DualTHOR: A Dual-Arm Humanoid Simulation Platform for Contingency-Aware Planning

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Abstract

Developing embodied agents capable of performing complex interactive tasks in real-world scenarios remains a fundamental challenge in embodied AI. Although recent advances in simulation platforms have greatly enhanced task diversity to train embodied Vision-Language Models (VLMs), most platforms rely on simplified robot morphologies and bypass the stochastic nature of low-level execution, which limits their transferability to real-world robots. To address these issues, we present a physics-based simulation platform **DualTHOR** for complex dual-arm humanoid robots, built upon an extended version of AI2-THOR. Our simulator includes real-world robot assets, a task suite for dual-arm collaboration, and inverse kinematics solvers for humanoid robots. We also introduce a contingency mechanism that incorporates potential failures through physics-based low-level execution, bridging the gap to real-world scenarios. Our simulator enables a more comprehensive evaluation of the robustness and generalization of VLMs in household environments. Extensive evaluations reveal that current VLMs struggle with dual-arm coordination and exhibit limited robustness in realistic environments with contingencies, highlighting the importance of using our simulator to develop more capable VLMs for embodied tasks. The code is available at https://github.com/ds199895/DualTHOR.git.

1 Introduction

The development of embodied intelligent agents [Song et al., 2023, Qian et al., 2025] capable of adapting to diverse environments [Zhao et al., 2024] and performing complex interactive tasks instead of humans [Chen et al., 2025, Yuan et al., 2025] remains a central challenge in the current research landscape. In recent years, the enrichment of simulation data for embodied agents, particularly in terms of task diversity and interaction complexity [Deitke et al., 2022, Yang et al., 2024a], has significantly enhanced the foundational capabilities of Vision-Language Models (VLMs). As a result, constructing sophisticated simulation environments and collecting diverse datasets have become prominent research directions. Platforms such as AI2-THOR [Kolve et al., 2022], Habitat [Puig et al., 2023], VirtualHome [Puig et al., 2018], and Isaac Gym [Makoviychuk et al., 2021a] have played a crucial role in advancing the generation of embodied data, improving scene understanding and task performance for VLM-based agents [Yang et al., 2024b, Li et al., 2024a], and contributing to reducing the sim-to-real gap for real-world deployments [Black et al., 2024, Bu et al., 2025].

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Figure 1: Overview of **DualTHOR**. Our simulator focuses on the H1 and X1 dual-arm humanoid robots, which serve as the primary embodied agents. We develop a diverse suite of dual-arm tasks and introduce a contingency mechanism during action execution to simulate real-world uncertainties. Building on these capabilities, our simulator provides a more challenging and complete benchmark to evaluate high-level planning capabilities for embodied VLMs and systems.

Existing simulators have mainly constructed physical simulations in household settings that emphasize the diversity of objects [Deitke et al., 2020], manipulation tasks [Ehsani et al., 2021], and observations [Zhou et al., 2024a]. However, the robotic platforms employed in these simulators are typically limited to wheeled robots and single-arm manipulators. In recent years, humanoid dual-arm robots have emerged as a promising direction in robotics research, enabling advances in dual-arm task planning [Wong et al., 2021, Zhou et al., 2024b], whole-body motion control [Fu et al., 2024a, Cheng et al., 2024], and multi-robot collaboration [Mandi et al., 2024]. Compared to single-arm robots, dual-arm robots provide embodied agents with a broader range of task capabilities [Sferrazza et al., 2024], facilitating more efficient, fine-grained, and realistic interactions. Including such robot morphologies is thus crucial for the development of more complex and generalizable embodied agents. Motivated by this, we aim to build a household simulator for humanoid dual-arm robots.

Implementing abundant low-level skills with high success rates, which is necessary to evaluate embodied VLMs in high-level planning [Smith et al., 2024, Fu et al., 2024b], is extremely difficult. Most prior simulation platforms [Kolve et al., 2022, Zhang et al., 2025] bypass this challenge by skipping a more physically realistic process of low-level skill execution. For example, they usually employ instantaneous, flash-like transitions [Deitke et al., 2022, Nasiriany et al., 2024] to guarantee that robot and objects transition to a success state of the skill. These approaches overlook the continuous process and potential failures of low-level execution and compromise the embodied agent's ability to perceive skill progression and evaluate its true performance, which significantly undermines the transferability of VLM-based planning for sim-to-real deployments [Balazadeh et al., 2024, Li et al., 2024b]. To overcome such limitation, we propose to build a simulation platform with probabilistic execution to simulate various real-world contingencies and unexpected situations. This maintains reproducibility while incorporating interaction-level contingencies, allowing for errors to occur during robot operations. Following this principle, we can provide a more realistic simulator for evaluating and improving task comprehension and planning capabilities of VLMs.

We introduce a physics-based simulation platform, **DualTHOR**, to address the existing limitations. Firstly, we employ humanoid dual-arm robots as primary agents and design a set of dual-arm tasks in which the two arms can either execute distinct actions in parallel or collaborate to accomplish a single complex task, as shown in the right side of Figure 1. This setup enables the collection of more realistic and diverse embodied data. Secondly, we optimize the control logic and introduce dedicated humanoid inverse kinematics (IK) functions to ensure continuous and realistic observation variations throughout the interaction process, encompassing both robot's states and environmental transitions. To further simulate real-world uncertainty, we incorporate a contingency mechanism that mimics potential execution errors during action operation, as shown in the left side of Figure 1. Finally, we extend the AI2-THOR [Kolve et al., 2022] environment by integrating richer physical

simulation details, including object collisions and fluid dynamics (*e.g.*, pouring and filling), thereby reducing the sim-to-real transfer challenges and enhancing scene understanding. Experimental results demonstrate that current VLMs still struggle with dual-arm collaborative tasks, and their ability to re-plan effectively in response to unexpected events remains limited. This highlights the importance of the DualTHOR simulator to develop more capable VLMs for embodied tasks in future research.

In summary, our contributions encompass the following key advancements:

- 1. We propose a humanoid dual-arm robot simulator **DualTHOR** (based on AI2-THOR) and introduce a task suite for dual-arm planning. We create a new benchmark tailored for household dual-arm tasks, providing a standardized evaluation framework for future research.
- 2. By integrating humanoid IK functions and a contingency mechanism, we enable the simulator to realize continuous transition and produce failure cases commonly encountered in real-world robotics, thereby increasing the realism of the simulation platform.
- 3. Our experimental results show that existing open-source and proprietary models have limited capabilities in planning for dual-arm embodied tasks and exhibit poor robustness, underscoring the potential for future research to develop more capable embodied agents.

