Large Language Models for Multi-Robot Systems: A Survey

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Abstract

The rapid advancement of Large Language Models (LLMs) has opened new possibilities in Multi-Robot Systems (MRS), enabling enhanced communication, task planning, and human-robot interaction. Unlike traditional single-robot and multi-agent systems, MRS poses unique challenges, including coordination, scalability, and real-world adaptability. This survey provides the first comprehensive exploration of LLM integration into MRS. It systematically categorizes their applications across high-level task allocation, mid-level motion planning, low-level action generation, and human intervention. We highlight key applications in diverse domains, such as household robotics, construction, formation control, target tracking, and robot games, showcasing the versatility and transformative potential of LLMs in MRS. Furthermore, we examine the challenges that limit adapting LLMs in MRS, including mathematical reasoning limitations, hallucination, latency issues, and the need for robust benchmarking systems. Finally, we outline opportunities for future research, emphasizing advancements in fine-tuning, reasoning techniques, and task-specific models. This survey aims to guide researchers in the intelligence and real-world deployment of MRS powered by LLMs. Based on the fast-evolving nature of research in the field, we keep updating the papers in the open-source GitHub repository.

1 Introduction

The rapid advancement of Large Language Models (LLMs) has significantly impacted various fields, including natural language processing and robotics. Initially designed for text generation and completion tasks, LLMs have evolved to demonstrate problem-understanding and problem-solving capabilities [121, 139]. This evolution is particularly vital for enhancing robot intelligence by enabling robots to process information and make decisions on coordination and action accordingly [45, 53]. With these capabilities, robots can more effectively interpret complex instructions, interact with humans, collaborate with robotic teammates, and adapt to dynamic environments [116]. As robotic systems evolve toward more sophisticated applications, integrating LLMs has become a transformative step, bridging the gap between high-level reasoning and real-world robotic tasks.
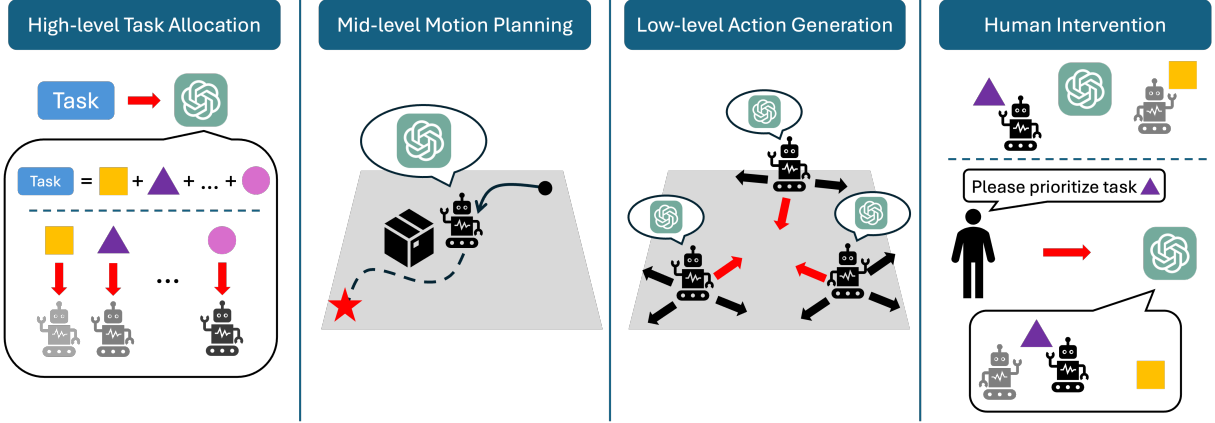
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Fig. 1 Overview of the applications of LLMs in MRS as introduced in Sec. 4.

On the other hand, Multi-Robot Systems (MRS), which consist of multiple autonomous robots working collaboratively [8, 95], have shown great potential in applications such as environmental monitoring [24, 81, 110], warehouse automation [67, 99, 111], and large-scale exploration [12, 27]. Unlike single-robot systems, MRS leverages collective intelligence to achieve high scalability, resilience, and efficiency [95]. The distributed nature of tasks across multiple robots allows these systems to be cost-effective by relying on simpler, specialized robots instead of a single highly versatile one. Moreover, MRS provides increased robustness, as the redundancy and adaptability of the collective can often mitigate the failures of individual robots [73, 149]. These features make MRS indispensable in scenarios where the scale, complexity, or risk is beyond the capabilities of a single robot.

Despite their importance, MRS introduces unique challenges, such as ensuring robot communication, maintaining coordination in dynamic and uncertain environments, and making collective decisions that adapt to real-time conditions [6, 30]. Researchers are working to integrate LLMs into MRS to address the unique challenges associated with deploying and coordinating MRS [18, 84]. For example, effective communication is essential for the MRS to share knowledge, coordinate tasks, and maintain cohesion in the dynamic environment among individual robots [30]. LLMs can provide a natural language interface for inter-robot communication, allowing robots to exchange high-level information more intuitively and efficiently instead of predefined communication structures and protocols [84]. Furthermore, the problem-understanding and problem-solving abilities of LLM can enhance the adaptability of MRS when given a particular goal without specific instructions. The LLMs can understand the mission, divide it into sub-tasks, and assign them to individual robots within the team based on their capabilities [15, 74]. The generalization ability across different contexts of LLMs can also allow MRS to adapt to new scenarios without extensive reprogramming, making them highly flexible during the deployment [120, 134].

The application of LLMs in MRS also aligns with the growing need for human-robot collaboration [44]. As the operators often do not have expertise in robot systems, using LLMs as a shared interface can enable operators using natural languages to communicate and command the robots to make decisions and complete complex real-world missions [2]. These capabilities enhance the efficiency of MRS and broaden their applicability to domains requiring close human-robot collaboration.

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Our paper is inspired by the survey [35] that comprehensively reviewed LLMs for multi-agent systems where abstract agents primarily serve virtual roles. Multi-agent systems differ from MRS in that the former emphasizes the roles of the agents, while the latter focuses on the interactions between the robots and the physical world. The limited coverage we find regarding MRS in their work pertains to LLM-embodied agents, but it still skims over related work and lacks detailed summaries. Hence, we recognize the necessity of summarizing recent works on using LLMs in MRS for decision-making, task planning, human-robot collaboration, and task execution. Fig. 1 illustrates the four categories outlined in this survey paper. We hope this survey can assist researchers in understanding the current progress of using LLMs in MRS, the challenges we face, and the potential opportunities to enhance multi-robot collective intelligence.

We structured our survey paper as follows to better provide a comprehensive introduction to researchers interested in applying LLMs to MRS. Sec. 2 lays the background for the MRS and LLMs for individuals to understand the topics better. Also, we summarize and compare several other existing survey papers about applying LLMs in robotics systems and multi-agent systems in general and explain the necessity of our work on MRS. Then, Sec. 3 reviews the communication structure among the LLMs in the MRS. After that, we review the usage of LLMs in three levels: (1) high-level task allocation and planning, (2) mid-level motion planning, and (3) low-level action execution in Sec. 4. Following reviewing the usage of LLMs, we review based on the applications of the MRS embodied by the LLMs in the real world in Sec. 5. In Sec. 6, we summarize the existing benchmark standards for evaluating the performance of LLMs in MRS and the existing simulation environments. In Sec. 7, we identify the challenges and limitations we face and the opportunities and future directions to enhance the LLMs' ability to handle MRS coordination and decision-making. Finally, we conclude our paper in Sec. 8.

2 Backgrounds

This section provides background knowledge on MRS and LLMs. While several other research papers have discussed on the applications of LLMs

in robotic systems, they do not specifically focus on the MRS. We will summarize their contributions and discuss why our survey on facilitating LLMs with MRS is necessary and impactful.

2.1 Multi-Robot Systems

A MRS consists of multiple robots that collaborate to complete specific tasks. Unlike single-robot systems, MRS leverages the combined capabilities of multiple robots to perform complex tasks more efficiently, reliably, and flexibly [5, 98, 147]. These systems are commonly employed in applications such as search and rescue [8, 55, 78, 95], target tracking [63, 71, 136, 144, 146], environmental monitoring [33, 101], coverage and exploration [12, 13, 75, 103, 105], and warehouse automation [4, 125], where the task's scale or complexity exceeds a single robot's capabilities. When all robots in the team are identical and share the same functionality, the team is called a **homogeneous** multi-robot team. In contrast, a **heterogeneous** multi-robot team consists of different types of robots [13, 92, 102]. The advantages of MRS include enhanced scalability, as tasks can be distributed among robots [16, 72, 143], and increased resilience, as the failure of one robot can often be mitigated by the others [60, 62, 73, 85, 97, 106, 142, 145, 148–150]. In contrast to designing a single, highly versatile robot, MRS usually relies on more uncomplicated, task-specific robots, reducing the cost and complexity of individual units while benefiting from collective intelligence [49]. However, these systems also present unique challenges, particularly in communication, coordination, and decision-making, as robots must operate cohesively in dynamic and uncertain environments [95]. Two primary control paradigms are commonly employed to manage the interaction and task distribution within an MRS: centralized and decentralized controllers [20, 130]. In a **centralized** controller, a single controller receives all the information and directs the actions of all robots in the system, allowing for optimized coordination and global planning. However, centralized systems can become a bottleneck when the group size increases and are vulnerable to single points of failure [77]. On the other hand, a **decentralized** controller distributes decision-making among the roots, enabling the robots to operate resiliently [98]. This approach enhances

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scalability and resilience but often introduces additional complexity to ensure seamless communication and coordination between robots. The choice between centralized and decentralized control depends on the specific application requirements, environmental conditions, and the desired balance between efficiency and robustness [130].

2.2 Large Language Models

LLMs are deep learning models with millions to billions of parameters [137]. Initially, the application of the LLMs is for text completion based on the context or text generation from the user's instruction [139]. LLMs are trained using an extensive collection of text from books, articles, websites, and other written sources. During this training process, LLMs learn to predict the next word in a sentence or fill in missing information using the **attention** mechanism [112]. This pre-training phase enables LLMs to develop a broad understanding of language, grammar, factual knowledge, and reasoning skills [89].

2.2.1 Fine-tuning and RAG

While LLMs are pre-trained on a diverse dataset for general tasks, the performance in specialized cases can be unideal since the training dataset might not fully cover the special usages [22, 152]. People can prepare a dataset dedicated to the specialized tasks and retrain the model. However, retraining the entire model is often challenging due to the limited computing resources and numerous parameters within the model [22]. One solution to address this issue is to use techniques like low-rank adaptation (LoRA) to **fine-tune** the LLMs with limited computational resources [39]. LoRA freezes the pre-trained model weights and injects trainable rank decomposition matrices into each layer of the Transformer architecture [112], significantly reducing the number of trainable parameters for the downstream tasks.

On the other hand, retrieval-augmented generation (**RAG**) is an alternative technique that integrates external knowledge sources to increase the zero-shot accuracy of the LLMs on specialized tasks [40, 58]. RAG addresses a key limitation of LLMs' reliance on pre-trained, static knowledge, which may not include domain-specific or up-to-date information. By combining a retrieval mechanism with the generative capabilities of LLMs, RAG allows the model to query external databases or knowledge repositories to retrieve relevant information during runtime [28]. This retrieved data is then used to guide the model's response, enhancing its accuracy and applicability in specialized contexts. For instance, RAG can provide real-time access to task-specific knowledge or environmental updates for robots, enabling better decision-making in dynamic scenarios [151]. Although RAG introduces additional complexity, such as managing retrieval latency and ensuring data relevance, it offers a powerful method for bridging the gap between static pre-trained knowledge and the dynamic requirements of real-world applications.

2.2.2 Multimodal LLMs

Traditional LLMs process only text, limiting their ability to directly interpret sensory data. In multi-robot systems, however, perception is often the primary source of situational awareness, coming from heterogeneous sensors such as onboard cameras, LiDAR, or aerial imagery. **Multimodal LLMs** address this gap by integrating inputs such as images, video, audio, or structured sensor data into a shared semantic space alongside language [132]. This allows robots to ground natural language reasoning in real-world observations— for example, identifying mission-relevant objects, understanding spatial relationships, or updating plans based on live visual feedback [53, 117].

Recent advances have led to the emergence of *Vision-Language Models* (VLMs), which couple perception and reasoning, and *Vision-Language-Action Models* (VLAs), which go further by linking perception and reasoning directly to executable actions. These models extend the role of LLMs in MRS from purely symbolic reasoning to perception-grounded decision-making and, in the case of VLAs, to closed-loop perception–action execution [141]. As discussed in Sec. 6.1, this evolution opens new possibilities for coordinated, perception-driven, and time-critical decision-making in multi-robot teams.

2.3 Related Survey Papers

Several survey papers have applied LLMs in the robotics and multi-agent field. Firoozi *et al.* [25], Zeng *et al.* [137], and Kim *et al.* [53] all explored how LLMs and foundation models could enhance

robotics in areas like perception, decision-making, and control. While they share this focus, their approaches and scopes differ. Firoozi *et al.* [25] provided a broad overview of foundation models in robotics, emphasizing their adaptability across various tasks but without specific attention to MRS. Zeng *et al.* [137] focused on the applications of LLMs in robotics, categorizing their impact on single-robot systems in areas like control and interaction without exploring collaborative systems. Wang *et al.* [117] concentrated on summarizing the applications of LLMs for manipulation tasks for a single robot. Kim *et al.* [53] divided LLM applications into communication, perception, planning, and control, offering practical guidelines for integration, but their work is also centered on single-robot applications. Hunt *et al.* [44] explored the use of language-based communication in robotics, categorizing applications of LLMs based on their roles in robotic systems, such as tasking robots, inter-robot communication, and human-robot interaction. Their focus is primarily on language as a medium for interaction without addressing the unique challenges of MRS. Guo *et al.* [35] reviewed LLM-based multi-agent systems, exploring their applications in problem-solving and world simulation. Although their work included embodied agents, their emphasis is on general multi-agent frameworks, which focus on abstract roles and interactions within systems that may not require physical embodiment or real-world interaction. Kawaharazuka *et al.* [51] examined real-world applications of foundation models in robotics, focusing on replacing components within robotic systems but without addressing inter-robot collaboration or the collective intelligence of MRS.

None of these surveys addresses the challenges and opportunities of integrating LLMs into MRS. While multi-agent systems provide a generalized framework for understanding roles and interactions, they are often abstract and virtual, lacking the physical embodiment and real-world constraints that characterize MRS [35]. MRS requires actual physical robots to collectively perceive, decide, and act within dynamic and uncertain environments, posing unique challenges in communication, coordination, and decision-making that go beyond the scope of virtual agents [114]. Moreover, MRS uniquely benefits from improved scalability, failure resilience, and cost-effective collective operations, making them fundamentally different from single-robot systems or general multi-agent frameworks. This gap highlights the need for a dedicated survey that explores how LLMs can facilitate communication, coordination, and collaborative task execution in MRS, providing critical insights into this emerging and impactful area of research.

3 Communication Types for LLMs in Multi-robot Systems

LLMs demonstrate remarkable abilities in understanding and reasoning over complex information. However, their performance can significantly vary depending on the communication architecture employed [18, 76]. This variability becomes particularly pronounced in scenarios involving embodied agents, where each agent operates with its own LLM for autonomous decision-making. The independence of these LLMs introduces unique challenges in maintaining consistency, coordination, and efficiency across the MRS. Understanding these dynamics is critical to optimizing LLM-based communication and decision-making frameworks in MRS.

