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Research on Multi-Robot Collaboration Methods under Unstructured Environments

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Abstract:

Recent technological development has made multi-robot collaboration a promising approach for tasks in unstructured and dynamically changeable environments. However, challenges still occur especially in reliability, efficiency and system integration. This review systematically examines former research and experiments, with focus on robust perception, collaborative planning and hybrid architectures. It poses that there requires advancement in communication-control co-design, lightweight collaboration models, and standardized tests. The study concludes that future progress should depend on adaptable and cost-effective systems capable of establishing positive human-robot relationship, which requires combination of robotics, AI and edge computing.

Keywords: Multi-robot collaboration, Unstructured environments, Efficiency, Communication

1. Introduction

Recently, with the rapid development of robotics technology, multi-robot collaboration has been widely adopted in unstructured environments. Meanwhile, its demand grows quickly, with the global collaborative robot market expanding at an annual rate of over 20% in many counties, like China, USA, Russia, UK. Especially in dynamic scenarios requiring complex path planning and real-time sensor fusion, they have incredible advantages like higher efficiency, reliability, and flexibility, compared to single robot systems [1]. However, despite the huge benefits they offer, there are still many problems waiting to be solved. For instance, it still lacks environmental adaptability, where sensor interference causes localization errors. Second is the coordination inefficiency, including task conflicts between robots. What's more, the cost is very high, as high-precision sensors and AI algorithms increase costs. Considering all the problems above, this research aims to solve the problem of cooperation between robots, and try to find how to make robots suitable for more working environments. Unfortunately, the researches from China or other counties still have limitations. They failed to consider all the aspects that may happen in real lives. Internationally, Carnegie Mellon University's reinforcement learning-based collaboration strategy dynamically adjusts task allocation ,but suffers from high computational costs, causing >200ms latency in AGV-arm collision avoidance, which makes it hard to maintain high efficiency [2]. The study from Zhe Jiang University also faced numerous difficulties [3]. Stanford University's distributed path planning achieves a 95% obstacle avoidance success rate in structured warehouse environments, but its performance drops sharply to 70% in unstructured scenarios [4]. Due to the complexity in unstructured environments, the existing methods may not apply to other aspects. All the examples show that there is still a long way to go in this field. Therefore it is necessary to carry out the research which gains better insights into robots in the unstructured environments.

Therefore, this essay aims to find ways to make robots work better in unstructured environments.

2. Research objectives, main contents and key issues

2.1 Research objectives

In order to carry out the survey on robots in real working environments, there are mainly two objectives settled, respectively Enhancing Collaborative Efficiency and Improving Environmental Adaptability.

First, in a gesture to make robots work better, we should try to increase the efficiency. Nowadays, robots can cooperate with each other to complete different kinds of works. However, due to the obstacles in works, the efficiency is still quite low. Thus, we need to find ways to improve the efficiency, for it is the most important thing in our works. To meet the target, we can enhance communication between robots. We can also put AI-Driven Collaborative Learning into it. Last but not least, Dynamic Task Allocation & Scheduling can help a lot.

Apart from that, Improving Environmental Adaptability can also help a lot. In a gesture to make robots work better, we should try to make robots' adaptability better. To let robots adapt better, we can follow the next few steps. For instance, we can add many sensors, like Integrate LiDAR (anti-light interference), 3D structured light (close-range precision), millimeter-wave radar (penetrating rain/fog), and thermal imaging (detecting living obstacles). Besides, we can prepare the robots with Adversarial Training, to test whether they are suitable for different working environments.

2.2 Main contents

Regarding the contents, there are mainly two parts. This research focuses on multi-robot collaboration methods for unstructured industrial scenarios, aiming to enhance adaptability, coordination efficiency.

2.2.1 Environment perception & modeling:

This part concludes multi-sensor fusion and Dynamic parameter decoupling. Multi-sensor fusion means that through Integrate LiDAR, vision, and force-torque sensors, to create real-time semantic maps. In this way, the interference problem can be solved. Using Dynamic parameter decoupling can classify adjustable parameters into robot-autonomous and human-assisted categories. After that, we can use a "human-robot collaboration ratio" to balance autonomy and manual control.

2.2.2 Collaborative decision-making:

This consists of RL and hierarchical coordination. RL, known as distributed reinforcement learning, by optimizing path planning and task allocation with FPGA-accelerated algorithms to reduce latency to less than 50ms. Hierarchical coordination means that a hybrid control strategy which combines centralized task allocation with distributed execution

2.3 Key scientific problems

How to build precise semantic maps when faced with obstacles and moving interference? Because these are the common scenes robots may encounter in real working places. If we want to make robots work better and contribute a lot to the industries, we should not ignore this.

