.0}	65.6 _{±4.1}	96.8 _{±1.6}	89.6 _{±4.1}	24.0 _{±7.6}	93.6 _{±4.8}	98.4 _{±2.0}
RVT-2	81.4	2.8	100.0 _{±0.0}	99.0 _{±1.7}	74.0 _{±11.8}	38.0 _{±4.5}	95.0 _{±3.3}	100.0 _{±0.0}		
SpatialActor	87.4 _{±0.8}	2.3	94.0 _{±4.2}	100.0 _{±0.0}	93.3 _{±4.4}	98.7 _{±2.1}	82.0 _{±3.3}	56.7 _{±8.5}	94.7 _{±4.8}	100.0 _{±0.0}

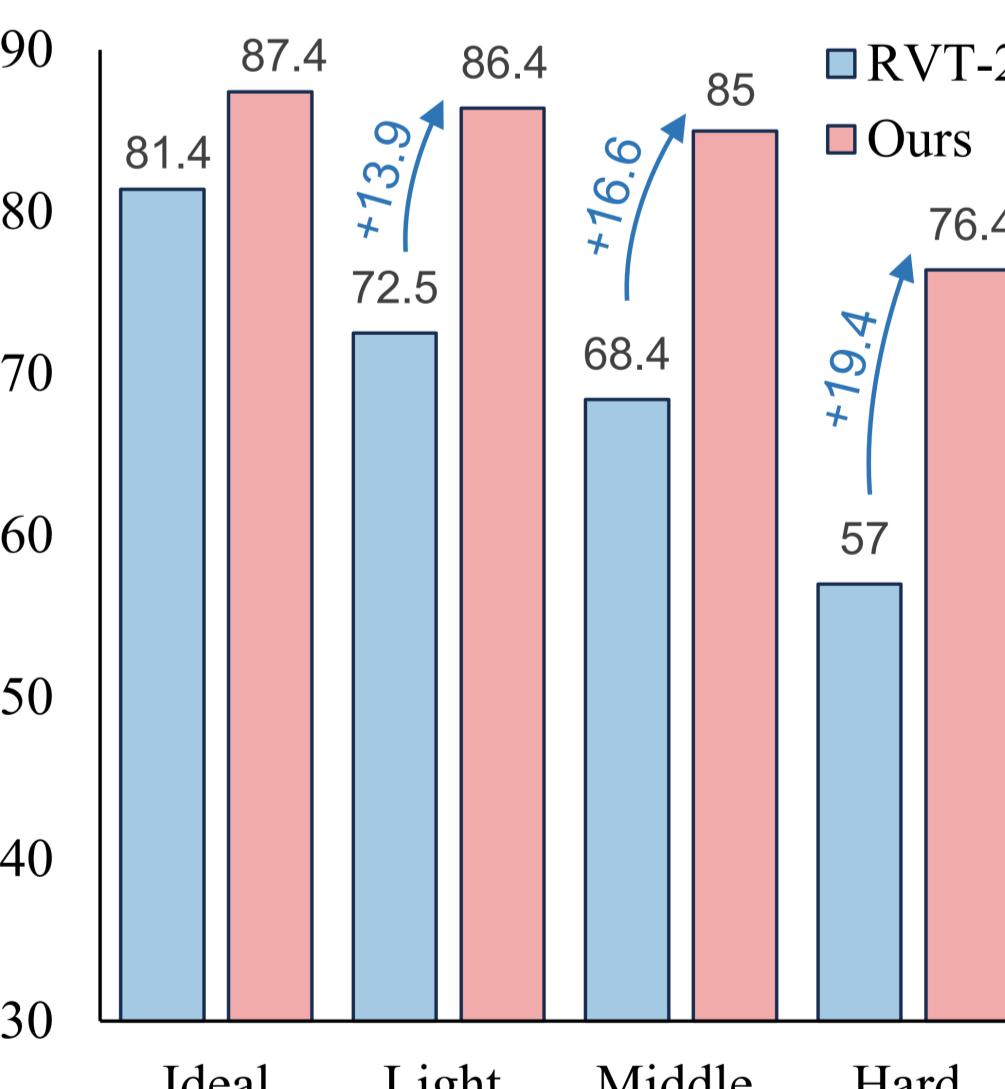
② Semantic-Guided Geometric Module



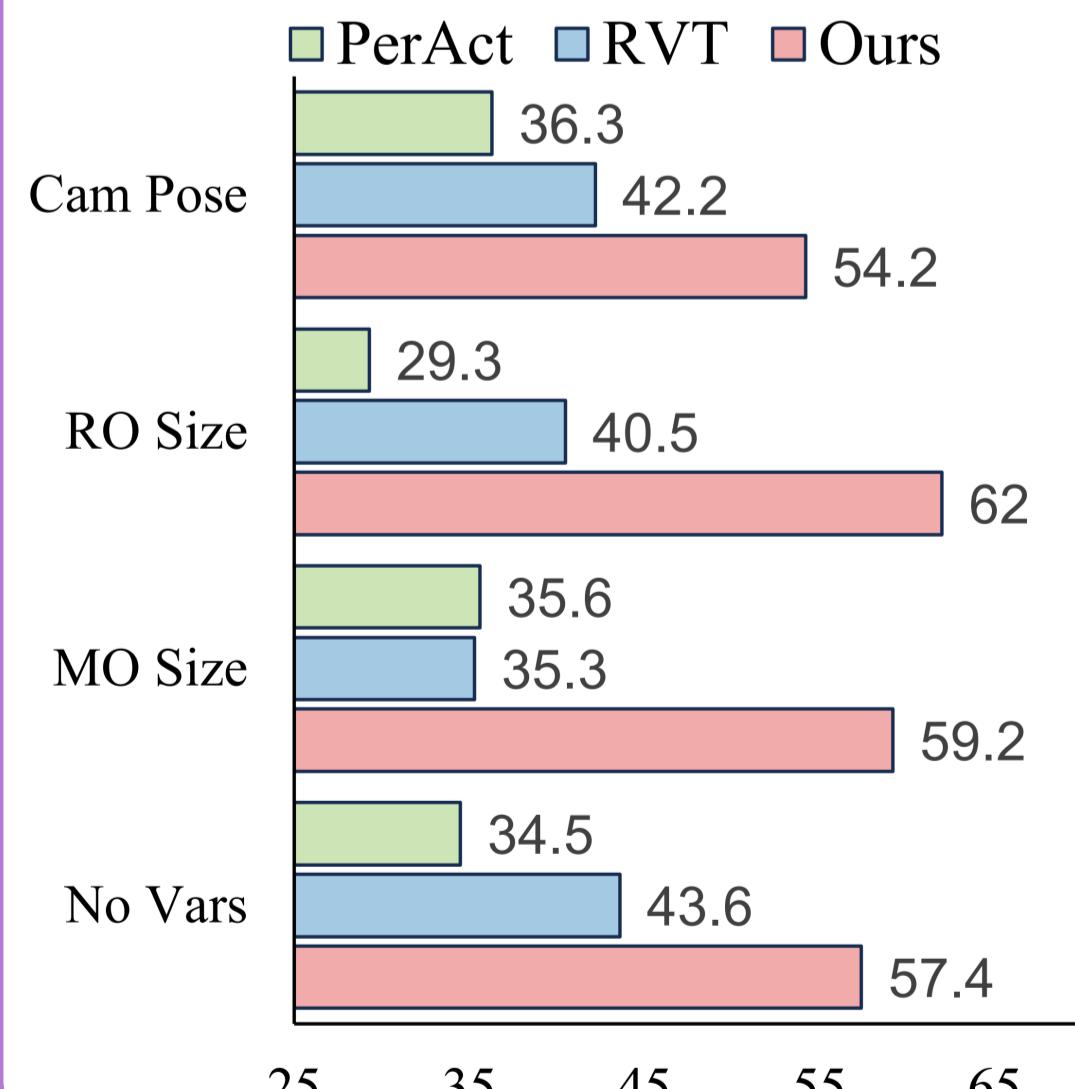