Liu *et al.* [76] provided a comprehensive comparison of LLM-augmented Autonomous Agents (LAAs), analyzing the architectures employed to integrate LLMs into agents. While their work primarily focuses on multi-agent systems rather than exclusively MRS, their insights into LLM architectures and agent orchestration offer valuable inspiration for multi-robot applications. Their study begins with a basic structure where LLMs perform zero-shot inference based solely on task instructions and observations. This architecture is then enhanced with a self-thinking loop, incorporating previous actions and observations into subsequent decision-making rounds to improve contextual consistency. They extended the architecture by incorporating few-shot prompts, including example actions to enhance the LLMs' ability to generate effective decisions. Regarding multi-agent orchestration, Liu *et al.* proposed a centralized architecture featuring a message distributor, which relays information to individual agents equipped with their own LLMs. These agents
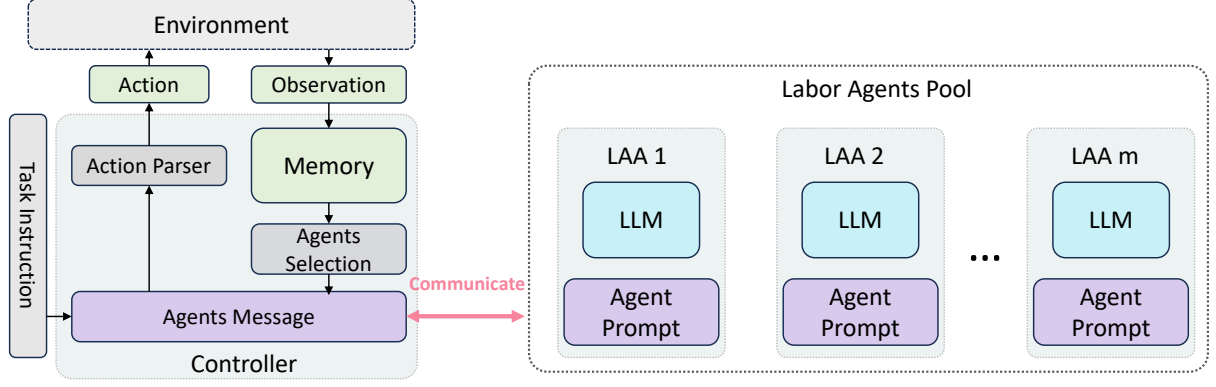
Fig. 2 The BOLAA architecture, which employs a controller to orchestrate multiple LAAs [76].

independently process the distributed messages to generate actions, as illustrated in Fig.2. As discussed in Sec.4, several studies have adopted similar self-thinking strategies to improve the consistency and reliability of decisions made by LLMs, demonstrating the utility of this approach in collaborative systems.

Additionally, Chen *et al.* [18] proposed four communication architectures: a fully decentralized framework (DMAS), a fully centralized framework (CMAS), and two hybrid frameworks that combine the decentralized and centralized frameworks (HMAS-1 and HMAS-2). These frameworks are visually represented in Fig. 3. Their study evaluated the performance of these structures in warehouse-related tasks, revealing notable distinctions among them. For scenarios involving six or fewer agents, both CMAS and HMAS-2 demonstrated comparable performance, although CMAS required more steps to complete tasks. In contrast, the performance of DMAS and HMAS-1 was notably inferior. Furthermore, their experiments indicated that HMAS-2 outperformed CMAS in handling more complex tasks, suggesting that hybrid frameworks with optimized structures offer greater scalability and adaptability for intricate multi-robot operations.

4 LLMs for Multi-robot Systems

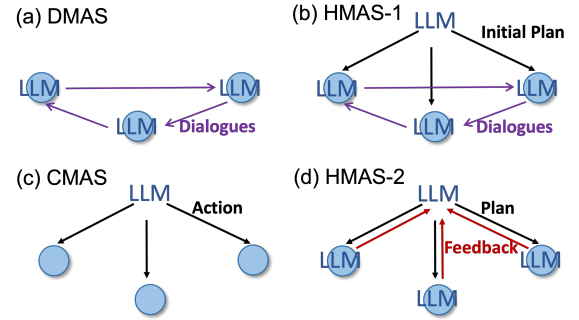In this section, we categorize the applications of LLMs in MRS into high-level task allocation,

Fig. 3 Four LLM-based multi-agent communication architectures introduced in Chen *et al.* [18]. The circles represent robots that may have actions in the current step and the 'LLM' text represents each LLM agent. The overlap between one circle and one 'LLM' text means that the robot is delegated with one LLM agent to express its special opinions to other agents. The 'LLM' text without the overlapped circle represents a central planning agent.

mid-level motion planning, low-level action generation, and human intervention scenarios. High-level task planning involves tasks that demand a higher degree of intelligence, such as task allocation and planning among multiple robots, where the LLM is required to exhibit logical reasoning and decision-making capabilities. Mid-level motion planning refers to navigation or path-planning scenarios. Low-level action generation uses LLMs to generate and directly control robots' posture or motion. On the other hand, human intervention involves using LLMs to interact with human operators and guide task planning and execution. Table 1 shows the list of papers based on those four categories.

4.1 High-Level Task Allocation and Planning

High-level task planning leverages LLMs' advanced reasoning and decision-making capabilities to handle complex and strategic tasks. This scenario often requires allocating tasks among robot teams, developing comprehensive task plans, or solving problems requiring contextual understanding and logic. Here, we explore studies illustrating LLMs' capability in these sophisticated domains.

Recent work has demonstrated that LLMs are capable of allocating tasks among multiple robots. Wu *et al.* [124] proposed a hierarchical LLMs framework consisting of two layers to solve the multi-robot multi-target tracking problem. In this scenario, the LLMs assign targets to each robot for tracking based on the current relative positions, velocities, and other relevant information between the robots and targets. As shown in Fig. 4, the outer task LLM receives human instruction and the long horizon information as inputs to provide strategic guidance and reconfiguration to the robot team. Meanwhile, the inner action LLM takes short horizon information as input and outputs control parameters for the controller. The outputs of the two LLMs are transformed into executable actions through the optimization solver. In addition, Brienza *et al.* [10] applied VLM and LLM to generate actionable plans for the robotic soccer team. Their approach involved providing the VLM coach with a training set comprising video frames paired with corresponding textual prompts, detailing tasks and constraints. The VLM coach generated schematic descriptions of the video frames along with high-level natural language plans. Two distinct LLMs further refined and synchronized these high-level plans to produce executable strategies suitable for various scenarios. In practical applications, the system selected pre-collected plans based on their similarity to the real-world situation. Additionally, RAG minimizes prompt size and mitigates hallucination, ensuring more reliable outputs. Moreover, Lykov *et al.* [79] developed an MRS to collect and sort colored object sets and count spherical objects. Their approach utilized a fine-tuned LLM to generate Behavior Trees (BTs) for robots to execute tasks and provide feedback to human

operators regarding their behaviors. They implemented a single LLM with two LoRA adapters, each handling specific functionalities to enhance efficiency and resource compactness. In addition, Ahn *et al.* [2] introduced an MRS framework featuring a recovery mechanism. The LLM controller received natural language instructions and a library of low-level robot skills to generate plans for task execution. A key innovation in their system was detecting deviations from the expected task progression and performing error recovery by replanning or seeking assistance from other robots or human operators. Li and Zhou [64] propose **LLM-Flock**, an approach that integrates decentralized LLM-driven planning with an influence-based consensus protocol for multi-robot formation control. This method mitigates inconsistent plan and behavior by refining local plans iteratively based on the influence of neighbors, achieving stable and adaptable flocking. Validated through simulations and drone experiments, their approach significantly enhances the coherence of multi-robot formations. The remaining studies in this domain can be further categorized into two key areas: multi-robot multi-task coordination and complex task decomposition, highlighting the breadth of LLM applications in MRS.

4.1.1 Multi-Robot Multi-Task Planning

In the multi-robot multi-task scenarios, a team of robots is tasked with completing multiple objectives simultaneously. LLMs play a critical role in devising actionable and efficient task distribution strategies in such settings. By interpreting high-level instructions and understanding the context of each task, LLMs can dynamically allocate tasks among robots, ensuring optimal utilization of resources and effective collaboration. This capability enables multi-robot teams to handle complex, multi-faceted operations with increased precision and adaptability.

Lakhnati *et al.* [56] proposed a framework where three heterogeneous robots aim to accomplish complex tasks instructed by human operators in VR simulation. First, each robot LLM is given an initial prompt to clarify its role and abilities. A central controller LLM analyzes human descriptions of the task and distributes them to the respective robots. Instructions from human operators can either directly specify what each
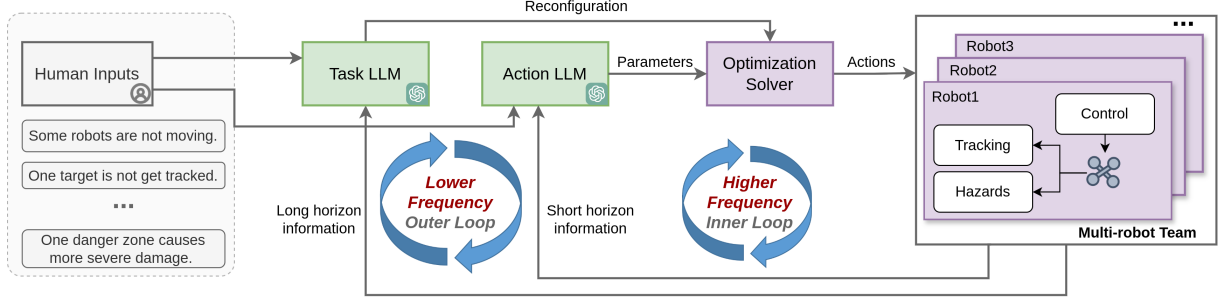
Fig. 4 The target tracking architecture proposed by Wu *et al.* [124]. The optimization solver acts as the controller for the multi-robot team. The "Task LLM" is a high-level task planner, while the "Action LLM" is a mid-level motion planner integrated with the optimization solver.

robot should do (e.g., "Jupiter needs to move to the dumbbell and pick it up, Neptune and Pluto have to move to the fridge.") or describe the tasks without assigning to specific robots (e.g., "Three dinner plates have to be put into the trash, and all agents need to end up next to the garbage bin."). Following this line, Chen *et al.* [15] proposed a centralized framework where an LLM controller distributes the human instructions to a multi-robot team. They aim to make a heterogeneous multi-robot team accomplish multiple heterogeneous household tasks. However, the task distribution process they introduced is in the form of a discussion between the "Central Planner" LLM and the robot-dedicated agent LLM on each robot. The original task information is a geometric representation from a SLAM system. It is constructed into a scene context to prompt LLM. The "Central Planner" LLM first assigns each task to each robot according to its analysis. Then, each robot-dedicated agent LLM provides feedback according to the assigned task, and its robot resume is generated from the robot's URDF code by the robot-dedicated agent LLM. If the task does not match the robot's resume, it prompts the "Central Planner" for a reassignment. This discussion between LLMs continues until no reassignments are required. Lim *et al.* [69] presented a centralized LLM-enabled control framework for dynamic task assignment in multi-robot manufacturing systems. The architecture consists of three main components. The Central Controller Agent (CCA) acts as a high-level decision-maker, leveraging LLM reasoning to reassign tasks when disruptions occur. The Robot Agents execute tasks using

configuration-defined capabilities and report failures to the CCA. The Sensor Module provides real-time perceptual input to ensure context-aware decisions. When a robot failure is detected, the CCA formulates a structured prompt containing system constraints and objectives, and sends it to the LLM to generate a valid new configuration for an alternative robot. If the LLM-generated configuration violates task constraints, structured feedback is appended, and the process is repeated until success is achieved. This loop ensures that reassignment is both feasible and safe. Once a valid configuration is found, the task is reallocated, and execution resumes seamlessly. Moreover, Jiang *et al.* [48] introduced a decentralized swarm robotics framework that leverages LLMs to enable spontaneous inter-robot communication and coordination. Each robot maintains its own LLM session and utilizes natural language to discover peers, share information, and coordinate collaborative actions without predefined roles. The system demonstrates that LLM-driven communication can give rise to emergent social behaviors such as negotiation, assistance, and conflict resolution, pushing swarm robotics toward more human-like, adaptive coordination. Chen *et al.* [18] took a step further to investigate the scalability of an LLM-based heterogeneous multi-task planning system. The efficiency and accuracy of four different communication architectures are compared, as shown in Fig. 3 under four distinct environments, including BoxNet, warehouse, and BoxLift. The results demonstrate that the HMAS-2 structure achieves the highest success rate while CMAS is the most token-efficient. On the other hand, Gupte *et al.* [37] proposed an

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LLM-based framework to solve Initial Task Allocation for a multi-robot multi-human system. In this centralized framework, LLM first generates prescriptive rules for each user's objective and then generates experiences based on those rules for each objective. After acquiring a practical knowledge of the rules generated, the LLM's performance is evaluated by inferencing, where the user provides instructions, and the LLM allocates the task according to the rules and experiences. Two distinct RAG workflows are leveraged in the inferencing stage to use the acquired knowledge fully. Moreover, Huang *et al.* [41] tested the ability of LLMs to solve the multi-robot Traveling Salesman Problem (TSP). By providing appropriate prompts, the LLM plans the optimal paths for multiple robots and generates Python code to control their movements. The study set up three frameworks: single attempt, self-debugging, where the LLM checks whether the generated Python code can be executed, and self-debugging with self-verification, where the LLM checks code executability and verifies whether the execution produces correct results. Their work reveals that LLMs perform poorly in handling such problems, with higher success rates that can only be observed in specific cases, such as the min-max multi-robot TSP. Chen *et al.* [14] presented a multi-agent LLM-based framework for robotic autonomy, integrating task analysis, robot design, and RL path planning. Experiments demonstrate the effectiveness of robot configuration generation and the feasibility of control strategies, showcasing significant improvements in the scalability and flexibility of LLM-driven robotic system development. Wan *et al.* [115] introduced a supervised fine-tuned LLM-based planning framework using the novel **MultiPlan** dataset for embodied multi-robot collaboration. Extensive indoor and outdoor field experiments illustrate significant improvements in task decomposition, robustness, and adaptability to novel environments compared to baseline LLM planners.

4.1.2 Complex Task Decomposition

Task decomposition refers to scenarios where MRS must collaborate to complete one or more complex tasks that require careful planning and division of labor. In such cases, LLM can be leveraged to break down the overall task into smaller, manageable subtasks that align with the capabilities of each robot in the team. By designing effective prompts, LLMs can generate logical and actionable task decompositions, ensuring that the workload is distributed efficiently and that the robots cooperate seamlessly to achieve the overarching objective.