2 Related Work

2.1 Simulation Platforms for Interactive Learning

Simulation environments are indispensable for advancing interactive learning in embodied AI, offering controllable settings for agent training and evaluation. AI2-THOR [Kolve et al., 2022] serves as a foundational framework, providing high-quality visual environments and interactive object dynamics that support a wide range of embodied AI tasks. Extensions such as RoboTHOR [Deitke et al., 2020], ManipulaTHOR [Ehsani et al., 2021], and ProcTHOR [Deitke et al., 2022] have enhanced the simulator by increasing task diversity, scene complexity, and object variety, yet the range of robot embodiments remains limited to single-arm and wheeled robots. HumanoidBench [Sferrazza et al., 2024] and Isaac Gym [Makoviychuk et al., 2021b] focus primarily on training low-level control policies for humanoid robots. Consequently, they do not support background rendering and are not suitable for assessing long-horizon planning capabilities for dual-arm tasks. To provide the necessary simulation capabilities along with a wide range of task categories and extended robot morphologies, we introduce our DualTHOR simulator.

2.2 Asynchronous Control for Dual-Arm Humanoid Robot

Existing simulation environments fall short in specifically addressing the nuanced motion control requirements of bimanual humanoid robots and often oversimplify the process of motion interaction [Kolve et al., 2022, Li et al., 2023, Zhang et al., 2025]. In robotics manipulation tasks, dual-arm systems are indispensable for executing complex operations that demand high stability and multi-point control. DA-VIL [Karim et al., 2024] employs reinforcement learning to address variable impedance control challenges, and LfDT [Kobayashi et al., 2023] introduces a novel imitation learning framework to leverage human demonstrations. HumanPlus [Fu et al., 2024a] indicates that reinforcement learning and imitation learning methods exhibit limited generalization capabilities when training data is scarce. As a result, we employ traditional control techniques and incorporate humanoid IK functions to ensure stable continuous action execution. Other techniques for building simulation environments and the differences to prior simulators are discussed in detail in Appendix C.

3 DualTHOR

We introduce DualTHOR, a simulator built upon AI2-THOR [Kolve et al., 2022] and extended to dual-arm humanoid robots. The environment integrates the Unity physics engine [Haas, 2014], humanoid-specific inverse kinematics (IK) functions [Habekost et al., 2024], and task-reversal capabilities. With these capabilities, we design a novel set of tasks tailored specifically for dual-arm robots, significantly increasing the complexity of embodied interactions in household settings. A key feature of our platform is its support for continuous interaction processes, as shown in Table 1, distinguishing it from existing simulation platforms that often rely on discrete or simplified transitions. Moreover, to model real-world uncertainty, the environment incorporates a stochastic contingency

Simulator	Category	Agents	Transition	Action Control	Contingency
ThreeDWorld [Gan et al., 2020]	Household	Wheel	Discrete	Discrete	×
iGibson [Li et al., 2021]	Navigation	Wheel	Discrete	Discrete	×
AI2-THOR [Kolve et al., 2022]	Household	Wheel	Discrete	Discrete	×
RoboThor [Deitke et al., 2020]	Navigation	Wheel	Discrete	Discrete	×
ManipulaThor [Ehsani et al., 2021]	Manipulation	Single Arm	Discrete	Discrete	×
ProcThor [Deitke et al., 2022]	Household	Wheel	Discrete	Discrete	×
Habitat [Puig et al., 2023]	Multi-Domain	Single Arm & Wheel	Discrete	Discrete & Continuous	×
OmniGibson [Li et al., 2023]	Multi-Domain	Single Arm & Wheel	Discrete	Discrete	×
MoMa-Kitchen [Zhang et al., 2025]	Manipulation	Single Arm	Discrete	Discrete	×
DualTHOR (ours)	Household	Dual Arm	Continuous	Discrete & Continuous	1

Table 1: A systematic comparison of DualTHOR and existing household simulation platforms.

mechanism, enabling agents to develop and refine their re-planning abilities in response to execution errors. With these enhancements, DualTHOR provides a highly interactive and flexible platform for advancing the development of robust dual-arm embodied systems.

3.1 Overview of DualTHOR

Physics Engine. DualTHOR leverages the Unity engine to enable embodied simulation with several key advantages tailored for dual-arm humanoid robotics. First, Unity facilitates parallel execution of bimanual actions [Tabiszewski, 2024], allowing precise coordination to execute complex manipulation tasks. Second, its control framework supports interpolation-based motion execution [Lee, 2024], ensuring smooth and continuous transitions between action steps. This leads to visually coherent interactions, which are particularly important for perception-driven tasks. Moreover, Unity offers high extensibility in both object modeling and scene configuration, enabling the creation of diverse and increasingly complex task scenarios. This flexibility allows for the construction of more realistic household environments.

Visual Perception. Similar to AI2-THOR [Kolve et al., 2022], DualTHOR is structured around multiple distinct rooms, as illustrated in Figure 7. Each room contains a unique set of objects, enabling the agent to perform a diverse range of tasks. Inspired by VirtualHome [Puig et al., 2018], our environment incorporates a multi-camera system that provides both first- and third-person perspectives. The first-person cameras are mounted on the robot's head and offer up to a 360-degree panoramic view to simulate the robot's visual perception. The third-person camera suite includes rear, frontal, left lateral views, and right lateral views, which are dynamically adjusted in real time to follow the robot's movements. This configuration minimizes occlusion from the robot's own limbs and provides enhanced situational awareness. Each camera supports omnidirectional rotation and features a 160-degree horizontal field of view, enabling comprehensive, real-time environmental observation.



(a) Bedroom

(c) Living room 1

(d) Living room 2

Figure 2: Example scenes of different rooms in DualTHOR. The types and quantities of objects vary across rooms, and the humanoid robot is capable of interacting with all objects within each room. We re-render all objects based on the AI2-THOR simulator to ensure that object heights are compatible with humanoid robots enabled in the simulation.

Humanoid Robots. DualTHOR mainly explores the long-horizon planning and adaptation capabilities for humanoid robots, including pre-defined Unitree H1 [Unitree, 2024a] and Agibot X1 [Agibot, 2024] robots.

• H1 excels in strength and stability, which is advantageous for tasks involving heavy lifting or high-force interactions, such as opening sealed containers or moving large furniture.

