Can a Robot Walk the Robotic Dog: Triple-Zero Collaborative Navigation for Heterogeneous Multi-Agent Systems

Yaxuan Wang[†1], Yifan Xiang[†2] Ke Li[3], Xun Zhang[2], Bowen Ye[2], Zhuochen Fan[4,2], Fei Wei[5] and Tong Yang[*2]

***Abstract*— We present Triple Zero Path Planning (TZPP), a collaborative framework for heterogeneous multi-robot systems that requires zero training, zero prior knowledge, and zero simulation. TZPP employs a coordinator–explorer architecture: a humanoid robot handles task coordination, while a quadruped robot explores and identifies feasible paths using guidance from a multimodal large language model. We implement TZPP on Unitree G1 and Go2 robots and evaluate it across diverse indoor and outdoor environments, including obstacle-rich and landmark-sparse settings. Experiments show that TZPP achieves robust, human-comparable efficiency and strong adaptability to unseen scenarios. By eliminating reliance on training and simulation, TZPP offers a practical path toward real-world deployment of heterogeneous robot cooperation. Our code and video are provided at: https://github.com/triple-zeropp/Triple-zero-robot-agent**

I. INTRODUCTION

Multi-robot systems (MRS) have shown significant potential in applications ranging from logistics to disaster response. In particular, heterogeneous MRS can leverage the complementary strengths of different platforms (e.g., the mobility of quadrupeds and the manipulation capabilities of humanoids) to perform complex tasks. Among these tasks, path planning is a key challenge for such collaboration. Currently, an emerging direction to address this problem is multi-robot collaboration and path planning based on large language models (LLMs)[1][2][3][4][5].

Existing studies on multi-agent collaborative path planning mainly fall into three categories: (1) learning-based approaches that rely on large-scale training or fine-tuning (e.g., Graph-Based[2], TaskExp[6]), which can tackle novel problems in unfamiliar environments to some extent but incur high training and deployment costs; (2) methods dependent on prior maps or scene modeling (e.g., ZeroCAP[7], COHERENT[8]), which perform well in known environments but tend to generalize poorly and fail in real, dynamic settings; and (3) simulation-driven approaches (e.g., SIGMA[9], Graph-Based[2]), which train and validate mainly in virtual environments and thus heavily depend on the quality of the simulation—if there is a large gap or poor fidelity between simulation and reality, the real-world performance can be severely affected. A summary of how representative prior works align with the three criteria is provided in Table I.

To address these limitations, this paper proposes a novel paradigm for multi-robot path planning—Triple Zero Path Planning (TZPP)—designed to support heterogeneous agents in autonomously exploring

[1]Yuanpei College, Peking University

[2]School of Computer Science, Peking University

[3]School of Computer Science, Beijing University of Posts and Telecommunications

[4]Pengcheng Laboratory

[5]Beijing Jinruyi Large Model Technology Co., Ltd.

[*]Corresponding author: Tong Yang. Email: yangtong@pku.edu.cn.

[†]These authors contributed equally to this work.

This work was supported by the National Key Research and Development Program of China under Grant No. 2024YFB2906603, and in part by the National Natural Science Foundation of China (NSFC) (No. 62372009). The authors would like to thank Beijing Jinruyi Large Model Technology Co., Ltd. for their strong support and close collaboration.The authors also thank Yuanpei College, Peking University, for its support.

TABLE I
COMPARISON AGAINST THE TRIPLE ZERO CRITERIA

Method	No Training	No Prior Knowledge	No Simulation
Ours	√	√	√
ZeroCAP [7]	√	×	×
TaskExp [6]	×	√	×
SIGMA [9]	×	×	×
Hybrid [10]	√	×	√
COHERENT [8]	√	×	√
Graph-Based [2]	×	×	×
MIM [11]	√	×	√

and reaching targets in unknown, complex environments. Taking the collaboration between a humanoid agent and a quadruped agent as an example, we construct a coordinator–explorer architecture: the humanoid handles high-level task coordination and navigation, while the quadruped undertakes environment exploration and feasible path identification. We deploy this framework in real-world environments, where the G1–Go2 multi-agent system achieves human-level collaborative efficiency across multiple tasks, stably accomplishing complex navigation missions and effectively emulating human exploration and decision-making behaviors. These results validate the soundness and innovation of the paradigm' s architecture and mechanisms. Overall, the main contributions of this paper are as follows:

- We propose the first heterogeneous agent path planning paradigm satisfying the "Triple Zero" constraints—zero training, zero prior knowledge, and zero simulation dependency. Without additional training or prior conditions, the approach enables multi-robot systems to autonomously explore and plan paths in real, dynamic, and human-free environments, reducing application costs and enhancing system robustness.
- We design and validate a heterogeneous robot collaboration mechanism in the real-world. We test the path planning paradigm in various settings, including open spaces, obstacle-rich environments, and both indoor and outdoor scenarios. The result demonstrate human-level performance, confirming the method' s practicality and scalability.

TZPP lays the groundwork for future LLM-based multi-robot systems in real-world applications. It not only accelerates the transition of multi-robot path planning from simulation to reality but also offers new insights and tools for heterogeneous robot collaboration. We have released part of our data and experimental benchmarks to facilitate further research.

II. RELATED WORKS

A. *Exploration and Navigation in Unknown Environments*

For tasks that involve exploration and navigation in unknown environments, a common approach is to enhance the generalization capability of the model in unfamiliar settings through pretraining[1][6][12][13], including the TaskExp method[6], diffusion-based approaches[12]. These methods demonstrate better adaptability compared to traditional map-dependent approaches[14][15][16][17] but rely heavily on large amounts of high-quality data for pre-training. Furthermore, due to the scarcity of real-world scene data, most research uses simulated environments[1][3][6]. However, studies trained and tested in simulated environments often struggle to translate into practical applications due to the gap between realistic and idealized settings.

B. *Collaboration of Heterogeneous Agents*

Homogeneous multiagent collaboration architectures[7][18][19][20][21] are relatively simple in structural design and control logic, making them easy to implement and scale. However, a lack of appropriate labor management can lead to problems such as planning confusion and resource wastage. In contrast, heterogeneous multi-agent collaboration systems consist of robots with different functionalities or morphologies. They improve execution efficiency through task allocation and specialized design, enabling more rational management over tasks such as navigation and transportation. Representative work includes the GATAR model and perception sharing among heterogeneous robots[1][2][3], which facilitate collaborative decision making among multiple agents and demonstrate favorable scalability and environmental adaptability.

C. Integration of VLMs and Robotics

Traditional robotic systems depend on predefined rules and specialized perception modules[22][23]. While these methods perform reliably in structured environments, their generalization capability is limited when faced with open-ended instructions and dynamic environments. Robotic systems incorporating Vision-Language Models (VLMs) significantly enhance the comprehension of natural language instructions and environmental adaptability through multi-modal fusion and semantic reasoning. This enables zero-shot generalization to unseen instructions[24], thereby supporting more intelligent decision-making.

III. Our TZPP System

A. Overview

This study focuses on the path planning problem of heterogeneous multi-agent systems, aiming to leverage the complementary strengths of different agents through division of labor and collaboration to achieve efficient exploration of complex real-world environments. The research covers a variety of representative scenarios (including both indoor and outdoor settings) and diverse terrains (such as slopes and staircases).