Kannan *et al.* [50] introduced **SMART-LLM**, a framework that utilizes LLMs to decompose high-level human instruction into subtasks and allocate them to heterogeneous robots based on their predefined skill sets. Unlike Chen *et al.* [15], where robot capabilities are inferred from their URDF code using LLMs, SMART-LLM adopts a more conventional approach by explicitly defining each robot's skill set for heterogeneous task allocation. The process involves decomposing instructions into sub-tasks, analyzing the required skills for each sub-task to form coalitions, and distributing robots accordingly to ensure efficient task execution. Wang *et al.* [120] propose Dependency-Aware Multi-Robot Task Decomposition and Execution LLMs (**DART-LLM**), a system designed to address complex task dependencies and parallel execution problems for MRS, as shown in Fig. 5. The framework utilizes LLMs to parse high-level natural language instructions, decompose them into interconnected subtasks, and define their dependencies using a Directed Acyclic Graph (DAG). DART-LLM facilitates logical task allocation and coordination by establishing dependency-aware task sequences, enabling efficient collaboration among robots. Notably, the system demonstrates robustness even with smaller models, such as Llama 3.1 8B, while excelling in handling long-horizon and collaborative tasks. This capability enhances the intelligence and efficiency of MRS in managing complex composite problems. Xu *et al.* [127] proposed a two-step framework that leverages LLMs to translate complex natural language instructions into a hierarchical linear temporal logic (LTL) representation for MRS. In the first step, the LLM decomposes the instruction into a hierarchical task tree, capturing logical and temporal dependencies between subtasks to avoid errors in sequence. In the second step, a fine-tuned LLM translates each subtask into flat LTL formulas, enabling precise execution using off-the-shelf planners. This framework emphasizes the importance of temporal reasoning in decomposing complex instructions, ensuring accurate
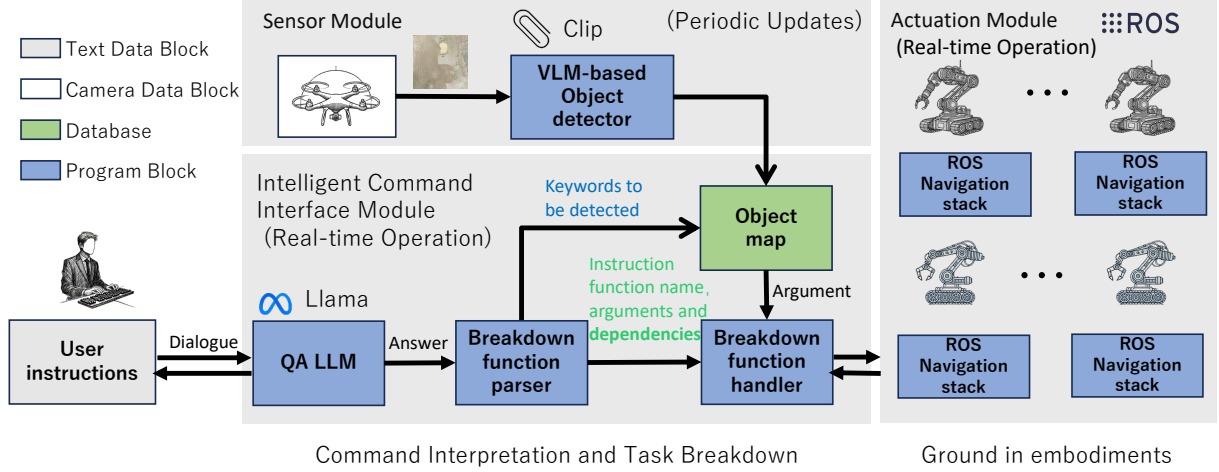
Fig. 5 The framework of DART-LLM proposed by Wang *et al.* [120]. The system consists of three modules: Sensor Module, Intelligent Command Interface Module, and Actuation Module. The task decomposition process happens in the Intelligent Command Interface Module.

task allocation and execution for long-horizon and interdependent multi-robot tasks. In contrast to the abovementioned approaches, Obata *et al.* [90] adopted a slightly different approach and proposed **LiP-LLM**, a framework integrating LLMs with linear programming for multi-robot task planning. Instead of providing end-to-end task allocation and execution, LiP-LLM utilizes LLMs to generate a skill set and a dependency graph that maps relationships and sequential constraints among tasks. The task allocation is then solved using linear programming to optimize task distribution among robots. This hybrid approach enhances task execution efficiency and success rates by combining LLMs' interpretative capabilities with the precision of optimization techniques. The results demonstrate the potential of integrating LLMs with traditional optimization techniques to improve the performance and coordination of MRS. On the other hand, Liu *et al.* [74] proposed the **COHERENT** framework, which utilizes a Proposal-Execution-Feedback-Adjustment (PEFA) mechanism for task planning in heterogeneous MRS. The PEFA process involves a centralized task assigner LLM that decomposes high-level human instructions into subgoals and assigns them to individual robots. Each robot evaluates the assigned subgoal, determines its feasibility, and provides feedback to the task assigner, enabling dynamic adjustments and iterative refinements in the task plan. This

process bears similarities to the robot discussion mechanism in the EMOS framework proposed by Chen *et al.* [15], where task decomposition and assignment leverage embodiment-aware reasoning based on robot resumes. However, COHERENT emphasizes a real-time, feedback-driven approach to handle task allocation and execution, making it particularly suited for dynamic and complex multi-robot environments. Huang *et al.* [42] proposed LAN2CB (Language to Collective Behavior), a framework that converts natural language mission descriptions into executable multi-robot code. The system performs mission parsing, dependency analysis, and behavior tree construction, then generates task code using a library of goal generation, allocation, and motion primitives. LAN2CB supports dynamic replanning by updating the behavior tree and regenerating code when triggers occur, enabling robust adaptation in changing environments. Experiments on nine diverse scenarios in both simulation and real-world tests demonstrated high success rates and resilience to complex dependencies and environmental events.

Liang *et al.* [68] proposed a communication-based, feedback-driven framework that enhances multi-robot cooperation through a novel retrospective actor-critic paradigm. Their system comprises two large language models: LLM_1, which facilitates real-time collaborative discussion among robots to devise initial plans, and

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LLM$_2$, which serves as both an action critic and proposer. After executing a task or simulation, LLM$_2$ conducts a retrospective evaluation based on environmental feedback, critiques the earlier plans, and proposes improved alternatives. The framework leverages short-term and long-term memory to retain only the most recent retrospectives, thus maintaining contextual relevance while minimizing computational overhead. This approach demonstrates improved performance on RoCoBench tasks compared to baselines, highlighting the value of integrating LLM-based reflection into the decision-making pipeline for dynamic and uncertain multi-robot environments. Differently, Mandi *et al.* [84] proposed RoCo, a decentralized communication architecture for multi-robot collaboration, focusing on both high-level task planning and low-level motion planning. In the RoCo framework, each robot is equipped with an LLM that engages in dialogue with other robots to discuss and refine task strategies. This dialogue process results in a proposed sub-task plan, which is validated by the environment for feasibility. If the plan fails (e.g., due to collisions or invalid configurations), feedback is incorporated into subsequent dialogues to improve the plan iteratively. Once validated, the sub-task plan generates goal configurations for robot arms, with a centralized motion planner computing collision-free trajectories. RoCo emphasizes flexibility and adaptability in multi-robot collaboration and has been evaluated using the RoCoBench benchmark, demonstrating robust performance across diverse task scenarios. This approach highlights the synergy between decentralized LLM-driven reasoning and centralized motion planning for complex, dynamic environments. Peng *et al.* [93] introduced a knowledge-augmented automated MILP formulation framework for multi-robot task allocation and scheduling. Their approach leverages locally deployed LLMs, combined with a structured knowledge base, to extract spatiotemporal constraints from natural language and translate them into executable MILP code. The two-step pipeline first interprets fuzzy natural instructions into mathematical constraints and then generates optimized Gurobi-compatible code. Notably, the entire process is locally deployable, ensuring data privacy in sensitive industrial settings. Experimental results on aircraft skin manufacturing tasks demonstrate that the framework achieves high accuracy and efficiency in both model construction and code generation, highlighting the potential of integrating LLMs with symbolic optimization techniques for practical, privacy-sensitive MRS applications. Cladera *et al.* [19] demonstrated air-ground collaborative planning using LLM-based semantic reasoning and mapping for language-specified missions. Their decentralized system enables dynamic mission adaptation, as validated through extensive field experiments in both urban and rural settings, highlighting effective semantic-based collaboration and robust task execution. Gupta *et al.* [36] proposed a hierarchical tree-based mission planning approach that leverages LLMs for automated decomposition into manageable subtasks, explicitly tailored for heterogeneous robot teams. The proposed heuristic method efficiently schedules tasks, considering robot-specific constraints, and demonstrates flexibility and scalability across varied, complex missions.

4.2 Mid-Level Motion Planning

Mid-level motion planning in MRS encompasses tasks such as navigation and path planning, where the focus lies on enabling robots to traverse or coordinate within an environment efficiently. These scenarios are more direct and practical than high-level applications but critical for multi-robot teams' seamless operation. LLMs contribute significantly to this domain by leveraging their contextual understanding and learned patterns to generate robust and adaptive solutions. By interpreting environmental data and dynamically adapting to changes, LLMs enable robots to collaboratively plan paths, avoid obstacles, and optimize movement within shared spaces. Integrating LLMs into mid-level motion planning enhances efficiency and resilience, making MRS more capable in dynamic and unpredictable environments.

Yu *et al.* [134] proposed **Co-NavGPT** framework to integrate LLMs as a global planner for multi-robot cooperative visual semantic navigation, as shown in Fig. 6. Each robot captures RGB-D vision data, which is converted into semantic maps. These maps are merged and combined with the task instructions and robot states to construct prompts for the LLMs. The LLMs then assign unexplored frontiers to individual robots for efficient target exploration. By

leveraging semantic representations, Co-NavGPT enhances the comprehension of the environment and guides collaborative exploration. In this framework, the LLMs are limited to allocating unexplored frontiers to each robot for navigation, serving primarily as a task allocation mechanism. Morad *et al.* [88] took a step further and proposed a novel framework combining LLMs with offline reinforcement learning (RL) to address path-finding challenges in MRS. Their approach involves leveraging LLMs to translate natural language commands into latent embeddings, which are then encoded with agent observations to create state-task representations. Using offline RL, policies are trained on these representations to generate navigation strategies that understand and follow high-level natural language tasks. A key advantage of this framework is its ability to train policies entirely on real-world data without requiring simulators, ensuring direct applicability to physical robots. The integration of LLMs enhances the flexibility of task instruction interpretation, while RL facilitates the generation of low-latency and reactive control policies, enabling efficient multi-robot navigation. Following this line, Godfrey *et al.* [31] developed **MARLIN** (Multi-Agent Reinforcement Learning Guided by Language-Based Inter-Robot Negotiation), a framework combining LLMs with Multi-Agent Proximal Policy Optimization (MAPPO) to enhance training efficiency and transparency in multi-robot navigation tasks. In MARLIN, robots equipped with LLMs engage in natural language negotiations to collaboratively generate task plans, which are then used to guide policy training. This hybrid approach dynamically switches between LLM-guided planning and standard MAPPO-based reinforcement learning, leveraging the reasoning capabilities of LLMs to improve training speed and sample efficiency without sacrificing performance. Experimental results demonstrate MARLIN's ability to achieve faster convergence and more consistent performance compared to conventional MARL approaches, with applications validated in both simulation and physical robot environments. This integration of negotiation-based planning highlights the potential of combining LLMs with MARL for scalable, explainable multi-robot coordination. On the other hand, Garg *et*

al. [29] leveraged LLMs for deadlock resolution in connected multi-robot navigation systems. In obstacle-laden environments, such systems can experience deadlocks that low-level control policies cannot resolve. To address this, the LLM selects a leader robot and plans waypoints for it to reach the target. The system reconfigures into a leader-follower formation, with a GNN-based low-level controller guiding the leader along the waypoints. Mahadevan *et al.* [83] directly tackled the challenge of multi-robot deadlocks by introducing **GameChat**, a role-based language negotiation framework for collaborative decision-making. In this system, agents engage in natural language dialogues to dynamically assign roles—such as "leader" or "blocker"—which help resolve spatial conflicts, task interdependencies, and bottlenecks that typically lead to deadlocks. These roles emerge through decentralized negotiation, without requiring pre-defined hierarchies or centralized control. The framework demonstrates robust performance across a variety of collaborative tasks, including navigation and manipulation, in both simulation and real-world experiments. GameChat showcases how emergent role-based reasoning and interactive dialogue can effectively address deadlock resolution in complex multi-agent environments. Moreover, Wu *et al.* [124] proposed a mid-level action LLM that uses short-horizon inputs, such as tracking errors and control costs, to generate parameters for an optimization-based robot controller, enabling it to follow planned waypoints effectively. While the aforementioned research primarily employs centralized systems where LLMs handle planning for all robots, Wu *et al.* [123] developed a decentralized multi-robot navigation system for household tasks. In this framework, each robot is equipped with an LLM to enable communication and collaboration. Robots dynamically recognize and approach target objects distributed across multiple rooms. Leadership is dynamically assigned through a communication-triggered mechanism, with the leader robot issuing orders based on the global information it gathers. This flexible and decentralized leadership strategy enhances adaptability and efficiency in collaborative navigation scenarios. Shen *et al.* [104] proposed a framework of decentralized semantic planning based on multimodal chain-of-thought reasoning. The MCoCoNav architecture consists of three modules
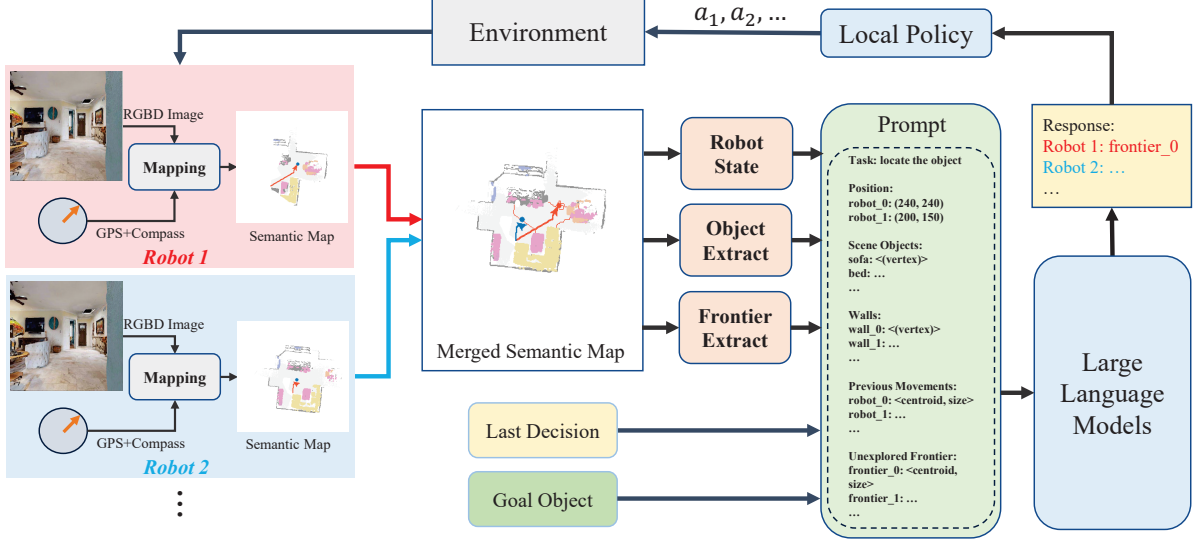
Fig. 6 The framework of Co-NavGPT proposed by Yu *et al.* [134].

and two auxiliary components. The Perception module evaluates the exploration value of the current scene using multimodal CoT reasoning; the Judgment module determines whether a robot should explore a new frontier or revisit a history node by analyzing the global semantic map; the Decision module selects the next long-term navigation goal based on predicted frontier scores or historical node scores. If the robots are stuck or trapped in place, the system resets their goal to a randomly sampled point on the global map to avoid deadlocks and ensure continued exploration. Ji *et al.* [46] proposed a reinforcement learning framework that groups LLM planners with collision and reachability constraints, ensuring physically valid multi-robot motion plans. Evaluations in two BoxNet environments demonstrate that constraint-aware small-scale LLMs significantly outperform larger ungrounded models in task success and generalization, highlighting the effectiveness of explicit constraint integration for reliable multi-robot planning. Rajvanshi *et al.* [96] introduced **SayCoNav**, a LLM-based decentralized adaptive planning approach. By dynamically updating collaboration strategies among heterogeneous robots, SayCoNav significantly improves multi-object search efficiency and adapts to changing robot conditions during mission execution, as validated through extensive simulation studies. Wang *et al.* [119] presented

SAMALM, a decentralized multi-agent LLM actor-critic framework that ensures socially aware robot navigation. Utilizing parallel LLM actors and critics for verification and cooperative navigation, the system effectively balances local autonomy and global coordination, validated through diverse multi-robot navigation scenarios.

