

Aligning Cyber Space with Physical World: A Comprehensive Survey on Embodied AI

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Abstract—Embodied Artificial Intelligence (Embodied AI) is crucial for achieving Artificial General Intelligence (AGI) and serves as a foundation for various applications that bridge cyberspace and the physical world. Recently, the emergence of Multi-modal Large Models (MLMs) and World Models (WMs) have attracted significant attention due to their remarkable perception, interaction, and reasoning capabilities, making them a promising architecture for the brain of embodied agents. However, there is no comprehensive survey for Embodied AI in the era of MLMs. In this survey, we give a comprehensive exploration of the latest advancements in Embodied AI. Our analysis firstly navigates through the forefront of representative works of embodied robots and simulators, to fully understand the research focuses and their limitations. Then, we analyze four main research targets: 1) embodied perception, 2) embodied interaction, 3) embodied agent, and 4) sim-to-real adaptation, covering the state-of-the-art methods, essential paradigms, and comprehensive datasets. Additionally, we explore the complexities of MLMs in virtual and real embodied agents, highlighting their significance in facilitating interactions in dynamic digital and physical environments. Finally, we summarize the challenges and limitations of embodied AI and discuss their potential future directions. We hope this survey will serve as a foundational reference for the research community and inspire continued innovation. The associated project can be found at https://github.com/HCPLab-SYSU/Embodied_AI_Paper_List.

Index Terms—Embodied AI, Cyber Space, Physical World, Multi-modal Large Models, World Models, Agents, Robotics

I. INTRODUCTION

EMBODIED AI was initially proposed from the Embodied Turing Test by Alan Turing in 1950 [1], which is designed to determine whether agents can display intelligence that is not just limited to solving abstract problems in a virtual environment (cyber space¹), but that is also capable of navigating the complexity and unpredictability of the physical world. The agents in the cyber space are generally referred

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¹The agents are the foundation of both disembodied and embodied AI. The agents can exist in both cyber and physical spaces, integrated with various entities. The entities include not only robots but also other devices.

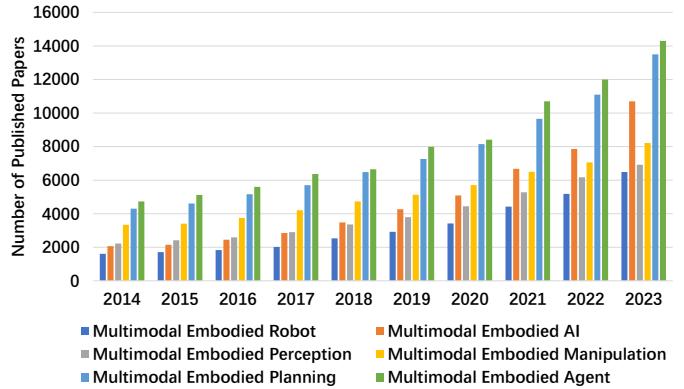


Fig. 1. Google Scholar search results for related topics of Embodied AI. The vertical and horizontal axes denote the number of related publications and the year, respectively. The publications grow exponentially since the breakthrough of MLMs in 2023.

to as disembodied AI, while those in the physical space are embodied AI (Table I). Recent advances in Multi-modal Large Models (MLMs) have injected strong perception, interaction and planning capabilities to embodied models, to develop general-purpose embodied agents and robots that actively interact with virtual and physical environments [2]. Therefore, the embodied agents are widely considered as the best carriers for MLMs. The recent representative embodied models are RT-2 [3] and RT-H [4]. Nevertheless, the capabilities of long-term memory, understanding complex intentions, and the decomposition of complex tasks are limited for current MLMs.

To achieve Artificial General Intelligence (AGI), the development of embodied AI stands as a fundamental avenue. Different from conversational agents like ChatGPT [5], embodied AI believes that the true AGI can be achieved by controlling physical embodiments and interacting with both simulated and physical environments [6]–[9]. As we stand at the forefront of AGI-driven innovation, it is crucial to delve deeper into the realm of embodied AI, unraveling their complexities, evaluating their current developmental stage, and contemplating the potential trajectories they may follow in the future. Nowadays, embodied AI contains various key techniques across Computer Vision (CV), Natural Language Processing (NLP), and robotics, with the most representative being embodied perception, embodied interaction, embodied agents, and sim-to-real robotic control. Therefore, it is imperative to capture the evolving landscape of embodied AI in the pursuit of AGI through a comprehensive survey.

Embodied agent is the most prominent basis of embodied AI. For an embodied task, the embodied agent must fully un-

Type	Environment	Physical Entities	Description	Representative Agents
Disembodied AI	Cyber Space	No	Cognition and physical entities are disentangled	ChatGPT [10], RoboGPT [11]
Embodied AI	Physical Space	Robots, Cars, Other devices	Cognition is integrated into physical entities	RT-1 [12], RT-2 [3], RT-H [4]

TABLE I
COMPARISON BETWEEN DISEMBODIED AI AND EMBODIED AI.

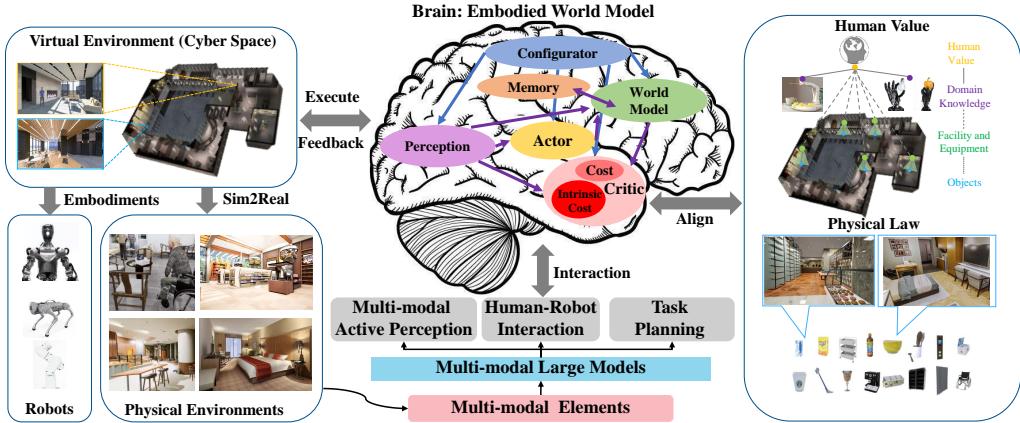


Fig. 2. The overall framework of the embodied agent based on MLMs and WMs. The embodied agent has a embodied world model as its “brain”. It has the capability to understand the virtual-physical environment and actively perceive multi-modal elements. It can fully understand human intention, align with human value, decompose complex tasks, and execute accurate actions, as well as interact with humans and utilize knowledge bases and tools.

derstand the human intention in language instructions, actively explore the surrounding environments, comprehensively perceive the multi-modal elements from both virtual and physical environments, and execute appropriate actions for complex tasks [13], [14], as shown in Fig. 2. The rapid progress in multi-modal models exhibits superior versatility, dexterity, and generalizability in complex environments compared to traditional deep reinforcement learning approaches. Pre-trained visual representations from state-of-the-art vision encoders [15], [16] provide precise estimations of object class, pose, and geometry, which makes the embodied models thoroughly perceive complex and dynamic environments. Powerful Large Language Models (LLMs) make robots better understand the linguistic instructions from humans. Numerous multi-modal fusion methods from MLMs give feasible approach for aligning the visual and linguistic representations from embodied robots. The world models [17], [18] exhibit remarkable simulation capabilities and promising comprehension of physical laws, which makes embodied models comprehensively understand both the physical and real environments. These innovations empower embodied agents to comprehensively perceive complex environment, interact with humans naturally, and execute tasks reliably.

The advancement of embodied AI has exhibited rapid progress, capturing significant attention within the research community (Fig. 1), and it is recognized as the most feasible path for achieving AGI. Google Scholar reports a substantial volume of embodied AI publications, with approximately 10,700 papers published in 2023 alone. This accounts for an average of 29 papers per day or more than one paper per hour. Despite the intensive interest in harvesting the powerful perception and reasoning ability from MLMs, the research community is short of a comprehensive survey that can help sort out existing embodied AI studies, the facing challenges, as well as future research directions. In the era of MLMs, we aim to fill up this gap by performing a systematic survey of embodied AI across cyber space to physical world. We conduct the

survey from different perspectives including embodied robots, simulators, four representative embodied tasks (visual active perception, embodied interaction, multi-modal agents and sim-to-real robotic controlling), and future research directions. We believe that this survey will provide a clear big picture of what we have achieved, and we could further achieve along this emerging yet very prospective research direction.

Differences from previous works: Although there have been several survey papers [7], [19]–[21] for embodied AI, most of them are outdated as they were published before the era of MLMs, which started around 2023. To the best of our knowledge, there is only one survey paper [9] after 2023, which only focused on vision-language-action embodied AI models. However, the MLMs, WMs and embodied agents are not fully considered. Additionally, recent developments in embodied robots and simulators are also overlooked. To address the scarcity of comprehensive survey papers in this rapidly developing field, we propose this comprehensive survey that covers representative embodied robots, simulators, and four main research tasks: embodied perception, embodied interaction, embodied agents, and sim-to-real robotic control.

In summary, the main contributions of this work are three-fold. First, it presents a systematic review of embodied AI including embodied robots, simulators, and four main research tasks: visual active perception, embodied interaction, embodied agents and sim-to-real robotic control. To the best of our knowledge, this is the first comprehensive survey of embodied AI from the perspective of the alignment of cyber and physical spaces based on MLMs and WMs, offering a broad overview with a thorough summary and categorization of existing studies. Second, it examines the latest progress in embodied AI, providing comprehensive benchmarking and discussion of current work across multiple simulators and datasets. Third, it identifies several research challenges and potential directions for future research in AGI for embodied AI.

The rest of this survey is organized as follows. Section 2 introduces various embodied robots. Section 3 describes gen-

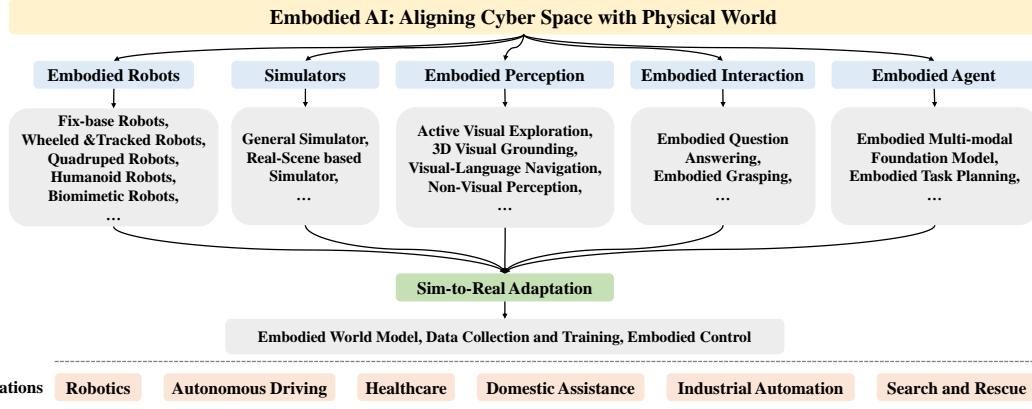


Fig. 3. This survey focuses on comprehensive analysis of the latest advancements in Embodied AI.

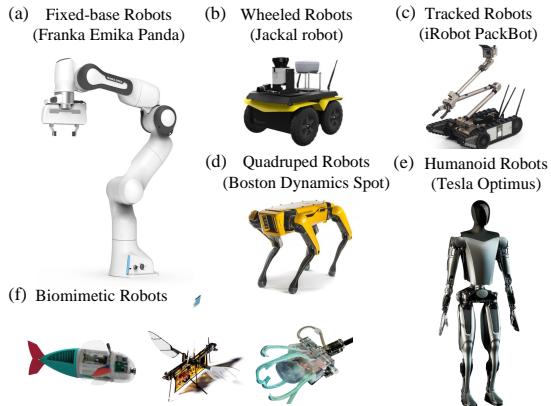


Fig. 4. The Embodied Robots include Fixed-base Robots, Quadruped Robots, Humanoid Robots, Wheeled Robots, Tracked Robots, and Biomimetic Robots.

eral and real-scene embodied simulators. Section 4 introduces embodied perception, including active visual perception, 3D visual grounding, visual language navigation and non-visual perception. Section 5 introduces embodied interaction. Section 6 introduces embodied agents including the embodied multimodal foundation model and embodied task planning. Section 7 introduces sim-to-real adaptation including embodied world model, data collection and embodied control. Finally, we share several promising research directions in Section 8.

II. EMBODIED ROBOTS

Embodied AI actively interacts with the physical environment and encompasses a broad spectrum of embodiments, including robots, smart appliances, smart glasses, autonomous vehicles, etc. Among them, robots stand out as one of the most prominent embodiments. Depending on the application, robots are designed in various forms to leverage their hardware characteristics for specific tasks, as shown in Fig. 4.

A. Fixed-base Robots

Fixed-base robots, as shown in Fig. 4 (a), are extensively employed in laboratory automation, educational training, and industrial manufacturing due to their compactness and high-precision operations. These robots feature robust bases and structures that ensure stability and high accuracy during operation. Equipped with high-precision sensors and actuators, they

achieve micron-level precision, making them suitable for tasks that require high accuracy and repeatability [22]. Moreover, fixed-base robots are highly programmable, allowing users to adapt them for various task scenarios, such as Franka (Franka Emika panda) [23], Kuka iiwa (KUKA) [24], and Sawyer (Rethink Robotics) [25]. Despite their excellent performance in many fields, fixed-base robots have certain disadvantages. Firstly, their fixed-base design limits their operational range and flexibility, preventing them from moving or adjusting positions over large areas and leading to their collaboration with humans and other robots. Secondly, fixed-base robots are generally expensive and require specialized personnel for installation and maintenance, which increases their initial investment and operational costs [22], [26].

B. Wheeled Robots and Tracked Robots

For mobile robots, they can face more complex and diverse application scenarios. Wheeled robots, as shown in Fig. 4 (b), known for their efficient mobility, are widely employed in logistics, warehousing, and security inspections. The advantages of wheeled robots include their simple structure, relatively low cost, high energy efficiency, and rapid movement capabilities on flat surfaces [22]. These robots are typically equipped with high-precision sensors such as LiDAR and cameras, enabling autonomous navigation and environmental perception, making them highly effective in automated warehouse management and inspection tasks, e.g., Kiva robots (Kiva Systems) [27] and Jackal robot (Clearpath Robotics) [28]. However, wheeled robots have limited mobility in complex terrains and harsh environments, particularly on uneven ground. Additionally, their load capacity and maneuverability are somewhat restricted.

In comparison, tracked robots, with their powerful off-road capabilities and high maneuverability, show significant potential in fields such as agriculture, construction, and disaster recovery, as shown in Fig. 4 (c). The track system provides a larger ground contact area, distributing the robot's weight and reducing the risk of sinking in soft terrain such as mud and sand. Moreover, tracked robots are typically equipped with robust power and suspension systems, allowing them to maintain stability and traction on complex terrains [29]. Consequently, reliable tracked robots are also used in sensitive areas such as the military. The iRobot PackBot is a versatile military-tracked robot capable of performing tasks such as

reconnaissance, explosive ordnance disposal, and search and rescue missions [30]. However, due to the high friction of the track system, tracked robots often suffer from low energy efficiency. Additionally, their movement speed on flat surfaces is not as fast as wheeled robots, and their flexibility and maneuverability are relatively lower.

C. Quadruped Robots

Quadruped robots, known for their stability and adaptability, are well-suited for complex terrain exploration, rescue missions, and military applications. Inspired by quadrupedal animals, these robots can maintain balance and mobility on uneven surfaces, as shown in Fig. 4 (d). The multi-jointed design allows them to mimic biological movements, achieving complex gaits and posture adjustments. High adjustability enables the robots to automatically adapt their stance to changing terrain, enhancing maneuverability and stability. Sensing systems, such as LiDAR and cameras, provide environmental awareness, allowing the robots to navigate autonomously and avoid obstacles [31]. Researchers commonly use several types of quadruped robots as research platforms: Unitree Robotics, Boston Dynamics Spot, and ANYmal C. Unitree Robotics' Unitree A1 and Go1 are noted for their cost-effectiveness and flexibility. The A1 [32] and Go1 [33] possess strong mobility and intelligent obstacle avoidance capabilities, suitable for various applications. Boston Dynamics' Spot is renowned for its superior stability and operational flexibility, which are commonly used in industrial inspections and rescue missions. It features powerful load-carrying capacity and adaptability, capable of performing complex tasks in harsh environments [34]. ANYbotics' ANYmal C, with its modular design and high durability, is widely employed in industrial inspection and maintenance. The ANYmal C is equipped with autonomous navigation and remote operation capabilities, suitable for prolonged outdoor tasks and even extreme lunar missions [35]. Like fixed-base robots, quadruped robots face similar drawbacks, such as high costs. The complex design and high manufacturing costs of quadruped robots result in substantial initial investments, limiting their use in cost-sensitive areas. Additionally, quadruped robots have limited battery endurance in complex environments, requiring frequent recharging or battery replacement for prolonged operation [36].

D. Humanoid Robots

Following the discussion on fixed-base and quadruped robots, humanoid robots are distinguished by their human-like form and are increasingly prevalent in sectors such as the service industry, healthcare, and collaborative environments. These robots can mimic human movements and behavioral patterns, providing personalized services and support. Their dexterous hand designs enable them to perform intricate and complex tasks, distinguishing them from other types of robots, as shown in Fig. 4 (e). These hands typically have multiple degrees of freedom and high-precision sensors, allowing them to emulate the grasping and manipulation capabilities of human hands, which is particularly crucial in fields such as medical surgery and precision manufacturing [37], [38].

Among current humanoid robots, Atlas (Boston Dynamics) is renowned for its exceptional mobility and stability. Atlas can perform complex dynamic actions such as running, jumping, and rolling, demonstrating the potential of humanoid robots in highly dynamic environments [39]. The HRP series (AIST) is utilized in various research and industrial applications, with a design focus on high stability and flexibility, making it effective in complex environments, particularly for collaborative tasks with humans [40]. ASIMO (Honda), one of the most famous humanoid robots, can walk, run, climb stairs, and recognize faces and gestures, making it suitable for reception and guide services [41]. Additionally, a small social robot, Pepper (Softbank Robotics) can recognize emotions and engage in natural language communication and is widely used in customer service and educational settings [42].