• X1 is characterized by its high dexterity and precision, making it particularly suitable for tasks that require fine motor control, such as picking up small objects or operating delicate mechanisms.

Both robots are equipped with dual-arm configurations, allowing for bimanual manipulation, which is essential for handling complex tasks that require coordinated arms. For manipulation tasks, X1 and H1 have different configurations: X1 uses grippers to interact with objects, while H1 uses dexterous hands. By integrating these two robots, DualTHOR is capable of addressing a broad range of manipulation and interaction scenarios.

Task Replay Mechanism. In data generation, exploring diverse task trajectories is crucial, particularly in scenarios where trajectories share common initial states but diverge at later stages. Traditional frameworks such as ALFWorld [Shridhar et al., 2020] require launching a new simulator instance for each trajectory variation, leading to substantial inefficiencies in resource utilization. To address this limitation, we introduce a task history management system featuring "Undo" and "Redo" functionalities, which enables efficient state tracking and restoration. This design allows for seamless exploration of alternative task trajectories without fully restarting the simulator, thus providing a robust foundation for generating and collecting diverse trajectory data. By supporting rapid iteration and experimentation, our system significantly accelerates the data collection process, while greatly reducing computational resource consumption.

3.2 Task Categories

DualTHOR supports a comprehensive range of interactive actions, broadly categorized into objectindependent and object-dependent actions. Object-independent actions encompass navigational and perceptual behaviors such as MOVE (forward, backward, left, right), ROTATE (full rotation), OBSERVE (environmental monitoring with configurable gaze angles), and posture adjustments including CROUCH and STAND. These actions facilitate flexible navigation and situational awareness without engaging the robot's manipulators. Object-dependent actions — such as PICKUP, OPEN, FILL, and TOGGLE — enable precise and context-aware object operation. This rich action space provides robust adaptability across a wide spectrum of interactive environments and task complexities.

With these actions, we categorize tasks into three types based on the number of robotic arms required: dual-arm essential tasks, dual-arm optional tasks, and single-arm tasks. Dual-arm essential tasks are those that necessarily require the involvement of both arms during interaction, such as lifting heavy objects or keeping a container open to place an item inside it. Dual-arm optional tasks are those that can be accomplished with a single arm, but benefit from dual-arm execution for improved realism and efficiency, for example, grasping multiple distinct items or toggling a coffee machine to get a cup of coffee. Single-arm tasks, primarily sourced from AI2-THOR, involve simpler interactions such as grasping a single object. This categorization enables a more nuanced evaluation of dual-arm embodied agents.

3.3 Low-Level Control

In the DualTHOR simulation environment, control commands are executed through a closed-loop system (enabled by bidirectional communication using JSON over TCP [Safeea and Neto, 2024] between the Python backend and the Unity engine). On the Python side, each invocation of the step function generates an action command that encodes parameters such as the action category, target object ID, and the selected robotic arm. These instructions are serialized into a JSON format and transmitted to the Unity engine. Which, upon receipt, parses the data and utilizes the AgentMovement component to interface with the IK system [Habekost et al., 2024], enabling the execution of either single- or dual-arm motions, while simultaneously monitoring for real-time physical collisions. The results of the execution — including motion outcome, collision feedback, and updates to the simulation scene — are then encapsulated into a JSON response and returned to the Python backend, thereby completing the closed-loop control cycle.

The IK system in DualTHOR is implemented as a cross-platform service accessible via HTTP [Javeed and Mehdi, 2024], ensuring both computational flexibility and modular architecture. When the Python backend sends a request containing the target object ID and the specified action type, the Unity engine first computes the interaction point on the object and transforms its coordinates into the base frame of the robot. This information is then submitted to a locally hosted IK server, which operates on a

designated port and solves the IK function, returning the corresponding joint configurations required for task execution. To achieve smooth and continuous motion, Unity applies cubic spline interpolation to the joint angles, enabling the robotic end-effector to follow precise and fluid trajectories toward the intended target.

We employ OmniManip [Pan et al., 2025] for pose computation and IK solving to generate accurate joint angles for each robotic arm. This computational framework facilitates the simulation of natural and precise grasping trajectories by also integrating dexterous hand models. The architecture of our simulator supports real-time visualization of complex manipulation tasks, including object grasping, manipulation, and release sequences, while ensuring adherence to physical plausibility and kinematic constraints.

The implementation of IK functions varies between the X1 and H1 humanoid robots due to their distinct control architectures. The X1 robot adopts a decoupled approach, solving the inverse kinematics independently for each arm using a simplified pose matrix (a 3×3 rotation matrix with a translation vector) relative to the base coordinate frame, and requires only the initial joint configuration for positioning. In contrast, the H1 robot utilizes a whole-body coordination model, simultaneously solving for both arms using a complete 4×4 homogeneous transformation matrix that incorporates full posture information. This model integrates current joint angles and velocities to perform dynamic optimization, with a particular focus on maintaining balance constraints during dual-arm collaborative operations.

3.4 Contingency Mechanism

Existing frameworks, such as AI2-THOR, typically assume deterministic state transitions following action execution, which fails to capture the inherent complexity and uncertainty of real-world interactions. This deterministic assumption introduces a substantial distributional gap between simulated environments and the real-world, thereby constraining the robustness and adaptability of trained agents. In scenarios where actions fail or yield unintended consequences, agents often lack the capacity for dynamic re-planning or error recovery, ultimately resulting in task failure. To address this limitation, we propose a probabilistic contingency mechanism designed to simulate the stochastic nature of physical environments, thereby enhancing agents' robustness and adaptability under uncertainty.



Contingency outcome 2 (10%): coffee spill

Contingency outcome 3 (80%): successfully pick up

Figure 3: **Example of picking up a "***pourable***" cup of coffee.** The possible results include success (80%), coffee spill (10%), and mug broken (10%). DualTHOR provides both visual observations and environmental feedback after the robot executes an action, enabling the evaluation of the effectiveness of the current plan and the acquisition of information necessary for VLM re-planning.

DualTHOR maps actions to multiple potential outcomes based on the current state of objects within the environment. As illustrated in Figure 3, this probabilistic contingency mechanism introduces outcome variability to reflect real-world uncertainties. For example, when a robot attempts to pick up a "*pourable*" cup, there is an 80% probability of successful grasping it, a 10% probability that the cup will break, and a 10% probability that its contents will be spilled.