4.3 Low-Level Action Generation

Low-level action generation focuses on controlling robot motion or posture at the hardware level, translating high-level goals into precise control commands. These tasks are critical for ensuring smooth and efficient operations in dynamic environments. While LLMs offer contextual reasoning and adaptability, their performance in low-level tasks, which demand high precision and real-time responsiveness, is often limited compared to traditional control methods. Hybrid approaches, combining LLMs with optimization-based controllers or reinforcement learning, show promise in leveraging LLMs' flexibility while maintaining the precision required for reliable robot actions.

Chen *et al.* [17] leveraged LLMs to address the Multi-Agent Path Finding (MAPF) problem, where LLMs actively navigate robots by generating actions incrementally. Each step concludes with a high-level conflict checker to identify collisions with robots or obstacles. While effective in
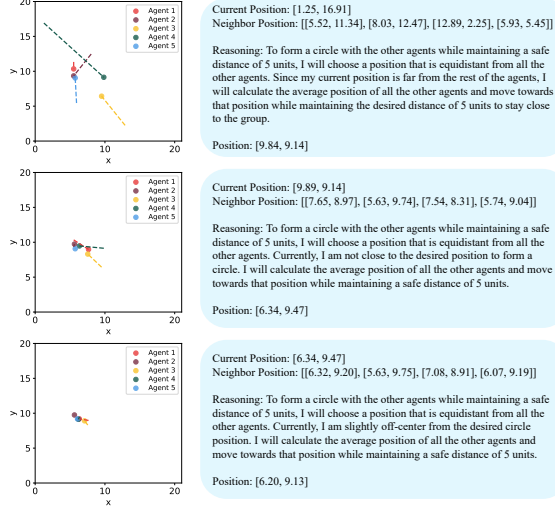
13

Fig. 7 Snapshots of five agents forming a circle [61]. The desired distance between each agent is 5 units. The decision of Agent 4's LLM is tracked.

obstacle-free environments, LLMs face challenges in maze-like maps due to limited reasoning capabilities, restricted context length, and difficulty understanding obstacle locations. Besides path finding, most studies on using LLMs for action generation focus on the problem of formation control. For example, Venkatesh *et al.* [113] proposed a centralized architecture where LLMs translate natural language instructions into robotic configurations, enabling swarms to form specific patterns. Despite their strengths as centralized controllers, Li *et al.* [61] highlighted the limitations of LLMs in decentralized systems. In a decentralized setup, each robot operates with its own LLM to achieve a desired formation through coordination with other robots. However, LLMs still face challenges in this task. In a test scenario shown in Fig. 7 where agents were tasked with forming a circle with a desired spacing of 5 units, the agent's LLM misinterpreted the instruction, moving to the circle's center instead of the perimeter. This misunderstanding caused the agent to perform consensus-based behavior rather than the intended flocking behavior, revealing the difficulties that LLMs face in this distributed coordination.

In the field of formation control and planning, Strobel *et al.* [107] introduced **LLM2Swarm**, a system that integrates LLMs with robot swarms through two approaches: centralized controller synthesis and decentralized direct integration. In the centralized approach, LLMs are used to design and validate controllers prior to deployment, enabling efficient and adaptive behavior generation. In the decentralized approach, each robot has its own LLM instance, enabling localized reasoning, planning, and collaboration for enhanced flexibility in dynamic environments. The results highlight the potential of LLMs in swarm robotics, demonstrating their applicability to both centralized and decentralized control paradigms. Lykov *et al.* [80] further showcased the potential of LLMs in swarm control with **FlockGPT**, a framework for orchestrating UAV flocks to achieve desired geometric formations. In this system, the LLM generates a signed distance function (SDF) to guide UAV movements relative to a target surface, while a dedicated control algorithm manages practical constraints such as collision avoidance. These studies underscore the versatility of LLMs in enhancing both centralized and decentralized swarm behaviors. Moreover, Xue *et al.* [129] proposed a novel framework that leverages LLMs to achieve communication-efficient multi-robot formation control. The approach encodes formation goals, robot roles, and spatial arrangements into compact natural language instructions, which are then distributed to individual robots. These instructions are decoded into actionable local goals by each agent. The framework demonstrates that LLM-generated descriptions can maintain formation integrity while significantly lowering communication bandwidth. Following this line, Ji *et al.* [47] proposed **GenSwarm**, an end-to-end framework that enables automatic code-policy generation and deployment for multi-robot systems. The system interprets natural language instructions to construct constraint-based skill graphs, then hierarchically generates executable code policies using LLM agents. These policies are automatically reviewed, tested in simulation, and deployed to real-world robots via scalable hardware and software infrastructure. By supporting zero-shot generalization and human/VLM-in-the-loop feedback, GenSwarm offers a highly adaptive and interpretable solution for dynamic multi-robot tasks. Moreover, it is worth mentioning that GenSwarm supports optional human intervention in the loop, allowing users to provide natural language feedback after observing execution outcomes. This feedback is interpreted by

LLM agents to iteratively refine control policies, enabling intuitive human-in-the-loop policy optimization.

4.4 Human Intervention

In MRS, LLMs typically focus on executing tasks based on human-provided instructions, emphasizing the interpretation of instructions and autonomous task completion. Once the instructions are delivered, human involvement is often minimized. However, emerging research explores scenarios that require continuous interaction between LLMs and humans, emphasizing cooperation, decision-making, or external observation throughout task execution. These studies highlight the potential for dynamic human intervention to address unexpected challenges, refine task strategies, or ensure safety in critical applications. By enabling iterative human-robot collaboration, such approaches enhance the adaptability and reliability of LLM-driven MRS. The simplest form of human-robot interaction is demonstrated by Lakhnati *et al.* [56], where robots operate in a straightforward cycle: receiving a human command, executing the corresponding task, reporting the completion status, and awaiting the next instruction. Building on this, Lykov *et al.* [79] introduced the LLM-MARS framework, which enables humans to inquire about each robot's current state and task progress at any time. In this system, both response generation and task execution are handled by a single LLM, enhanced with distinct LoRA adapters for efficiency. Hunt *et al.* [43] proposed a more interactive approach, requiring human approval before executing any plan generated through LLM-driven discussions. If the proposed plan is deemed unreasonable, the human supervisor can provide feedback, prompting the LLMs to refine their approach through further dialogue. Ahn *et al.* [2] introduced the VADER system, further enhancing human involvement. When a robot encounters a task-related issue, it posts a request for assistance on the Human-Robot Fleet Orchestration Service (HRFS), a shared platform accessible to both human operators and robotic agents. Any agent or human can respond to the request, and once the issue is resolved, the robot resumes its task. Li *et*

al. [66] introduced HMCF, which integrates LLM-driven multi-robot coordination with human oversight. Their framework mitigates hallucination via human verification, significantly improving task success rates and providing robust zero-shot generalization capabilities in diverse robotic tasks. These examples illustrate the varying degrees of human involvement in LLM-driven MRS, ranging from simple command execution to active collaboration and dynamic problem-solving.

5 Application

The integration of LLMs into MRS has enabled advancements across a variety of application domains, each with unique challenges and opportunities. These applications leverage LLMs' capabilities in understanding, planning, and coordinating tasks, offering solutions ranging from indoor to outdoor scenarios. The adaptability of LLMs has driven innovation in tasks requiring precise navigation, task allocation, and dynamic decision-making, demonstrating their potential to address both structured and unstructured environments.

In this section, we categorize studies based on their application scenarios, focusing on two primary domains. First, the household domain highlights MRS addressing indoor challenges such as navigation, task decomposition, and object manipulation. These systems often emphasize collaboration among heterogeneous robots to execute intricate tasks, from identifying targets in multi-room settings to organizing household appliances. Second, applications in construction, formation, target tracking, and game illustrate the versatility of LLMs in specialized fields. These studies showcase MRS solving complex problems in outdoor or competitive environments, such as drone formations for search-and-rescue missions, robotic soccer strategies, and navigation in hazardous areas. Together, these domains underscore the growing impact of LLMs in advancing MRS capabilities across diverse real-world contexts.

Household. The household domain represents a significant focus in studies with well-defined application scenarios, addressing challenges such as navigation, task allocation, and task decomposition. For example, Wu *et al.* [123] and Yu *et al.* [134] investigated navigation and multi-target localization in complex indoor environments,

Table 1 Comparison of LLM-based MRS.

Work	Communication	MRS Type	Modality	Human Intervention	Evaluation	Application	Model Type
High level Task Allocation and Task Planning							
Wu et al. [124]	Cent	Homo	T		Sim(ROS,RViz), Real	Target Tracking	GPT-4o, GPT-3.5 Turbo
Brienza et al. [10]	Cent	Homo	T, I		Sim(SimRobot)	Game	V: GPT-4 Turbo, L: GPT-3.5 Turbo
Lykov et al. [79]	Cent	Homo	T, A		Real	General Purpose	Falcon
Ahn et al. [2]	Dec	Hetero	T, I	✓	Real	General Purpose	V: CLIP, ViLD, PaLI, L: PaLM
Lakhnati et al. [56]	Hier	Hetero	T, A	✓	Sim(VR)	General Purpose	GPT-4
Chen et al. [15]	Hier	Hetero	T	✓	Real	Household	GPT-4o
Lim et al. [69]	Cent	Homo	T, I		Real	Manufacturing	GPT-4o
Jiang et al. [48]	Dec	Homo	T		Sim	General Purpose	GPT-4o, Gemini-2.0-Flash, DeepSeek-V3
Chen et al. [18]	Hier	Hetero	T		Sim(AI2THOR)	General Purpose	GPT-4, GPT-3.5 Turbo
Gupte et al. [37]	Cent	Hetero	T		Sim(GAMA)	General Purpose	-
Huang et al. [41]	Cent	Homo	T		Sim	General Purpose	GPT-4 Turbo
Kannan et al. [50]	Cent	Homo	T		Sim(AI2THOR), Real	Household	GPT-4, GPT-3.5, Llama2, Claude3
Wang et al. [120]	Cent	Hetero	T, I		Sim	Construction	L: Llama-3.1, Claude 3.5, GPT-4o,GPT-3.5 Turbo, V: CLIP
Xu et al. [127]	Cent	Homo	T		Sim(AI2THOR+ALFRED), Real	Household	Minstral, GPT-4
Obata et al. [90]	Cent	Hetero	T		Sim(ROS)	General Purpose	GPT
Liu et al. [74]	Hier	Hetero	T		Sim(BEHAVIOR-1K), Real	General Purpose	GPT-4
Liang et al. [68]	Cent	Homo	T		Sim(RoCoBench)	General Purpose	Llama3.1, Nemotron LLM
Mandi et al. [84]	Dec	Homo	T		Sim, Real	Household	GPT-4
Peng et al. [93]	Cent	Homo	T		Sim	General Purpose	DeepSeek-R1-Distill-Qwen-32B, SFT-Qwen2.5-Coder-7B-Instruct
Yu et al. [135]	Dec	Hetero	T		Sim(PyBullet)	Household	GPT-3.5 Turbo, GPT-4o, Llama3.1
Sueoka et al. [108]	Dec	Hetero	T, I		Real	Construction	V: GPT-4v, L: GPT-4
Hunt et al. [43]	Cent	Homo	T	✓	Real	General Purpose	GPT-4
Yoshida et al. [133]	Dec	Hetero	T, I		-	General Purpose	-
Wang et al. [118]	Cent	Hetero	T	✓	Sim(AI2THOR)	General Purpose	GPT-3.5, Llama-2, Llama-3
Guzman-Merino et al. [38]	Cent	Hetero	T		-	General Purpose	GPT-4o
Cladera et al. [19]	Dec	Hetero	T, I		Sim, Real	General Purpose	GPT-4o
Chen et al. [14]	Cent	Homo	T		Sim	Target Tracking	GPT-4o, GPT, DeepSeek-R1
Gupta et al. [36]	Cent	Homo	T		Sim, Real	Field	GPT-4, Gemini, Llama
Wan et al. [115]	Cent	Hetero	T, I		Sim, Real	Field	GPT-4, fine-tuned MultiPlan
Huang et al. [42]	Cent	Homo	T		Sim, Real	Formation	GPT-4.1
Mid level Motion Planning							
Yu et al. [134]	Cent	Homo	T		Sim(HM3D)	Household	GPT-3.5 Turbo
Morad et al. [88]	Dec	Homo	T		Real	General Purpose	GTE-Based
Godfrey et al. [31]	Cent	Homo	T		Sim, Real	General Purpose	Llama-3.1
Garg et al. [29]	Cent	Homo	T, I		Sim, Real	General Purpose	V: Claude-3 Sonnet/Opus, GPT-4 Turbo, GPT-4o, L: GPT-4, GPT-3.5, Claude-2, Claude-3
Mahadevan et al. [83]	Dec	Homo	T		Sim	Game	GPT-4o-mini
Wu et al. [124]	Cent	Homo	T		Sim(ROS, RViz), Real	Target Tracking	GPT-4o, GPT-3.5 Turbo
Wu et al. [123]	Dec	Homo	T		Sim	Household	GPT-4o
Shen et al. [104]	Cent	Homo	T, I		Sim(HM3D, MP3D)	Target Tracking	GLM-4V-9B
Ji et al. [46]	Dec	Homo	T		Sim	Warehouse	GPT-3.5, GPT-4
Li and Zhou [64]	Dec	Homo	T		Sim, Real	Formation	o3-mini, Llama3.2, Qwen-Max, DeepSeek-R1, Claude-3.5 Sonnet
Rajwanshi et al. [96]	Dec	Hetero	T		Sim	Household	GPT-4
Wang et al. [119]	Dec	Homo	T		Sim	Household	GPT-4o
Low level Action Execution							
Chen et al. [17]	Cent	Homo	T		Sim	General Purpose	GPT-4
Venkatesh et al. [113]	Cent	Homo	T, I		Sim(Pygame), Real	General Purpose	GPT-4, Llama-2, Claude-3 Opus
Li et al. [61]	Dec	Homo	T		Sim	General Purpose	GPT-3.5 Turbo
Strobel et al. [107]	Dec	Homo	T		Sim(ARGoS), Real	General Purpose	GPT-3.5, GPT-4
Lykov et al. [80]	Cent	Homo	T		Sim	Formation	GPT-4
Xue et al. [129]	Cent	Homo	T		Sim	Formation	GPT-4 Turbo
Ji et al. [47]	Cent	Homo	T, I	✓	Sim(ROS)	Formation	o1-mini, GPT-4o, MetaGPT, CaP
Li et al. [66]	Dec	Hetero	T, I	✓	Sim	Field	GPT-4

Table 1 Comparison of LLM-based MRS. Abbreviations: Communication: Cent (Centralized), Dec (Decentralized), Hier (Hierarchical); System: Homo (Homogeneous), Hetero (Heterogeneous); Modal: T (Text), I (Image/Video), A (Audio); Evaluation: Sim (Simulation), Real (Real-world experiments); Model Type: V (VLM), L (LLM).

such as identifying objects across multiple rooms, showcasing advancements in spatial awareness and adaptability. Furthermore, Mandi *et al.* [84], Yu *et al.* [135], Kannan *et al.* [50], and Xu *et al.* [127] explored task decomposition and multi-robot collaboration to execute intricate tasks, such as preparing sandwiches or organizing dishwashers. Chen *et al.* [18] emphasized task allocation for heterogeneous MRS in multi-floor indoor settings, tackling coordination challenges in dynamic environments. Notably, they proposed an EMOS framework, an embodiment-aware operating system that facilitates effective collaboration among heterogeneous robots through a novel "robot resume" approach, enabling robots to interpret their physical constraints from URDF files autonomously rather than relying on predefined roles. These studies address the temporal sequencing of subtasks while leveraging diverse robot capabilities, demonstrating the potential of MRS to solve complex, real-world problems in home environments.