Despite their excellent performance in many fields, humanoid robots face significant challenges in maintaining operational stability and reliability in complex environments due to their sophisticated control systems. These challenges include robust bipedal walking control algorithms and dexterous hand grasping algorithms [37]. Furthermore, traditional humanoid robots based on hydraulic systems, with their bulky structures and high maintenance costs, are gradually being replaced by motor-driven systems. Recently, Tesla and Unitree Robotics have introduced their humanoid robots based on motor systems. With the integration of LLMs, humanoid robots are expected to handle various complex tasks more intelligently, filling labor gaps in manufacturing, healthcare, and the service industry, thereby improving efficiency and safety [43].

E. Biomimetic Robots

Unlike the previously mentioned robots, biomimetic robots perform tasks in complex and dynamic environments by simulating the efficient movements and functions of natural organisms. By emulating biological entities' forms and movement mechanisms, these robots demonstrate significant potential in fields such as healthcare, environmental monitoring, and biological research [22]. Typically, they utilize flexible materials and structures to achieve lifelike, agile movements. These materials not only enhance the robots' adaptability and flexibility but also minimize environmental impact. Furthermore, biomimetic robots are often equipped with advanced sensors and control systems, enabling real-time environmental sensing and rapid response, thereby enhancing their autonomous navigation and task execution capabilities. Importantly, biomimetic designs can significantly improve the robots' energy efficiency by mimicking the efficient movement mechanisms of biological organisms, making them more economical regarding energy consumption [54], [55]. These biomimetic robots include fish-like robots [56], [57], insect-like robots [58], [59], and soft-bodied robots [60], as shown in Fig. 4 (f). Despite their impressive performance, biomimetic robots face several challenges. First, their design and manufacturing processes are often complex and costly, limiting large-scale production and widespread application. Second, due to their use of flexible materials and complex movement mechanisms, the durability and reliability of biomimetic robots need improvement in extreme environments.

Simulator	Year	HFPS	HQGR	RRL	DLS	LSPC	ROS	MSS	CP	Physics Engine	Main Applications
Isaac Sim [44]	2023	○	○	○	○	○	○	○	○	PhysX	Nav, AD
Isaac Gym [45]	2019	○			○	○				PhysX	RL,LSPS
Gazebo [46]	2004	○	○				○	○	○	ODE, Bullet, Simbody, DART	Nav,MR
PyBullet [47]	2017				○				○	Bullet	RL,RS
Webots [48]	1996	○	○					○	○	ODE	RS
MuJoCo [49]	2012	○			○				○	Custom	RL, RS
Unity ML-Agents [50]	2017	○			○				○	Custom	RL, RS
AirSim [51]	2017	○							○	Custom	Drone sim, AD, RL
MORSE [52]	2015							○	○	Bullet	Nav, MR
CoppeliaSim (V-REP) [53]	2013	○	○					○	○	Bullet, ODE, Vortex, Newton	MR, RS

TABLE II

GENERAL SIMULATOR. **HFPS**: HIGH-FIDELITY PHYSICAL SIMULATION; **HQGR**: HIGH-QUALITY GRAPHICS RENDERING; **RRL**: RICH ROBOT LIBRARY; **DLS**: DEEP LEARNING SUPPORT; **LSPC**: LARGE-SCALE PARALLEL COMPUTING; **ROS**: TIGHT INTEGRATION WITH ROS; **MSS**: MULTIPLE SENSOR SIMULATION; **CP**: CROSS-PLATFORM NAV: ROBOT NAVIGATION **AD**: AUTO DRIVING; **RL**: REINFORCEMENT LEARNING **LSPS**: LARGE-SCALE PARALLEL SIM **MR**: MULTI-ROBOT SYSTEMS **RS**: ROBOT SIMULATION. ○ INDICATES THAT THE SIMULATOR EXCELS IN THIS ASPECT.

III. EMBODIED SIMULATORS

Data scarcity has been a persistent challenge in embodied AI research. Nonetheless, collecting real world robot data poses numerous challenges. First, real world robot training proceeds slowly due to its real-time nature, which cannot be parallelized. The associated costs are prohibitively high, demanding dedicated deployment sites, expert operational control for data collection, and substantial hardware expenses. Moreover, the most significant challenge lies in reproducibility, stemming from vast differences in robot hardware configurations, control methods, and implementation frameworks, impeding data transferability. In such circumstances, simulators offer a novel solution for collecting and training data for embodied AI.

Embodied simulators are vital for embodied AI as they offer cost-effective experimentation, ensuring safety by simulating potentially hazardous scenarios, scalability for testing in diverse environments, rapid prototyping capabilities, accessibility to a wider research community, controlled environments for precise studies, data generation for training and evaluation, and standardized benchmarks for algorithm comparison. To enable agents to interact with the environment, it is necessary to construct a realistic simulated environment. This requires consideration of the physical characteristics of the environment, the properties of objects, and their interactions.

This section will introduce the commonly used simulation platforms in two parts: the general simulator based on underlying simulation and the simulator based on real scenes.

A. General Simulator

The physical interactions and dynamic changes present in real environments are irreplaceable. However, deploying embodied models in the physical world often incurs high costs and faces numerous challenges. The ultimate goal of embodied AI is to transfer findings from virtual environments to real-world applications. Researchers can select simulators that best suit their needs to aid their studies. General-purpose simulators provide a virtual environment that closely mimics the physical world, allowing for algorithm development and model training, which offers significant cost, time, and safety advantages.

Isaac Sim [44] developed by NVIDIA, is an advanced simulation platform tailored for robotics and AI research. The primary features of Isaac Sim include high-fidelity physical simulation, real-time ray tracing, an extensive library of robotic models, and deep learning support. Pixar's USD



Fig. 5. Examples of General Simulators.

(Universal Scene Description) format is also introduced to describe robots and complex scenes. Isaac Sim offers a variety of pre-built robotic models and environments, and it supports user-defined models. Its application scenarios include robotic navigation and control, autonomous driving, industrial automation, and human-robot interaction. By providing a robust and versatile platform, Isaac Sim significantly enhances the efficiency and effectiveness of robotics and AI research.

Gazebo [61] is an open-source simulator developed by Open Robotics, is widely used in robotics research and education. It offers high-fidelity physical simulation and rich features, making it a preferred tool for researchers and developers. Gazebo's key features include high-fidelity physical simulation, diverse sensor simulation, extensive robot libraries, and tight integration with ROS. Gazebo supports the simulation of various sensors, including cameras, LiDAR, and sonar, and offers numerous pre-built robot models and environments with support for custom models. Its application scenarios include robot navigation and control and multi-robot systems.

PyBullet [47] is the Python interface for the Bullet physics engine, providing an easy-to-use simulation environment. PyBullet's key features include ease of use, real-time physical simulation, diverse sensor simulation, and deep learning integration. PyBullet supports real-time physical simulation, including rigid body dynamics, collision detection, and constraint solving. Its application scenes include robot navigation and control, reinforcement learning, and computer graphics.

Table. II presents the key features and primary application scenarios of 10 general-purpose simulators. They each offer unique advantages in the field of embodied AI. Researchers can select the most appropriate simulator based on their specific research needs, thereby accelerating the development and application of embodied AI technologies. Fig. 5 shows the visualization effects of the general simulators.

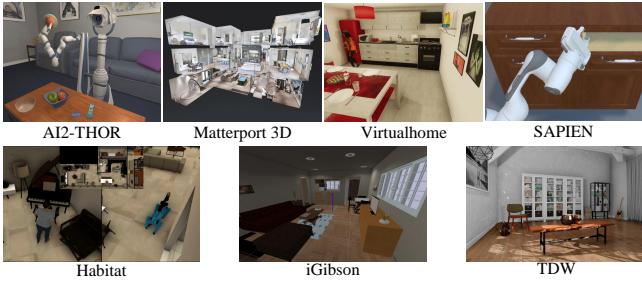


Fig. 6. Examples of Real-Scene Based Simulators.

B. Real-Scene Based Simulators

Achieving universal embodied agents in household activities has been a primary focus in the field of embodied AI research. These embodied agents need to deeply understand human daily life and perform complex embodied tasks such as navigation and interaction in indoor environments. To meet the demands of these complex tasks, the simulated environments need to be as close to real world as possible, which places high demands on the complexity and realism of the simulators. This led to the creation of simulators based on real world environments. These simulators mostly collect data from the real world, create photorealistic 3D assets, and build scenes using 3D game engines like UE5 and Unity. The rich and realistic scenes make simulators based on real world environments the top choice for research on embodied AI in household activities.

AI2-THOR [62] is an indoor embodied scene simulator based on Unity3D, launched in 2017 and led by the Allen Institute for Artificial Intelligence. As a high-fidelity simulator built in the real world, the biggest feature of AI2-THOR is its richly interactive scene objects and the physical properties assigned to them (such as open/close or even cold/hot). AI2-THOR consists of two parts: iTHOR and RoboTHOR. iTHOR contains 120 rooms categorized as kitchens, bedrooms, bathrooms, and living rooms, with over 2000 unique interactive objects, and supports multi-agent simulation; RoboTHOR contains 89 modular apartments with 600+ objects, the uniqueness of which is that these apartments correspond to real scenes in the real world. This means that researchers can remotely deploy their models in the real environment. So far, more than a hundred works have been published based on AI2-THOR.

Matterport 3D [63] is proposed in R2R [64] in 2018, is more commonly used as a large-scale 2D-3D visual dataset rather than an embodied simulator. The Matterport3D dataset includes 90 architectural indoor scenes, comprises 10,800 panoramas and 194,400 RGB-D images, and provides surface reconstruction, camera posture, and 2D and 3D semantic segmentation annotations. In embodied AI, Matterport3D is mainly used for visual language navigation. Matterport3D transforms 3D scenes into discrete ‘viewpoints’, and embodied agents move between adjacent ‘viewpoints’ in Matterport3D scenes. At each ‘viewpoint’, embodied agents can obtain a 1280x1024 panorama image (18× RGB-D) centered on the ‘viewpoint’. The advantage of Matterport3D lies in its large, diverse, and detailed annotated 2D-3D data, as well as the ease of use and flexibility brought about by simulator-deploy-free. In the field of embodied navigation, Matterport3D is already

one of the most important benchmarks.

Virtualhome [65] is a home activity embodied AI simulator brought by Puig et al. in 2018. What makes Virtualhome special most is its environment represented by an environment graph. Specifically, the environment graph is a dictionary composed of nodes (corresponding to objects) and edges (corresponding to relationships). Nodes include all objects in the current environment, as well as corresponding ID, status, and other information. This kind of environment graph provides a new way for embodied agents to understand the environment. In addition, users can customize and modify the environment graph to achieve the custom configuration of scene objects. Similar to AI2-THOR, Virtualhome also provides a large number of interactive objects, and embodied agents can interact with them and change their status. Virtualhome also provides 6 humanoid agents that can be deployed at the same time and support the acquisition of RGB-D and semantic information from multiple perspectives. Another feature of Virtualhome is its simple and easy-to-use API. The actions of embodied agents are simplified to the format of ‘operation + object’. This feature makes Virtualhome widely used in the research fields of embodied planning, instruction decomposition, etc.

Habitat [66] is an open-source simulator for large-scale human-robot interaction research launched by Meta in 2019. Habitat includes three parts: Habitat-sim, Habitat-lab, and Habitat-challenge. Among them, Habitat-sim is a high-performance 3D simulator based on the Bullet physics engine, which is the foundation of Habitat; Habitat-lab is an embodied simulation framework for reinforcement learning, encapsulated based on Habitat-sim; Habitat-challenge is a series of benchmarks based on Habitat. The biggest feature of Habitat is its extremely high degree of openness. Researchers can import and create their 3D scenes in Habitat or use the rich open resources on the Habitat platform for expansion. This gives Habitat several scenes that other simulation platforms cannot match. Habitat has a wealth of customizable sensors and supports multi-agent simulation. Multiple embodied agents from open resources or customizations (such as humans and robot dogs) can cooperate in the simulation scene, move freely, and perform simple interactions with the scene. Based on these advantages, Habitat is attracting increasing attention.

Different from other simulators that focus more on the scene, **SAPIEN** [67] pays more attention to simulating the interaction of objects in the scene. Based on the PhysX physics engine, SAPIEN provides fine-grained embodied control, which can implement joint control based on force and torque through the ROS interface, and the high-level action interface can also support the motion planning for embodied agents to avoid collisions. Based on the PartNet-Mobility Dataset, SAPIEN provides indoor simulation scenes containing rich interactive objects and supports the import of custom resources. Different from the API provided by simulators like AI2-THOR that directly changes the status of objects, SAPIEN supports simulated physical interactions, and embodied agents can control the hinged parts of objects through physical actions, thereby changing the status of objects. These features make SAPIEN very suitable for training the fine-grained object operation of embodied AI.

Simulation Platform	Year	Num of Scenes	Continuous Action	3D Scene Scans	Sensors	Physics	Multiple Agents	Object States	3D Assets
AI2-THOR [62]	2017	120	✓	✗	RGB-D, S	✓	✓	✓	✓
Matterport 3D [63]	2018	90	✗	✓	RGB-D, S	✗	✗	✗	✗
Habitat [66]	2019	1000+	✓	✓	RGB-D, S	✓	✓	✗	✓
Virtual Home [65]	2018	50	✗	✗	RGB-D, S	✓	✓	✓	✓
SAPIEN [67]	2020	46	✓	✗	RGB-D, S	✓	✗	✓	✓
iGibson [68] [69]	2021	15	✓	✓	RGB-D, S, L	✓	✗	✓	✓
TDW [70]	2021	-	✓	✓	RGB-D, S, A	✓	✓	✓	✓

TABLE III

COMPARISON OF REAL-SCENE BASED SIMULATORS. FOR THE SENSOR, S REFERS TO SEMANTIC, L REFERS TO LiDAR AND A REFERS TO AUDIO.

iGibson [68] [69] is an open-source simulator launched by the Li team at Stanford in 2021. iGibson is built on the Bullet physics engine, provides 15 high-quality indoor scenes, and supports the import of assets from other datasets such as Gibson and Matterport3D, enabling a total of over 10,000 simulated scenes. As an object-oriented simulator, iGibson assigns rich changeable attributes to objects, not limited to the kinematic properties of objects (posture, speed, acceleration, joint configuration of articulated objects), but also includes temperature, humidity, cleanliness, switch status, etc. This allows iGibson to implement more complex embodied interactions and build more difficult, long-term embodied tasks. In addition, besides the depth and semantic sensors that are standard in other simulators, iGibson also provides LiDAR for embodied agents, allowing embodied agents to obtain 3D point clouds in the scene easily. Regarding embodied agent configuration, iGibson supports continuous action control and fine-grained joint control. This allows the embodied agents in iGibson to interact delicately with the objects in the scene while moving freely.

TDW [70] was launched by MIT in 2021. As one of the latest embodied AI simulators, TDW combines high-fidelity video and audio rendering, realistic physical effects, and a single flexible controller, making certain progress in the perception and interaction of the simulated environment. TDW integrates multiple physics engines into one framework, which can realize the physical interaction simulation of various materials such as rigid bodies, soft bodies, fabrics, and fluids, and provides situational sounds when interacting with objects. In this respect, TDW has taken an important step compared to other simulators. TDW supports the deployment of multiple intelligent agents and provides users with a rich API library and asset library, allowing users to freely customize scenes and tasks according to their own needs, even outdoor scenes and related tasks. The extremely high degree of freedom gives TDW higher potential.

Table III summarizes all the simulators based on the real scenarios mentioned above. Sapien is quite special among these, it is completely designed for simulating interactions with joint objects (such as doors, cabinets, and drawers); Virtualhome's unique environment graph makes it widely used for high-level embodied planning based on the natural-language-described environment; AI2Thor provides a wealth of interactive scenes, but these interactions, like Virtualhome, are only implemented through scripts and do not have real physical interactions. However, such a design is sufficient for embodied tasks that do not focus on fine-grained interactions; both iGibson and TDW provide fine-grained embodied control and highly simulated physical interactions, among

which iGibson provides more abundant and realistic large-scale scenes, which makes iGibson suitable for more complex and long-term mobile operation tasks, while TDW provides users with higher freedom, users can freely expand the scene, and TDW's unique audio and flexible, fluid simulation make it irreplaceable in related simulation scenarios; Matterport3D, as a basic 2D-3D visual dataset, is widely used and extended in the current embodied AI benchmark; in Habitat, the embodied agent lacks interaction capabilities, but Habitat's huge indoor scenes and easy-to-use interfaces, open framework, make it highly regarded in the field of embodied navigation.

Besides, automated simulation scene construction is greatly beneficial for obtaining high-quality embodied data. **RoboGen** [71] customizes tasks from randomly sampled 3D assets through large language models, thereby creating scenes and automatically training agents; **HOLODECK** [72] can automatically customize corresponding high-quality simulation scenes in AI2-THOR based on human instructions; **PhyScene** [73] generates interactive and physically consistent high-quality 3D scenes based on conditional diffusion. The Allen Institute for Artificial Intelligence expanded AI2-THOR and proposed **ProcTHOR** [74], which can automatically generate simulated scenes with sufficient interactivity, diversity, and rationality. These methods provide new insight into the development of embodied AI.

IV. EMBODIED PERCEPTION

The “north stars” of the future of visual perception is embodied-centric visual reasoning and social intelligence [75]. Unlike merely recognizing objects in images [76]–[78], agent with embodied perception must move in the physical world and interact with the environment. This requires a deeper understanding of 3D space and dynamic environments. Embodied perception requires visual perception and reasoning, understanding the 3D relations within a scene, and predicting and performing complex tasks based on visual information.

A. Active Visual Perception

Active visual perception systems require fundamental capabilities such as state estimation, scene perception, and environment exploration. As shown in Fig. 7, these capabilities have been extensively studied within the domains of Visual Simultaneous Localization and Mapping (vSLAM) [119], [120], 3D Scene Understanding [121], and Active Exploration [13]. These research areas contribute to developing robust active visual perception systems, facilitating improved environmental interaction and navigation in complex, dynamic settings. We briefly introduce these three components and summarize the methods mentioned in each part in Table IV.