How to make robots work better together, without interacting problems? Communication is quite important in works. If robots can interact with each other properly, the efficiency will drop a lot, and sometimes this may cause economy loss. However, since learning effective strategies often requires s a large number of interaction samples, relevant cost and time spent would be massive [5]. Even worse, safety problems may also happen if not communicating successfully.

3. Research methods, technical route, experimental scheme to be adopted and feasibility analysis.

3.1 Research methods

In this part, we have three methods. There are Multi-Robot Dynamics & Perception Models, Hybrid Control Framework and Mixture Learning.

3.2 Technical route

The technical route is right below.

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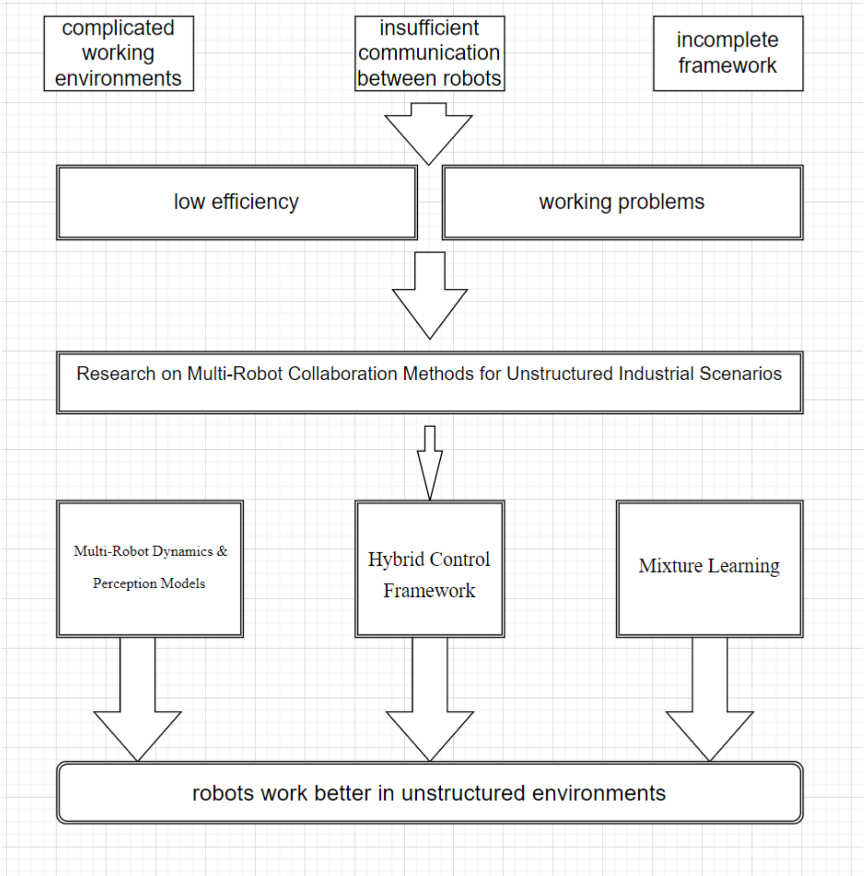

Figure 1. Technical route

This technical roadmap outlines a systematic approach to address multi-robot collaboration challenges in unstructured industrial environments. It begins by identifying three critical pain points: (1) complicated working environments that hinder robot operations, (2) insufficient communication between robots limiting coordination, and (3) incomplete existing frameworks, all leading to low efficiency and operational problems. The proposed solution - "Research on Multi-Robot Collaboration Methods for Unstructured Industrial Scenarios" - develops three parallel technical pillars: Multi-Robot Dynamics & Perception Models to handle environmental complexity, a Hybrid Control Framework for robust system architecture, and Mixture Learning techniques to enhance collaborative intelligence. These integrated methodologies collectively enable robots to achieve significantly better performance in unstructured environments.

3.3 Experimental scheme to be adopted

3.3.1 Simulation experiments:

Scenario 1: Dynamic obstacle avoidance test
Compare the path planning efficiency of traditional A* algorithms versus reinforcement learning (RL) algorithms in dynamic environments. Key Metrics: Path optimization time, collision avoidance success rate, computational resource usage.
Scenario 2: Multi-robot collaborative transport task
Validate the load-balancing advantages of task allocation algorithms in distributed multi-robot systems. Key Metrics: Task completion time, energy consumption distribution, idle time reduction.