Others Including Construction, Formation, Target Tracking, and Game. Several studies focused on applications in open-world environments, highlighting the versatility and innovative potential of LLM-integrated robotic systems. For instance, Wang *et al.* [120] and Sueoka *et al.* [108] explored the use of LLMs in orchestrating robotic systems for excavation and transportation tasks, showcasing their applicability in construction and complex terrain rescue operations. In drone formations applications, Lykov *et al.* [80] emphasized the coordination and adaptability needed for outdoor tasks such as search-and-rescue missions and environmental monitoring. Similarly, Wu *et al.* [124] addressed open-world target tracking by integrating danger zone recognition, providing robust solutions for autonomous navigation in hazardous environments. These scenarios further demonstrate the potential of LLMs in dynamic and structured environments. Brienza *et al.* [10] introduced **LLCoach**, a framework for robotic soccer applications, where LLMs enhance strategic decision-making and team coordination. Collectively, these studies underscore the potential of LLM-driven MRS to tackle diverse and complex challenges across various domains.

6 LLMs, Simulations, and Benchmarks

6.1 LLMs, VLMs, and VLAs

6.1.1 Extending LLM Capabilities

As discussed in Sec. 3-5, LLMs form the backbone of many recent advances in MRS, enabling robots to follow natural language instructions, perform multi-step reasoning, allocate tasks, plan motions, and interact with human operators. Their strengths include flexible problem-solving across diverse scenarios, integration of symbolic or structured data, and the ability to generalize to new missions without retraining.

However, LLMs primarily operate on textual or symbolic representations of the environment. They rely on external perception modules to provide structured inputs such as maps, object lists, or state summaries. This separation between perception and reasoning can limit adaptability in visually complex or fast-changing environments where world states must be updated and integrated in real time.

To address these limitations, researchers have introduced multi-modal extensions, most notably VLMs and Vision-Language-Action models (VLAs) [91, 141]. VLMs incorporate visual information directly into the reasoning process, allowing robots to ground their decisions in raw sensory data [11, 52]. VLAs take this one step further by integrating perception, reasoning, and action generation into a single pipeline, enabling faster, more reactive responses in dynamic settings [11].

6.1.2 VLMs vs. Traditional CV

Traditional computer vision (CV) in MRS is typically task-specific, using separate modules for detection, segmentation, mapping, or action recognition. These components produce structured outputs that are passed to independent reasoning or control systems. While this modularity can yield strong performance for narrow tasks, it often lacks the flexibility and adaptability needed for unstructured or dynamic missions.

VLMs bridge this gap by embedding visual features into a shared semantic space with language, enabling unified perception and reasoning. This allows recognition of previously unseen

objects without retraining, switching between perception tasks by altering prompts, and direct connection between sensory input and high-level reasoning without intermediate, hand-coded logic. In MRS, these capabilities have been leveraged for perception-informed coordination, such as in Brienza *et al.* [10], where a VLM coach transformed soccer match video into schematic scene descriptions for strategic planning, and in the VADER framework [2], where PaLI and CLIP grounded instructions in real-time affordance detection for replanning and recovery.

6.1.3 VLA Models in MRS

VLAs extend VLMs by coupling perception and reasoning directly with action generation [141]. Instead of outputting textual task plans, they can map visual observations and natural language commands to executable control sequences. This closed-loop capability shortens the cycle between sensing and actuation, allowing robots to respond faster to dynamic changes.

In an MRS setting, each VLA-equipped robot could combine the onboard camera feed, interpret the cooperative context, and directly issue motor commands for joint manipulation or navigation without routing through a separate planning layer. Although still relatively new in MRS research, VLAs are being explored in embodied AI for scenarios requiring fast perception–action loops, such as swarm coordination or hazard avoidance.

6.1.4 Comparative Capabilities and Integration Patterns

From an MRS perspective, LLMs, VLMs, and VLAs have complementary strengths. LLMs excel at long-horizon reasoning, symbolic planning, and high-level negotiation between agents. VLMs add environmental grounding through perception, enabling multi-robot teams to share and reason about visual context. VLAs integrate perception and action for rapid, local decision-making.

Integration patterns in the literature generally follow three approaches: (1) *visual grounding with language reasoning*, where a vision encoder produces scene features that an LLM uses for planning and coordination [10, 29]; (2) *direct multi-modal prompting*, where visual and textual inputs are processed jointly for end-to-end reasoning [29, 108]; and (3) *perception-to-action mapping*, where VLA-style architectures produce executable actions directly from multi-modal inputs, bypassing explicit textual reasoning.

Hybrid systems can combine these strengths. For example, a central LLM might manage mission-level strategy, VLMs on individual robots could process onboard sensor data for situational awareness, and VLAs could execute low-latency control in fast-changing conditions.

6.2 Simulation Environments

We have summarized the simulation platforms used in related works, highlighting their contributions to evaluating and advancing the field. **AI2-THOR** has been adapted for MRS in [18, 50, 118, 127] to evaluate embodied AI agents operating in complex indoor environments [54]. While originally designed for single-agent tasks such as object manipulation and scene understanding, recent research extends its use to MRS scenarios, including cooperative object retrieval, shared perception, and collaborative planning in constrained environments. The physics-enabled interactions allow researchers to test LLM-driven coordination strategies in dynamic and physically grounded environments, where multiple agents must navigate, manipulate objects, and resolve conflicts dynamically. **PyBullet** is an open-source physics engine widely used for simulating robotic systems, including articulated manipulators, wheeled robots, and multi-agent interactions [21]. It provides real-time physics simulations, supporting tasks like collision detection, rigid body dynamics, and reinforcement learning in robotics. In the context of MRS, PyBullet enables accurate modeling of decentralized collaboration, object manipulation, and dynamic environment interactions [135]. **BEHAVIOR-1K**, utilized by Liu *et al.* [74], serves as the foundation for the COHERENT framework, which focuses on large-scale, heterogeneous multi-robot collaboration [59]. This platform facilitates training and evaluation in complex household-like environments where different types of robots (e.g., manipulators, mobile bases) must coordinate to accomplish everyday tasks such as table setting, object handoff, and multi-step assembly processes. The benchmark ensures that LLM-enhanced systems can handle

dynamic task dependencies and ambiguous role assignments. The **Pygame** platform is a cross-platform Python module set designed for video game writing. Robots are modeled as point-mass entities, focusing on formation control, decentralized consensus algorithms, and motion coordination without obstacle avoidance. This platform is particularly useful for analyzing emergent behaviors in swarms, where LLM-based controllers guide self-organized formations through simple local interactions [113]. **Habitat-MAS**, an extension of Habitat, introduces explicit multi-agent communication for indoor navigation and exploration [94, 100, 109]. Unlike the single-agent focus of its predecessor, Habitat-MAS enables studies on cooperative search, simultaneous localization and mapping (SLAM), and inter-agent strategy adaptation, crucial for deploying multi-robot exploration teams in disaster response and service robotics [15]. **ROS**-based simulation is a middleware framework widely used for MRS, enabling inter-robot communication [57] , decentralized control, and real-time data sharing. It provides essential tools for swarm coordination, collaborative mapping, and distributed task allocation. With built-in simulation environments like Gazebo and RViz, ROS allows researchers to develop and test MRS strategies for exploration, target tracking, and cooperative manipulation [124]. **VR** platform introduces immersive simulations for human-robot collaboration and reinforcement learning. These environments are used to test human-in-the-loop control strategies for heterogeneous robot teams, such as coordinating robotic arms and mobile robots in warehouse logistics through natural language instructions [56]. **GAMA** offers a multi-agent modeling environment suited for large-scale robot interactions [37]. It supports evaluations of distributed swarm intelligence, multi-agent task negotiation, and behavior adaptation in unstructured environments, making it ideal for testing decentralized LLM-driven controllers in logistics and autonomous fleet management. **SimRobot**, utilized by Brienza *et al.* [10], is specialized for multi-robot teamwork in robotic soccer. The LLCoach framework, trained using SimRobot, enhances robot coordination and strategic planning by processing match data and optimizing multi-agent role assignments dynamically.

ARGoS, chosen by Strobel *et al.* [107], is a scalable platform for swarm robotics research. It enables controlled experiments on decentralized control mechanisms, including aggregate-then-disperse behaviors, leader election, and emergent self-organization. LLMs integrated into ARGoS are evaluated on their ability to generate adaptive communication protocols and handle task partitioning in dynamic environments. These diverse platforms provide essential tools for evaluating LLM-driven MRS across different scales, from small collaborative teams to large autonomous swarms. By leveraging these environments, researchers refine multi-agent coordination, communication, and decision-making strategies, advancing the integration of LLMs in MRSs for real-world applications.

6.3 Benchmarks

Benchmarks are essential for evaluating LLM-driven MRS, providing standardized environments to measure coordination, adaptability, and performance across diverse scenarios. They enable consistent comparisons, helping identify strengths, limitations, and the effectiveness of MRS in real-world applications. **RoCoBench**, introduced by Mandi *et al.* [84], focuses on human-robot collaboration in fine-grained manipulation tasks. While primarily designed for single-robot control, RoCoBench also provides insights into multi-robot collaboration, particularly in tasks requiring shared manipulation, coordinated actions, and real-time adjustments to changing conditions. The benchmark provides detailed metrics on precision, task success rates, and robustness under unpredictable physical conditions, making it valuable for evaluating LLM-assisted multi-robot cooperation in human-shared workspaces. **ALFRED**, utilized in Xu *et al.* [127], integrates language and vision benchmarks to test agents' ability to follow natural language instructions and execute multi-step tasks in household environments. Though originally focused on single-agent evaluations, ALFRED's framework can be extended to multi-robot task coordination, testing MRS on collaborative planning, sequential action execution, and efficient division of labor in domestic or service robotics applications. **BOLAA**, proposed by Liu *et al.* [76], introduces a multi-agent orchestration benchmark specifically

designed for LLM-augmented autonomous agents (LAAs). Unlike conventional evaluations that focus on individual agents, BOLAA assesses how LLMs manage multi-agent interactions, optimizing task distribution, decision-making, and real-time adaptability. This makes it a useful benchmark for LLM-driven MRS, where autonomous robots benefit from effective communication and collaboration to tackle complex, long-horizon objectives. **COHERENT**-Benchmark, developed by Liu *et al.* [74], is specifically designed for heterogeneous multi-robot collaboration in dynamic and realistic scenarios. Built on the BEHAVIOR-1K platform, this benchmark evaluates MRS across diverse environments, requiring coordinated task execution among robots with distinct capabilities—such as quadrotors for aerial mapping, robotic dogs for agile mobility, and robotic arms for precise manipulation. Key evaluation metrics include task allocation efficiency, inter-robot communication, and collaborative problem-solving, making it a comprehensive benchmark for testing LLM-driven coordination strategies in MRS.

7 Challenges, and Opportunities

Despite the progress in integrating LLMs into MRS, significant challenges that limit their broader adoption and effectiveness remain. These challenges span areas such as reasoning capabilities, real-time performance, and adaptability to dynamic environments. Addressing these issues is critical to unlocking the full potential of LLMs in MRS. This section identifies key challenges the field faces and outlines promising opportunities for future research, offering a roadmap for enhancing the utility and robustness of LLM-driven MRS.

7.1 Challenges

Insufficient Mathematical Capability. LLMs struggle with tasks requiring precise calculations or logical reasoning, such as multi-robot path planning or trajectory optimization. This limitation reduces their effectiveness in scenarios where quantitative accuracy is critical. Mirzadeh *et al.* [87] performed a detailed comparison and investigation on the mathematical

understanding and problem-solving ability of several state-of-the-art LLMs. Specifically, LLMs exhibit noticeable variance when responding to different variations of the same question, with performance declining significantly when only the numerical values are altered. Furthermore, their reasoning capabilities are fragile; they often mimic patterns observed in training data rather than performing genuine logical deduction. This fragility is exacerbated by an increase in the number of clauses within a question, even when the added clauses are irrelevant to the reasoning chain, leading to performance drops of up to 65% in state-of-the-art models. These vulnerabilities present serious challenges for MRS, where precise calculations and robust reasoning are essential for collision-free trajectories, spatial planning, and efficient task execution. Addressing these limitations is critical for deploying LLMs reliably in mathematically intensive applications.

Hallucination. LLMs are prone to generating content that appears plausible but lacks factual accuracy, a phenomenon known as hallucination. This issue is particularly concerning in MRS, where precise and reliable output is crucial for effective collaboration and operation. According to a comprehensive survey on hallucination in LLMs by Huang *et al.* [40], hallucination can be categorized into two main types: actuality hallucinations and faithfulness hallucinations. Factuality hallucinations involve discrepancies between generated content and verifiable real-world facts, leading to incorrect outputs. Faithful hallucinations occur when the generated content diverges from the user's instructions or the provided context, resulting in outputs that do not accurately reflect the intended information. In the context of MRS, such hallucinations can lead to misinterpretations, faulty decision-making, and coordination errors among robots, potentially compromising mission success and safety. Addressing these challenges requires developing methods to detect and mitigate hallucinations, ensuring that LLMs produce outputs that are both factually accurate and contextually appropriate.

Difficulties in Field Deployment. Current options for using LLMs include server-based models, which are usually closed-source, and open-source models that individuals can deploy

locally. Examples of server-based models include OpenAI GPT [1], Anthropic Claude [7], and Google Gemini (formerly known as Bard) [32], and open-sourced LLMs that individuals can run locally includes Meta Llama [23], Falcon [3], Alibaba Qwen [131], and DeepSeek V3 [70] and R1 [34]. The server-based models require a reliable internet connection to send inquiries and receive responses, thus making deploying the MRS with LLMs in remote locations unachievable, which is typical for field robot systems. Moreover, server-based LLMs heavily rely on the performance of the server, where a server outage can interrupt the systems built on LLMs entirely. This issue is especially vital for multi-robot teams as the LLM guides the inter-robot collaboration and decision-making. On the other hand, local models can avoid using the servers but require hardware onboard that is powerful enough to run LLMs locally.

Relatively High Latency. Real-time information exchange and decision-making are critical for the effective operation of MRS in real-world scenarios. However, a notable challenge of using LLMs lies in their relatively high and variable response times, which can depend on model complexity, hardware capabilities, and server availability. For example, Chen *et al.* [17] reported that in a multi-agent path finding scenario utilizing GPT-4 from OpenAI, the response time per step ranged between 15 and 30 seconds, significantly impacting real-time feasibility. While local processing on more powerful hardware can reduce latency, this approach is costly and becomes less scalable as the number of robots increases. Addressing this challenge requires exploring optimized LLM architectures, efficient inference techniques, and scalable solutions that balance computational demands with real-time operational requirements.

Multi-modal Integration Difficulties. While VLMs and VLAs extend the role of LLMs in MRS by grounding reasoning in perception and linking directly to action, they also introduce new challenges. Multi-modal inference often incurs higher latency due to the added cost of processing images, video, or sensor streams alongside text [65]. Domain shift remains a significant issue, as models trained on internet-scale vision-language corpora may not generalize reliably to the specialized sensing modalities of robots (e.g., LiDAR, thermal cameras, aerial views) [82]. Moreover, fusing heterogeneous and asynchronous sensor data across multiple robots introduces synchronization and consistency problems, especially in decentralized settings [82]. VLAs face the additional challenge of grounding action outputs across diverse robot morphologies, making it difficult to generalize learned behaviors across heterogeneous teams. Addressing these multi-modal integration difficulties is critical for ensuring that perception-grounded LLMs can operate robustly in real-world MRS deployments.