Function	Type	Methods
vSLAM	Traditional vSLAM	MonoSLAM [79], MSCKF [80], PTAM [81], ORB-SLAM [82], DTAM [83], LSD-SLAM [84]
	Semantic vSLAM	SLAM++ [85], CubeSLAM [86], HDP-SLAM [87], QuadricSLAM [88], So-SLAM [89], DS-SLAM [90], DynaSLAM [91], SG-SLAM [92], OVD-SLAM [93], GS-SLAM [94]
3D Scene Understanding	Projection-based	MV3D [95], PointPillars [96], MVCNN [97]
	Voxel-based	VoxNet [98], SSCNet [99], MinkowskiNet [100], SSCNs [101], EmbodiedScan [102]
	Point-based	PointNet [103], PointNet++ [104], PointMLP [105], PointTransformer [106], Swin3d [107], PT2 [108], PT3 [109], PointMamba [110], PCM [111], Mamba3D [112]
Active Exploration	Interacting with the environment	Pinto et al. [113], Tatiya et al. [114]
	Changing the viewing direction	Jayaraman et al. [115], Neu-NBV [116], Hu et al. [117], Fan et al. [118]

TABLE IV
THE COMPARISON OF THE ACTIVE VISUAL PERCEPTION METHODS.

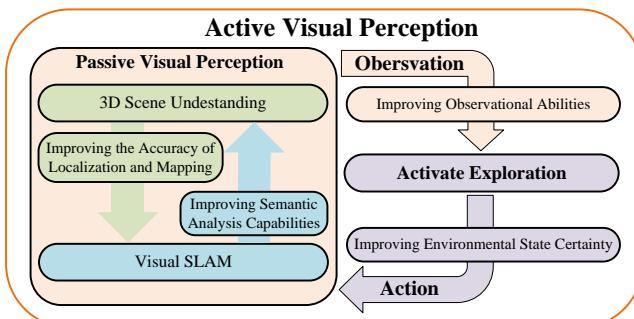


Fig. 7. The schematic diagram of active visual perception. Visual SLAM and 3D Scene Understanding provide the foundation for passive visual perception, while active exploration can provide activeness to the passive perception system. These three elements complement each other and are essential to the active visual perception system.

1) *Visual Simultaneous Localisation and Mapping*: Simultaneous Localization and Mapping (SLAM) is a technique that determines a mobile robot's position in an unknown environment while concurrently constructing a map of that environment [122], [123]. Range-based SLAM [124]–[126] creates point cloud representations using rangefinders (e.g., laser scanners, radar, and/or sonar), but is costly and provides limited environmental information. Visual SLAM (vSLAM) [119], [120] uses on-board cameras to capture frames and construct a representation of the environment. It has gained popularity due to its low hardware cost, high accuracy in small-scale scenarios, and ability to capture rich environmental information. Classical vSLAM techniques can be divided into Traditional vSLAM and Semantic vSLAM [120].

Traditional vSLAM systems estimate the robot's pose in an unknown environment using image information and multi-view geometry principles to construct a low-level map (e.g., sparse maps, semi-dense maps, and dense maps) composed of point clouds, such as filter-based methods (e.g., MonoSLAM [79], MSCKF [80]), keyframe-based methods (e.g., PTAM [81], ORB-SLAM [82]), and direct tracking methods (e.g., DTAM [83], LSD-SLAM [84]). Since the point clouds in these low-level maps do not correspond to objects in the environment, they are difficult for embodied robots to understand and use directly. With the rise of semantic concepts, semantic vSLAM systems combined with semantic information solutions have significantly enhanced robots' ability to perceive the unexplored environment.

Early works, such as SLAM++ [85], use real-time 3D object recognition and tracking to create efficient object graphs, enabling robust loop closure, relocalization, and object detection in cluttered environments. CubeSLAM [86] and HDP-SLAM [87] introduce 3-D rectangular into the map to

construct a lightweight semantic map. QuadricSLAM [88] employs semantic 3D ellipsoids to achieve precise modeling of object shapes and poses in complex geometrical environments. So-SLAM [89] incorporates fully coupled spatial structure constraints (coplanarity, collinearity, and proximity) in indoor environments. To meet the challenges of dynamic environments, DS-SLAM [90], DynaSLAM [91] and SG-SLAM [92] employ semantic segmentation for motion consistency checks and multiview geometry algorithms to identify and filter dynamic objects, ensuring stable localization and mapping. OVD-SLAM [93] leverages semantic, depth, and optical flow information to distinguish dynamic regions without predefined labels, achieving more accurate and robust localization. GS-SLAM [94] utilizes 3D Gaussian representation that balances efficiency and accuracy through a real-time differentiable splatting rendering pipeline and adaptive expansion strategy.

2) *3D Scene Understanding*: 3D scene understanding aims to distinguish objects' semantics, identify their locations, and infer the geometric attributes from 3D scene data, which is fundamental in autonomous driving [127], robot navigation [128], and human-computer interaction [129] etc. A scene may be recorded as 3D point clouds using 3D scanning tools like LiDAR or RGB-D sensors. Unlike images, point clouds are sparse, disordered, and irregular, [121] makes scene interpretation extremely challenging.

In recent years, numerous deep learning methods for 3D scene understanding have been proposed, which can be divided into projection-based, voxel-based, and point-based methods. Concretely, projection-based methods (e.g., MV3D [95], PointPillars [96], MVCNN [97]) project 3D points onto various image planes and employ 2D CNN-based backbones for feature extraction. Voxel-based methods convert point clouds into regular voxel grids to facilitate 3D convolution operations (e.g., VoxNet [98], SSCNet [99]), and some works improve their efficiency through sparse convolution (e.g., MinkowskiNet [100], SSCNs [101], EmbodiedScan [102]). In contrast, point-based methods process point clouds directly (e.g., PointNet [103], PointNet++ [104], PointMLP [105]). Recently, to achieve model scalability, Transformers-based (e.g., PointTransformer [106], Swin3d [107], PT2 [108], PT3 [109]) and Mamba-based (e.g., PointMamba [110], PCM [111], Mamba3D [112]) architectures have emerged.

3) *Active Exploration*: The previously introduced 3D scene understanding methods endow robots with the ability to perceive the environment in a passive manner. In such cases, the perception system's information acquisition and decision-making do not adapt to the evolving scene. However, passive perception serves as a crucial foundation for active exploration. Given that robots are capable of movement and frequent

Type	Method	Years	Visual Input	LLM-base
Two-stage	ScanRefer [130]	2020	3D	✗
	ReferIt3D [131]	2020	3D	✗
	TGNN [132]	2021	3D	✗
	SAT [133]	2021	3D+2D	✗
	FFL-3DOG [134]	2021	3D	✗
	3DVG-Transformer [135]	2021	3D	✗
	LanguageRefer [136]	2022	3D	✗
	LAR [137]	2022	3D	✗
	MVT [138]	2022	3D	✗
	LLM-Grounder [139]	2023	3D	✓
One-stage	ZSVG3D [140]	2023	3D	✓
	3D-SPS [141]	2022	3D+2D	✗
	BUTD-DETR [142]	2022	3D	✗
	EDA [143]	2023	3D	✗
	ReGround3D [144]	2024	3D+2D	✓

TABLE V
COMPARISON OF DIFFERENT 3D VG METHODS.

interaction with their surroundings, they should also be able to explore and perceive their environment actively. The relationship between them is shown in Fig. 7. Current methods addressing active perception focus on interacting with the environment [113], [114] or by changing the viewing direction to obtain more visual information [115]–[118].

For example, Pinto et al. [113] proposed a curious robot that learns visual representations through physical interaction with the environment rather than relying solely on category labels in a dataset. To address the challenge of interactive object perception across robots with varying morphologies, Tatiya et al. [114] innovatively propose a multi-stage projection framework that transfers implicit knowledge through learned exploratory interactions, enabling robots to effectively recognize object properties without the need to relearn from scratch. Recognizing the challenge of autonomously capturing informative observations, Jayaraman et al. [115] propose a reinforcement learning method where an agent learns to actively acquire informative visual observations by reducing its uncertainty about unobserved parts of its environment, using recurrent neural networks for the active completion of panoramic scenes and 3D object shapes. NeU-NBV [116] introduces a mapless planning framework that iteratively positions an RGB camera to capture the most informative images of an unknown scene, using a novel uncertainty estimation in image-based neural rendering to guide data collection towards the most uncertain views. Hu et al. [117] develop a robot exploration algorithm that predicts the value of future states using a state value function, combining offline Monte-Carlo training, online Temporal Difference adaptation, and an intrinsic reward function based on sensor information coverage. To be able to address the issue of accidental input in open-world environments, Fan et al. [118] propose a strategy that treats active recognition as a sequential evidence-gathering process, providing step-by-step uncertainty quantification and reliable prediction under evidence combination theory while effectively characterizing the merit of actions in open-world environments through a specially developed reward function.

B. 3D Visual Grounding

Unlike traditional 2D visual grounding (VG), which operates within the confines of flat images, 3D VG incorporates depth, perspective, and spatial relationships between objects, providing a more robust framework for agents to interact with their environment. The task of 3D VG involves locating objects

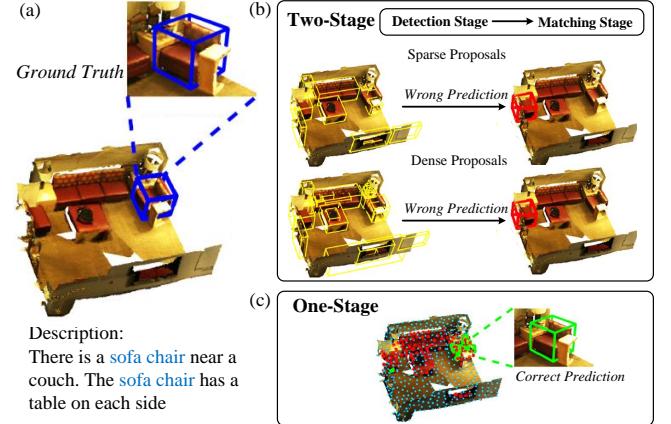


Fig. 8. The diagram of two-stage (upper) and one-stage (bottom) 3D visual grounding methods [141]. (a) shows the example of 3D visual grounding. (b) two-stage method includes Sparse proposals that may overlook the target in the detection stage and Dense proposals that may confuse the matching stage. (c) one-stage methods can progressively select keypoints (blue points → red points → green points) with the guidance of the language description.

within a 3D environment using natural language descriptions [130], [131]. As summarized in Table V, recent methodologies in 3D visual grounding can be roughly divided into two categories: two-stage and one-stage methods [145].

1) *Two-stage 3D Visual Grounding methods:* Similar to corresponding 2D tasks [146], early research in 3D grounding predominantly utilized a two-stage detect-then-match pipeline. They initially employ pretrained detector [147] or segmentor [148]–[150] to extract features from numerous object proposals within a 3D scene, which are then fused with linguistic query features to match the target object. The focus of the two-stage research is mainly on the second stage, such as exploring the correlation between object proposal features and linguistic query features to select the best-matched object. ReferIt3D [131] and TGNN [132] not only learn to match the proposal features with textual embedding but also encode the contextual relationship among the objects via graph neural networks. To enhance 3D visual grounding in free-form descriptions and irregular point cloud, FFL-3DOG [134] utilizes a language scene graph for phrase correlations, a multi-level 3D proposal relation graph for enriching visual features, and a description-guided 3D visual graph for encoding global contexts.

Recently, as the transformer architecture has demonstrated outstanding performance in natural language processing [151], [152] and computer vision tasks [15], [153], research has increasingly focused on using transformers for extracting and fusing visual language features in 3D visual grounding tasks. For example, LanguageRefer [136] employs a transformer-based architecture combining 3D spatial embeddings, language descriptions, and class label embeddings to achieve robust 3D visual grounding. 3DVG-Transformer [135] is a relation-aware visual grounding method for 3D point clouds, featuring a coordinate-guided contextual aggregation module for relation-enhanced proposal generation and a multiplex attention module for cross-modal proposal disambiguation. To enable more fine-grained reasoning of 3D objects and referring expressions, TransRefer3D [154] enhances cross-modal feature representation using entity-and-relation aware attention, incorporating

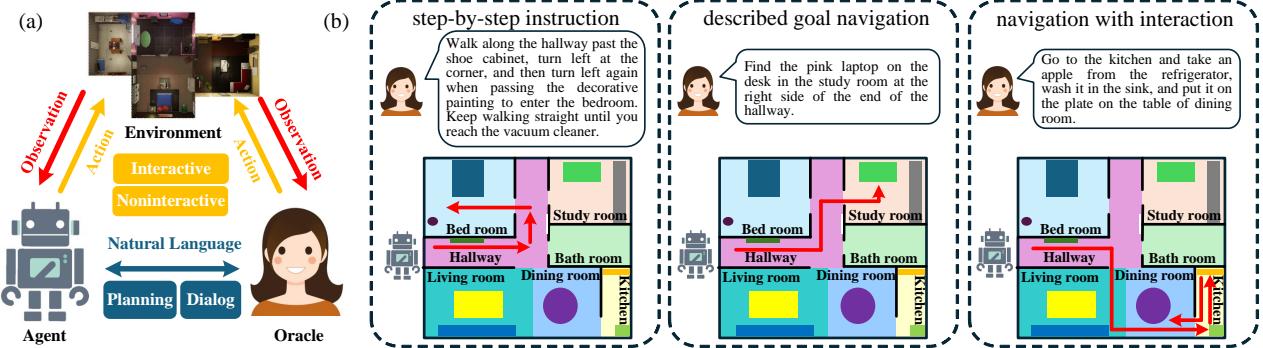


Fig. 9. (a) Overview of VLN. The embodied agent communicates with humans through natural language. Humans issue instructions to the embodied agent, who completes tasks such as planning and dialog. Subsequently, through collaborative cooperation or the embodied agent’s independent actions, actions are made in interactive or non-interactive environments based on visual observations and instructions, (b) Different tasks of VLN.

self-attention, entity-aware attention and relation-aware attention. Most of the above methods for 3D VG focus on specific viewpoints, but the learned visual-linguistic correspondences may fail when the viewpoint changes. In order to learn more view-robust visual representations, MVT [138] proposes a multi-view transformer that learns view-independent multimodal representations. To mitigate the limitations of sparse, noisy, and incomplete point clouds, various methods have explored the incorporation of detailed 2D visual features from captured (e.g., SAT [133] or synthesized (e.g., LAR [137]) images to enhance 3D visual grounding tasks.

Existing 3D VG methods often rely on extensive labeled data for training or show limitations in processing complex language queries. Inspired by the impressive language understanding capabilities of LLMs, LLM-Grounder [139] proposes an open vocabulary 3D visual grounding pipeline that requires no labeled data, leveraging LLM to decompose queries and generate plans for object identification, followed by evaluating spatial and commonsense relations to select the best matching object. To capture view-dependent queries and decipher spatial relations in 3D space, ZSVG3D [140] designs a zero-shot open-vocabulary 3D visual grounding method that uses LLM to identify relevant objects and perform reasoning, transforming this process into a scripted visual program and then into executable Python code to predict object locations.

However, as shown in Fig. 8 (b), these two-stage methods face the dilemma of determining the number of proposals because the 3D detectors used in the first stage require sampling several keypoints to represent the entire 3D scene and generate corresponding proposals for each keypoint. Sparse proposals may overlook targets in the first stage, making them unmatchable in the second stage. Conversely, dense proposals may contain inevitable redundant objects, leading to difficulties in distinguishing targets in the second stage due to overly complex inter-proposal relationships. Moreover, the keypoint sampling strategy is language-agnostic, which increases the difficulty for detectors to identify language-related proposals.

2) *One-stage 3D Visual Grounding methods:* As shown in Fig. 8 (c), in contrast to two-stage 3D VG methods, one-stage 3D VG methods integrate object detection and feature extraction guided by language queries, making it easier to locate objects relevant to the language.

3D-SPS [141] takes the 3D VG task as a keypoint selection problem and avoids the separation of detection and matching. Specifically, 3D-SPS initially coarsely samples language-related keypoints through the description-aware keypoint sampling module. Subsequently, it finely selects target keypoints and predicts the foundation using the goal-oriented progressive mining module. Inspired by the 2D image language pre-train model such as MDETR [155] and GLIP [156], BUTD-DETR [142] proposes a bottom-up top-down detection transformer that can be used for 2D and 3D VG. Concretely, BUTD-DETR utilizes labeled bottom-up box proposals and top-down language descriptions to guide the decoding of target objects and corresponding language spans through the prediction head.

However, the aforementioned methods either extract sentence-level features that couple all words or focus more on object names in the description, which would lose the word-level information or neglect other attributes. To address these issues, EDA [143] explicitly decouples the textual attributes in a sentence and conducts dense alignment between such fine-grained language and point cloud objects. Firstly, the long text is decoupled into five semantic components, including main object, auxiliary object, attributes, pronoun, and relationship. Subsequently, the dense alignment is designed to align all object-related decoupled textual semantic components with visual features. To be able to reason human intentions from implicit instructions, ReGround3D [144] designs a visual-centric reasoning module, powered by a Multi-modal Large Language Model, and a 3D grounding module that accurately obtains object locations by revisiting enhanced geometry and fine-grained details from 3D scenes. Additionally, a Chain-of-Grounding mechanism is employed to improve 3D reasoning grounding through interleaved reasoning and grounding steps.