These outcomes are modeled using categorical distributions, enabling discrete and mutually exclusive results. For actions involving repetition or multiple sequential steps, the system can be extended to multinomial distributions to capture more complex dependencies and temporal dynamics. This

probabilistic framework ensures that the simulation environment more accurately reflects the inherent uncertainties of real-world interactions, thereby providing richer and more informative training data for agents to learn how to recover from failure scenarios. The supported object categories (*e.g.*, *pourable*) and this contingency mechanism implementation are described in detail in Appendix A.

Moreover, actions in our system are constrained by the current state of the objects. For example, an ingredient labeled as "Cooked" cannot undergo an additional "COOK" action, as it has already reached its terminal state. However, it may still be classified as "*pickupable*," allowing for continued manipulation even after its state has changed. This state-dependent execution model prevents unrealistic or logically inconsistent action sequences, while supporting multi-state representations that more accurately capture the complexity of real-world interactions.

The proposed stochastic contingency mechanism enables agents to learn from unsuccessful attempts and develop effective recovery plans. When an action fails or yields an unintended outcome, the agent is required to reassess the current state and adapt its plan accordingly. Such adaptability is essential for long-horizon tasks, where early-stage errors can propagate and substantially hinder overall task completion.

4 **Experiments**

4.1 Experimental Setup

We conduct experiments on 356 tasks across 10 distinct room environments, involving 68 unique objects. Distributions of object categories, task categories, and the proportion of each task type are illustrated in Figure 4. Most dual-arm essential tasks and dual-arm optional tasks are composed of multiple single-arm tasks, while a smaller portion is manually designed. More details of all tasks are described in Appendix B.



(a) Distribution of interactive object (b) Distribution of single-arm inter- (c) Distribution of the three task cattypes in DualTHOR. egories in DualTHOR.

Figure 4: Distribution of objects and tasks in our experiments.

4.2 Baselines

We evaluate three distinct classes of baselines in DualTHOR: proprietary VLMs, open-source VLMs, and prompt-enhanced VLMs. The planning capabilities of these models for dual-arm tasks are assessed mainly by their success rates across all task categories.

- **Proprietary VLMs** refer to closed-source systems developed by commercial entities, typically optimized for performance through extensive pretraining on large-scale non-public datasets, and fine-tuned for specific downstream tasks. We select GPT-40 [Hurst et al., 2024] and Gemini 1.5 Pro [Team et al., 2023] as representatives to evaluate the performance of such large-scale models on dual-arm tasks within the DualTHOR environment.
- **Open-source VLMs** are publicly available systems, usually developed by the research community, and often trained on more transparent datasets. We select Qwen2.5-VL-7B [Bai et al., 2025] and InternVL2.5-8B [Chen et al., 2024] as representative lightweight models that demonstrate strong performance in embodied scenarios, evaluating their performance in handling dual-arm tasks.
- **Prompt-enhanced VLMs** incorporate structured or task-specific prompts to guide model reasoning, enabling improved performance in complex scenarios by aligning model outputs more closely with desired behaviors or contextual requirements. LLM Planner [Song et al.,

Table 2: Performance of baselines across different task configurations in DualTHOR. Each task includes results for both X1 and H1 robots. The evaluation metric is the success rate over 50 trials for each task. The robot is initialized in the same position within the environment for each trial to ensure the validity of the task-related trajectories for prompt-enhanced VLMs.

	Dual-Arm Essential Tasks		Dual-Arm Optional Tasks		Single-Arm Tasks	
	X1	H1	X1	H1	X1	H1
GPT-40	23.56%	27.34%	39.53%	41.37%	51.67%	55.39%
Gemini-1.5-Pro	25.31%	26.33%	37.31%	36.23%	42.37%	43.64%
Qwen2.5-VL-7B-Ins	18.33%	17.54%	21.17%	19.56%	23.33%	25.31%
InternVL2.5-8B	9.71%	15.63%	23.51%	25.17%	23.57%	31.62%
LLM-Planner	28.36%	31.73%	43.35%	45.69%	55.43%	55.73%
RAP	27.63%	33.51%	45.37%	47.51%	53.31%	54.26%
DAG-Plan	36.54%	41.53%	51.25%	52.31%	55.47%	57.86%

2023] and RAP [Kagaya et al., 2024] are representative frameworks that retrieve task-related trajectories for few-shot embodied planning in visually-perceived environments. DAG-Plan [Gao et al., 2024] is the state-of-the-art method for dual-arm planning that utilizes a graph-based structure to represent dual-arm tasks. The base model used is GPT-40. We adopt this approach to assess the difficulties imposed by DualTHOR in benchmarking VLM-based planning with dual-arm tasks.

4.3 Main Results for Dual-Arm Tasks

We test all baselines in the three task categories described in Section 3.2. Each task is evaluated on both X1 and H1 robots with 50 trials to ensure statistical reliability. While initial positions vary across different rooms, they are kept consistent within the same room to ensure the reliability of historical trajectories used by prompt-enhanced VLMs. Different baselines are tested under identical experimental settings. For consistency, all models are configured with a temperature of 0 and a maximum token length of 2048 for response generation. Input images are scaled to a resolution of 500×500 pixels. The maximum number of environment steps for high-level planning is set to 50. Further experimental details are provided in Appendix B.

Can existing VLMs understand dual-arm tasks? Our experimental results, presented in Table 2, indicate that current methods struggle with long-horizon planning in dual-arm scenarios. Owing to the larger physical structure, the H1 robot possesses a broader interaction range than X1, leading to a higher average task success rate. Notably, performance on dual-arm essential tasks is consistently lower than performance on other task categories across all baselines, highlighting the limited ability of current VLMs to understand and perform coordinated bimanual control. These tasks require reasoning over the temporal sequencing of object interactions under dual-arm control, as well as effective decision-making regarding arm selection and target positioning. A common failure case arises when an object is located in front of the robot, but is unreachable due to arm constraints. For example, sometimes the target object is to the left side of the robot, but the left hand is already occupied based on the VLM's prior plan, and the right hand cannot reach the object. This often necessitates re-planning for revised navigation and manipulation, significantly decreasing task completion within the limited timesteps. These results emphasize the importance of enhancing VLMs' understanding of how to properly coordinate dual arms.

Does the bimanual structure provide useful information for high-level planning? For dual-arm optional tasks in Table 2, although the overall success rates are lower compared to single-arm tasks, DAG-Plan demonstrates the smallest performance drop among the baselines. This indicates that leveraging dual-arm structural information can meaningfully improve high-level planning ability for VLMs. However, there remains a significant space for improvement, as the success rate still lags behind that of single-arm tasks. DualTHOR can provide a diverse and comprehensive suite of data and evaluation settings for dual-arm tasks, serving as a valuable resource for advancing the development of more capable embodied agents.