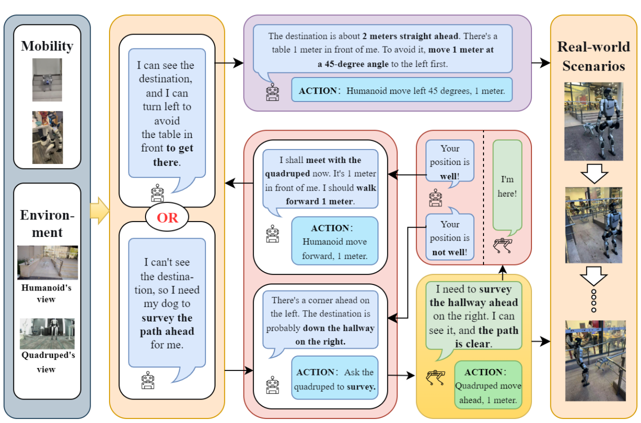

Fig. 1. The System Pipeline of TZPP[1]

[1]Robot icons created by Good Ware, robot dog icons created by Izwar Muis - Flaticon

In this work, we take a humanoid agent and a quadruped agent as a typical interaction pair: the humanoid serves as a valuable but relatively less mobile "core" agent, while the quadruped acts as a lower-value but more mobile auxiliary agent. The objective is to guide the core agent, with the collaborative support of the auxiliary agent, to explore unknown environments and reach designated target locations L_T.

It's noteworthy that complex real-world environments pose significant challenges for path planning and task recognition in agent systems. In scenarios lacking salient landmarks, agents struggle to obtain effective localization information, leading to unreliable position estimates, reducing the accuracy of action decisions. What's more, in environments where direct access to the target is not possible, agents often need to detour for the goal.

To address these challenges, this study adopts a coordinator–explorer architecture design. Specifically, the humanoid, as the representative of the core agent, is responsible for task coordination and reaching the designated location, while the quadruped, as the auxiliary agent, undertakes environment exploration and the identification of feasible paths or intermediate waypoints. A typical pipeline of the design is shown in Fig. 1.

TABLE II
Description of Variables

Variable	Description
L_T	High-level task target location (natural language)
L_W	Quadruped waypoint location (natural language)
C	Inter-agent interaction context
I_B	Humanoid's forward perceptual data
I_D	Quadruped's forward perceptual data
d_{dt}	Euclidean distance to target
X	Landmark-sparse mode
Y	Obstacle-rich mode
R_{scan}	Search half-angle

B. Humanoid Pipeline

The humanoid manages high-level coordination through an iterative cycle of path evaluation–pilot exploration–task execution as shown in Fig. 2. In the path-evaluation stage, it assesses the feasibility of reaching the global target L_T based on perceived

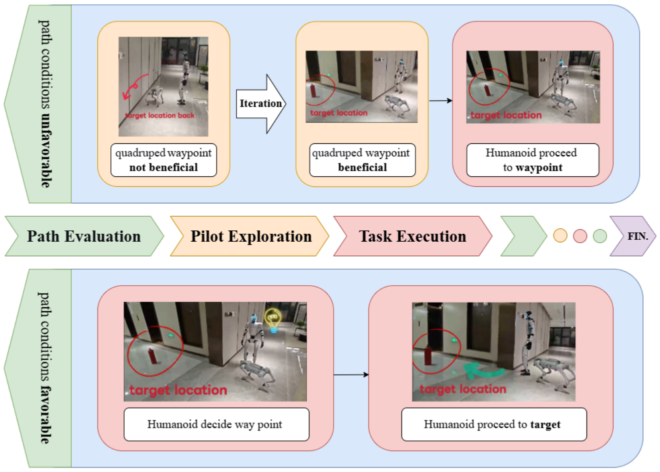

Fig. 2. Iteration logic of the humanoid

environmental information I_B. If conditions are favorable, it proceeds directly to task execution; otherwise, it initiates pilot exploration by assigning intermediate waypoints to the quadruped.

During exploration, the humanoid continuously incorporates perceptual feedback and selectively integrates beneficial waypoints into its navigation plan. In the task-execution stage, it autonomously updates its motion strategy based on the latest environmental observations, progressively approaching and ultimately reaching the target location.