C. Visual Language Navigation

Visual Language Navigation (VLN) stands as a key research problem of Embodied AI, aiming at enabling agents to navigate in unseen environments following linguistic instructions. VLN requires robots to understand complex and diverse visual observations and meanwhile interpret instructions at different granularities. The input for VLN typically consists of two parts: visual information and natural language instructions. The visual information can either be a video of past trajectories or a set of historical-current observation images. The natural

Dataset	Year	Simulator	Environment	Feature	Size
R2R [64]	2018	Matterport3D	Indoor, Discrete	Step-by-step instructions	21,567
R4R [157]	2019	Matterport3D	Indoor, Discrete	Step-by-step instructions	200,000+
VLN-CE [158]	2020	Habitat	Indoor, Continuous	Step-by-step instructions	-
TOUCHDOWN [159]	2019	-	Outdoor, Discrete	Step-by-step instructions	9,326
REVERIE [160]	2020	Matterport3D	Indoor, Discrete	Described goal navigation	21,702
SOON [161]	2021	Matterport3D	Indoor, Discrete	Described goal navigation	3,848
DDN [162]	2023	AI2-THOR	Indoor, Continuous	Demand-driven navigation	30,000+
ALFRED [163]	2020	AI2-THOR	Indoor, Continuous	Navigation with interaction	25,743
OVMM [164]	2023	Habitat	Indoor, Continuous	Navigation with interaction	7,892
BEHAVIOR-1K [165]	2023	OmniGibson	Indoor, Continuous	Long-span navigation with interaction, Dialog, oracle	1,000
CVDN [166]	2020	Matterport3D	Indoor, Discrete	Dialog, oracle	2,050
DialFRED [167]	2022	AI2-THOR	Indoor, Continuous	Dialog, oracle	53,000

TABLE VI
COMPARISON OF DIFFERENT VLN DATASETS.

language instructions include the target that the embodied agent needs to reach or the task that the embodied agent is expected to complete. The embodied agent must use the above information to select one or a series of actions from a list of candidates to fulfill the requirements of the natural language instructions. This process could be represented as:

$$Action = \mathcal{M}(O, H, I) \quad (1)$$

where *Action* is the chosen action or a list of action candidates, *O* is the current observation, *H* is the historical information, and *I* is the natural language instruction.

SR (Success Rate), **TL** (Trajectory Length), and **SPL** (Success Weighted by Path Length) are the most commonly used metrics in VLN. Among them, SR directly reflects the navigation performance of the embodied agent, TL reflects the navigation efficiency, and SPL combines both to indicate the overall performance of the embodied agent.

Below, we will introduce visual-linguistic navigation divided into two parts: datasets and methods.

1) *Datasets*: In visual-linguistic navigation, natural language instructions can be a series of detailed action descriptions, a fully described goal, or just a roughly described task, even only the demands of human. The tasks that embodied agents need to complete maybe just a single navigation, or navigation with interaction, or multiple navigation tasks that need to be completed in sequence. These differences bring different challenges to visual-linguistic navigation, and many different datasets have been born as a result. Based on these differences, we will introduce the important datasets in visual-linguistic navigation separately.

Room to Room [64] is a visual-linguistic navigation dataset created by Anderson et al. based on Matterport3D. In R2R, embodied agents navigate according to step-by-step instructions, choosing the next adjacent navigation graph node to advance based on visual observations until they reach the target location. Embodied agents need to dynamically track progress to align the navigation process with fine-grained instructions. Room-for-Room [157] extends the paths in R2R to longer trajectories, requires higher for the long-distance instruction and history alignment capabilities of embodied agents. VLN-CE [158] extends R2R and R4R to continuous environments, embodied agents can move freely in the scene. This makes the action decision of embodied agents more difficult. Different from the above datasets based on indoor scenes, Chen et al. created the TOUCHDOWN dataset [159] based on Google Street View. In TOUCHDOWN, embodied agents

follow instructions to navigate in the street view rendering simulation of New York City to find the specified object.

Similar to R2R, the REVERIE dataset [160] is also built based on the Matterport3D simulator. REVERIE requires embodied agents to accurately locate the distant invisible target object specified by concise, human-annotated high-level natural language instructions, which means that embodied agents need to find the target object among a large number of objects in the scene. In SOON [161], agents receive a long and complex instruction from coarse to fine to find the target object in the 3D environment. During navigation, agents first search a larger area, and then gradually narrow the search range according to the visual scene and instructions. This makes SOON's navigation target-oriented and independent of the initial position. DDN [162] moves a step further beyond these datasets, only providing human demands without specifying explicit objects. The agent needs to navigate through the scene to find objects that meet human needs.

Shridhar et al. proposed the ALFRED dataset [163] based on the AI2-THOR simulator. In ALFRED, embodied agents need to understand environmental observations and complete household tasks in an interactive environment according to coarse-grained and fine-grained instructions. The core task of OVMM [164] is to pick any object in any unseen environment and place it in a specified location. Embodied agents need to locate the target object in the home environment, navigate and grab it, and then navigate to the target location to put down the object. OVMM provides a simulation based on Habitat and a framework for implementation in the real world. Behavior-1K [165], based on the survey of human needs, designed 1000 long-sequence, complex skill-dependent daily tasks in OmniGibson, which is an extension of iGibson. Embodied agents need to complete long-span navigation-interaction tasks which may contain thousands of low-level action steps based on visual information and natural language instructions. Such complex tasks pose higher requirements for the understanding and memory of embodied agents.

There are also some more special datasets. CVDN [166] requires embodied agents to navigate to the target based on dialogue history, and ask questions for help to decide the next action when uncertain. DialFRED [167], an extension of ALFRED, allows agents to ask questions during the navigation and interaction process to get help. These datasets all introduce additional oracles, and embodied agents need to obtain more information beneficial to navigation by asking questions.

2) *Method*: VLN has made great strides in recent years. With the astonishing performance of large models in various

Method	Model	Year	Feature
Memory-Understanding Based	LVERG [168]	2020	Graph Learning
	CMG [169]	2020	Adversarial Learning
	RCM [170]	2021	Reinforcement learning
	FILM [171]	2022	Semantic Map
	LM-Nav [172]	2022	Graph Learning
	HOP [173]	2022	History Modeling
	NaviLLM [174]	2024	Large Model
	FSTT [175]	2024	Test-Time Augmentation
	DiscussNav [176]	2024	Large Model
	GOAT [177]	2024	Causal Learning
Future-Prediction Based	VER [178]	2024	Environment Encoder
	NaVid [179]	2024	Large Model
Else	MCR-Agent [186]	2023	Multi-Level Model
	OVLM [187]	2023	Large Model

TABLE VII
COMPARISON OF VLN METHODS.

fields, the direction and focus of VLN research have been profoundly influenced. But overall, the research methods of VLN can still be roughly divided into two directions: **Memory-Understanding Based**, and **Future-Prediction Based**.

Memory-Understanding based methods focus on the perception and understanding of the environment, as well as model design based on historical observations or trajectories, which is a method based on past learning. Future-Prediction based methods pay more attention to modeling, predicting, and understanding the future state, which is a method for future learning. Since VLN can be regarded as a partially observable Markov decision process, where future observations depend on the current environment and actions of the intelligent agent, historical information has important significance for navigation decisions, especially long-span navigation decisions, hence Memory-Understanding based methods have always been the mainstream of VLN. However, Future-Prediction based methods still have important significance. Its essential understanding of the environment has great value in VLN in continuous environments, especially with the rise of the concept of world model, Future-Prediction based methods are receiving more and more attention from researchers.

Memory-Understanding based. Graph-based learning is a very important part of the methods based on understanding and memory of the past. Graph-based learning usually represents the navigation process in the form of a graph, where the information obtained by the embodied agent at each time step is encoded as nodes of the graph. Embodied agent obtains global or partial navigation graph information as a representation of the historical trajectory. In LVERG [168], the authors encode the language information and visual information of each node separately, design a new language and visual entity relationship graph to model the inter-modal relationship between text and vision, and the intra-modal relationship between visual entities. LM-Nav [172] uses a goal-conditioned distance function to infer connections between original observation sets and construct a navigation graph, and extracts landmarks from the instructions through a large language model, uses a visual language model to match them with the nodes of the navigation graph. Although HOP [173] is not based on graph learning, its method is similar to the graph,

requiring the model to model time-ordered information at different granularities, thereby achieving a deep understanding of historical trajectories and memories.

The navigation graph discretizes the environment, but concurrently understanding and encoding the environment is also important. FILM [171] uses RGB-D observations and semantic segmentation to gradually build a semantic map from 3D voxels during the navigation. VER [178] quantifies the physical world into structured 3D units through 2D-3D sampling, providing fine-grained geometric details and semantics.

Different learning schemes also explore how to utilize historical trajectories and memories better. Through adversarial learning, CMG [169] alternates between imitation learning and exploration encouragement schemes, effectively strengthening the understanding of instructions and historical trajectories, shortening the difference between training and inference. GOAT [177] directly trains unbiased models through Backdoor Adjustment Causal Learning (BACL) and Frontdoor Adjustment Causal Learning (FACL), conducts contrastive learning with vision, navigation history, and their combination to instructions, enabling the agent to make fuller use of information. The enhanced cross-modal matching method proposed by RCM [170] uses goal-oriented external rewards and instruction-oriented internal rewards to perform cross-modal grounding globally and locally and learns from its own historical good decisions through self-supervised imitation learning. FSTT [175] introduces TTA into visual-linguistic navigation and optimizes the model in terms of gradients and model parameters at two scales of time steps and tasks, effectively improving model performance.

The specific application of large models in Memory-Understanding based methods is to understand the representation of historical memory and to understand the environment and tasks based on its extensive world knowledge. NaviLLM [174] integrates the historical observation sequence into the embedding space through the visual encoder, inputs the multi-modal information of the fusion encoding into the large language model and fine-tunes it, reaching the state-of-the-art on multiple benchmarks. NaVid [179] makes improvements in the encoding of historical information, achieves different degrees of information retention on historical observations and current observations through different degrees of pooling. DiscussNav [176] assigns large model experts with different abilities to different roles, drives the large models to discuss before navigation actions to complete navigation decisions, and achieves excellent performance in zero-shot visual-linguistic navigation.

Future-Prediction Based. Graph-based learning is also widely used in Future-Prediction based methods. BGBL [182] and ETPNav [185] use a similar method to design a waypoint predictor that can predict movable path points in a continuous environment based on the observation of the current navigation graph node. They aim to migrate complex navigation in a continuous environment to node-to-node navigation in a discrete environment, thereby bridging the performance gap from discrete environments to continuous environments.

Improving the understanding and perception of the future environment through environmental encoding is also one of the research directions for predicting and exploring the future.

NvEM [181] uses a theme module and a reference module to perform fusion encoding of neighbor views from the global and local perspectives. This is actually an understanding and learning of future observations. HNR [184] uses a large-scale pre-trained hierarchical neural radiation representation model to directly predict the visual representation of the future environment rather than pixel-level images using three-dimensional feature space encoding, and builds a navigable future path tree based on the representation of the future environment. They predict the future environment from different levels, providing effective references for navigation decisions.

Some reinforcement learning methods are also applied to predict and explore future states. LookBY [180] employs reinforcement prediction to enable the prediction module to imitate the world and forecast future states and rewards. This allows the agent to directly map “current observations” and “predictions of future observations” to actions, achieving state-of-the-art performance at the time. The rich world knowledge and zero-shot performance of large models provide many possibilities for Future-Prediction based methods. MiC [183] requires the large language model to directly predict the target and its possible location from the instructions and provides navigation instructions through the description of scene perception. This method requires the large language model to fully exert its ‘imagination’ and build an imagined scene through prompts.

In addition, there are some methods that both learn from the past and for the future. MCR-Agent [186] designs a three-layer action strategy, which requires the model to predict the target from the instructions, predict the pixel-level mask for the target to be interact, and learn from the previous navigation decision; OVLM [187] requires the large language model to predict the corresponding operations and landmark sequences for the instructions. During the navigation process, the visual language map will be continuously updated and maintained, and the operations will be linked to the waypoints on the map.

D. Non-Visual Perception: Tactile

The skin facilitates human tactile perception. The skin changes shape when touched, and its abundant nerve cells send electrical signals [188]. This tactile perception allows humans to grasp handy work fully. Therefore, touch is vital for robots to interact with the real world. A sense of touch enables robots to acquire information such as material, shape, temperature, and even objects' contact force and gravity. Current work on tactile perception focuses on three areas: sensor design, dataset construction, and application. Tactile perception undoubtedly enhances the human-computer interaction experience and holds great promise [189]–[191].

1) *Sensor Design:* Tactile sensor design methods can be divided into three categories: non-vision-based, vision-based, and multi-modal. At early time, tactile sensors were chiefly engineered to register fundamental, low-dimensional sensory outputs such as force, pressure, vibration, and temperature [192]–[197]. Their principles are mostly related to electricity and physical mechanics and their data is often low-dimension series with temporal correlations. One of the notable representatives is BioTac [198] and its simulator [199]. Since

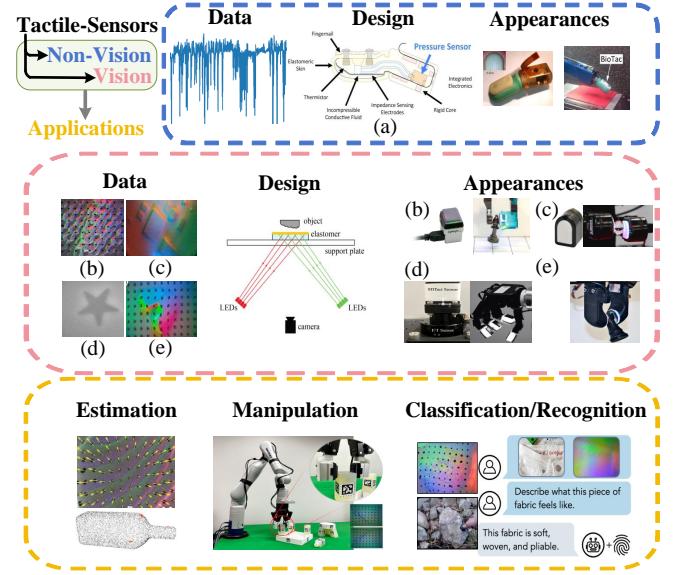


Fig. 10. Different types of Tactile Sensors. **Non-vision sensors** (a) mainly use sensors of force, pressure, vibration and temperature to get tactile knowledge. **Vision-based tactile sensors** ((b)-(e)) are based on optical principles. A camera is placed behind the gel to record the image of its deformation, using illumination from light sources at different directions. (a)-(e) are the details from BioTac, Gelsight, DIGIT, 9DTact and Gelslim.

computer vision had a wonderful performance, there has been a growing focus on vision-based tactile sensors which obtains tactile through optical principles. Using images of the gel's deformation as tactile information, vision-based tactile sensors such as GelSight [200], Gelslim [201], DIGIT [202], 9DTact [203], TacTip [204], GelTip [205] and AllSight [206] have been used for numerous applications. At the same time, the simulation of tactile sensors like TACTO [207] and Taxim [208], incorporating elastomer deformation together with the optical simulation, are also widely used. Recent work has focused on low costs [203] and the installation on robotic hands [202], [209], [210]. Recently, multi-modal tactile sensors are also emerging. Inspired by the touch mechanism of human skin, works progressed in multi-modal tactile skin which comprised multi information like pressure, proximity, acceleration and temperature detectors. Solutions often involve techniques like flexible materials and modular design.

2) *Datasets:* The datasets of non-vision sensors are contained with electrode values 3D net force vectors, and contact location. Therefore, the objects in the datasets are usually force samples and grasping samples. Its tasks are mainly the estimation of force types, force value and grasping details. The datasets mainly collected by BioTac series [198]. As for vision-based sensors, with their high-resolution images of deformation gel, except estimating the force information and sliding, they focus more on texture classification and 3D reconstruction. The objects in the datasets are usually household object, wildlife environments, different materials and grasping items. At the same time, as the image information can be easily aligned and bound with the other modalities (images, language, audio, etc) [15], [211], the perception of touch in embodied agent mainly revolves around visual-based sensors. The datasets revolves around the Geisight sensors,

Dataset	Year	Sensor Types	Data Format	Type	Real/Simulated	Sensor/Simulator	Size	Continuous
The Feeling of Success [212]	2017	Vision	Tac,Vision,Label	Daily Necessities	Real	Gelsight	106 Objects	✓
SynTouch [199]	2019	Non-vision	Tac,Force,Location	-	Real	BioTac	300k Readings	-
BioTac Force Estimation [199]	2019	Non-vision	Tac,Force	-	Real	BioTac	20k Samples	✓
Decoding the BioTac [213]	2020	Non-vision	Tac,Force,Location	-	Real	BioTac	50k Points	✓
ObjectFolder 1.0 [214]	2021	Vision	Tac,Vision,Audio	Household Object	Simulate	TACTO	100 Objects	✓
ObjectFolder 2.0 [215]	2022	Vision	Tac,Vision,Audio	Household Object	Simulate	Taxim	1000 Objects	✓
SSVTP [216]	2022	Vision	Tac,Vision	Clothings& Metal Material	Real	DIGIT	4500 Pairs	✗
YCB-Slide [217]	2022	Vision	Tac,Vision,Other	Daily Necessities	BOTH	TACTO & DIGIT	10 Objects	✓
ObjectFolder Real [218]	2023	Vision	Tac,Vision,Audio	Household Object	Real	Gelslim	100 Objects	✓
TVL [219]	2024	Vision	Tac,Vision,Text	Clothings& Metal Material	Real	DIGIT	44K Pairs	✗

TABLE VIII
COMPARISON OF DIFFERENT VISION-BASED TACTILE DATASETS.

DIGIT sensor and their simulators [200], [202], [203], [207]. We introduce ten commonly used tactile datasets, which are summarized in Table VIII.

3) *Methods:* Tactile perception has numerous applications. The information acquired from sensor enables robots to perform accurate robotic manipulation task, finish multi-modal work and even enhance their abilities in 3D reconstruction and localization.

1. Robotic Manipulation. In these task, bridging the sim-to-real gap is more than important. Reinforcement learning and GAN-based methods have been proposed to address variations in accurate, on-time robotic manipulation tasks.

Reinforcement Learning method. Visuotactile-RL [220] proposed several methods to existing RL methods, including tactile gating, tactile data augmentation and visual degradation. Rotateit [221] is a system that enables fingertip-based object rotation along multiple axes by leveraging multimodal sensory inputs. It trained the network by reinforcement learning policies with privileged information and enabled online inference. [222] proposed a deep RL approach to object pushing using only tactile perception. It came up with a goalconditioned formulation that allows both model-free and modelbased RL to obtain accurate policies for pushing an object to a goal. Any-Rotate [223] focused on in-hand manipulation. It is a system for gravity-invariant multi-axis in-hand object rotation using dense featured sim-to-real touch, constructing a continuous contact feature representation to provide tactile feedback for training a policy in simulation and introduce an approach to perform zero-shot policy transfer by training an observation model to bridge the sim-to-real gap.