How effectively can VLMs handle contingency? To assess the re-planning capabilities of the baselines, each task is further divided into three difficulty levels — Easy (100% action success rate), Medium (50%), and Hard (20%) — with increasing skill failure rates. Experimental results shown in Table 3 reveal that even for single-arm tasks, existing baselines exhibit a significant performance drop

Table 3: Performance of re-planning across different VLM baselines in DualTHOR. Tasks are categorized into three difficulty levels based on the success rate of low-level skills: Easy (100%), Medium (50%), and Hard (20%). To accomplish such tasks, agents must analyze failure scenarios and re-plan accordingly. For example, they should locate a new cup when the original one is broken.

Task Category	Baseline		X1			H1		
		Easy	Medium	Hard	Easy	Medium	Hard	
Dual-Arm	GPT-40	23.56%	20.63%	11.54%	27.34%	21.51%	13.67%	
Essential	InternVL2.5-8B	9.71%	6.31%	2.67%	15.63%	6.87%	3.15%	
Tasks	DAG-Plan	36.54%	23.17%	11.69%	41.53%	20.33%	15.53%	
Dual-Arm	GPT-40	39.53%	31.69%	23.34%	41.37%	35.87%	21.19%	
Optional	InternVL2.5-8B	23.51%	17.39%	8.51%	25.17%	19.67%	7.94%	
Tasks	DAG-Plan	51.25%	43.13%	27.37%	52.31%	39.63%	23.34%	
Single Arm	GPT-40	51.67%	44.69%	28.31%	55.39%	45.87%	26.69%	
Single-Ann Teelse	InternVL2.5-8B	23.57%	20.39%	10.13%	31.62%	23.67%	11.33%	
Tasks	DAG-Plan	55.47%	52.67%	31.42%	57.86%	48.63%	36.53%	

under both Medium and Hard conditions. This suggests that the high-level planning components of current VLMs lack robustness and rely on high success rates of low-level control policies. This issue is particularly critical in real-world deployment of embodied agents: high-level planners must be resilient to execution-level failures and capable of timely recovery to prevent the persistence of unsafe or ineffective behaviors. In our experiments, DAG-Plan responds to unexpected events by constructing new nodes and restarting the planning process from scratch, reflecting limited robustness. This limitation highlights the need for further research in handling dynamic and realistic scenarios.

4.4 Realistic Environment Transitions

In addition to the contingency mechanism designed to mimic real-world environmental nondeterminism, DualTHOR further enhances realism by continuously updating the rendering of scenes. As illustrated in Figure 5, the simulator includes dynamic changes such as the gradual filling of a sink after turning on the faucet. This feature provides a more immersive and realistic environment, enabling VLMs to better comprehend scene transformations and assess whether planned actions are being or have been successfully executed. By incorporating such fine-grained physical interactions, DualTHOR not only improves the fidelity of the simulation, but also challenges VLMs to adapt their action plans in response to continuous environmental changes, thereby advancing their applicability in real-world scenarios.



Figure 5: Rendered observations showing a sink gradually filling up with water. DualTHOR uses improved physics rendering techniques to provide agents with detailed action effects.

5 Conclusion and Limitations

We present DualTHOR, a high-fidelity simulation environment designed to enable realistic bimanual humanoid robot interaction. DualTHOR provides novel capabilities like parallel dual-arm control, contingency supported by probabilistic action failures, and an advanced physical engine (including fluid dynamics and robust collision handling). We evaluate several representative embodied VLMs in

our simulator. Experimental results demonstrate that current methods struggle with both dual-arm planning and failure recovery. Our simulator surfaces these limitations, establishing a challenging and extensible benchmark for the development of more capable embodied AI agents.

Flexible asset generation tools and support for a broader range of robots are under development, as the current scene diversity in DualTHOR remains limited. Further refinements to support non-grid-based positioning, more controllable failure modes, and multi-room environments are also planned. Additionally, future work should incorporate multi-agent cooperative evaluation.

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A Simulator Details

This section details the different capability areas of DualTHOR and its implementation details.

A.1 Visual Input

DualTHOR is a high-fidelity embodied AI simulation environment that supports advanced visual perception capabilities. It enables multi-view visual input by allowing agents to access and integrate observations from multiple camera perspectives within the same scene. This multi-view configuration facilitates comprehensive spatial understanding and enhances the agent's ability to reason about occluded or partially observed regions. In addition to RGB input, DualTHOR provides depth images aligned with each visual frame, offering rich geometric information essential for tasks such as 3D scene reconstruction, object localization, and affordance estimation. The combination of multi-angle RGB views and depth sensing positions DualTHOR as a versatile platform for developing and evaluating vision-based embodied AI models.





(c) Right Camera Observation (d) Backwards Camera Observation

Figure 6: Multi-view visual observations in the DualTHOR simulation environment. The agent captures RGB images from four distinct egocentric perspectives: (a) first person front-facing camera, (b) left-side camera, (c) right-side camera, and (d) backwards-facing camera. This multi-view configuration enables comprehensive scene understanding by providing complementary viewpoints that facilitate perception of object relationships, spatial context, and occluded regions.

A.2 Humanoid Robots

DualTHOR provides two humanoid robot embodiments, Unitree H1 [Unitree, 2024a] and Agibot X1 [Agibot, 2024]. Additional humanoid agents such as Unitree G1 [Unitree, 2024b] are currently under implementation, and DualTHOR is easily extendable to include additional robots. Both H1 and X1 are equipped with dual-arm configurations capable of coordinated manipulation. To support continuous control, we introduce dedicated inverse kinematics (IK) functions for each agent, along with optimized control logic, ensuring smooth action execution during the interaction process.



(c) Dual-arm lift action with H1

(d) Concurrent pick up actions with X1

Figure 7: The two humanoid robots initially supported in DualTHOR. (a) H1 robot, a larger humanoid platform with a wider interaction range, suitable for complex manipulation tasks. (b) X1 robot, a more compact humanoid agent designed for efficient interaction and navigation in constrained environments. (c) (d) Both robots are equipped with dual-arm configurations to enable coordinated bimanual manipulation (*e.g.*, lift a coffee machine or pick up two objects at the same time).

The H1 robot has a larger overall structure compared to X1, and thus also possesses a broader interaction range. This partly explains why H1 demonstrates superior performance in Tables 2 and 3, as object localization and navigation tasks can become relatively easier due to its extended reach and physical capabilities.