Lack of Benchmarks. Performance evaluation is essential for the new research on MRS with LLMs. However, existing benchmarking systems are primarily designed for indoor environments and household applications, which limits their applicability to the diverse and evolving scenarios where MRS operates. As current research often represents initial efforts to apply LLMs to MRS, performance comparisons typically focus on demonstrating feasibility by contrasting LLMs with traditional methods. While this approach is valuable for establishing a baseline, future advancements will likely yield significant performance and functionality improvements. A unified benchmarking framework tailored to multi-robot applications would provide researchers with consistent metrics to evaluate and quantify progress. Such a system would not only facilitate a clearer understanding of the impact of new research but also promote standardization and comparability across studies, accelerating innovation in this emerging field.

7.2 Opportunities

Fine-tuning and RAG. Fine-tuning LLMs on domain-specific datasets and incorporating RAG techniques are promising avenues for improving their performance in multi-robot applications. Fine-tuning allows researchers to adapt pre-trained LLMs to specific tasks, enhancing their contextual understanding and reducing issues like hallucination. RAG complements this by integrating external knowledge retrieval mechanisms, enabling LLMs to access relevant information dynamically during runtime. Together, these

techniques can significantly improve LLMs' accuracy, reliability, and adaptability in diverse and complex multi-robot scenarios.

High-quality Task-specific Datasets. Creating high-quality and task-specific datasets is essential for advancing LLM capabilities in MRS. Leveraging more capable models, such as the latest LLMs, to generate synthetic datasets can accelerate the development of training materials tailored to specific tasks or environments. These datasets should include diverse scenarios, reasoning-focused labels, and context-specific knowledge to improve LLMs' problem-solving and decision-making capabilities. Task-specific datasets are particularly important for preparing MRS to operate in unstructured or open-world environments.

Advanced Reasoning Techniques. Improving the reasoning capabilities of LLMs is critical for addressing their current limitations in logical and mathematical tasks. Techniques such as Chain of Thought (CoT) prompting [122], fine-tuning with explicit reasoning labels [138], integrating symbolic reasoning, and training with RL can enhance the ability of LLMs to handle complex multi-step problems. By advancing reasoning methods, LLMs can better support tasks that require precision and logical deduction, such as multi-robot path planning and coordination.

Task-specific and Lightweight Models. While large-scale LLMs offer superior performance, they are often impractical for resource-constrained environments. Developing task-specific and lightweight models tailored for multi-robot applications can mitigate this issue [9]. Models like SmolVLM, Moondream 2B, PaliGemma-2 3B, and Qwen2-VL 2B demonstrate how smaller architectures can reduce computational demands and latency while maintaining adequate performance for specific tasks. Model distillation is another approach to make small models more capable by distilling knowledge from a more capable LLM, like DeepSeek-R1-Distill-Qwen-1.5B, where the knowledge from DeepSeek R1 is distilled into a small Qwen2.5-Math-1.5B model [128]. Balancing efficiency and effectiveness is key to enabling scalable deployments of LLMs in field robotics.

Multi-modal and Embodied Extensions. Emerging research on multi-modal LLMs suggests promising opportunities for extending MRS capabilities. Video-language transformers, point cloud-language models [26], and spatio-temporal VLAs could enable richer reasoning over dynamic events [140], 3D spatial layouts, and real-time cooperative interactions. These architectures would allow multi-robot teams to better interpret evolving environments and adapt their strategies accordingly. As multi-modal and embodied extensions mature, they could bridge the gap between high-level symbolic reasoning and low-level perception-action execution, unlocking more adaptive and autonomous multi-robot coordination [9].

Expanding to Unstructured Environments. Most current applications and benchmarks focus on indoor or structured environments, leaving significant gaps in outdoor and unstructured scenarios. Research should prioritize expanding MRS capabilities to include operations in open-world contexts, such as agricultural fields, disaster zones, and remote exploration sites. Addressing the unique challenges of these environments, including variability, noise, and unpredictable dynamics, will broaden the applicability of LLM-enabled MRS.

Latest More Capable LLMs. The continued development of state-of-the-art LLMs opens new possibilities for MRS. Models such as PaliGemma-2, Qwen-3, Claude 4 Sonnet/Opus, GPT o3 or o4-mini, GPT-5, and DeepSeek V3 and R1 offer enhanced reasoning, understanding, and multitasking capabilities [86, 126]. Incorporating these advanced models into MRS research can accelerate progress by providing improved baseline performance and enabling innovative applications. Exploring their integration with robotics systems can further push the boundaries of what multi-robot teams can achieve.

8 Conclusion

This survey provides the first comprehensive exploration of integrating LLMs into MRS, a topic at the intersection of robotics and artificial

intelligence that is rapidly gaining prominence. Unlike general robotics or multi-agent systems, MRS pose unique challenges and opportunities due to their reliance on physical embodiment and real-world interaction. This paper highlights how LLMs can address these challenges, offering novel possibilities for collective intelligence and collaboration in MRS.

We introduced a structured framework for understanding the role of LLMs in MRS, spanning high-level task allocation and planning, mid-level motion planning, low-level action execution, and human intervention. This framework reflects the diverse functionalities enabled by LLMs, including decomposing complex tasks, coordinating multi-robot multi-task scenarios, and facilitating seamless human-robot interaction. Additionally, we reviewed applications of MRS across various domains, from household tasks to construction, formation control, target tracking, and game-/competition, demonstrating the versatility and transformative potential of LLMs in these systems.

The significance of integrating LLMs into MRS lies in their ability to augment individual and collective intelligence, enabling robots to operate autonomously and collaboratively in increasingly complex environments. As LLMs continue to demonstrate their potential in everyday applications, their adoption in robotics promises to unlock new possibilities for innovation and efficiency in MRS.

Looking ahead, both immediate and long-term perspectives present exciting opportunities for research and development. In the near term, addressing challenges such as benchmarking, reasoning capabilities, and real-time performance will be critical for bridging the gap between lab-based simulations and real-world applications. Long-term prospects include leveraging LLMs to enable more complex missions, such as disaster response, space exploration, and large-scale autonomous operations, expanding the boundaries of what MRS can achieve.

We hope this survey will be a valuable resource for researchers, providing an overview of current progress, identifying gaps, and highlighting opportunities for future exploration. By advancing our understanding of LLMs in MRS, we aim to inspire innovation and foster collaboration across disciplines, accelerating the transition from theoretical studies to practical deployments that benefit society.

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References

[1] Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. arXiv preprint arXiv:2303.08774, 2023.

[2] Michael Ahn, Montserrat Gonzalez Arenas, Matthew Bennice, Noah Brown, Christine Chan, Byron David, Anthony Francis, Gavin Gonzalez, Rainer Hessmer, Tomas Jackson, Nikhil J. Joshi, Daniel Lam, Tsang-Wei Edward Lee, Alex Luong, Sharath Maddineni, Harsh Patel, Jodilyn Peralta, Jornell Quiambao, Diego Reyes, Rosario M. Jauregui Ruano, Dorsa Sadigh, Pannag Sanketi, Leila Takayama, Pavel Vodenski, and Fei Xia. VADER: Visual Affordance Detection and Error Recovery for Multi Robot Human Collaboration. arXiv preprint arXiv:2405.16021, May 2024.

[3] Ebtesam Almazrouei, Hamza Alobeidli, Abdulaziz Alshamsi, Alessandro Cappelli, Ruxandra Cojocaru, Mérouane Debbah, Étienne Goffinet, Daniel Hesslow, Julien Launay, Quentin Malartic, et al. The falcon series of open language models. arXiv preprint arXiv:2311.16867, 2023.

[4] Javier Alonso-Mora, Ross Knepper, Roland Siegwart, and Daniela Rus. Local motion planning for collaborative multi-robot manipulation of deformable objects. In 2015 IEEE international conference on robotics and automation (ICRA), pages 5495–5502. IEEE, 2015.

[5] Javier Alonso-Mora, Eduardo Montijano, Mac Schwager, and Daniela Rus. Distributed multi-robot formation control among obstacles: A geometric and optimization approach with consensus. In 2016 IEEE international conference on robotics and automation (ICRA), pages 5356–5363. IEEE, 2016.

[6] Xing An, Celimuge Wu, Yangfei Lin, Min Lin, Tsutomu Yoshinaga, and Yusheng Ji. Multi-robot systems and cooperative object transport: Communications, platforms, and challenges. IEEE Open Journal of the Computer Society, 4:23–36, 2023.

[7] Anthropic. Claude, 2024. Accessed via Anthropic API.

[8] Joseph L Baxter, EK Burke, Jonathan M Garibaldi, and Mark Norman. Multi-robot search and rescue: A potential field based approach. Autonomous robots and agents, pages 9–16, 2007.

[9] Peter Belcak, Greg Heinrich, Shizhe Diao, Yonggan Fu, Xin Dong, Saurav Muralidharan, Yingyan Celine Lin, and Pavlo Molchanov. Small language models are the future of agentic ai. arXiv preprint arXiv:2506.02153, 2025.

[10] Michele Brienza, Emanuele Musumeci, Vincenzo Suriani, Daniele Affinita, Andrea Pennisi, Daniele Nardi, and Domenico Daniele Bloisi. LLCoach: Generating Robot Soccer Plans using Multi-Role Large Language Models. arXiv preprint arXiv:2406.18285, June 2024.

[11] Anthony Brohan, Noah Brown, Justice Carbajal, Yevgen Chebotar, Xi Chen, Krzysztof Choromanski, Tianli Ding, D Driess, A Dubey, C Finn, et al. Rt-2: Vision-language-action models transfer web knowledge to robotic control. arxiv. arXiv preprint arXiv:2307.15818, 2023.

[12] Wolfram Burgard, Mark Moors, Cyrill Stachniss, and Frank E Schneider. Coordinated multi-robot exploration. IEEE Transactions on robotics, 21(3):376–386, 2005.

[13] Bill Cai, Fei Lu, and Lifeng Zhou. Energy-aware routing algorithm for mobile ground-to-air charging. In 2024 IEEE International Symposium of Robotics Research (ISRR). IEEE, 2024.

[14] Junhong Chen, Ziqi Yang, Haoyuan G Xu, Dandan Zhang, and George Mylonas. Multi-agent systems for robotic autonomy with llms. In Proceedings of the Computer Vision and Pattern Recognition Conference, pages 4194–4204, 2025.

[15] Junting Chen, Checheng Yu, Xunzhe Zhou, Tianqi Xu, Yao Mu, Mengkang Hu, Wenqi Shao, Yikai Wang, Guohao Li, and Lin Shao. EMOS: Embodiment-aware Heterogeneous Multi-robot Operating System with LLM Agents. arXiv preprint arXiv:2410.22662, October 2024.

[16] Siji Chen, Yanshen Sun, Peihan Li, Lifeng Zhou, and Chang-Tien Lu. Learning decentralized flocking controllers with spatiotemporal graph neural network. In 2024 IEEE International Conference on Robotics and Automation (ICRA), pages 2596–2602. IEEE, 2024.

[17] Weizhe Chen, Sven Koenig, and Bistra Dilkina. Why Solving Multi-agent Path Finding with Large Language Model has not Succeeded Yet. arXiv preprint arXiv:2401.03630, feb 2024.

[18] Yongchao Chen, Jacob Arkin, Yang Zhang, Nicholas Roy, and Chuchu Fan. Scalable Multi-Robot Collaboration with Large Language Models: Centralized or Decentralized Systems? In 2024 IEEE International Conference on Robotics and Automation (ICRA), pages 4311–4317, May 2024.

[19] Fernando Cladera, Zachary Ravichandran, Jason Hughes, Varun Murali, Carlos Nieto-Granda, M Ani Hsieh, George J Pappas, Camillo J Taylor, and Vijay Kumar. Air-ground collaboration for language-specified missions in unknown environments. arXiv preprint arXiv:2505.09108, 2025.

[20] Jorge Cortés and Magnus Egerstedt. Coordinated control of multi-robot systems: A survey. SICE Journal of Control, Measurement, and System Integration, 10(6):495–503, 2017.

[21] Erwin Coumans and Yunfei Bai. Pybullet, a python module for physics simulation for games, robotics and machine learning. http://pybullet.org, 2016–2021.

[22] Ning Ding, Yujia Qin, Guang Yang, Fuchao Wei, Zonghan Yang, Yusheng Su, Shengding Hu, Yulin Chen, Chi-Min Chan, Weize Chen, et al. Parameter-efficient fine-tuning of large-scale pre-trained language models. Nature Machine Intelligence, 5(3):220–235, 2023.

[23] Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, et al. The llama 3 herd of models. arXiv preprint arXiv:2407.21783, 2024.

[24] Maria Valera Espina, Raphael Grech, Deon De Jager, Paolo Remagnino, Luca Iocchi, Luca Marchetti, Daniele Nardi, Dorothy Monekosso, Mircea Nicolescu, and Christopher King. Multi-robot teams for environmental monitoring. Innovations in Defence Support Systems–3: Intelligent Paradigms in Security, pages 183–209, 2011.

[25] Roya Firoozi, Johnathan Tucker, Stephen Tian, Anirudha Majumdar, Jiankai Sun, Weiyu Liu, Yuke Zhu, Shuran Song, Ashish Kapoor, Karol Hausman, Brian Ichter, Danny Driess, Jiajun Wu, Cewu Lu, and Mac Schwager. Foundation Models in Robotics: Applications, Challenges, and the Future. arXiv preprint arXiv:2312.07843, December 2023.

[26] Tsu-Jui Fu, Linjie Li, Zhe Gan, Kevin Lin, William Yang Wang, Lijuan Wang, and Zicheng Liu. Violet: End-to-end video-language transformers with masked visual-token modeling. arXiv preprint arXiv:2111.12681, 2021.

[27] Yuman Gao, Yingjian Wang, Xingguang Zhong, Tiankai Yang, Mingyang Wang, Zhixiong Xu, Yongchao Wang, Yi Lin, Chao Xu, and Fei Gao. Meeting-merging-mission: A multi-robot coordinate framework for large-scale communication-limited exploration. In 2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pages 13700–13707. IEEE, 2022.

[28] Yunfan Gao, Yun Xiong, Xinyu Gao, Kangxiang Jia, Jinliu Pan, Yuxi Bi, Yi Dai, Jiawei Sun, and Haofen Wang. Retrieval-augmented generation for large language models: A survey. arXiv preprint arXiv:2312.10997, 2023.

[29] Kunal Garg, Songyuan Zhang, Jacob Arkin, and Chuchu Fan. Foundation Models to the Rescue: Deadlock Resolution in Connected Multi-Robot Systems. arXiv preprint arXiv:2404.06413, September 2024.

[30] Jennifer Gielis, Ajay Shankar, and Amanda Prorok. A critical review of communications in multi-robot systems. Current robotics reports, 3(4):213–225, 2022.

[31] Toby Godfrey, William Hunt, and Mohammad D. Soorati. MARLIN: Multi-Agent Reinforcement Learning Guided by Language-Based Inter-Robot Negotiation. arXiv preprint arXiv:2410.14383, October 2024.

[32] Google. Gemini, 2024. Accessed [Date accessed], Google AI system.

[33] Ben Grocholsky, James Keller, Vijay Kumar, and George Pappas. Cooperative air and ground surveillance. IEEE Robotics & Automation Magazine, 13(3):16–25, 2006.

[34] Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, et al. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. arXiv preprint arXiv:2501.12948, 2025.

[35] Taicheng Guo, Xiuying Chen, Yaqi Wang, Ruidi Chang, Shichao Pei, Nitesh V. Chawla, Olaf Wiest, and Xiangliang Zhang. Large Language Model based Multi-Agents: A Survey of Progress and Challenges. arXiv preprint arXiv:2402.01680, April 2024.