C. Quadruped Pipeline

The quadruped agent is responsible for environmental exploration and feasible path identification. We designed two different exploration strategies, *Mode X* and Mode Y, to help the quadruped to better accommodate landmark-sparse and obstacle-rich environments respectively. Its logical workflow, as shown in Algorithm 1, proceeds as follows. First, the agent performs pattern matching based on environmental information to determine whether the current situation corresponds to a obstacle-rich environment. It then enters a cyclic process consisting of four phases: "environment detection -task execution - target detection –environment exploration."

In the environment-detection phase, the quadruped performs omnidirectional rotational scanning to assess the visibility of the assigned waypoint. If the waypoint is not visible, it immediately terminates the task and reports infeasibility to the humanoid agent. If the waypoint is visible, it proceeds to the task-execution phase, moves to the waypoint, returns environmental perception information to the humanoid, and enters the target-detection phase.

Algorithm 1: Quadruped Robot Pipeline

```
Input: Humanoid's target location L_T, Quadruped's
       waypoint location L_W
Output: Reach waypoint successful/failed
if EnvAllReachable(I_D) then
    mode ← X
else
    mode ← Y
end
for 360 degrees rotation do
    if InspectFor(L_W, I_D) = false then
        return false
    end
end
while true do
    MoveTo(L_W, I_D);
    for 360 degrees rotation do
        if InspectFor(L_T, I_D) = true and
          PathIdeal(L_T, I_D) = true then
            return true
        end
    end
    if mode is Y then
        for -R_scan to +R_scan degrees rotation do
            if InspectFor('passage', I_D) = true then
                return true
            end
        end
    end
    return false
end
```

In the target-detection phase, the quadruped performs full-range scanning to detect the visibility of the high-level task target and assess path feasibility. If the target is visible and a feasible path exists, it sends a exploration successful signal and current environmental information to the humanoid. If the target is not in sight, or is visible but unreachable from the current position while the system is operating under a landmark-sparse mode, the quadruped terminates the task and reports current environmental information. In a non–globally accessible mode, the agent additionally performs a locally bounded, angle-restricted scan to probe for the existence of potential passages or corridors.

D. Adaptive Mode X/Y Strategy

To ensure robust navigation across heterogeneous environments, the robot employs an adaptive switching mechanism between two operational modes: Mode X (landmark-sparse) and Mode Y (obstacle-dense).

Mode selection is governed by an environmental accessibility assessment derived from the current perceptual observation I_D.

Mode X is activated in regions characterized by high global reachability but a dearth of salient features. In this state, the system prioritizes extensive repositioning and 360° panoramic scanning. This strategy maximizes target visibility and mitigates redundant exploration resulting from perceptual aliasing in feature-poor environments.

Mode Y is triggered when topographical constraints or high obstacle density impede direct global navigation. Beyond standard waypoint execution, the robot performs constrained scanning within a localized search half-angle R_{scan} to identify traversable corridors or detours. This allows for calculated deviations from the goal-directed path to circumvent obstacles in complex spaces.

This dual-mode framework enables the system to autonomously adapt its exploration behavior to the environmental structure, eliminating the need for environment-specific parameter tuning.

IV. EXPERIMENT

This experiment aims to address the following questions:

- To what extent can our TZPP paradigm solve the problem of collaborative exploration in complex environments by heterogeneous multi-agent systems?
- How capable are our TZPP and its two integrated versions (X and Y) when handling scenes with missing landmarks and indirectly navigable scenarios?
- What is the application prospect of our heterogeneous multi-agent combination in path planning problems?

A. Experimental Setup

The proposed TZPP method is evaluated across multiple structurally complex, previously unseen physical environments to assess navigation performance in scenarios where the target is non-line-of-sight (NLOS) from the agent' s initial position. The experimental framework utilizes the Unitree G1 Edu humanoid and Unitree Go2 Edu quadruped platforms. The perception and decision-making architecture is powered by the Doubao-vision-3.6 large vision-language model. All trials were conducted in real-world settings without prior simulation or environment-specific fine-tuning to ensure the validity of the system's zero-shot generalization capabilities.