A.3 Interactive Objects

The objects initially supported in DualTHOR are listed in Table 4 along with their properties. These objects are primarily derived from the Unity assets provided by AI2-THOR (for matching environment characteristics and facilitate scenario comparisons). To accommodate the interaction ranges of H1 and X1, all objects are re-rendered to ensure physical plausibility. Additional objects can easily be added to DualTHOR.

Table 4: Overview of object distribution in DualTHORThe same object type may appear multiple times within the same *Scene*. *Actionable properties* specify the set of permissible interactions for each object. *State* reflects an object's current situation in the environment, supporting the implementation of contingency mechanisms.

Object Type	Scene(s)	Actionable Properties	States
AlarmClock	Bedroom	Pickupable	IsPickedUp
Apple	Kitchen	Pickupable, Sliceable	IsPickedUp, IsSliced
BaseballBat	Bedroom	Pickupable	IsPickedUp
Book	Living Room	Pickupable, Openable	IsPickedUp, IsOpen
Bottle	Kitchen	Pickupable	IsPickedUp, IsFilled
Bowl	Kitchen	Pickupable	IsPickedUp, IsFilled
Bread	Kitchen	Pickupable, Sliceable	IsPicked Up, IsSliced, IsCooked
Cabinet	Kitchen/Bedroom	Openable	IsOpen
Candle	Living Room	Pickupable, Toggleable	IsPickedUp, IsToggledOn/Off
Coat	Living Room	Pickupable	IsPickedUp
CoffeeMachine	Kitchen	Toggleable, Movable	IsToggledOn/Off, IsLifted

Object Type	Scene(s)	Actionable Properties	States
Cup	Kitchen	Pickupable	IsPickedUp, IsFilled
Curtains	Kitchen	Openable	IsOpen
DeskLamp	Bedroom/Living Room	Toggleable	IsToggledOn/Off
Drawer	Kitchen	Openable	IsOpen
Egg	Kitchen	Pickupable	IsPickedUp, IsCooked
Faucet	Kitchen/Bathroom	Toggleable	IsToggledOn/Off
Fork	Kitchen	Pickupable	IsPickedUp
Fridge	Kitchen	Openable	IsOpen
Knife	Kitchen	Pickupable	IsPickedUp
Laptop	Living Room	Pickupable, Toggleable	IsPickedUp, IsToggledOn/Off
Lettuce	Kitchen	Pickupable, Sliceable	IsPickedUp, IsSliced
LightSwitch	Bedroom/Living Room	Toggleable	IsToggledOn/Off
Microwave	Kitchen	Openable, Toggleable	IsOpen, IsToggledOn/Off
Mug	Kitchen	Pickupable, Fillable	IsPickedUp, IsFilled
Onion	Kitchen	Pickupable, Sliceable	IsPickedUp, IsSliced
Orange	Kitchen	Pickupable, Sliceable	IsPickedUp, IsSliced
Pan	Kitchen	Pickupable	IsPickedUp
Pant	Living Room	Pickupable	IsPickedUp
Pen	Living Room/Bedroom	Pickupable	IsPickedUp
Pencil	Living Room/Bedroom	Pickupable	IsPickedUp
PepperShaker	Kitchen	Pickupable	IsPickedUp
Picture	Living Room/Bedroom	Pickupable	IsPickedUp
Pillow	Bedroom/Living Room	Pickupable	IsPickedUp
Pizza	Kitchen	Pickupable, Sliceable	IsPickedUp, IsSliced
Plant	All	Pickupable	IsPickedUp
Plate	Kitchen	Pickupable	IsPickedUp
Plunger	Bathroom	Pickupable	IsPickedUp
Pot	Kitchen	Pickupable	IsPickedUp, IsFilled
RemoteControl	Living Room	Pickupable	IsPickedUp
SaltShaker	Kitchen	Pickupable	IsPickedUp
SoapBar	Bathroom	Pickupable	IsPickedUp
SoapBottle	Bathroom/Kitchen	Pickupable	IsPickedUp, IsFilled
Shirt	Living Room	Pickupable	IsPickedUp
StoveKnob	Kitchen	Toggleable	IsToggledOn/Off
Television	Living Room	Toggleable, Movable	IsToggledOn/Off, IsLifted
Toaster	Kitchen	Toggleable, Movable	IsToggledOn/Off, IsLifted
ToiletPaper	Bathroom	Pickupable	IsPickedUp, IsUsedUp
Tomato	Kitchen	Pickupable, Sliceable	IsPickedUp, IsSliced, IsCooked
Towel	Bathroom	Pickupable	IsPickedUp
Watch	Bedroom	Pickupable	IsPickedUp
WineBottle	Kitchen	Pickupable	IsPickedUp, IsFilled
Window	All	Openable	IsOpen

A.4 Action Set

With the optimization of control logic for both H1 and X1 in DualTHOR, alongside the integration of corresponding IK models, our simulator supports both continuous and discrete control for the humanoid robots. To facilitate the evaluation of VLMs high-level planning, we design a set of language-based actions/skills for dual-arm humanoid agents, drawing inspiration from the AI2-THOR framework. The specific details are provided in Table 5.

Action Type	Command Format	Description and Parameters
MoveAhead, MoveBack, MoveLeft, MoveRight	(MoveXXX, Magnitude)	Move the robot in a given direction. Parameter Magnitude indicates the distance of movement. <i>e.g.</i> , (MoveAhead, Magnitude=1)
RotateLeft, RotateRight	(RotateXXX, Magnitude)	Rotate the robot by a given angle. Parameter Magnitude = 1 corresponds to 90°. <i>e.g.</i> , (RotateRight Magnitude=1)
Pick	(pick, arm, objectID)	Grab the object specified by objectID using the specified arm. <i>e.g.</i> , (pick, arm=left, objectID=Kitchen_Cup_01).
Lift	(lift, objectID)	Lift the object specified by objectID using both arms. <i>e.g.</i> , (lift, objectID=CoffeeMachine_01).
Place	(place, arm, objectID, containerID)	Place the currently held object into the target container using the specified arm. <i>e.g.</i> , (place, arm=right, objectID=Kitchen_Mug_01, containerID=Kitchen_CoffeeMachine_01).
Toggle	(toggle, arm, objectID)	Toggle objects such as switches using the specified arm. <i>e.g.</i> , (toggle, arm=left, objectID=Bedroom_LightSwitch_01).
Open	(open, arm, objectID)	Open interactable objects such as cabinets using the specified arm. <i>e.g.</i> , (open, arm=right, objectID=Bedroom_Cabinet_01).
Teleport	(tp, objectID)	Teleport the robot near the specified object, preparing it for subsequent interaction. <i>e.g.</i> , (tp, objectID=Living Room_Window_01).
Undo / Redo	(undo), (redo)	Undo reverts to the last state of the simulator, and Redo re-executes the last action again from the last state. <i>e.g.</i> , (undo), (redo).
LoadState	loadstate	Load the state feedback from the current environment, including robot states (action result, arm state, etc.) and object states (open, picked, etc.). <i>e.g.</i> , (loadstate).