GAN-based method. ACTNet [224] proposed an unsupervised adversarial domain adaptation method to narrow the domain gap for pixel-level tactile perception tasks. An adaptively correlative attention mechanism was introduced to improve the generator, which is capable of leveraging global information and focusing on salient regions. However, pixel-level domain adaptation lead to error accumulation, degrade performance, and increased structural complexity and training costs. In comparison, STR-Net [225] proposed a feature-level unsupervised framework for tactile images, narrowing the domain gap for feature-level tactile perception tasks.

Moreover, some methods focus on sim-to-real. For example, the Tactile Gym 2.0 [226]. However, due to its complexity

and high cost, it is challenging for practical application.

2. Classification&Recognition. Tactile representations learning focused on material classification work and multi-modal understanding. Method can be divided into 2 categories: Traditional Methods and LLMs&VLMs Methods.

Traditional Methods. Various traditional approaches have been employed to enhance tactile representation learning. Autoencoder frameworks have been instrumental in developing compact tactile data representations. Polic et al. [227] used a convolutional neural network autoencoder for dimensionality reduction of optical-based tactile sensor images. Gao et al. [228] created a supervised recurrent autoencoder to handle heterogeneous sensor datasets, while Cao et al. [229] created TacMAE used a masked autoencoder for incomplete tactile data. Zhang et al. [230] introduced MAE4GM, a multimodal autoencoder integrating visuo-tactile data. Since tactile acts as a complement to other modes, Joint Training methods are used to fuse multiple modalities. Yuan et al. [231] trained CNNs with modalities included depth, vision, and tactile data. Similarly, Lee et al. [232] used a variational Bayesian approach for modalities like force sensors series and end-effector metrics. For better learning representation, Self-supervised methods like contrastive learning are also a key technique in binding modalities together. Researches differ in contrastive methods. Lin et al. [233] simply paired tactile inputs with multiple visual inputs and Yang et al. [234] employed visuo-tactile contrastive multiview features. Kerr et al. [216] used InfoNCE loss inspired by CLIP and Guzey et al. [235] used BYOL. These traditional methods have established a solid foundation for tactile representation learning.

LLMs&VLMs Methods. Large Language Models (LLM) and Vision-Language Models (VLM) shows the amazing understanding of cross-modal interactions and strong zero-shot performance recently. Recent works from Yang et al. [190], Fu et al. [219] and Yu et al. [236] encoded and aligned tactile data with visual and language modalities by contrastive pretrained method. Then a large language models like LLaMA would be applied, using fine-tune method to fit tasks like tactile description. The advent of LLM and VLM techniques has further advanced the field, enabling more comprehensive and robust cross-modal tactile representations.

3. 3D Reconstruction. Suresh et al. [237] incrementally reconstructed the local shape of 3D household objects from a



Fig. 11. The top gray box displays the scenes an agent observes during exploration. Below are various types of question answering tasks. Except for the task of answering questions based on episodic memory, the agent ceases exploration once it has gathered sufficient information to answer the question.

sequence of tactile images and a noisy depth map, representing the 3D shape as a signed distance function sampled from a Gaussian process and reformulated it as probabilistic inference on a spatial graph, providing a robust method for local shape reconstruction. Smith et al. [238] presented an effective chart-based approach. It took grasping parameters, a group of touch readings and an RGB image of the object as input and encoded them to charts, using a neural network to reconstruct 3D shape estimate. Then, the grop updated them into active touch learned models with sliding sensors [239]. Comi et al. [240] employed deep learning for 3D shape reconstruction solely based on tactile input. They used a CNN to map tactile images into local meshes and a DeepSDF-based model to predict the complete 3D shape.

4) Difficulties: 1) Disadvantages of sensors with different principles: traditional sensors provides simple, limited and low-dimension data, posing challenges for multi-modal learning. Meanwhile, vision-based sensors and electronic skins, although offering high accuracy, are cost-prohibitive. And vision-based sensors are unable to provide temperature information. 2) Difficulties in data acquisition: tactile datasets are rare and heterogeneous, lacking the standardized, extensive repositories found in fields like vision. Additionally, data collection is difficult. It is difficult to gather both tactile and visual information together, although some efforts have been made in simplified collection devices. 3) Difficulties in inconsistent standards: there are a variety of sensors on the market, with inconsistent standards and principles. Even with similar imaging patterns, vision-based tactile sensors' design and calibration still results in a significant domain gap. Unlike

standardized formats for visual and auditory data, tactile data formats vary widely among sensor manufacturers, which makes it difficult for large-scale learning on data collected from heterogeneous sensors, limiting the usefulness of publicly available tactile datasets.

V. EMBODIED INTERACTION

Embodied interaction tasks refer to scenarios where agents interact with humans and environment in a physical or simulated space. The typical embodied interaction tasks are Embodied Question Answering (EQA) and embodied grasping.

A. Embodied Question Answering

For Embodied Question Answering (EQA) task, the agent needs to explore the environment from a first-person perspective to gather information necessary to answer the given questions. An agent with autonomous exploration and decision-making capabilities must not only consider which actions to take to explore the environment but also determine when to stop exploring to answer questions. Existing works focus on different types of questions, some of which are shown in Fig. 11. In this section, we first introduce the existing datasets and then discuss related methods.

1) Datasets: Conducting robot experiments in real environments is often constrained by scenarios and robot hardware. As virtual experimental platforms, simulators offer suitable environmental conditions for constructing embodied question answering datasets. Training and testing models on datasets created in simulators significantly reduce experimental costs

Dataset	Year	Type	Data Sources	Simulator	Query Creation	Answer	Size
EQA v1 [241]	2018	Active EQA	SUNCG	Simulator based on MINOS	Rule-Based	open-ended	5,000+
MT-EQA [242]	2019	Active EQA	SUNCG		Rule-Based	open-ended	19,000+
MP3D-EQA [243]	2019	Active EQA	MP3D		Rule-Based	open-ended	1,136
IQUAD V1 [244]	2018	Interactive EQA	-		AI2THOR	multi-choice	75,000+
VideoNavQA [245]	2019	Episodic Memory EQA	SUNCG		House3D	Rule-Based	101,000
K-EQA [246]	2023	Active EQA	-		AI2THOR	Rule-Based	60,000
OpenEQA [247]	2024	Active EQA, Episodic Memory EQA	ScanNet, HM3D		Habitat	Manual	open-ended
HM-EQA [248]	2024	Active EQA	HM3D		Habitat	VLM	multi-choice
S-EQA [249]	2024	Active EQA	-		VirtualHome	LLM	binary

TABLE IX
COMPARISON OF DIFFERENT EQA DATASETS.

and enhance the success rate of deploying models on real machines. We briefly introduce nine embodied question answering datasets, which are summarized in Table IX.

EQA v1 [241] is the first dataset designed for embodied question answering. Built on synthetic 3D indoor scenes from the SUNCG dataset [99] within the House3D [250] simulator, EQA v1 comprises four types of questions: location, color, color_room, and preposition. It features over 5,000 questions distributed across more than 750 environments. The questions are constructed via functional program execution, using templates to select and combine basic operations.

Similar to EQA v1, **MT-EQA** [242] is built in House3D using SUNCG by executing functional programs consisting of some basic operations. However, it further extends the single-object question answering task to a multi-object setting. Six types of questions are designed, involving the comparison of color, distance, and size between multiple objects. The dataset contains 19,287 questions in 588 environments.

MP3D-EQA [243] is built on a simulator developed based on MINOS [251] using the Matterport3D dataset [252], expanding the question-answering task to a realistic 3D environment. Referring to EQA v1, MP3D-EQA utilizes three types of templates: location, color, and color_room, generating a total of 1,136 questions in 83 home environments.

IQUAD V1 [244] is built upon AI2-THOR and consists of three types of questions: existence, counting, and spatial relationships. It uses a set of templates written down a priori to generate more than 75,000 multiple choice questions, each accompanied by a unique scene configuration. Unlike other datasets, answering IQUAD V1 questions requires the agent to have a good understanding of affordances and interact with the dynamic environment.

VideoNavQA [245] decouples the visual reasoning from the navigation aspect of the EQA problem. In this task, the agent accesses videos corresponding to exploration trajectories with sufficient information to answer questions. Still referring to EQA v1, VideoNavQA generates questions according to functional, template-style representation. It also renders shortest trajectories to simulate near-optimal navigation paths, creating videos corresponding to what an agent would see while exploring the environment. VideoNavQA generates about 101,000 pairs of videos and questions in the House3D environment using SUNCG, covering 28 types of questions belonging to 8 categories such as existence, counting, and localization.

Unlike previous datasets that explicitly specify target objects in questions, **K-EQA** [246] features complex questions with logical clauses and knowledge-related phrases, requiring prior knowledge to answer. It is built in AI2Thor and includes

four types of questions: existence, counting, enumeration, and comparison. Each entity is mapped to a knowledge base and a knowledge graph is further constructed. In this work, the templates provided in IQA and MT-EQA are extended to a set of grammars. After specifying objects and logical relationships, knowledge graphs, scene graphs, etc. are introduced to generate questions and compute the ground truth answer. The resulting K-EQA dataset consists of 60,000 questions across 6000 different environment setups.

OpenEQA [247] is the first open-vocabulary dataset for EQA, supporting both episodic memory and active exploration cases. The episodic memory EQA (EM-EQA) tasks involve an agent developing an understanding of the environment from its episodic memory to answer questions, similar to VideoNavQA. In active EQA (A-EQA) tasks, the agent answers questions by taking exploratory actions to gather necessary information. Using ScanNet [253] and HM3D [254], human annotators constructed over 1,600 high-quality questions from more than 180 real world environments in Habitat.

Utilizing GPT4-V, **HM-EQA** [248] is constructed in the Habitat simulator using the Habitat-Matterport 3D dataset. It includes 500 questions across 267 different scenes, which can be roughly categorized into identification, counting, existence, status, and location. For consistency, each question in the dataset has four multiple choices.

S-EQA [249] leverages GPT-4 in VirtualHome for data generation and employs cosine similarity calculations to decide whether to retain the generated data, thereby enhancing dataset diversity. In S-EQA, answering questions requires the assessment of a collection of consensus objects and states to reach an existential “Yes/No” answer.

2) *Methods:* The embodied question answering task mainly involves navigation and question-answering subtasks, with implementation methods broadly categorized into two types: neural network-based and LLMs/VLMs-based.

Neural Network Methods. In early work, researchers mainly addressed the embodied question answering task by building deep neural networks. They trained and fine-tuned these models using techniques such as imitation learning and reinforcement learning to improve performance.

The EQA task was first proposed by Das et al. [241]. In their work, the agent consists of four main modules: vision, language, navigation, and answering. These modules are primarily constructed using traditional neural building blocks - Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). These modules undergo training in two phases. Initially, the navigation and response modules are trained independently on automatically generated expert navigation demonstrations using imitation or supervised

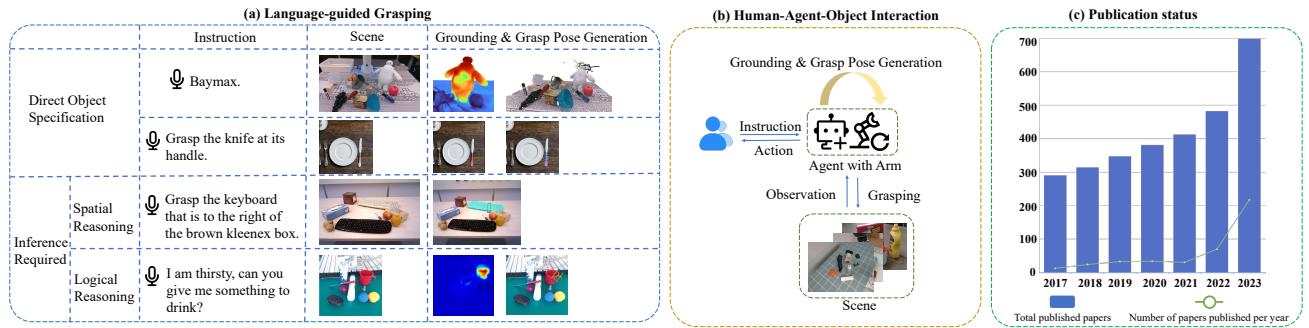


Fig. 12. The overview of the embodied grasping task. (a) demonstrates examples of language-guided grasping for different types of tasks, (b) provides an overview of human-agent-object interaction, (c) shows Google Scholar search results for topics of “Language-guided Grasping”.

learning. Subsequently, in the second phase, the navigation architecture is fine-tuned using policy gradients. Some subsequent works [255], [256] retain modules like the question answering module proposed by Das et al. [241] and improve the model. Additionally, Wu et al. [256] proposed integrating the navigation and QA modules into a unified SGD training pipeline for joint training, thereby avoiding employing deep reinforcement learning to simultaneously train the separately trained navigation and question answering modules.

There are also some works that attempt to increase the complexity and completeness of question answering tasks. From the perspective of task singularity, several works [242], [257] expand the task to include multiple objectives and multi-agent, respectively, making it necessary for the model to store and integrate the information obtained by the agent’s exploration through methods such as feature extraction and scene reconstruction. Taking into account the interaction between the agent and the dynamic environment, Gordon et al. [244] introduce the Hierarchical Interactive Memory Network. Control alternates between the planner, responsible for task selection, and the low level controllers, which carry out task execution. During this process, an Egocentric Spatial GRU (esGRU) is utilized to store spatial memory, enabling the agent to navigate and provide answers. There is also a limitation in previous works where agents are unable to use external knowledge to answer complex questions and lack knowledge of the explored parts of the scene. To address this, Tan et al. [246] propose a framework that leverages the neural program synthesis method and the table converted from the knowledge and 3D scene graphs, allowing the action planner to access object-related information. Additionally, an approach based on Monte Carlo Tree Search (MCTS) is used to determine the next location for the agent to move to.

LLMs/VLMs Methods. In recent years, large language models (LLMs) and visual language models (VLMs) have made continuous progress and demonstrated outstanding capabilities across various fields. Consequently, researchers attempt to apply these models to solve embodied question answering tasks without any additional fine-tuning.

Majumdar et al. [247] explore using LLMs and VLMs for episodic memory EQA (EM-EQA) task and Active EQA (A-EQA) task. For EM-EQA task, they consider Blind LLMs, Socratic LLMs with language descriptions of the episodic memory, Socratic LLMs with descriptions of the constructed scene graph , and VLMs processing multiple scene frames.

The A-EQA task extends EM-EQA methods with frontier-based exploration (FBE) [258] for problem-independent environment exploration. Some other works [248], [259] also employ frontier-based exploration method to identify areas for subsequent exploration and to build semantic maps. They end the exploration early utilizing conformal prediction or image-text matching to avoid over-exploration. Patel et al. [260] emphasize the question answering aspect of the task. They leverage multiple LLM-based agents to explore the environment and enable them to independently answer questions with “yes” or “no” answers. These individual responses are utilized to train a Central Answer Model, responsible for aggregating the responses and generating robust answers.

3) Metrics: Researchers primarily assess the model’s performance based on two key aspects: navigation and question answering. In the navigation aspect, many researchers adhere to the approach introduced by Das et al [241]. and utilize indicators like the distance to the target object upon completion of navigation (d_T), the change in distance to target from initial to final position (d_Δ) and the smallest distance to the target at any point in the episode (d_{min}) to evaluate the performance of the model. They are tested at 10, 30, or 50 actions away from the target. There are also works that measure it based on indicators such as trajectory length, intersection-over-union score for target object (IoU), etc. Regarding question answering, the evaluation mainly involves mean rank (MR) of the ground-truth answer in the answer list and accuracy of the answers. Recently, Majumdar et al. [247] introduce the concept of an aggregate LLM-based correctness metric (LLM-Match) to evaluate the accuracy of open-vocabulary answers. Additionally, they assess efficiency by incorporating the normalized length of the agent’s path as a weight for the correctness metric.

4) Limitations: 1) Dataset: Constructing datasets requires substantial manpower and resources. Additionally, there are still few large-scale datasets, and the metrics for evaluating model performance vary across different datasets, complicating the testing and comparison of performance, 2) Model: Despite the advancements brought by LLMs, the performance of these models still lags significantly behind human levels. Future work may focus more on effectively storing environmental information explored by agents and guiding them to plan actions based on environmental memory and questions, while also enhancing the interpretability of their actions.

Dataset	Year	Type	Modality	Grasp Label	Gripper finger	Objects	Grasps	Scenes	Language
Cornell [265]	2011	Real	RGB-D	Rect.	2	240	8K	Single	✗
Jacquard [264]	2018	Sim	RGB-D	Rect.	2	11K	1.1M	Single	✗
6-DOF GraspNet [269]	2019	Sim	3D	6D	2	206	7.07M	Single	✗
ACRONYM [268]	2021	Sim	3D	6D	2	8872	17.7M	Multi	✗
MultiGripperGrasp [270]	2024	Sim	3D	-	2-5	345	30.4M	Single	✗
OCID-Grasp [263]	2021	Real	RGB-D	Rect.	2	89	75K	Multi	✗
OCID-VLG [271]	2023	Real	RGB-D,3D	Rect.	2	89	75K	Multi	✓
ReasoningGrasp [272]	2024	Real	RGB-D	6D	2	64	99.3M	Multi	✓
CapGrasp [274]	2024	Sim	3D	-	5	1.8K	50K	Single	✓

TABLE X
EMBODIED GRASPING DATASETS.

B. Embodied Grasping

Embodied interaction, in addition to engaging in question-answering interactions with humans, can also involve performing operations based on human instructions, such as grasping and placing objects, thereby completing interactions among the robots, humans and objects. Embodied grasping requires comprehensive semantic understanding, scene perception, decision-making, and robust control planning. The embodied grasping methods integrate traditional robotic kinematic grasping with large models such as large language models (LLMs) [261] and vision-language foundation models [15], which enables agents to perform grasping tasks under multi-sensory perceptions, including visual active perception, language understanding and reasoning. Figure 12 (b) illustrates an overview of human-agent-object interaction, where the agent accomplishes embodied grasping tasks.

1) *Gripper*: The current research focus in grasping technology is on two-finger parallel grippers and five-finger dexterous hands. For two-finger parallel grippers, grasping postures are generally categorized into two types: 4-DOF and 6-DOF [262]. The 4-DOF grasp synthesis [263]–[265] defines the grasp using a three-dimensional position and a top-down hand orientation (yaw), commonly referred to as “top-down grasping”. In contrast, 6-DOF grasp synthesis [266]–[268] defines the grasp posture through a six-dimensional position and orientation. For five-finger dexterous hand grippers, the ShadowHand, a widely used five-finger robotic dexterous hand, features 26 degrees of freedom (DOF). This high dimensionality significantly increases the complexity of generating effective grasp postures and planning execution trajectories.