We evaluate the interaction paradigm across six dimensions using 16 metrics. **Global Task Efficiency (Dimension 1)** is quantified by the total completion time $TIME$, the humanoid' s cumulative travel distance D, and its total rotation angle R. **Path Planning Fidelity (Dimension 2)** is assessed via the task completion rate CR; the path score PS, defined as $100 \times (L_{\text{optimal}}/L_{\text{actual}})$, where L_{optimal} and L_{actual} represent the optimal and actual path lengths, respectively; and the root mean square error ($RMSE$) of the humanoid' s vertical path deviation:

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\min_{i}\|P_j - p(P_j, L_i)\|^2} \quad (1)$$

Autonomous Exploration (Dimension 3) and **Multi-Agent Coordination (Dimension 4)** evaluate the quadruped' s utility. These include the key point discovery count N_K; the effective exploration rate EER; the scouting frequency N_E, which is the total number of instances where the quadruped performs reconnaissance for the humanoid agent; the humanoid movement count (N_{move}); and the guidance efficiency coefficient $V_{GE} = D_h/D_q$, where D_h and D_q represent the cumulative distances traveled by the humanoid and quadruped, respectively. A V_{GE} value approaching unity from the left signifies optimal coordination. **Environmental Robustness (Dimension 5)** evaluates adaptability in feature-poor scenes via the quadruped's command compliance rate CCR_q, revisit counts for both agents $N^h_{\text{rev}}, N^q_{\text{rev}}$, and the quadruped' s redundant rotation count N^q_{rot}.

For **Constrained Navigation (Dimension 6)**, we introduce the obstacle avoidance coefficient V_{avoid}. Let $P(t)$ be a point on the trajectory and $Q(t) = \text{argmin}_{X\in\mathcal{O}}\|P(t) - X\|$ be its projection onto the obstacle surface $\mathcal{O}$. The avoidance magnitude is defined by the arc length L_{avoid} of the trajectory formed by $Q(t)$:

$$L_{\text{avoid}} = \text{ArcLength}\Big(\{Q(t) \mid t \in [0,1]\}\Big) \tag{2}$$

$$V_{\text{avoid}} = \frac{L_{\text{avoid}}^{(\text{actual})}}{L_{\text{avoid}}^{(\text{optimal})}} \tag{3}$$

The evaluation encompasses five distinct real-world scenarios: an L-turn sofa search (Scene 1); a unilateral-access narrow pillar (Scene 2); a bilateral-passable pillar (Scene 3); a Z-turn fire extinguisher localization (Scene 4); and a ramp-mediated detour to bypass structural steps (Scene 5).

Unless otherwise specified, the following default parameter settings are employed across all experimental trials: maximum displacement and rotation of agents per turn: $d_{\max} = 2$ m and $R_{\max} = \pi/2$ rad respectively; target achievement threshold $d_{\text{achieve}} = 0.5$ m; localized search half-angle $R_{\text{scan}} = \pi/2$ rad.

B. Comparative Evaluation of TZPP and Human Operators in Collaborative Path Planning

In this section, we conduct a comparative evaluation between TZPP and human operators on the same navigation tasks. To ensure fairness, two naive participants were provided with the same information as the robotic system: real-time first-person visual streams from both the humanoid and quadruped sensors, without access to any global or third-person view. The control interface and action constraints were identical to those used by the autonomous system.

TABLE III
Task finish comparison of TZPP vs. human baseline

	TZPP System			Human baseline		
	$TIME\downarrow$ (s)	$D\downarrow$ (m)	$R\downarrow$ (rad)	$TIME\downarrow$ (s)	$D\downarrow$ (m)	$R\downarrow$ (rad)
scene 1	64.00	4.00	1.57	53.30	3.80	1.57
scene 2	18.22	2.60	1.05	17.47	2.57	0.79
scene 3	28.58	4.55	2.83	28.01	4.53	2.09
scene 4	120.58	6.80	4.71	80.00	6.47	4.71
scene 5	154.89	14.60	11.78	94.21	13.83	4.29

Tables III to VI present the results. The G1–Go2 system achieves performance comparable to human operators across most metrics. In particular, for the humanoid movement distance (D), the autonomous system reaches over 95% of human performance. While performance gaps remain in certain scenarios, the results indicate that the proposed system can achieve competitive collaborative efficiency under equivalent information and control conditions. These findings suggest that TZPP provides a viable coordination mechanism with promising robustness and generalization capability in unseen environments.