[36] Piyush Gupta, David Isele, Enna Sachdeva, Pin-Hao Huang, Behzad Dariush, Kwonjoon Lee, and Sangjae Bae. Generalized mission planning for heterogeneous multi-robot teams via llm-constructed hierarchical trees. arXiv preprint arXiv:2501.16539, 2025.

[37] Arjun Gupte, Ruiqi Wang, Vishnunandan L. N. Venkatesh, Taehyeon Kim, Dezhong Zhao, and Byung-Cheol Min. REBEL: Rule-based and Experience-enhanced Learning with LLMs for Initial Task Allocation in Multi-Human Multi-Robot Teams. arXiv preprint arXiv:2409.16266, September 2024.

[38] Miguel Guzmán-Merino and Nils Sören Krause. LLM Assistant for heterogeneous multi-robot system dynamic task planning. September 2024. Publisher: Technische Universität Hamburg, Institut für Digitales und Autonomes Bauen.

[39] Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. Lora: Low-rank adaptation of large language models. arXiv preprint arXiv:2106.09685, 2021.

[40] Lei Huang, Weijiang Yu, Weitao Ma, Weihong Zhong, Zhangyin Feng, Haotian Wang, Qianglong Chen, Weihua Peng, Xiaocheng Feng, Bing Qin, et al. A survey on hallucination in large language models: Principles, taxonomy, challenges, and open questions. ACM Transactions on Information Systems, 2023.

[41] Zhehui Huang, Guangyao Shi, and Gaurav S Sukhatme. From words to routes: Applying large language models to vehicle routing. arXiv preprint arXiv:2403.10795, 2024.

[42] Zhehui Huang, Guangyao Shi, Yuwei Wu, Vijay Kumar, and Gaurav S Sukhatme. Compositional coordination for multi-robot teams with large language models. arXiv preprint arXiv:2507.16068, 2025.

[43] William Hunt, Toby Godfrey, and Mohammad D Soorati. Conversational language models for human-in-the-loop multi-robot coordination. arXiv preprint arXiv:2402.19166, 2024.

[44] William Hunt, Sarvapali D. Ramchurn, and Mohammad D. Soorati. A Survey of Language-Based Communication in Robotics. arXiv preprint arXiv:2406.04086, September 2024.

[45] Hyeongyo Jeong, Haechan Lee, Changwon Kim, and Sungtae Shin. A survey of robot intelligence with large language models. Applied Sciences, 14(19):8868, 2024.

[46] Jiabao Ji, Yongchao Chen, Yang Zhang, Ramana Rao Kompella, Chuchu Fan, Gaowen Liu, and Shiyu Chang. Collision- and reachability-aware multi-robot control with grounded llm planners. arXiv preprint arXiv:2505.20573, 2025.

[47] Wenkang Ji, Huaben Chen, Mingyang Chen, Guobin Zhu, Lufeng Xu, Roderich Groß, Rui Zhou, Ming Cao, and Shiyu Zhao. Genswarm: Scalable multi-robot code-policy generation and deployment via language models. arXiv preprint arXiv:2503.23875, 2025.

[48] Yitao Jiang, Luyang Zhao, Alberto Quattrini Li, Muhao Chen, and Devin Balkcom. Exploring spontaneous social interaction swarm robotics powered by large language models.

[49] Chris Jones, Dylan Shell, Maja J Mataric, and Brian Gerkey. Principled approaches to the design of multi-robot systems. In Proc. of the Workshop on Networked Robotics, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2004), 2004.

[50] Shyam Sundar Kannan, Vishnunandan L. N. Venkatesh, and Byung-Cheol Min. SMART-LLM: Smart Multi-Agent Robot

Task Planning using Large Language Models. arXiv preprint arXiv:2309.10062, March 2024.

[51] Kento Kawaharazuka, Tatsuya Matsushima, Andrew Gambardella, Jiaxian Guo, Chris Paxton, and Andy Zeng. Real-World Robot Applications of Foundation Models: A Review. arXiv preprint arXiv:2402.05741, October 2024.

[52] Moo Jin Kim, Karl Pertsch, Siddharth Karamcheti, Ted Xiao, Ashwin Balakrishna, Suraj Nair, Rafael Rafailov, Ethan Foster, Grace Lam, Pannag Sanketi, Quan Vuong, Thomas Kollar, Benjamin Burchfiel, Russ Tedrake, Dorsa Sadigh, Sergey Levine, Percy Liang, and Chelsea Finn. OpenVLA: An Open-Source Vision-Language-Action Model. arXiv preprint arXiv:2406.09246, September 2024.

[53] Yeseung Kim, Dohyun Kim, Jieun Choi, Jisang Park, Nayoung Oh, and Daehyung Park. A Survey on Integration of Large Language Models with Intelligent Robots. arXiv preprint arXiv:2404.09228, August 2024.

[54] Eric Kolve, Roozbeh Mottaghi, Winson Han, Eli VanderBilt, Luca Weihs, Alvaro Herrasti, Daniel Gordon, Yuke Zhu, Abhinav Gupta, and Ali Farhadi. AI2-THOR: An Interactive 3D Environment for Visual AI. arXiv, 2017.

[55] Vijay Kumar and Nathan Michael. Opportunities and challenges with autonomous micro aerial vehicles. The International Journal of Robotics Research, 31(11):1279–1291, 2012.

[56] Younes Lakhnati, Max Pascher, and Jens Gerken. Exploring Large Language Models to Facilitate Variable Autonomy for Human-Robot Teaming. arXiv preprint arXiv:2312.07214, March 2024.

[57] Bastian Lampe, Lennart Reiher, Lukas Zanger, Timo Woopen, Raphael van Kempen, and Lutz Eckstein. Robotkube: Orchestrating large-scale cooperative multi-robot systems with kubernetes and ros. In

2023 IEEE 26th International Conference on Intelligent Transportation Systems (ITSC), pages 2719–2725. IEEE, 2023.

[58] Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, et al. Retrieval-augmented generation for knowledge-intensive nlp tasks. Advances in Neural Information Processing Systems, 33:9459–9474, 2020.

[59] Chengshu Li, Ruohan Zhang, Josiah Wong, Cem Gokmen, Sanjana Srivastava, Roberto Martín-Martín, Chen Wang, Gabrael Levine, Michael Lingelbach, Jiankai Sun, et al. Behavior-1k: A benchmark for embodied ai with 1,000 everyday activities and realistic simulation. In Conference on Robot Learning, pages 80–93. PMLR, 2023.

[60] Peihan Li, Jiazhen Liu, Yuwei Wu, and Lifeng Zhou. Failure-aware multi-robot coordination for resilient and adaptive target tracking. arXiv preprint arXiv:2508.02529, 2025.

[61] Peihan Li, Vishnu Menon, Bhavanaraj Gudiguntla, Daniel Ting, and Lifeng Zhou. Challenges Faced by Large Language Models in Solving Multi-Agent Flocking. Distributed Autonomous Robotics Systems (DARS), April 2024.

[62] Peihan Li, Yuwei Wu, Jiazhen Liu, Gaurav S Sukhatme, Vijay Kumar, and Lifeng Zhou. Resilient and adaptive replanning for multi-robot target tracking with sensing and communication danger zones. arXiv preprint arXiv:2409.11230, 2024.

[63] Peihan Li and Lifeng Zhou. Assignment algorithms for multi-robot multi-target tracking with sufficient and limited sensing capability. In 2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pages 11035–11041. IEEE, 2023.

[64] Peihan Li and Lifeng Zhou. Llm-flock: Decentralized multi-robot flocking via large

language models and influence-based consensus. arXiv preprint arXiv:2505.06513, 2025.

[65] Songtao Li and Hao Tang. Multimodal alignment and fusion: A survey. arXiv preprint arXiv:2411.17040, 2024.

[66] Zhaoxing Li, Wenbo Wu, Yue Wang, Yanran Xu, William Hunt, and Sebastian Stein. Hmcf: A human-in-the-loop multi-robot collaboration framework based on large language models. arXiv preprint arXiv:2505.00820, 2025.

[67] Zhi Li, Ali Vatankhah Barenji, Jiazhi Jiang, Ray Y Zhong, and Gangyan Xu. A mechanism for scheduling multi robot intelligent warehouse system face with dynamic demand. Journal of Intelligent Manufacturing, 31:469–480, 2020.

[68] Jiazhao Liang, Hao Huang, Yu Hao, Geeta Chandra Raju Bethala, Congcong Wen, and Yi Fang. Integrating retrospective framework in multi-robot collaboration. In 2025 11th International Conference on Automation, Robotics, and Applications (ICARA), pages 195–199. IEEE, 2025.

[69] Jonghan Lim and Ilya Kovalenko. Dynamic task adaptation for multi-robot manufacturing systems with large language models. arXiv preprint arXiv:2505.22804, 2025.

[70] Aixin Liu, Bei Feng, Bing Xue, Bingxuan Wang, Bochao Wu, Chengda Lu, Chenggang Zhao, Chengqi Deng, Chenyu Zhang, Chong Ruan, et al. Deepseek-v3 technical report. arXiv preprint arXiv:2412.19437, 2024.

[71] Jiazhen Liu, Peihan Li, Yuwei Wu, Gaurav S Sukhatme, Vijay Kumar, and Lifeng Zhou. Multi-robot target tracking with sensing and communication danger zones. Distributed Autonomous Robotic Systems (DARS), 2024.

[72] Jiazhen Liu, Lifeng Zhou, Ragesh Ramachandran, Gaurav S Sukhatme, and Vijay Kumar. Decentralized risk-aware tracking of multiple targets. In International Symposium on Distributed Autonomous Robotic Systems, pages 408–423. Springer, 2022.

[73] Jun Liu, Lifeng Zhou, Pratap Tokekar, and Ryan K Williams. Distributed resilient submodular action selection in adversarial environments. IEEE Robotics and Automation Letters, 6(3):5832–5839, 2021.

[74] Kehui Liu, Zixin Tang, Dong Wang, Zhigang Wang, Bin Zhao, and Xuelong Li. COHERENT: Collaboration of Heterogeneous Multi-Robot System with Large Language Models. arXiv preprint arXiv:2409.15146, September 2024.

[75] Xu Liu, Ankit Prabhu, Fernando Cladera, Ian D Miller, Lifeng Zhou, Camillo J Taylor, and Vijay Kumar. Active metric-semantic mapping by multiple aerial robots. In 2023 IEEE International Conference on Robotics and Automation (ICRA), pages 3282–3288. IEEE, 2023.

[76] Zhiwei Liu, Weiran Yao, Jianguo Zhang, Le Xue, Shelby Heinecke, Rithesh Murthy, Yihao Feng, Zeyuan Chen, Juan Carlos Niebles, Devansh Arpit, Ran Xu, Phil Mui, Huan Wang, Caiming Xiong, and Silvio Savarese. BOLAA: Benchmarking and Orchestrating LLM-augmented Autonomous Agents. arXiv preprint arXiv:2308.05960, August 2023.

[77] Ryan Luna and Kostas E Bekris. Efficient and complete centralized multi-robot path planning. In 2011 IEEE/RSJ International Conference on Intelligent Robots and Systems, pages 3268–3275. IEEE, 2011.

[78] Cai Luo, Andre Possani Espinosa, Danu Pranantha, and Alessandro De Gloria. Multi-robot search and rescue team. In 2011 IEEE International Symposium on Safety, Security, and Rescue Robotics, pages 296–301. IEEE, 2011.

[79] Artem Lykov, Maria Dronova, Nikolay Naglov, Mikhail Litvinov, Sergei Satsevich, Artem Bazhenov, Vladimir Berman, Aleksei

Shcherbak, and Dzmitry Tsetserukou. LLM-MARS: Large Language Model for Behavior Tree Generation and NLP-enhanced Dialogue in Multi-Agent Robot Systems. arXiv preprint arXiv:2312.09348, December 2023.

[80] Artem Lykov, Sausar Karaf, Mikhail Martynov, Valerii Serpiva, Aleksey Fedoseev, Mikhail Konenkov, and Dzmitry Tsetserukou. Flockgpt: Guiding uav flocking with linguistic orchestration. arXiv preprint arXiv:2405.05872, 2024.

[81] Kai-Chieh Ma, Zhibei Ma, Lantao Liu, and Gaurav S Sukhatme. Multi-robot informative and adaptive planning for persistent environmental monitoring. In Distributed Autonomous Robotic Systems: The 13th International Symposium, pages 285–298. Springer, 2018.

[82] Yueen Ma, Zixing Song, Yuzheng Zhuang, Jianye Hao, and Irwin King. A survey on vision-language-action models for embodied ai. arXiv preprint arXiv:2405.14093, 2024.

[83] Vagul Mahadevan, Shangtong Zhang, and Rohan Chandra. Gamechat: Multi-llm dialogue for safe, agile, and socially optimal multi-agent navigation in constrained environments. arXiv preprint arXiv:2503.12333, 2025.

[84] Zhao Mandi, Shreeya Jain, and Shuran Song. RoCo: Dialectic Multi-Robot Collaboration with Large Language Models. In 2024 IEEE International Conference on Robotics and Automation (ICRA), pages 286–299, May 2024.

[85] Siddharth Mayya, Ragesh K Ramachandran, Lifeng Zhou, Vinay Senthil, Dinesh Thakur, Gaurav S Sukhatme, and Vijay Kumar. Adaptive and risk-aware target tracking for robot teams with heterogeneous sensors. IEEE Robotics and Automation Letters, 7(2):5615–5622, 2022.

[86] Shervin Minaee, Tomas Mikolov, Narjes Nikzad, Meysam Chenaghlu, Richard Socher, Xavier Amatriain, and Jianfeng Gao. Large language models: A survey.

arXiv preprint arXiv:2402.06196, 2024.

[87] Iman Mirzadeh, Keivan Alizadeh, Hooman Shahrokhi, Oncel Tuzel, Samy Bengio, and Mehrdad Farajtabar. GSM-Symbolic: Understanding the Limitations of Mathematical Reasoning in Large Language Models. arXiv preprint arXiv:2410.05229, October 2024.

[88] Steven Morad, Ajay Shankar, Jan Blumenkamp, and Amanda Prorok. Language-Conditioned Offline RL for Multi-Robot Navigation. arXiv preprint arXiv:2407.20164, July 2024.

[89] Humza Naveed, Asad Ullah Khan, Shi Qiu, Muhammad Saqib, Saeed Anwar, Muhammad Usman, Naveed Akhtar, Nick Barnes, and Ajmal Mian. A comprehensive overview of large language models. arXiv preprint arXiv:2307.06435, 2023.

[90] Kazuma Obata, Tatsuya Aoki, Takato Horii, Tadahiro Taniguchi, and Takayuki Nagai. LiP-LLM: Integrating Linear Programming and dependency graph with Large Language Models for multi-robot task planning. arXiv preprint arXiv:2410.21040, October 2024.

[91] Abby O'Neill, Abdul Rehman, Abhiram Maddukuri, Abhishek Gupta, Abhishek Padalkar, Abraham Lee, Acorn Pooley, Agrim Gupta, Ajay Mandlekar, Ajinkya Jain, et al. Open x-embodiment: Robotic learning datasets and rt-x models: Open x-embodiment collaboration 0. In 2024 IEEE International Conference on Robotics and Automation (ICRA), pages 6892–6903. IEEE, 2024.

[92] Lynne E Parker. Handbook of robotics chapter 40: Multiple mobile robot systems, 2008.

[93] Mingming Peng, Zhendong Chen, Jie Yang, Jin Huang, Zhengqi Shi, Qihao Liu, Xinyu Li, and Liang Gao. Automatic milp model construction for multi-robot task allocation and scheduling based on large language models. arXiv preprint arXiv:2503.13813,

2025.