Table 5: DualTHOR's Action Set. For object-dependent actions (pick, toggle, etc.), DualTHOR supports parallel execution of actions to demonstrate the advantages of dual-arm operation.

A.5 DualTHOR Tasks

The DualTHOR simulator introduces a new task set in three categories: dual-arm essential tasks, dual-arm optional tasks, and single-arm tasks. The specific tasks are shown in Table 6.

Distinctions between dual-arm optional and dual-arm essential tasks depend heavily on specific characteristics of the interactable objects being supported in the simulator. For example, when filling an object with water, the task category is primarily determined by the presence or absence of a supporting platform where to place the object to be filled.

In cases like operating a faucet to fill an object, where no suitable surface is available to temporarily hold the object, it becomes necessary to concurrently execute the holding and toggling (named in the table as "*Hold objects filled with liquid*"). This simultaneous coordination inherently demands the use of both arms.

Conversely, for tasks involving devices such as coffee machines, where the object to be filled can typically be placed in position beforehand, the toggling operation to be carried out independently. As a result, such tasks are considered as dual-arm optional tasks, *i.e.*, they could be executed separately in sequence with one arm, but are more naturally executed with two arms.

A.6 Contingency Mechanism Implementation Details

Currently, DualTHOR introduces contingency exclusively for object-dependent actions, as discussed in Section 3.2. Object-independent actions are not subject to probabilistic outcomes at this stage. During action execution, DualTHOR utilizes probabilistic models to predict the outcome based on the current state of the interactive objects. When the robot arm approaches the object, inverse kinematics (IK) is computed as usual; once the distance to the object falls below a predefined threshold, the simulator renders the predicted outcome. The types of contingencies are defined in accordance with the object's current state, as summarized in the Table 7. Their probabilities can be designed by users to satisfy any requirement for re-plan capability. This mechanism allows DualTHOR to simulate realistic outcome variability.

Task Category	Task Name	Task Counts
	Pick objects	20
	Toggle objects	12
	Open objects	12
Single-Arm Tasks	Fill objects with liquid	6
	Use up objects	4
	Slice objects	2
	Cook objects	2
	Pick different objects and place in different	63
	containers	
Dual-Arm Optional Tasks	Pick different objects and place in the same container	27
	Open general containers and pick/place objects	19
	Pick and slice the same object	15
	Pick objects filled with liquid	9
	Open affordance-specific containers and	97
Dual-Arm Essential Tasks	pick/place objects	
	Lift objects	39
	Hold objects filled with liquid	32

Table 6:	Tasks	in	DualTHOR.
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Table 7: Contignency setup for different states. When an object have multiple states, the contingency mechanism randomly selects an outcome based on the full set of possible contingencies.

State	Contingency Outcomes
IsPickedUp	success, broken, nothing happens
IsFilled	success, liquid spill, nothing happens
IsSliced	success, partial slice, nothing happens
IsLifted	success, broken, nothing happens
IsOpen	success, locked, half open, nothing happens
IsToggledOn/Off	success, stuck, nothing happens

B Experiment Details

B.1 Vision Language Models

Table 8 lists the versions or full names of the models used in our experiments. We accessed proprietary models through API calls and open-source models via local deployment.

Model Name	Creator	Full Name
GPT-40	OpenAI	gpt-4o-2024-08-06
Gemini-1.5-Pro	Google	gemini-1.5-pro
InternVL2.5-8B	OpenGVLab	OpenGVLab/InternVL2.5-8B
Qwen2-VL-7B-Ins	Qwen	Qwen/Qwen2-VL-7B-Instruct

Table 8: Full names of VLMs used in our experiments.

B.2 Experiment Parameters

As mentioned in Section 4.3, all models are configured with a temperature of 0 and a maximum token length of 2048 for response generation. Input images are scaled to a resolution of 500×500 pixels. The maximum number of environment steps for high-level planning is set to 50. For prompt-enhanced VLMs, retrieval parameters follow the official implementation to ensure consistency. The number of retrieved trajectories is fixed at the minimum value of 3, as adopted in RAP [Kagaya et al., 2024], to facilitate fair comparison across all baselines. The list of parameters is provided in Table 9.

Table 9: Parameter List for Experiments.				
Proprietary/Open-source VLMs				
Parameter	Value			
Response generation temperature	0			
Maximum token length	2048			
Input image resolution	500×500 pixels			
Maximum environment steps	50			
Prompt-enhanced VLMs				
Parameter	Value			
Retrieve Buffer	20			
KNN Retrieves(LLM Planner [Song et al., 2023])	9			
Multimodal Retrieves(RAP [Kagaya et al., 2024])	5			
Retrieve Trajectories Input	3			
Number of Candidate Nodes [Gao et al., 2024]	6 (3 for each arm)			

B.3 Computer Resources

We conduct development and experimental evaluation of the DualTHOR simulation environment on a workstation equipped with an NVIDIA RTX 4090 GPU (40 GB). The environment supports seamless interaction between Windows and Linux systems, facilitating cross-platform compatibility for both development and deployment.

B.4 Experiment Results Showcase

Continuous Action Control Showcase. As in the experiments in Section 4.4, DualTHOR employs an optimized control logic and integrates humanoid inverse kinematics (IK) solvers to enable continuous transitions of robot actions, as shown in Figure 8. This is in contrast to the flash-like transitions commonly seen in previous simulation platforms, *i.e.*, DualTHOR provides more detailed data for VLMs to understand robotic actions.

Plan Failure Showcase. Failure cases, as illustrated in Figure 9, highlight several challenges that VLMs face in dual-arm task planning. Subfigures 1–6 depict the object search process, a task extensively addressed in prior work and well-supported by existing simulators. Subfigures 7 and 8, however, reveal limitations in the VLMs' ability to perform effective pre-planning for dual-arm robots. While subfigure 7 illustrates a successful configuration in which both arms can simultaneously interact with two objects, subfigure 8 demonstrates a failure, as such coordination is no longer possible.