TABLE IV
Task planning comparison of G1-Go2 system vs. human baseline

	G1-Go2 System		Human baseline	
	$PS\uparrow$	$RMSE\downarrow$	$PS\uparrow$	$RMSE\downarrow$
scene 1	68.18	85.99	82.19	56.05
scene 2	98.08	14.42	99.23	6.24
scene 3	96.74	40.75	97.13	21.21
scene 4	92.35	120.91	97.06	58.52
scene 5	88.18	56.54	93.13	33.22

TABLE V
Quadrupedal Agent exploration comparison of G1-Go2 system vs. human baseline

	G1-Go2 System		Human baseline	
	$N_K\uparrow$	$EER\uparrow$	$N_K\uparrow$	$EER\uparrow$
scene 1	2	100%	2	100%
scene 2	2	100%	2	100%
scene 3	2	100%	2	100%
scene 4	4	80%	2	100%
scene 5	6	100%	6	100%

TABLE VI
Collaboration comparison of G1-Go2 system vs. human baseline

	G1-Go2 System			Human baseline		
	N_E	$V_{GE}\downarrow$	$N_{\text{move}}\downarrow$	N_E	$V_{GE}\downarrow$	$N_{\text{move}}\downarrow$
scene 1	2	0.98	5	2	0.98	2
scene 2	1	0.86	2	1	0.91	2
scene 3	2	0.76	5	1	0.91	2
scene 4	5	0.72	6	4	0.88	5
scene 5	6	0.96	9	5	1.03	6

C. Ablation Study on Mode X/Y Mechanism

To evaluate the contribution of the adaptive exploration strategy, we compare the full G1–Go2 system with two degraded variants: one with Mode X disabled (G1–Go2(-X)) and one with Mode Y disabled (G1–Go2(-Y)), under identical task settings. Human operators are included as a reference baseline under the same perceptual and control constraints.

TABLE VII

Comparative Ablation Study on Heterogeneous Agents

	G1-Go2				G1-only			
	TIME↓	PS↑	CR↑	RSME↓	TIME↓	PS↑	CR↑	RSME↓
scene 1	64.00	68.18	100%	85.99	43.12	67.47	100%	86.69
scene 2	18.22	98.08	100%	14.42	16.14	75.59	100%	124.12
scene 3	28.58	96.74	100%	40.75	N/A	N/A	33.33%	N/A
scene 4	120.58	92.35	100%	120.91	N/A	N/A	40.00%	N/A

TABLE VIII

Open area comparison of G1-Go2(without Mode X), G1-Go2 system and human baseline

	Time↓	CCR_q↑	N_1↓	N_2↓	N_3↓
G1(no X)-Go2	43.78	56.27%	0.6	1.4	3
G1-Go2	46.28	86.00%	0	0.2	0.6
Human	54.60	80.00%	0	0	0.2

N_1, N_2, N_3 represent N^h_{rev}, N^q_{rev}, N^q_{rot} respectively.

TABLE IX

Obstacle Handling comparison of G1-Go2(without Mode Y), G1-Go2 system and human baseline

	Time↓	V_{avoid}
G1(no Y)-Go2 System	N/A	0.23
G1-Go2 System	154.89	1.00
Human baseline	94.21	1.00

1) In Open Scenarios Lacking Landmarks: The experiments were conducted in open environments without salient visual references (e.g., locating a sofa in a corridor).