[94] Xavi Puig, Eric Undersander, Andrew Szot, Mikael Dallaire Cote, Ruslan Partsey, Jimmy Yang, Ruta Desai, Alexander William Clegg, Michal Hlavac, Tiffany Min, Theo Gervet, Vladimir Vondrus, Vincent-Pierre Berges, John Turner, Oleksandr Maksymets, Zsolt Kira, Mrinal Kalakrishnan, Jitendra Malik, Devendra Singh Chaplot, Unnat Jain, Dhruv Batra, Akshara Rai, and Roozbeh Mottaghi. Habitat 3.0: A co-habitat for humans, avatars and robots, 2023.

[95] Jorge Pena Queralta, Jussi Taipalmaa, Bilge Can Pullinen, Victor Kathan Sarker, Tuan Nguyen Gia, Hannu Tenhunen, Moncef Gabbouj, Jenni Raitoharju, and Tomi Westerlund. Collaborative multi-robot search and rescue: Planning, coordination, perception, and active vision. Ieee Access, 8:191617–191643, 2020.

[96] Abhinav Rajvanshi, Pritish Sahu, Tixiao Shan, Karan Sikka, and Han-Pang Chiu. Sayconav: Utilizing large language models for adaptive collaboration in decentralized multi-robot navigation. arXiv preprint arXiv:2505.13729, 2025.

[97] Ragesh K Ramachandran, Lifeng Zhou, James A Preiss, and Gaurav S Sukhatme. Resilient coverage: Exploring the local-to-global trade-off. In 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pages 11740–11747. IEEE, 2020.

[98] Yara Rizk, Mariette Awad, and Edward W Tunstel. Cooperative heterogeneous multi-robot systems: A survey. ACM Computing Surveys (CSUR), 52(2):1–31, 2019.

[99] Ariel Rosenfeld, A Noa, O Maksimov, and S Kraus. Human-multi-robot team collaboration for efficient warehouse operation. Autonomous Robots and Multirobot Systems (ARMS), 2016.

[100] Manolis Savva, Abhishek Kadian, Oleksandr Maksymets, Yili Zhao, Erik Wijmans, Bhavana Jain, Julian Straub, Jia Liu, Vladlen Koltun, Jitendra Malik, Devi Parikh, and Dhruv Batra. Habitat: A Platform for Embodied AI Research. In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), 2019.

[101] Mac Schwager, Brian J Julian, Michael Angermann, and Daniela Rus. Eyes in the sky: Decentralized control for the deployment of robotic camera networks. Proceedings of the IEEE, 99(9):1541–1561, 2011.

[102] Vishnu D Sharma, Maymoonah Toubeh, Lifeng Zhou, and Pratap Tokekar. Risk-aware planning and assignment for ground vehicles using uncertain perception from aerial vehicles. In 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pages 11763–11769. IEEE, 2020.

[103] Vishnu Dutt Sharma, Lifeng Zhou, and Pratap Tokekar. D2coplan: A differentiable decentralized planner for multi-robot coverage. In 2023 IEEE International Conference on Robotics and Automation (ICRA), pages 3425–3431. IEEE, 2023.

[104] Zhixuan Shen, Haonan Luo, Kexun Chen, Fengmao Lv, and Tianrui Li. Enhancing multi-robot semantic navigation through multimodal chain-of-thought score collaboration. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 39, pages 14664–14672, 2025.

[105] Guangyao Shi, Ishat E Rabban, Lifeng Zhou, and Pratap Tokekar. Communication-aware multi-robot coordination with submodular maximization. In 2021 IEEE International Conference on Robotics and Automation (ICRA), pages 8955–8961. IEEE, 2021.

[106] Guangyao Shi, Lifeng Zhou, and Pratap Tokekar. Robust multiple-path orienteering problem: Securing against adversarial attacks. IEEE Transactions on Robotics, 39(3):2060–2077, 2023.

[107] Volker Strobel, Marco Dorigo, and Mario Fritz. LLM2Swarm: Robot Swarms that Responsively Reason, Plan, and Collaborate through LLMs. arXiv preprint arXiv:2410.11387, October 2024.

[108] Yuichiro Sueoka, Yuki Kato, Takahiro Yoshida, Koichi Osuka, Ryosuke Yajima, Shota Chikushi, Keiji Nagatani, and Hajime Asama. Adaptivity of a Multi-Robot Coordination System based on Functional Expressions using Large Language Models. Distributed Autonomous Robotics Systems (DARS), 2024.

[109] Andrew Szot, Alex Clegg, Eric Undersander, Erik Wijmans, Yili Zhao, John Turner, Noah Maestre, Mustafa Mukadam, Devendra Chaplot, Oleksandr Maksymets, Aaron Gokaslan, Vladimir Vondrus, Sameer Dharur, Franziska Meier, Wojciech Galuba, Angel Chang, Zsolt Kira, Vladlen Koltun, Jitendra Malik, Manolis Savva, and Dhruv Batra. Habitat 2.0: Training home assistants to rearrange their habitat. In Advances in Neural Information Processing Systems (NeurIPS), 2021.

[110] Kshitij Tiwari and Nak Young Chong. Multi-robot Exploration for Environmental Monitoring: The Resource Constrained Perspective. Academic Press, 2019.

[111] Kam Fai Elvis Tsang, Yuqing Ni, Cheuk Fung Raphael Wong, and Ling Shi. A novel warehouse multi-robot automation system with semi-complete and computationally efficient path planning and adaptive genetic task allocation algorithms. In 2018 15th International Conference on Control, Automation, Robotics and Vision (ICARCV), pages 1671–1676. IEEE, 2018.

[112] A Vaswani. Attention is all you need. Advances in Neural Information Processing Systems, 2017.

[113] Vishnunandan L. N. Venkatesh and Byung-Cheol Min. ZeroCAP: Zero-Shot Multi-Robot Context Aware Pattern Formation via Large Language Models. arXiv preprint arXiv:2404.02318, September 2024.

[114] Sebastian Wallkötter, Silvia Tulli, Ginevra Castellano, Ana Paiva, and Mohamed Chetouani. Explainable embodied agents through social cues: a review. ACM Transactions on Human-Robot Interaction (THRI), 10(3):1–24, 2021.

[115] Hanwen Wan, Yuhan Zhang, Junjie Wang, Donghao Wu, Mengkang Li, Xilun Chen, Yixuan Deng, Yuxuan Huang, Zhenglong Sun, Lin Zhang, et al. Toward universal embodied planning in scalable heterogeneous field robots collaboration and control. Journal of Field Robotics, 2025.

[116] Chao Wang, Stephan Hasler, Daniel Tanneberg, Felix Ocker, Frank Joublin, Antonello Ceravola, Joerg Deigmoeller, and Michael Gienger. Large language models for multi-modal human-robot interaction. arXiv preprint arXiv:2401.15174, 2024.

[117] Jiaqi Wang, Zihao Wu, Yiwei Li, Hanqi Jiang, Peng Shu, Enze Shi, Huawen Hu, Chong Ma, Yiheng Liu, Xuhui Wang, et al. Large language models for robotics: Opportunities, challenges, and perspectives. arXiv preprint arXiv:2401.04334, 2024.

[118] Jun Wang, Guocheng He, and Yiannis Kantaros. Safe Task Planning for Language-Instructed Multi-Robot Systems using Conformal Prediction. arXiv preprint arXiv:2402.15368, October 2024.

[119] Weizheng Wang, Ike Obi, and Byung-Cheol Min. Multi-agent llm actor-critic framework for social robot navigation. arXiv preprint arXiv:2503.09758, 2025.

[120] Yongdong Wang, Runze Xiao, Jun Younes Louhi Kasahara, Ryosuke Yajima, Keiji Nagatani, Atsushi Yamashita, and Hajime Asama. DART-LLM: Dependency-Aware Multi-Robot Task Decomposition and Execution using Large Language Models. arXiv preprint arXiv:2411.09022 version: 1, November 2024.

[121] Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, et al. Emergent abilities of large language models. arXiv preprint arXiv:2206.07682, 2022.

[122] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-of-thought prompting elicits reasoning in large language models. Advances in neural information processing systems, 35:24824–24837, 2022.

[123] Pengying Wu, Yao Mu, Kangjie Zhou, Ji Ma, Junting Chen, and Chang Liu. CAMON: Cooperative Agents for Multi-Object Navigation with LLM-based Conversations. arXiv preprint arXiv:2407.00632, June 2024.

[124] Yuwei Wu, Yuezhan Tao, Peihan Li, Guangyao Shi, Gaurav S. Sukhatmem, Vijay Kumar, and Lifeng Zhou. Hierarchical LLMs In-the-loop Optimization for Real-time Multi-Robot Target Tracking under Unknown Hazards. arXiv preprint arXiv:2409.12274, September 2024.

[125] Peter R Wurman, Raffaello D'Andrea, and Mick Mountz. Coordinating hundreds of cooperative, autonomous vehicles in warehouses. AI magazine, 29(1):9–9, 2008.

[126] Fengli Xu, Qianyue Hao, Zefang Zong, Jingwei Wang, Yunke Zhang, Jingyi Wang, Xiaochong Lan, Jiahui Gong, Tianjian Ouyang, Fanjin Meng, et al. Towards large reasoning models: A survey of reinforced reasoning with large language models. arXiv preprint arXiv:2501.09686, 2025.

[127] Shaojun Xu, Xusheng Luo, Yutong Huang, Letian Leng, Ruixuan Liu, and Changliu Liu. Scaling Up Natural Language Understanding for Multi-Robots Through the Lens of Hierarchy. arXiv preprint arXiv:2408.08188, August 2024.

[128] Xiaohan Xu, Ming Li, Chongyang Tao, Tao Shen, Reynold Cheng, Jinyang Li, Can Xu, Dacheng Tao, and Tianyi Zhou. A survey on knowledge distillation of large language models. arXiv preprint arXiv:2402.13116, 2024.

[129] Dong Xue, Xuanjie Zhou, Ming Wang, and Fangzhou Liu. Formation control and path planning of multi-robot systems via large language models. Science China Information Sciences, 68(5):150205, 2025.

[130] Zhi Yan, Nicolas Jouandeau, and Arab Ali Cherif. A survey and analysis of multi-robot coordination. International Journal of Advanced Robotic Systems, 10(12):399, 2013.

[131] An Yang, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chengyuan Li, Dayiheng Liu, Fei Huang, Haoran Wei, Huan Lin, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Yang, Jiaxi Yang, Jingren Zhou, Junyang Lin, Kai Dang, Keming Lu, Keqin Bao, Kexin Yang, Le Yu, Mei Li, Mingfeng Xue, Pei Zhang, Qin Zhu, Rui Men, Runji Lin, Tianhao Li, Tingyu Xia, Xingzhang Ren, Xuancheng Ren, Yang Fan, Yang Su, Yichang Zhang, Yu Wan, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, and Zihan Qiu. Qwen2.5 technical report. arXiv preprint arXiv:2412.15115, 2024.

[132] Shukang Yin, Chaoyou Fu, Sirui Zhao, Ke Li, Xing Sun, Tong Xu, and Enhong Chen. A survey on multimodal large language models. arXiv preprint arXiv:2306.13549, 2023.

[133] Takahiro Yoshida, Yuichiro Sueoka, and Koichi Osuka. Verification of a Two-Step Inference Model for Cooperative Evaluation of Robot Actions Using Foundation Models. Distributed Autonomous Robotics Systems (DARS), 2024.

[134] Bangguo Yu, Hamidreza Kasaei, and Ming Cao. Co-NavGPT: Multi-Robot Cooperative Visual Semantic Navigation using Large Language Models. arXiv preprint arXiv:2310.07937, December 2023.

[135] Wenhao Yu, Jie Peng, Yueliang Ying, Sai Li, Jianmin Ji, and Yanyong Zhang. MHRC: Closed-loop Decentralized Multi-Heterogeneous Robot Collaboration with Large Language Models. arXiv preprint arXiv:2409.16030, September 2024.

[136] Rahul Zahroof, Jiazhen Liu, Lifeng Zhou, and Vijay Kumar. Multi-robot localization and target tracking with connectivity maintenance and collision avoidance. In 2023 American Control Conference (ACC), pages 1331–1338. IEEE, 2023.

[137] Fanlong Zeng, Wensheng Gan, Yongheng Wang, Ning Liu, and Philip S. Yu. Large Language Models for Robotics: A Survey. arXiv preprint arXiv:2311.07226, November 2023.

[138] Shengyu Zhang, Linfeng Dong, Xiaoya Li, Sen Zhang, Xiaofei Sun, Shuhe Wang, Jiwei Li, Runyi Hu, Tianwei Zhang, Fei Wu, et al. Instruction tuning for large language models: a survey. arxiv. arXiv preprint arXiv:2308.10792, 2023.

[139] Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, et al. A survey of large language models. arXiv preprint arXiv:2303.18223, 2023.

[140] Ruijie Zheng, Yongyuan Liang, Shuaiyi Huang, Jianfeng Gao, Hal Daumé III, Andrey Kolobov, Furong Huang, and Jianwei Yang. Tracevla: Visual trace prompting enhances spatial-temporal awareness for generalist robotic policies. arXiv preprint arXiv:2412.10345, 2024.

[141] Yifan Zhong, Fengshuo Bai, Shaofei Cai, Xuchuan Huang, Zhang Chen, Xiaowei Zhang, Yuanfei Wang, Shaoyang Guo, Tianrui Guan, Ka Nam Lui, et al. A survey on vision-language-action models: An action tokenization perspective. arXiv preprint arXiv:2507.01925, 2025.

[142] Lifeng Zhou and Vijay Kumar. Robust multi-robot active target tracking against sensing and communication attacks. IEEE Transactions on Robotics, 39(3):1768–1780, 2023.

[143] Lifeng Zhou, Vishnu D Sharma, Qingbiao Li, Amanda Prorok, Alejandro Ribeiro, Pratap Tokekar, and Vijay Kumar. Graph neural networks for decentralized multi-robot target tracking. In 2022 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR), pages 195–202. IEEE, 2022.

[144] Lifeng Zhou and Pratap Tokekar. Active target tracking with self-triggered communications in multi-robot teams. IEEE Transactions on Automation Science and Engineering, 16(3):1085–1096, 2018.

[145] Lifeng Zhou and Pratap Tokekar. An approximation algorithm for risk-averse submodular optimization. In International workshop on the algorithmic foundations of robotics, pages 144–159. Springer, 2018.

[146] Lifeng Zhou and Pratap Tokekar. Sensor assignment algorithms to improve observability while tracking targets. IEEE Transactions on Robotics, 35(5):1206–1219, 2019.

[147] Lifeng Zhou and Pratap Tokekar. Multi-robot coordination and planning in uncertain and adversarial environments. Current Robotics Reports, 2:147–157, 2021.

[148] Lifeng Zhou and Pratap Tokekar. Risk-aware submodular optimization for multi-robot coordination. IEEE Transactions on Robotics, 38(5):3064–3084, 2022.

[149] Lifeng Zhou, Vasileios Tzoumas, George J Pappas, and Pratap Tokekar. Resilient active target tracking with multiple robots. IEEE Robotics and Automation Letters, 4(1):129–136, 2018.

[150] Lifeng Zhou, Vasileios Tzoumas, George J Pappas, and Pratap Tokekar. Distributed attack-robust submodular maximization for multirobot planning. IEEE Transactions on Robotics, 38(5):3097–3112, 2022.

[151] Yichen Zhu, Zhicai Ou, Xiaofeng Mou, and Jian Tang. Retrieval-augmented embodied agents. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 17985–17995, 2024.

[152] Daniel M Ziegler, Nisan Stiennon, Jeffrey Wu, Tom B Brown, Alec Radford, Dario Amodei, Paul Christiano, and Geoffrey Irving. Fine-tuning language models from human preferences. arXiv preprint arXiv:1909.08593, 2019.