Action: pick up the mug



Figure 8: Showcase of continuous action control in the X1 humanoid robot. In DualTHOR all action executions involve continuous transitions rather than flash-like changes, providing abundant data for VLMs to analyze scene and actions.



Figure 9: Plan failure showcase by DAG-Plan [Gao et al., 2024]. This example clearly highlights the current limitations of existing VLMs in understanding bimanual configurations and the spatial relationships between objects. In the final subfigure, the plan fails to consider the interactive reachability of the left arm, underscoring the need for re-planning based on arm interaction ranges or the pre-assignment of objects to each arm. DualTHOR aims to emphasize these limitations for dual-arm embodied VLMs.

DAG-Plan still generates a plan to move from the configuration in subfigure 7 to that in subfigure 8. A possible explanation is that existing embodied datasets primarily consist of sequentially executed task instructions. Consequently, VLMs trained on such data tend to overemphasize the current interaction target, often neglecting the spatial and temporal requirements of subsequent actions involving future objects.

Subfigure 9 further underscores the VLM's limited understanding of dual-arm morphology. Despite the right arm already being occupied, the VLM continues to attempt interactions with it, indicating a lack of structural reasoning in the planning process. This reflects a broader limitation stemming from the insufficient availability of data that captures dual-arm configurations and constraints. Ideally, the model should either place the object held in the right hand before attempting to open the drawer

or reposition the robot (move right) to enable the left arm to perform the action. This failure case highlights the necessity of developing the DualTHOR simulator and constructing a dual-arm task suite.

Successful Re-Plan Showcase including Contingency.

Figure 10 presents a successful planning case under the influence of contingency, highlighting two key challenges for robot planning. The first challenge involves overcoming the effects of contingency mechanisms by enabling the VLM to re-plan in response to failed actions. As illustrated in subfigures 1–3, when a contingency event such as a failed pickup ("nothing happens" in Table 7) occurs, the VLM is expected to respond with an appropriate recovery action, such as reattempting the pickup action. While this represents a relatively simple scenario, more complex contingencies—such as object broken—require re-navigation and re-identification of an equivalent object. These cases demand significantly stronger re-planning capabilities, which current VLMs struggle to achieve within limited environment steps. The second challenge involves dynamically adjusting the robot's interaction position based on environmental feedback and visual input. In subfigures 4–5, after an initial failure attempt to open a drawer, the VLM infers from feedback that the robot is too far from the target and accordingly modifies the plan to move closer, ultimately completing the task. These challenges emphasize the need for robust planning capabilities in embodied VLMs for reducing the deployment difficulties in real-world applications.



Figure 10: Showcase of a successful plan by DAG-Plan [Gao et al., 2024] with contingency mechanism. Subfigures 1–3 show the necessity to recover from a basic contingency scenario. Subfigures 4–6 illustrate the importance of adjusting the robot's position to successfully complete the interaction. This example highlights key challenges in robust planning and adaptive behavior required for real-world deployment of embodied VLMs.

C Additional Related Work

C.1 Simulation Platforms for Interactive Learning

Simulation environments are indispensable for advancing interactive learning in embodied AI, offering controllable settings for agent training and evaluation. AI2-THOR [Kolve et al., 2022] serves as a foundational framework, providing high-quality visual environments and interactive object dynamics that support a wide range of embodied AI tasks. RoboTHOR [Deitke et al., 2020] extends AI2-THOR by introducing interconnected environments with a topological floorplan structure, enabling research on long-horizon embodied navigation across multiple rooms. ManipulaTHOR [Ehsani et al., 2021] focuses on robotic manipulation tasks, particularly with articulated robotic arms, while ProcTHOR addresses scalability and diversity through procedurally generated environments, ensuring agents are trained on varied layouts, objects, and lighting conditions to improve generalization [Deitke et al., 2022]. These extensions have enhanced the simulator by increasing task diversity, scene complexity, and object variety, yet the range of robot embodiments remains limited to single-arm and wheeled robots. iGibson [Li et al., 2021] is another widely used physics-rich simulation environment

reconstructed from real-world scans and built on the PyBullet engine, but it is also limited to wheeled robot embodiments. Although HumanoidBench [Sferrazza et al., 2024] and Isaac Gym [Makoviychuk et al., 2021b] provide humanoid robot control frameworks, they only focus primarily on training low-level control policies for humanoid robots. Consequently, they do not support background rendering and are not suitable for assessing long-horizon planning capabilities for dual-arm tasks. To provide the necessary simulation capabilities along with a wide range of task categories and extended robot morphologies, we introduce our DualTHOR simulator.

C.2 Visual Rendering Technology in Embodied Simulators

Visual environments span a spectrum from simplistic, abstract representations to highly detailed, photorealistic 3D models. Achieving accurate 3D reconstruction for sim-to-real transfer remains a persistent challenge, traditionally addressed through multi-view geometry techniques [Snavely et al., 2006, Furukawa and Ponce, 2009] that rely on feature matching [Lowe, 2004, Rublee et al., 2011]. While effective under optimal lighting and texture conditions, these methods struggle with low-texture surfaces, transparent materials, and dynamic scenes. To enhance robustness, approaches such as [Izadi et al., 2011, Leutenegger et al., 2015, Bloesch et al., 2015, Campos et al., 2021, Laidlow et al., 2017, Rosinol et al., 2020, Fei and Soatto, 2018, Ren et al., 2022 integrate depth sensors, inertial measurement units (IMUs), or object-level anchors. Recent advancements, including Neural Radiance Fields (NeRFs) [Mildenhall et al., 2020, Müller et al., 2022] and 3D Gaussian Splatting [Kerbl et al., 2023], have enabled photorealistic novel view synthesis and real-time rendering, significantly benefiting downstream robotic tasks [Abou-Chakra et al., 2024, Ji et al., 2024, Kapelyukh et al., 2024]. However, these methods require dense scene coverage, limiting their effectiveness with sparse views. Generative models [Liu et al., 2023a,b, Long et al., 2024, Melas-Kyriazi et al., 2023, Shi et al., 2023, Voleti et al., 2025, Kong et al., 2024] address this limitation by synthesizing plausible views from limited input, while scene-level generalization techniques [Wu et al., 2024, Yu et al., 2021, Zhu et al., 2024] leverage prior knowledge to accelerate reconstruction. Nevertheless, these algorithms still face challenges in generating complex objects with movable hinges and are prone to issues such as distortion and rough edges.