3.3.2 Physical experiments:

Industrial warehouse test:
Deploy 5 AGVs and 2 robotic arms, achieving real-time collaboration via 5G networks.
Objective: Improve the worker-robot command ratio from 1:2 to 1:5, reducing human intervention

3.4 Feasibility analysis

3.4.1 Theory feasibility: This phase evaluates whether the proposed project aligns with established scientific principles and theoretical frameworks. It involves empirical testing, ensuring mathematical models are grounded in peer-reviewed research, and quantifying key metrics like the "human-robot collaboration ratio" to balance autonomy and intervention. The analysis

also benchmarks against existing literature to confirm novelty and avoid redundancy, while identifying gaps that the project aims to address. Theoretical feasibility serves as the foundation for subsequent technical and operational steps, ensuring the project is scientifically viable before resource allocation.

3.4.2 Technology feasibility:

This section assesses the practicality of implementing the proposed technology, focusing on resource availability, technical maturity, and integration challenges. Key considerations include evaluating sensor fusion frameworks for dynamic occlusion handling, verifying distributed RL algorithms can meet real-time latency targets (<50ms), and ensuring edge-computing nodes support 5G mitigation in HIL simulations. The analysis also examines scalability, compatibility with existing infrastructure, and team expertise to mitigate risks of technical debt or obsolescence. A go/no-go decision hinges on whether the technology can achieve targets like 30% collision reduction while maintaining cost-effectiveness.

4. Novelties of the proposed topic

This study aims to address the problem of complicated task execution in unstructured environments, through a heterogeneous robotic cooperative system. The core innovation mainly lies in two aspects listed below.

4.1 Cross-model heterogeneous robot collaboration

Traditional multimodal multi-robot systems are typically compromised of homogeneous platforms, which indicate limitations in data and information perception, decision-making and execution. This project innovatively integrates multiple cutting-edge technologies, with the orientation of achieving deep coordination in heterogeneous robot swarms. In detail, the study combines the wide-area mobility capabilities of autonomous ground vehicles (AGVs) with the precise operational capabilities of robotic arms, and integrates multimodal perception (such as vision, laser radar and force perception) and semantic understanding to construct a unified environment and task representation. Through cross modal information fusion and sharing, the system can achieve functional complementarity, dramatically enhancing overall adaptability and task completion robustness in dynamic, unknown and unstructured environments.

4.2 Consider multiple environments

Also, traditional studies may only focus on other factors, instead of the environment. However, in our study, we try to evaluate the impact of environment and attempt to strengthen the ability to adapt to different environments. Normally, environments matter a lot in real works, even the tiny change in surroundings may result in huge change in the way that robots coordinate with each other.

5. Research schedule, and expected outcomes

5.1 Research schedules

This research will be divided into three stages to ensure both systematicity, feasibility and the ultimate practical outcomes. The specific arrangements are as follows:
Phase 1: Theoretical modeling:
The task of this phase is to establish a theoretical foundation for the multi robot collaborative operation. Specific tasks include developing multi-robot dynamics models and semantic mapping frameworks, and validating sensor fusion algorithms in Gazebo/ROS simulations.
Phase 2: Algorithm development:
The task of this phase is to develop task allocation and decision-making algorithms with high efficiency, and test their performance in hardware in different environment. Specific tasks include optimizing distributed RL and Hungarian algorithms and conducting large-scale scenario stress tests on the developed algorithm on the HIL platform. Requirements for the comprehensive delay should be under 50 milliseconds.
Phase 3: Physical deployment:
The task of this phase is to deploy validated algorithm systems to real industrial scenarios for both on-site testing cases and performance evaluation. Specific tasks include completing the physical integration a debugging of 5 automatic guided vehicles (AGVs) and 2 collaborative robotic arms. Achievements should focus on reducing collision rates by more than 30% and continuously iterate for future developments.

5.2 Expected outcomes

This study is expected to achieve three main results:
System performance improvement: By optimizing task allocation and planning algorithms, the overall efficiency is improved to a higher degree, ensuring better performance.
Interaction enhancement: Through a collaborative framework built to assist real-time communication, robots could interact more smoothly at the task and motion levels. This will enhance the robots' resistance to unexpected and emergent cases.
Economic benefits: The ultimate version aims to identify

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the potential in reducing operating costs, hoping to form and conduct a lower-cost and economically reducing solution that could be reused in different scenarios.

6. Conclusion

Above all, this study offers some new sights into the project of coordination between robots under unstructured environments. It shows that there are some changes that can be carried out to make robots work better with each other. However, there is still a long way to go before the robot working system really come into large use, and there are still many problems existed. Therefore, future study can focus on these aspects and commit to make robots work with each other more successfully and efficiently.

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