2) *Datasets*: Recently, a substantial number of grasping datasets [264], [265], [268]–[270] have been generated. These datasets typically contain annotated grasping data based on images (RGB, depth), point clouds, or 3D scenes. With the advent of multimodal large models and the application of foundational language models to robotic grasping, there is an urgent need for datasets that include linguistic text. Consequently, existing datasets have been extended or reconstructed to create semantic-grasping datasets [271]–[274]. These datasets are instrumental in studying grasping models grounded in language, enabling agents to develop a broad understanding of semantics.

Traditional grasping datasets encompass data for both single objects [265] and cluttered scenes [263], providing stable grasp annotations (4-DOF or 6-DOF) that conform to kinematics for each object. These data can be collected from real desktop environments [265], typically including RGB, depth, and point cloud data, or from virtual environments [268],

which include image data, point clouds, or scene models. While these datasets are useful for grasping models, they lack semantic information. To bridge this gap, these datasets have been augmented or extended with semantic expressions [271], [275], thereby linking language, vision, and grasping. By incorporating semantic information, agents can better understand and execute grasping tasks. This enhancement allows for the development of more sophisticated and semantically aware grasping models, facilitating more intuitive and effective interaction with the environment. Table X presents the datasets described above, including traditional grasping datasets and language-based grasping datasets.

3) *Language-guided grasping*: The concept of Language-guided grasping [271], [272], [275], which has evolved from this integration, combines MLMs to provide agents with the capability of semantic scene reasoning. This allows the agent to execute grasping operations based on implicit or explicit human instructions. Figure 12 (c) illustrates the publication trends in recent years on the topic of language-guided grasping. With the advancement of LLMs, researchers have shown increasing interest in this topic. Currently, grasping research is increasingly focused on open-world scenarios, emphasizing the open-set generalization [276] methods. By leveraging the generalization capabilities of MLMs, robots can perform grasping tasks in open-world environments with greater intelligence and efficiency.

In language-guided grasping, semantics can originate from explicit instructions [276], [277] and implicit instructions [272], [274]. Explicit instructions clearly specify the category of the object to be grasped, such as a banana or an apple. Implicit instructions, however, require reasoning to identify the object or a part of the object to be grasped, involving spatial reasoning and logical reasoning.

Spatial reasoning [271] refers to instructions that may include the spatial relationship of the object or part to be grasped, necessitating the inference of grasping posture based on the spatial relationships of objects within the scene. For example, “Grasp the keyboard that is to the right of the brown kleenex box” involves understanding and inferring the spatial arrangement of objects.

Logical reasoning [272], on the other hand, involves instructions that may contain logical relationships requiring inference to discern human intent and subsequently grasp the target. For instance, “I am thirsty, can you give me something to drink?” would prompt the agent to potentially hand over a glass of water or a bottle of a beverage. The agent must ensure that the liquid does not spill during the handover, thus generating a reasonable grasping posture.

In both cases, the integration of semantic understanding

with spatial and logical reasoning enables the agent to perform complex grasping tasks effectively and accurately. Figure 12 (a) depicts instances of various types of language-guided grasping tasks described above.

4) End-to-End Approaches: CLIPORT [275] is a language-conditioned imitation learning agent that combines the vision-language pre-trained model CLIP with the Transporter Net to create an end-to-end dual-stream architecture for semantic understanding and grasp generation. It is trained using a large number of expert demonstration data collected from virtual environments, enabling the agent to perform semantically guided grasping. Based on the OCID dataset, CROG [271] proposes a vision-language-grasping dataset and introduces a competitive end-to-end baseline. It leverages CLIP's visual foundation capabilities to learn grasp synthesis directly from image-text pairs. Reasoning Grasping [272] introduces the first reasoning grasping benchmark dataset based on the GraspNet-1 Billion dataset and proposes an end-to-end reasoning grasping model. The model integrates multimodal large language models (LLMs) with vision-based robotic grasping frameworks to generate grasps based on semantics and vision. SemGrasp [274] is a method for semantic-based grasp generation that incorporates semantic information into grasp representations to generate dexterous hand grasp postures. It introduces a discrete representation aligning grasp space with semantic space, enabling the generation of grasp postures according to language instructions. To facilitate training, a large-scale grasp-text alignment dataset CapGrasp is proposed.

5) Modular Approaches: F3RM [276] seeks to elevate CLIP's text-image priors into 3D space, using extracted features for language localization followed by grasp generation. It combines precise 3D geometry with rich semantics from 2D foundational models, utilizing features extracted from CLIP to specify objects for manipulation through free-text natural language. It demonstrates the ability to generalize to unseen expressions and new object categories. GaussianGrasper [277] utilizes a 3D Gaussian field to achieve language-guided grasping tasks. The proposed methodology begins with the construction of a 3D Gaussian field, followed by feature distillation. Subsequently, language-based localization is performed using the extracted features. Finally, grasp pose generation is carried out based on a SOTA pre-trained grasping network [278]. It integrates open-vocabulary semantics with precise geometry, enabling grasping based on language instructions.

These approaches advance the field of language-guided grasping by leveraging both end-to-end and modular frameworks, thereby enhancing the ability of robotic agents to understand and execute complex grasping tasks through natural language instructions. Embodied grasping allows robots to interact with objects, thus improving their intelligence and utility in home services and industrial manufacturing. However, existing embodied grasping methods have limitations, such as reliance on extensive data and poor generalization to unseen data. Future research will focus on improving the generality of agents, enabling robots to understand more complex semantics, grasp a wider variety of unseen objects, and complete intricate grasping tasks.

VI. EMBODIED AGENT

An agent is defined as an autonomous entity capable of perceiving its environment and acting to achieve specific objectives. Initially, Symbolic Agents, rooted in symbolic reasoning, and Reactive Agents, known for their rapid responsiveness, were widely utilized. However, these agents were limited in handling complex strategies under uncertainty. Learning-based agents were subsequently developed to mitigate this limitation, yet they remained inadequate for large-scale real-world problems. Recent advancements in MLMs have further expanded the application of agents to practical scenarios. When these MLM-based agents are embodied in physical entities, they can effectively transfer their problem-solving capabilities from virtual space to the physical world, thereby becoming Embodied Agents [279].

To enable embodied agents to operate in the information-rich and complex real world, the Embodied Multimodal Foundation Model has been developed to provide these agents with multimodal perception and reasoning capabilities. To complete a task, embodied agents typically involves the following process: 1) decomposing the abstract and complex task into specific subtasks, which is referred to as high-level Embodied Task Planning. 2) gradually implementing these subtasks by effectively utilizing Embodied Perception and Embodied Interaction models or leveraging the Foundation Model's policy function, named low-level Embodied Action Planning. It is worth noting that task planning involves thinking before acting, and is therefore typically considered in cyber space. In contrast, action planning must account for effective interaction with the environment and feedback on this information to the task planner to adjust task planning. Thus, it is crucial for embodied agents to align and generalize their abilities from the cyber space to the physical world.

A. Embodied Multimodal Foundation Model

Embodied agents are required to recognize their environment visually, understand instructions audibly, and comprehend their own state to enable complex interactions and operations. This demands a model that integrates multiple sensory modalities and natural language processing capabilities to enhance the agent's understanding and decision-making by synthesizing diverse data types. Thus, the Embodied Multimodal Foundation Model is emerging. Google DeepMind initiated research in the Robotics Foundation Model field eight years ago, continually exploring ways to scale models and data more effectively. Their findings revealed that leveraging foundation models and large, diverse datasets is the optimal strategy. They developed a series of works based on the Robotic Transformer (RT) [12], offering substantial insights for future research on embodied agents.

Significant progress has been made in foundational robotics models, evolving from the initial approach in SayCan [280], which used three separate models for planning, affordance, and low-level policy. Q-Transformer [281] later unified affordance and low-level policy, and PaLM-E [282] integrated planning and affordance. Then, RT-2 [283] achieved a breakthrough by consolidating all three functions into a single model, enabling

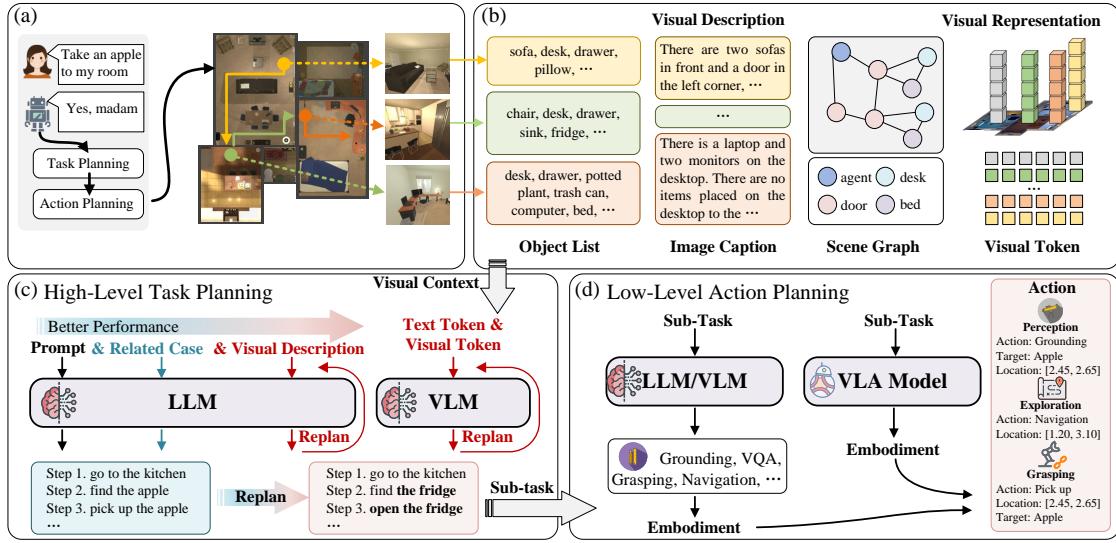


Fig. 13. The overall architecture of the embodied agent. It consists of the embodied multimodal foundation model, visual perception module, high-level task planning module, and low-level action planning module.

joint scaling and positive transfer. This represents a substantial advancement in robotics foundational models. RT-2 introduced the Vision-Language-Action (VLA) model, featuring “chain-of-thought” reasoning abilities that enable multi-step semantic reasoning, such as selecting alternative tools or beverages in various contexts. Ultimately, RT-H [4] achieved an end-to-end robot transformer with action hierarchies, to reason about the task planning at a fine-grained level.

To address the generalization limitations of embodied models, Google collaborated with 33 leading academic institutions to create the comprehensive Open X-Embodiment dataset [284], integrating 22 diverse data types. Using this dataset, they trained the universal large model RT-X. The diverse, cross-entity training data enabled RT-1 and RT-2 to achieve superior performance, demonstrating better generalization and new functionalities compared to models trained on domain-specific data. This has also promoted the participation of more open-source VLMs in the robotics community, such as EmbodiedGPT [285] based on LLaVA and RoboFlamingo [286] based on Flamingo. Although Open X-Embodiment provides a vast array of datasets, constructing datasets remains a challenge given the rapid evolution of embodied robotic platforms. To address this issue, AutoRT [287] created a system for deploying robots in new environments to collect training data, leveraging LLMs to enhance learning capabilities through more comprehensive and diverse data.

Additionally, transformer-based architectures face inefficiency problems, especially since embodied models require long contexts that include information from vision, language, and embodied states, as well as memory related to the currently executed tasks. For instance, RT-2, despite its strong performance, has an inference frequency of only 1-3Hz. Several efforts are being made to improve this, such as deploying models on the edge through quantization and distillation, and using the Mixture of Experts (MoE) architecture to utilize only a subset of parameters during inference, resulting in faster inference speeds compared to dense models with the same number of parameters. Moreover, SARA-RT [288] employs

a novel model fine-tuning method called “up-training,” which converts quadratic computational complexity into simple linear complexity, significantly enhancing model efficiency. This makes RT faster and more streamlined, with the potential for large-scale adoption of RT technology. In addition to RT, the Mamba architecture is used for tasks requiring longer sequences. RoboMamba [289] employs an efficient fine-tuning strategy called Policy Head, which masters various operational skills with minimal fine-tuning parameters (0.1% of the model) and time (20 minutes). Furthermore, its inference speed is seven times faster than existing robotic MLMs.

Due to RT being based on generative models, it demonstrates significant advantages in understanding abstract tasks and high-level task planning, but it has shortcomings in low-level action planning. One issue is that generative models cannot precisely generate control action parameters, and another is the gap between high-level task planning and low-level action planning, which prevents agents from effectively replanning. To address this, Google proposed RT-Trajectory [290], which can automatically add robot trajectories, providing low-level, practical visual cues for the model to learn robot control strategies and helping robots generalize better. These technologies enable robots to make decisions faster, better understand their environments, and more effectively guide themselves in completing tasks. Moreover, building on the RT-2 framework, the Robot Transformer with Action Hierarchies (RT-H) introduced a hierarchical action framework, linking high-level task descriptions with low-level robotic motions through intermediate linguistic actions [4]. This innovation improved cross-task data sharing and enhanced task performance by 15%. RT-H also exhibits greater adaptability and generalization in dynamic environments, excelling in complex multi-task scenarios. Furthermore, the emergent capabilities of VLA models are currently confined to high-level planning and affordance tasks related to VLMs. They cannot exhibit new skills in low-level physical interactions and are limited by the skill categories in their datasets. Physical actions often exhibit clumsiness, such as unstable gripping or inaccurate placement.

Future efforts should aim to incorporate reinforcement learning into the training framework of large models to enhance generalization. This would enable VLA models to autonomously learn and optimize low-level physical interaction strategies in real-world environments, resulting in more dexterous and precise execution of various physical actions.

B. Embodied Task Planning

As previously discussed, a task “*put an apple on a plate*”, the task planner will divide it into sub-tasks “*find the apple*, *pick the apple*”, “*find the plate*”, “*put down the apple*”. Since how to find (navigation task) or pick/put down actions (grasping task) are not within the scope of task planning. These actions are typically predefined within simulators or executed in real-world scenarios using pre-trained policy models, such as using CLIPort [275] for grasping tasks.

Traditional embodied task planning methods are often based on explicit rules and logical reasoning. For example, symbolic planning algorithms such as STRIPS [291] and PDDL [292], and search algorithms like MCTS [293] and A* [294], are used to generate plans. However, these methods often rely on predefined rules, constraints, and heuristics that are rigid and may not adapt well to dynamic or unforeseen changes in the environment. With the popularity of LLMs trained on large-scale data, many researchers have recently attempted to use LLMs for planning or to combine traditional methods with LLMs, leveraging the rich world knowledge embedded within them for reasoning and planning without the need for handcrafted definitions, greatly enhancing the model’s generalization capabilities.

1) Planning utilizing the Emergent Capabilities of LLMs:

Before the scale-up of natural language models, task planners were similarly implemented by training models like BERT on embodied instruction datasets such as Alfred [295] and Alfworld [296], as demonstrated by FILM [297]. However, this approach was limited by the examples in the training set and could not effectively align with the physical world. Nowadays, thanks to the emergent capabilities of large language models (LLMs), LLMs can decompose abstract tasks using their internal world knowledge and chain-of-thought reasoning, similar to how humans reason through task completion steps before acting. For example, Translated LM [298] and Inner Monologue [299] can break down complex tasks into manageable steps and devise solutions using their internal logic and knowledge systems without additional training.

To increase the success rate of these solutions, some methods provide more reference examples as context, such as pre-including a successful plan in the prompt [300]. The semantic relevance of these examples also affects task planning accuracy [301]. Therefore, methods like LLM-Planner have been developed to retrieve the most appropriate examples as context using KNN to find task-type similar and semantically relevant examples [302]. Additionally, some approaches abstract past successful examples into a series of skills stored in a memory bank to consider during inference and improve planning success rates [303]–[305]. Interestingly, improving chain-of-thought (CoT) reasoning [306] is also a viable approach. ReAct [307] incorporates CoT reasoning with plan

generation, providing more logical action generation. And some works utilize code as the reasoning medium instead of natural language. The Chain of Code method is particularly suitable for embodied agents in reasoning and executing tasks, where task planning is generated as code based on the available API library [308]–[310]. Furthermore, multi-turn reasoning can effectively correct potential hallucinations in task planning, a focus of many LLM-based agent studies. For instance, Socratic Models [311] and Socratic Planner [312] use Socratic questioning to derive reliable planning.

However, if LLM is considered as the plan generator since LLM’s plan generation is based on token probability distribution rather than logical inference, it cannot ensure that the plans it generates are logically correct. Therefore, some works consider LLMs as world models rather than plan generators, using MCTS [293] for plan sequence search [313]–[315]. Another line of work considers LLMs as instruction translators, leveraging their powerful semantic understanding capabilities to translate plans into planning-specific languages such as PDDL, than leveraging traditional AI planners for planning [316]–[319].

During task planning, potential failures that may occur during execution must be considered. These failures often result from the planner not fully accounting for the complexity of the real environment and the difficulty of task execution [299], [302]. Multi-agent collaboration framework ReAd [320] is proposed for efficient self-refinement of plans. Due to a lack of visual information, planned subtasks may deviate from the actual scenario, leading to task failure. Therefore, integrating visual information into planning or replanning during execution is necessary. This approach can significantly enhance the accuracy and feasibility of task planning, better addressing the challenges of real-world environments.

2) Planning utilizing the visual information from embodied perception model:

Based on the above discussion, it is particularly important to further integrate visual information into task planning (or replanning). In this process, object labels, locations, or descriptions provided by visual input can offer critical references for task decomposition and execution by large language models (LLMs). For instance, through visual information, LLMs can more accurately identify target objects and obstacles in the current environment, thereby optimizing task steps or modifying subtask objectives. Some works use an object detector to query the objects present in the environment during task execution and feed this information back to the LLM, allowing it to modify unreasonable steps in the current plan [302], [311], [321]. RoboGPT considers the different names of similar objects within the same task, further improving the feasibility of replanning [322]. However, the information provided by labels is still too limited. Can further scene information be provided? SayPlan [323] proposes using hierarchical 3D scene graphs to represent the environment, effectively mitigating the challenges of task planning in large, multi-floor, and multi-room settings. Similarly, ConceptGraphs [324] also adopts 3D scene graphs to provide environmental information to LLMs. Compared to SayPlan, it offers more detailed open-world object detection and presents task planning in a code-based format, which is more efficient

and better suited to the demands of complex tasks.