As shown in Table VIII, disabling Mode X leads to a noticeable decrease in exploration efficiency and task stability. This result suggests that Mode X improves performance in landmark-sparse scenes by reducing repeated exploration caused by visual ambiguity and limited reference cues.

2) In Scenarios without Direct Accessible Paths: The experiments were conducted in obstacle-rich environments requiring detour-based navigation (e.g., navigating around structural barriers or staircases).

As shown in Table IX, removing Mode Y significantly reduces success rates and planning efficiency. The results indicate that Mode Y enhances navigation in structurally constrained environments by enabling corridor probing and temporary deviation from the direct goal direction.

Overall, the results show that Mode X and Mode Y address different environmental challenges and jointly improve system adaptability across heterogeneous scenarios.

D. Ablation Study on the Necessity of Heterogeneous Multi-Agent Systems for Navigation

As shown in Table VII, on path planning tasks, the heterogeneous multi-agent system composed of G1 and Go2 demonstrates significantly superior performance compared to using only a single G1 agent. This comparison illustrates that by integrating the complementary capabilities of heterogeneous agents, the heterogeneous multi-agent system can more effectively address path planning challenges in complex environments. It not only highlights its significant advantages in perception coverage, decision-making coordination, and task allocation but also demonstrates the considerable potential and promising development prospects of this method for future practical applications.

V. CONCLUSIONS

This paper introduced Triple Zero Path Planning (TZPP), a heterogeneous robot collaboration mechanism that requires no training, no prior knowledge, and no simulation. By leveraging a coordinator–explorer architecture between humanoid and quadruped robots, TZPP enables robust exploration, efficient path planning, and adaptive navigation in diverse, unseen real-world environments. Our experiments demonstrate that TZPP achieves human-comparable performance while maintaining strong adaptability under landmark-sparse and obstacle-rich scenarios. These results verify the feasibility and practicality of TZPP for real-world deployment, laying the foundation for scalable heterogeneous multi-agent systems in dynamic environments.

References

[1] L. Ratnabala, A. Fedoseev, R. Peter, and D. Tsetserukou, "Magnnet: Multi-agent graph neural network-based efficient task allocation for autonomous vehicles with deep reinforcement learning," 2025.

[2] J. Peng, H. Viswanath, and A. Bera, "Graph-based decentralized task allocation for multi-robot target localization," *IEEE Robotics and Automation Letters*, vol. 9, no. 11, pp. 10676–10683, 2024.

[3] Y. Chen and J. Xiao, "Target search and navigation in heterogeneous robot systems with deep reinforcement learning," *Machine Intelligence Research*, vol. 22, p. 79–90, Jan. 2025.

[4] Z. Mandi, S. Jain, and S. Song, "Roco: Dialectic multi-robot collaboration with large language models," 2023.

[5] Y. Chen, J. Arkin, Y. Zhang, N. Roy, and C. Fan, "Scalable multi-robot collaboration with large language models: Centralized or decentralized systems?," 2024.

[6] S. Zhu, Y. Zhao, Y. Xu, A. Chen, J. Chen, and J. Xu, "Taskexp: Enhancing generalization of multi-robot exploration with multi-task pre-training," in *2025 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 6559–6565, 2025.

[7] V. L. N. Venkatesh and B.-C. Min, "Zerocap: Zero-shot multi-robot context aware pattern formation via large language models," 2025.

[8] A. Author, B. Author, and C. Author, "Coherent: Collaboration of heterogeneous models for autonomous agents," *arXiv preprint*, 2024. arXiv:2409.15146.

[9] X. Author, Y. Author, and Z. Author, "Sigma: Sheaf-informed geometric multi-agent pathfinding," *arXiv preprint*, 2025. arXiv:2502.06440.

[10] K. de Vos, E. Torta, H. Bruyninckx, C. L. Martinez, and R. van de Molengraft, "Hybrid decision making for scalable multi-agent navigation: Integrating semantic maps, discrete coordination, and model predictive control," 2024.