③ Spatial Transformer



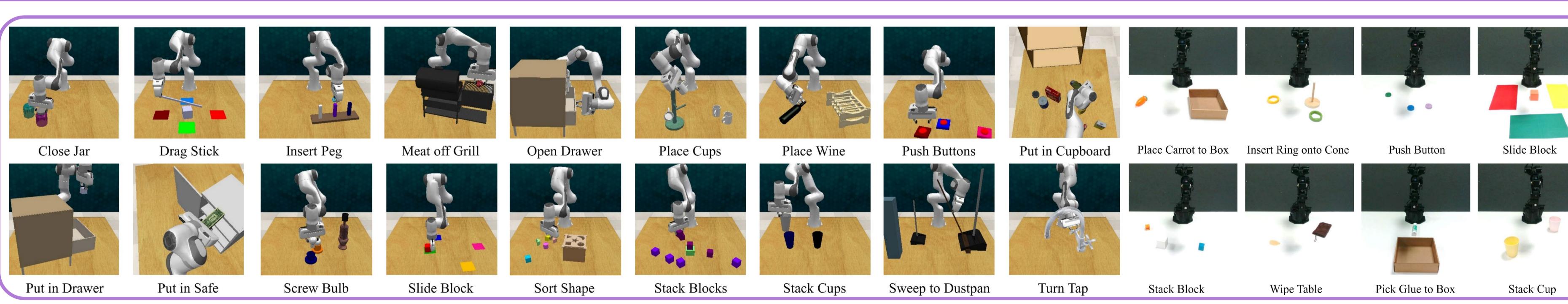
② Robust to Noise



③ Spatial Variant



4 Visualization & Further Work



Equip Robot with Human-like Hippocampus Memory

Robust Spatial Perception

From Spatial to Temporal

Physical Grounding: Map observations to a physically grounded pose.

General Robot

Temporal Decision: Make long-term decisions based on current and past.



④ Real-World Performance