However, limited visual information may lead to insufficient environmental understanding by the agent. Although visual input can provide important environmental cues, its limitation lies in the inability to capture the complexity and dynamic changes of the environment fully. Without comprehensive visual information, the agent may misinterpret the environmental conditions, resulting in task failure. For instance, if a towel is locked in the bathroom cabinet, the agent may repeatedly search the bathroom without realizing this possibility [322]. Therefore, it is necessary to develop more robust algorithms that integrate multiple sensory data to compensate for the shortcomings of visual information. By incorporating multimodal perception technologies, such as vision, touch, and hearing, the agent's understanding of the environment can be enhanced. Additionally, leveraging historical data and contextual reasoning can assist the agent in making reasonable judgments and decisions even with limited visual information. This planning approach, combining multimodal fusion and contextual reasoning, not only increases the success rate of task execution but also offers new perspectives for the further development of embodied AI.

3) Planning utilizing the VLMs: Compared to converting environmental information into text using external visual models, VLM models can capture visual details in latent space, particularly contextual information that is difficult to represent with object labels, as per Lecun's insights on world models. VLMs can discern rules underlying visual phenomena; for instance, even if a towel is not visible in the environment, it can be inferred that the towel might be stored in a cabinet. This process essentially demonstrates how abstract visual features and structured textual features can be more effectively aligned in latent space.

In the EmbodiedGPT framework, the Embodied-Former module aligns embodied, visual, and textual information, effectively considering the agent's state and environmental information during task planning [325]. Similarly, the EIF-Unknow model utilizes Semantic Feature Maps extracted from Voxel Features as visual tokens, which are input along with text tokens into a trained LLaVA model for task planning [326]. Furthermore, embodied multimodal foundation models, or VLA models, have been extensively trained with large datasets in studies like the RT series [12], [283] and PaLM-E [282] to achieve alignment of visual and textual features in embodied scenarios. Additionally, innovative research such as Matcha [327] explores the integration of large language models (LLMs) with multimodal perception modules (e.g., weight, touch, sound) to enhance robot planning capabilities. For example, when executing the task "pick up a plastic block," the robot can assess its weight by lifting it, determine if the sound it makes when tapped matches expected plastic sounds, or use tactile feedback to sense the block's hardness or softness. Moreover, the VLP [328] model enhances planning by considering historical information and predicting future visual states. Once an LLM generates an action, the video model can simulate multiple potential video representations for each action. These video models then serve as heuristic functions to evaluate the proximity of each action

to the goal, thereby improving planning effectiveness.

However, task planning is only the first step for an agent in completing an instruction task; subsequent action planning determines whether the task can be accomplished. In the experiments from RoboGPT [322], the accuracy of task planning reached 96%, but the overall task completion rate was only 60%, limited by the performance of the low-level planner. Therefore, whether an embodied agent can transition from the cyber space of "imagining how tasks are completed" to the physical world of "interacting with the environment and completing tasks" hinges on effective action planning.

C. Embodied Action Planning

Section VI-B discusses the definitions and differences between task planning and action planning. It is evident that action planning must address real-world uncertainties because the granularity of subtasks provided by task planning is insufficient to guide agents in efficient environmental interaction. Generally, agents can approach action planning in two ways: first, by using pre-trained embodied perception models and embodied intervention models as tools, incrementally completing the subtasks specified by task planning through APIs; second, by utilizing the VLA model's inherent capabilities to derive action planning. Furthermore, the results of the action planner's execution are fed back to the task planner to adjust and improve task planning.

1) Action utilizing APIs: A typical approach involves providing LLMs with the definitions and descriptions of various well-trained policy models as context, enabling them to understand these tools and determine how and when to invoke them for specific tasks [280], [302]. Additionally, by generating code, a series of more granular tools can be abstracted into a function library for invocation rather than directly passing the parameters needed for sub-tasks to navigation and grasping models [310]. Given the uncertainty of the environment, Reflexion can further adjust these tools during execution to achieve better generalization [329]. Optimizing these tools can enhance the robustness of the agent, and new tools may be required to complete unknown tasks. DEPS, under the premise of zero-shot learning, endows LLMs with various role settings to learn diverse skills while interacting with the environment. During subsequent interactions, LLMs can learn to select and combine these skills to develop new ones [330].

This hierarchical planning paradigm allows agents to focus more on high-level task planning and decision-making while delegating specific action execution to policy models, simplifying the agent's development process. Additionally, this modularization of task planners and action planners enables independent development, testing, and optimization, thereby enhancing system flexibility and maintainability. This approach allows agents to adapt to various tasks and environments by invoking different action planners and facilitating modifications to the action planner without significant changes to the agent's structure. However, invoking external policy models may introduce latency, particularly in real-time tasks, potentially affecting system response speed and efficiency. The most critical issue to address is that the agent's performance

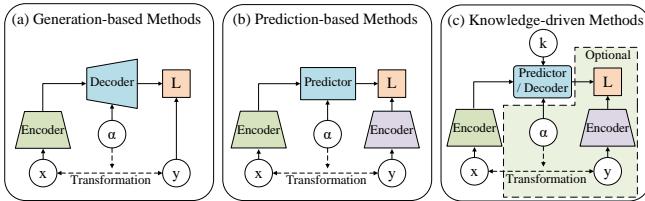


Fig. 14. Embodied world models can be roughly divided into three type. (a) **Generation-based Methods** train to learn the transformation relationship between the input space and the output space using an autoencoder framework. (b) **Prediction-based Methods** can be seen as a more general framework where a world model is trained in latent space. (c) **Knowledge-driven Methods** inject artificially constructed knowledge into the model, giving the model world knowledge to obtain output that meets the given knowledge constraints. Note that the components within the dashed line are optional.

is highly dependent on the quality of the policy model. If the policy model fails to solve the tasks effectively, the overall performance of the agent will be compromised.

2) *Action utilizing VLA model*: This paradigm leverages the capabilities of embodied multimodal foundation models for planning and executing actions, unlike the previous approach, where task planning and action execution are performed within the same system, reducing communication latency and improving system response speed and efficiency. In VLA models, the tight integration of perception, decision-making, and execution modules allows the system to handle complex tasks and adapt to changes in dynamic environments more efficiently. This integration also facilitates real-time feedback, enabling the agent to self-adjust strategies, thereby enhancing the robustness and adaptability of task execution [3], [285], [331]. However, this paradigm is undoubtedly more complex and costly, particularly when dealing with intricate or long-term tasks. Additionally, a key issue is that an action planner, without an embodied world model, cannot simulate physical laws using only the internal knowledge of an LLM. This limitation hinders the agent to accurately and effectively complete various tasks in the physical world, preventing the seamless transfer from cyber space to physical world.

VII. SIM-TO-REAL ADAPTATION

Sim-to-Real adaptation in Embodied AI refers to the process of transferring capabilities or behaviors learned in simulated environments (cyber space) to real-world scenarios (physical world). It involves validating and improving the effectiveness of algorithms, models, and control strategies developed in simulation to ensure they perform robustly and reliably in physical environments. To achieve sim-to-real adaptation, embodied world models, data collection and training methods, and embodied control algorithms are three essential components.

A. Embodied World Model

Sim-to-Real involves creating world models in simulation that closely resemble real-world environments, helping algorithms generalize better when transferred. The world model approach aims to build an end-to-end model that maps vision to action, or even anything to anything, by predicting the next state in a generative or predictive manner to make decisions. The biggest difference between such world models and VLA models is that VLA models are first trained on large-scale

internet datasets to achieve high-level emergent capabilities and then co-finetuned with real world robot data. In contrast, world models are trained from scratch on physical world data, gradually developing high-level capabilities as the amount of data increases. However, they remain low-level physical world models, somewhat akin to the mechanism of human neural reflex systems. This makes them more suitable for scenarios where both inputs and outputs are relatively structured, such as autonomous driving (input: vision, output: throttle, brake, steering wheel) or object sorting (input: vision, instructions, numerical sensors, output: grasping the target object and placing it in the target location). They are less suited for generalization to unstructured, complex embodied tasks.

Learning world models is promising of the physical simulation field. Compared to traditional simulation methods, it offers significant advantages, such as the ability to reason about interactions with incomplete information, meet real-time computation requirements, and improve prediction accuracy over time. The predictive capability of such world models is crucial, enabling robots to develop the physical intuition necessary to operate in the human world. As shown in Fig. 14, according to the learning pipeline of the world environment, they can be divided into Generation-based Methods, Prediction-based Methods and Knowledge-driven Methods. We briefly summarize the methods mentioned in Table XI.

1) *Generation-based Methods*: As the scale of models and data progressively increases, generative models have demonstrated the ability to understand and generate images (e.g., World Models [332]), videos (e.g., Sora [18], Pandora [333]), point clouds (e.g., 3D-VLA [334]) or other formats of data (e.g., DWM [335]) that conform to physical laws. This ability indicates that generative models can learn and internalize world knowledge. Specifically, after being exposed to vast amounts of data, generative models can not only capture the statistical properties of the data but also simulate the physical and causal relations of the real world through their intrinsic structures and mechanisms. Therefore, these generative models can be considered more than simple pattern recognition tools: they exhibit characteristics of world models. Consequently, the world knowledge embedded in generative models can be leveraged to enhance the performance of other models. By mining and utilizing the world knowledge represented in generative models, we can improve model generalization and robustness. This approach not only enhances the model's adaptability to new environments but also increases its predictive accuracy on unknown data [333], [334]. However, generative models also have certain limitations and drawbacks. For instance, when data distribution is significantly biased or training data is insufficient, generative models may produce inaccurate or distorted outputs. Additionally, the training process for these models typically requires substantial computational resources and time, and the models often lack interpretability, which complicates their practical application. Overall, while generative models have shown great potential in understanding and generating content that conforms to physical laws, several technical and practical challenges must be addressed for their effective application. These challenges include improving model efficiency, enhancing interpretability, and addressing

Type	Method	Years	Main tasks
Generation-based	World Models [332]	2018	Car Racing
	Sora [18]	2024	Video Generation
	Pandora [333]	2024	Real-time Controllable Video Generation
	3D-VLA [334]	2024	Embody Reasoning and Localization, Multimodal Goal Generation, Robot Planning
	DWM [335]	2024	D4RL Offline RL
Prediction-based	I-JEPA [17]	2023	Visual Representation Learning, Image Classification, Object Counting, Depth Prediction
	MC-JEPA [336]	2023	Visual Representation Learning, Optical Flow Estimation, Instance Segmentation, Video Segmentation
	A-JEPA [337]	2023	Audio Representation Learning, Audio and Speech Classification
	IWM [338]	2024	Visual Representation Learning, Image Classification, Image Segmentation
	iVideoGPT [339]	2024	Video Prediction, Visual Planning, Visual Model-based RL
	STP [340]	2024	Robotic Motor Control
Knowledge-driven	MuDreamer [341]	2024	DeepMind Visual Control Suite, Natural Background Setting
	Lionel et al. [342]	2023	Probabilistic Reasoning, Relational Reasoning, Perceptual and Physical Reasoning, Social Reasoning
	ElastoGen [343]	2024	4D Elastodynamics Generation
	Liu et al. [344]	2024	Single-image 3D Reconstruction
	Holodeck [72]	2024	3D Environments Generation
	LEGENT [345])	2024	3D Environments Generation

TABLE XI
SUMMARY OF THE EMBODIED WORLD METHODS DISCUSSED IN VII-A.

issues related to data bias. With ongoing research and development, generative models are expected to demonstrate even greater value and potential in future applications.

2) *Prediction-based Methods:* The prediction-based world model predicts and understands the environment by constructing and utilizing internal representations. By reconstructing corresponding features in the latent space based on provided conditions, it captures deeper semantics and associated world knowledge. This model maps input information to a latent space and operates within that space to extract and utilize high-level semantic information, thereby enabling the robots to perceive the essential representation of the world environment (e.g., I-JEPA [17], MC-JEPA [336], A-JEPA [337], Point-JEPA [346], IWM [338]) and more accurately perform embodied downstream tasks (e.g., iVideoGPT [339]), STP [340], MuDreamer [341]). Compared to pixel-level information, features in the latent space can abstract and decouple various forms of knowledge, allowing the model to handle complex tasks and scenes more effectively and improve its generalization capability [347]. For instance, in spatiotemporal modeling, the world model needs to predict the post-interaction state of an object based on its current state and the nature of the interaction, combining this information with its internal knowledge. Specifically, an embodied world model generates dynamic predictions of the environment by integrating perceptual information and prior knowledge. This approach relies not only on sensory data but also on inherent world knowledge to infer and predict environmental changes, thereby producing more accurate spatiotemporal predictions [339]–[341]. This process considers both the current state of objects and their historical data and contextual information.

Similarly, leveraging the world knowledge embedded in its representations can further enhance the model's perception and robustness [17], [336], [338], [348]. By operating in latent space, it is expected that robots can maintain high performance in different environments at a lower cost [341]. The key to this approach lies in abstract processing and knowledge decoupling, enabling efficient adaptation to complex situations. However, such models may exhibit limitations and instability when dealing with previously unseen environments and conditions. Additionally, the world knowledge decoupled in the latent space may have interpretability issues.

3) *Knowledge-driven Methods:* Knowledge-driven world models inject artificially constructed knowledge into the mod-

els, endowing them with world knowledge. This method has shown broad application potential in the field of embodied AI. For example, in the real2sim2real approach [349], real-world knowledge is used to build physics-compliant simulators, which are then used to train robots, enhancing model robustness and generalization capabilities. Additionally, artificially constructing common sense or physics-compliant knowledge and applying them to generative models or simulators is a common strategy (e.g., ElastoGen [343], Liu et al. [344], Lionel et al. [342]). This approach imposes more physically accurate constraints on the model, enhancing its reliability and interpretability in generation tasks. These constraints ensure the model's knowledge is both accurate and consistent, reducing uncertainty during training and application. Some approaches combine artificially created physical rules with large language models (LLMs) or large multimodal models (LMMs). By leveraging the commonsense capabilities of LLMs and LMMs, these approaches (e.g., Holodeck [72], LEGENT [345]) generate diverse and semantically rich scenes through automatic spatial layout optimization. This greatly advances the development of general-purpose embodied agents by training them in novel and diverse environments.

B. Data Collection and Training

For sim-to-real adaptation, the high-quality data is important. Traditional data collection methods involve expensive equipment, precise operations, and are time-consuming and labor-intensive, often lacking flexibility. Recently, some efficient and cost-effective methods have been proposed for high-quality demonstration data collection and training. This section will discuss various methods for data collection in both real-world and simulated environments. Fig. 15 presents demonstration data from both real-world and simulated environments.

1) *Real-World Data:* Training large, high-capacity models on high-volume, rich datasets has demonstrated remarkable capabilities and significant success in effectively addressing downstream applications. For instance, large language models such as ChatGPT, GPT-4, and LLaMA have not only excelled in the field of NLP but have also provided excellent problem-solving capabilities for downstream tasks. Therefore, is it possible to train an embodied large model in the robotics field, one that possesses strong generalization capabilities through

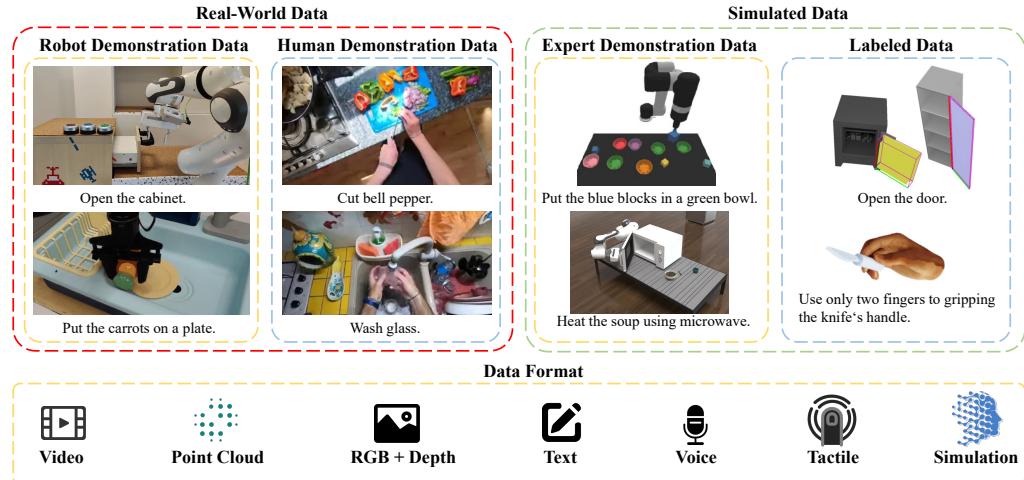


Fig. 15. The illustration of demonstration data collection. The yellow box on the left features operational demonstrations of the Franka and WidowX robotic arms, while human demonstrations are shown in the blue box. On the right, the yellow box showcases operational scenarios of the UR5e and Franka robotic arms in simulation environments, and the blue box displays labeled simulation data. The yellow box at the bottom presents the data formats of these datasets.

training and can adapt to new scenarios and robotic tasks? This requires a large volume of embodied datasets to provide data for model training. Open X-Embodiment [284]: A collaboration of 21 institutions collected an embodied dataset from 22 different robots, showcasing 527 skills and 160,266 tasks. The data they collected consisted of authentic demonstration data from robots, obtained by recording the process of executing operations. This primarily focused on domestic and kitchen settings, involving items such as furniture, food, and tableware. The operations mainly centered around pick-and-place tasks, with a small portion involving more complex maneuvers. The high-capacity model RT-X trained on this dataset demonstrated excellent transfer capabilities. UMI [350]: proposed a data collection and policy learning framework. They designed a handheld gripper and an elegant interface for data collection, enabling portable, low-cost, and information-rich data collection for challenging bimanual and dynamic demonstration data. By simply modifying the training data, the robot can achieve zero-shot generalizable, bimanual, and precise tasks. Mobile ALOHA [351]: proposed Mobile ALOHA, a low-cost full-body mobile manipulation system. It can be used to collect task data for bimanual operations under full-body mobility, such as frying shrimp and serving dishes. Training agents with data collected by this system and static ALOHA can improve the performance of mobile manipulation tasks. Such agents can serve as home assistants or work assistants. In human-agent collaboration [352], humans and agents learn together during data collection, reducing human workload, accelerating data acquisition, and improving data quality. Specifically, in an embodied scenario, during data collection, humans provide initial action inputs. Subsequently, the agent refines these actions through iterative perturbation and denoising processes, gradually optimizing them to produce precise, high-quality operational demonstrations. This entire process can be summarized as follows: humans contribute intuition and diversity in operations, while agents handle optimization and stability, reducing reliance on operators, enabling execution of more complex tasks, and gathering higher-quality data.