[11] A. J. Sathyamoorthy, K. Weerakoon, M. Elnoor, M. Russell, J. Pusey, and D. Manocha, "Mim: Indoor and outdoor navigation in complex environments using multi-layer intensity maps," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 10917–10924, 2024.

[12] C. Pan, Z. Yi, G. Shi, and G. Qu, "Model-based diffusion for trajectory optimization," 2024.

[13] K. Su, X. Zhang, S. Zhang, J. Zhu, and B. Zhang, "To boost zero-shot generalization for embodied reasoning with vision-language pre-training," *IEEE Transactions on Image Processing*, vol. 33, pp. 5370–5381, 2024.

[14] K. Rana, J. Haviland, S. Garg, J. Abou-Chakra, I. Reid, and N. Suenderhauf, "Sayplan: Grounding large language models using 3d scene graphs for scalable robot task planning," 2023.

[15] M. Booker, G. Byrd, B. Kemp, A. Schmidt, and C. Rivera, "Embodiedrag: Dynamic 3d scene graph retrieval for efficient and scalable robot task planning," 2024.

[16] A. Werby, C. Huang, M. Büchner, A. Valada, and W. Burgard, "Hierarchical open-vocabulary 3d scene graphs for language-grounded robot navigation," in *First Workshop on Vision-Language Models for Navigation and Manipulation at ICRA 2024*, 2024.

[17] A. Meysami, S. Kelouwani, J.-C. Cuilliere, V. Francois, A. Amamou, and B. Allani, "An efficient indoor large map global path planning for robot navigation," *Expert Systems with Applications*, vol. 248, p. 123388, 2024.

[18] W. Zhang, C. Street, and M. Mansouri, "Multi-nonholonomic robot object transportation with obstacle crossing using a deformable sheet," in *2025 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 7349–7355, 2025.

[19] S. Wu, C. Wang, J. Pan, D. Han, and Z. Zhao, "Bayesian-guided evolutionary strategy with rrt for multi-robot exploration," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 12720–12726, 2024.

[20] Z. Xiao, P. Li, C. Liu, H. Gao, and X. Wang, "Macns: A generic graph neural network integrated deep reinforcement learning based multi-agent collaborative navigation system for dynamic trajectory planning," *Information Fusion*, vol. 105, p. 102250, 2024.

[21] T. Soualhi, N. Crombez, Y. Ruichek, A. Lombard, and S. Galland, "Learning decentralized multi-robot pointgoal navigation," *IEEE Robotics and Automation Letters*, vol. 10, no. 4, pp. 4117–4124, 2025.

[22] F. Khadivar, K. Chatzilygeroudis, and A. Billard, "Self-correcting quadratic programming-based robot control," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 53, no. 8, pp. 5236–5247, 2023.

[23] A. Ghorbanpour, "Cooperative robot manipulators dynamical modeling and control: An overview," *Dynamics*, vol. 3, no. 4, pp. 820–854, 2023.

[24] A. Brohan, N. Brown, J. Carbajal, Y. Chebotar, X. Chen, K. Choromanski, T. Ding, D. Driess, A. Dubey, C. Finn, P. Florence, C. Fu, M. G. Arenas, K. Gopalakrishnan, K. Han, K. Hausman, A. Herzog, J. Hsu, B. Ichter, A. Irpan, N. Joshi, R. Julian, D. Kalashnikov, Y. Kuang, I. Leal, L. Lee, T.-W. E. Lee, S. Levine, Y. Lu, H. Michalewski, I. Mordatch, K. Pertsch, K. Rao, K. Reymann, M. Ryoo, G. Salazar, P. Sanketi, P. Sermanet, J. Singh, A. Singh, R. Soricut, H. Tran, V. Vanhoucke, Q. Vuong, A. Wahid, S. Welker, P. Wohlhart, J. Wu, F. Xia, T. Xiao, P. Xu, S. Xu, T. Yu, and B. Zitkovich, "Rt-2: Vision-language-action models transfer web knowledge to robotic control," 2023.