2) *Simulated Data*: The aforementioned data collection methods involve directly collecting demonstration data in the real world for agent training. Such collection methods often require significant manpower, material resources, and time, leading to inefficiency. Therefore, in most cases, researchers can choose to collect datasets in simulation environments for model training. Collecting data in simulation environments does not require extensive resources and can generally be automated by programs, saving a lot of time. CLIPORT [275], Transporter Networks [353]: They collected demonstration data from the Pybullet simulator for end-to-end network model training and successfully transferred the models from simulation to real world. GAPartNet [354]: constructed a large-scale part-centric interactive dataset GAPartNet, providing rich part-level annotations for perception and interaction tasks. They proposed a pipeline for domain-generalized 3D part segmentation and pose estimation, which can generalize well to unseen object categories in both simulators and the real world. SemGrasp [274]: built a large-scale grasping text-aligned dataset CapGrasp, a semantically rich dexterous hand grasping dataset from virtual environments.

3) *Sim2Real Paradigms*: Recently, several sim2real paradigms have been introduced. These methods aim to mitigate the need for extensive and costly real-world demonstration data by conducting extensive learning in simulation environments firstly, followed by migration to real-world settings. This section outlines five paradigms for sim2real transfer, as shown in Fig. 16.

Real2Sim2Real [355] is an approach that enhances imitation learning in real-world scenarios by leveraging reinforcement learning trained in a “digital twin” simulation environment. The method involves strengthening strategies through extensive RL within the simulation, followed by transferring these strategies to the real world to address data scarcity and achieve effective robotic operational imitation learning. Initially, existing methods such as Nerf and VR are used for scene scanning and reconstruction, and the constructed scene assets are imported into the simulator to achieve real-to-simulation fidelity. Subsequently, RL in the simulation fine-tunes the

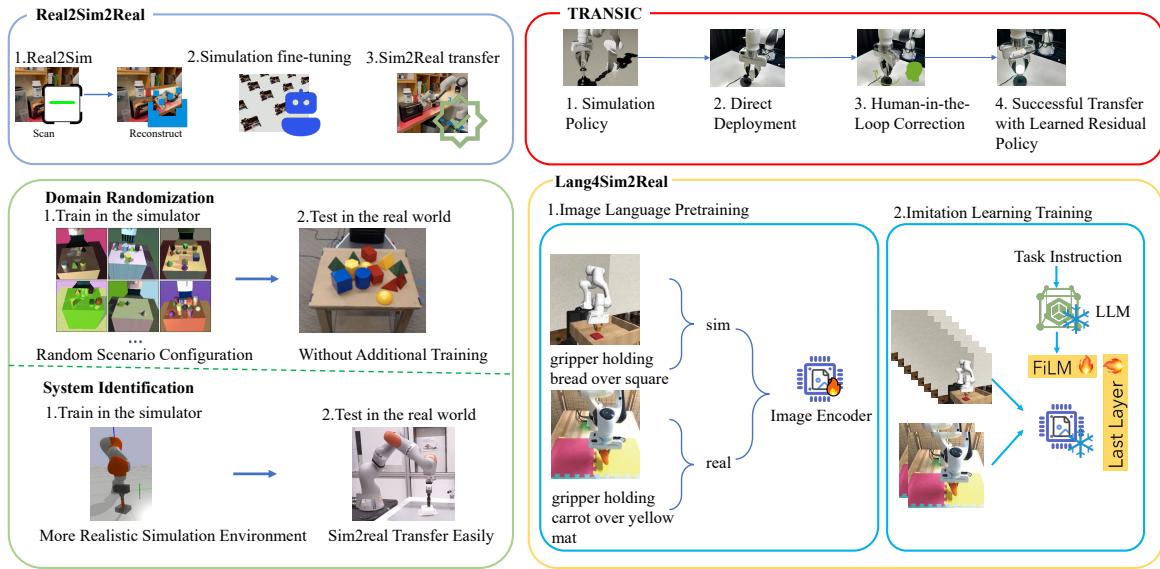


Fig. 16. Five pipelines to achieve sim2real gap. “**Sim2Real2Sim**” reduces the gap by reconstructing real scenes. “**TRANSIC**” compensates for the sim2real transfer gap through human-corrected interventions. “**Domain Randomization**” enhances model transfer adaptability by simulating environmental diversity. “**System Identification**” improves sim-to-real environment similarity, thereby mitigating the sim-real gap. “**Lang4Sim2Real**” uses natural language to bridge two domains, learning invariant image representations and reducing visual gaps.

initial strategies derived from sparse expert demonstrations collected in the real world. Finally, the refined strategies are transferred to real-world settings. TRANSIC [356] is a novel idea that narrows the sim-to-real gap by enabling real-time human intervention to correct robot behaviors in real-world scenes. The method enhances sim-to-real transfer performance through a series of steps: initially, robots are trained using RL to establish foundational strategies within a simulation environment. Subsequently, these strategies are implemented on real robots, with humans intervening and correcting behaviors in real-time via remote control when errors occur. The data collected from these interventions are used to train a residual policy. Finally, integrating both foundational and residual policies ensures smoother trajectories in real-world applications following sim-to-real transfer. This approach significantly reduces the need for real-world data collection, thereby mitigating the burden while achieving sim2real. Domain Randomization [357]–[359] enhances the generalization of models trained in simulated environments to real-world scenarios by introducing parameter randomization during simulation. While both simulated and real environments involve perception through camera-acquired visual images, differences such as object friction and gloss make accurate simulation challenging. Therefore, by randomizing parameters during simulation training, a wide range of conditions can be covered, potentially encompassing variations that might occur in real-world settings. This approach boosts the robustness of trained models, enabling direct deployment from simulation to real environments. System Identification [360], [361] constructs an accurate mathematical model of physical scenes in real-world environments, encompassing parameters such as dynamics and visual rendering. This effort aims to make simulation environments closely resemble real-world settings, facilitating smooth transitions of models and strategies trained in simulation to real environments. Lang4Sim2Real [362] uses natural language as a bridge to address the gap between

simulation and real-world environments, specifically by using textual descriptions of images as a cross-domain unified signal. This approach aids in learning domain-invariant image representations, thereby improving generalization performance across simulation and real environments. Initially, an encoder is pretrained on image data annotated with cross-domain language descriptions. Subsequently, using the learned domain-invariant representations, a multi-domain, multi-task language-conditioned behavioral cloning policy is trained. This method compensates for the scarcity of real-world data by leveraging additional information from abundant and inexpensive simulated data, thereby enhancing sim-to-real transfer.

C. Embodied Control

Embodied control aims to enable robots to acquire new skills through interaction and learning from their environment, thereby adapting to and completing complex tasks. Embodied control learns through interaction with the environment and optimizes behavior using a reward mechanism to obtain the optimal policy, thereby avoiding the drawbacks of traditional physical modeling methods. Embodied control methods can be divided into two types:

- 1) Deep Reinforcement Learning (DRL). DRL can handle high-dimensional data and learn complex behavior patterns, making it suitable for decision-making and control. The hybrid and dynamic policy gradient (HDPG) [363] is proposed for biped locomotion, allowing the control policy to be simultaneously optimized by multiple criteria dynamically. DeepGait [364] is a neural network policies for terrain-aware locomotion, which combines methods for model-based motion planning and reinforcement learning. It includes a terrain-aware planner for generating gait sequences and base motions guiding the robot towards target directions, along with a gait and base motion controller for executing these sequences while maintaining balance. Both the planner and controller are

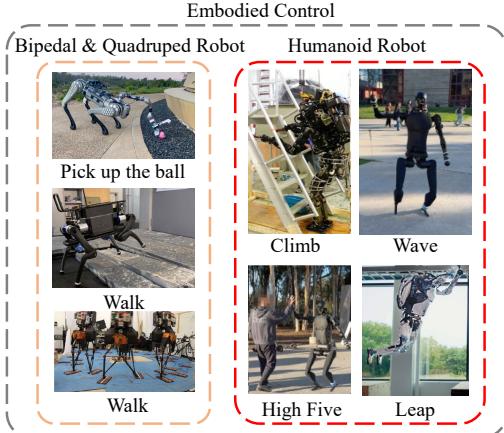


Fig. 17. Examples of embodied control for various locomotion modes, demonstrating the robots' agile movement and interaction capabilities. The orange box on the left showcases the locomotion of two quadruped robots (Unitree B1, ANYmal) and one biped robot (ATRIAS). The red box on the right displays motion scenes of the Atlas Robot climbing stairs, Unitree H1 waving and high-fiving, and the Boston robot leaping.

parameterized using neural network function approximators and optimized using deep reinforcement learning algorithms.

2) Imitation Learning. The DRL has its drawbacks of requiring a large amount of data from numerous trials. To address this issue, imitation learning was introduced, which aims to minimize data usage by collecting high-quality demonstrations. To improve data efficiency, Offline RL + Online RL was proposed to reduce interaction costs and ensure safety. This method first employs offline RL to learn policies from static, pre-collected large datasets. These policies are then deployed in the real environment for real-time interaction and exploration, with adjustments made based on feedback. The representative imitation learning methods from human demonstrations are ALOHA [365] and Mobile ALOHA [351].

Although embodied AI encompasses high-level algorithms, models, and planning modules, its most fundamental and essential component is embodied control. Therefore, it is imperative to consider how to control physical entities and endow them with physical intelligence. Embodied control is closely related to hardware, such as controlling joint movements, end-effector positions, and walking speeds. For robotic arms, knowing the end-effector's position, how to plan joint trajectories to move the arm to the target? For humanoid robots, knowing the motion patterns, how to control the joints to achieve the target posture? These are critical issues that need to be addressed in control. Several works focus on robotic control, enhancing the flexibility of robotic actions. [366] proposed a vision-based full-body control framework. By connecting a robotic arm and a robotic dog, utilizing all degrees of freedom (12 joints in the legs, 6 joints in the arm, and 1 in the gripper), it tracks the robot dog's speed and the robotic arm's end-effector position, achieving more flexible control. Some works [367], [368] employ traditional methods to control bipedal robot walking. MIT's Cheetah 3 [369], ANYmal [370], and Atlas [371] use robust walking controllers to manage the robots. These developed robots can be used for more agile motion tasks, such as jumping or overcoming various obstacles [372]–[376]. Other works [377], [378] focus

on the control of humanoid robots, enabling them to perform various actions like humans and mimic human behaviors. Fig. 17 illustrates some examples the robotic control.

Embodied control incorporates RL and sim2real techniques to optimize strategies through interaction with the environment, explore unknown domains, potentially surpass human capabilities, and adapt to unstructured environments. While robots can mimic many human behaviors, tasks often cannot be effectively completed without RL training based on environmental feedback. The most challenging scenes include contact-intensive tasks where manipulation requires real-time adjustments based on feedback such as the state, deformation, material, and force of manipulated objects, tasks where only RL proves adequate. In the era of MLMs, large models possess a generalized understanding of scene semantics, which can provide excellent reward functions for RL. Moreover, RL is also important for aligning large models. In the future, embodied agents, after pre-training and fine-tuning, still need RL to align with the physical world in order to better deploy themselves in real-world.

VIII. CHALLENGES AND FUTURE DIRECTIONS

Despite of the rapid progress of embodied AI, it faces several challenges and presents exciting future directions.

High-quality Robotic Datasets: Obtaining sufficient real world robotic data remains a significant challenge. Collecting this data is both time-consuming and resource-intensive. Relying solely on simulation data worsens the sim-to-real gap problem. Creating diverse real world robotic datasets necessitates close and extensive collaboration among various institutions. Additionally, the development of more realistic and efficient simulators is essential for improving the quality of simulated data. Current work RT-1 [12] used pre-trained models based on robot images and natural language commands. RT-1 has achieved good results in navigation and grasping tasks, but acquiring real world robot datasets is very challenging. For building generalizable embodied models capable of cross-scenario and cross-task applications in robotics, it is essential to construct large-scale datasets, leveraging high-quality simulated environment data to assist real world data.

Efficient Utilization of Human Demonstration Data: Efficient utilization of human demonstration data involves leveraging the actions and behaviors demonstrated by humans to train and improve robotic systems. This process includes collecting, processing, and learning from large-scale, high-quality datasets where humans perform tasks that robots are intended to learn. Current work R3M [379] used action labels and human demonstration data to learn generalizable representations has shown high success rates in some robot grasping tasks, but the efficiency for complex tasks still needs improvement. Therefore, it is important to effectively utilize large amounts of unstructured, multi-label, and multi-modal human demonstration data combined with action label data to train embodied models that can learn various tasks in relatively short periods. By efficiently utilizing human demonstration data, robotic systems can achieve higher levels of performance and adaptability, making them more capable of performing complex tasks in dynamic environments.

Cognition of Complex Environment: Cognition of complex environment refers to the ability of embodied agents in physical or virtual environments, to perceive, understand, and navigate complex real world environments. Based on extensive commonsense knowledge, the Say-Can [380] utilized pre-trained LLM models' task decomposition mechanism, which relies heavily on large amounts of commonsense knowledge for simple task planning but lacking understanding of long-term tasks in complex environments. For unstructured open environments, current works usually rely on pre-trained LLMs' task decomposition mechanism using extensive common-sense knowledge for simple task planning, while lacking specific scene understanding. It is vital to enhance the ability of knowledge transfer and generalization in complex environments. A truly versatile robotics system should be capable of comprehending and executing natural language instructions across diverse and unseen scenes. This necessitates the development of adaptable and scalable embodied agent architectures.

Long-Horizon Task Execution: Executing single instructions can often entail long-horizon tasks for robots, exemplified by commands like “clean the kitchen,” which involve activities such as rearranging objects, sweeping floors, wiping tables, and more. Accomplishing such tasks successfully necessitates the robot’s ability to plan and execute a sequence of low-level actions over extended time spans. While current high-level task planners have shown initial success, they often prove inadequate in diverse scenarios due to their lack of tuning for embodied tasks. Addressing this challenge requires the development of efficient planners equipped with robust perception capabilities and much commonsense knowledge.

Unified Embodied Foundation Model: Exploring foundation models for embodied robot tasks remains a nascent area of research, primarily due to the wide array of embodiments, environments, and tasks inherent in robotics. Compounding this challenge are isolated datasets and evaluation setups. Establishing a robust and unified foundation model for embodied robotics demands leveraging large-scale internet datasets and cutting-edge LLMs, MLMs and WMs.

Causal Relation Discovery: Existing data-driven embodied agents make decisions based on the intrinsic correlations within the data. However, this modeling approach does not allow the models to truly understand the causal relations between knowledge, behavior, and environment, resulting in biased strategies. This makes it difficult to ensure that they can operate in real-world environments in an interpretable, robust, and reliable manner. Therefore, it is important for embodied agents to construct embodied perception, reasoning, and interaction framework driven by world knowledge, capable of autonomous causal reasoning. By understanding the world through interaction and learning its workings via abductive reasoning, we can further enhance the adaptability, decision reliability, and generalization capabilities of multimodal embodied agents in complex real-world environments.

For embodied tasks (such as embodied question answering, visual language navigation, and instruction following), it is necessary to introduce embodied interactive causal representation learning. This involves establishing spatial-temporal causal relations across modalities through interactive instruc-

tions and state predictions, forming a representation learning system based on interaction and deduction. Moreover, agents need to understand the affordances of objects to achieve adaptive task planning and long-distance autonomous navigation in dynamic scenes. To optimize decision-making, it is necessary to combine counterfactual and causal intervention strategies [381]–[384], trace causality from counterfactual and causal intervention perspectives, reduce exploration iterations, and optimize decisions. Constructing a causal graph based on world knowledge and driving sim-to-real transfer of agents through active causal reasoning will form a unified framework for embodied perception, reasoning, and interaction.

Continual Learning: In robotics applications, continual learning [385] is crucial for deploying robot learning policies in diverse environments, yet it remains a largely unexplored domain. While some recent studies have examined sub-topics of continual learning—such as incremental learning, rapid motor adaptation, and human-in-the-loop learning—these solutions are often designed for a single task or platform and do not yet consider foundational models. Open research problems and viable approaches include: 1) mixing different proportions of prior data distribution when fine-tuning on the latest data to alleviate catastrophic forgetting [386], 2) developing efficient prototypes from prior distributions or curricula for task inference in learning new tasks, 3) improving training stability and sample efficiency of online learning algorithms, 4) identifying principled ways to seamlessly incorporate large-capacity models into control frameworks, potentially through hierarchical learning or slow-fast control, for real-time inference.

Unified Evaluation Benchmark: While numerous benchmarks exist for evaluating low-level control policies, they often vary significantly in the skills they assess. Furthermore, the objects and scenes included in these benchmarks are typically limited by simulator constraints. To comprehensively evaluate embodied models, there is a need for benchmarks that encompass a diverse range of skills using realistic simulators. Regarding high-level task planners, many benchmarks focus on assessing planning capability through question-answering tasks. However, a more desirable approach involves evaluating both the high-level task planner and the low-level control policy together for executing long-horizon tasks and measuring success rates, rather than relying solely on isolated assessments of the planner. This integrated approach offers a more holistic assessment of the capabilities of embodied AI systems.

IX. CONCLUSION

Embodied AI allows agents to sense, perceive, and interact with various objects from both cyber space and physical world, which exhibits its vital significance toward achieving AGI. This survey extensively reviews embodied robots, simulators, four representative embodied tasks: visual active perception, embodied interaction, embodied agents and sim-to-real robotic control, and future research directions. The comparative summary of the embodied robots, simulators, datasets, and approaches provides a clear picture of the recent development in embodied AI, which greatly benefits the future research along this emerging and promising research direction.

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