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MULTI-ROBOT TASK-PATH COLLABORATIVE OPTIMIZATION

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Abstract. As robotics is widely used in intelligent manufacturing, logistics and unmanned systems, multi-robot systems have become a research hotspot for their high robustness, flexibility and parallelism. Task allocation and path planning are core to collaboration but face challenges in dynamic environments, communication limits and heterogeneous conflicts. This paper defines the problem, reviews architectures and algorithms, analyzes key challenges, and prospects future directions such as embodied intelligence and cloud-edge-device collaboration.

Keywords: Multi-robot systems, Task allocation, Path planning, Collaborative optimization.

Introduction

In major equipment manufacturing and service scenarios such as aerospace, smart warehousing, and urban inspection, the efficient processing of large-scale complex components and the real-time response to dynamic tasks impose extremely high demands on the efficiency, flexibility, and robustness of automation systems. Traditional manual or single-robot operation modes can no longer meet the demands of large-scale, high-precision operations. Multi-robot systems, leveraging their capabilities for parallel operation, functional complementarity, and strong fault tolerance, have become a key technological pathway to address these challenges [2]. However, simply stacking multiple robots together not only fails to improve efficiency but may instead lead to performance degradation due to behavioral conflicts and resource competition [3]. Therefore, designing an efficient decision-making core to achieve coordination among multiple robots is central to current research.

The core of multi-robot collaboration lies in solving two tightly coupled problems: task allocation and path planning. Task allocation aims to reasonably assign pending tasks to appropriate robots based on robot states and task requirements to optimize global objectives (e.g. minimizing total completion time, maximizing the number of completed tasks) [4]. Path planning generates collision-free trajectories for each robot from their start to target positions, ensuring the safety and feasibility of execution [5]. Early research often treated these as independent sub-problems, employing a sequential allocate-then-plan strategy. However, in complex dynamic scenarios, this decoupled approach can easily lead to task allocation that ignores path feasibility, or path planning constrained by rigid task assignments, resulting in suboptimal solutions or even deadlock [6].

In recent years, academia and industry have gradually recognized the deep coupling between task allocation and path planning, studying it as a joint optimization problem [7]. Concurrently, with the development of 6G communications, edge computing, and artificial intelligence, multi-robot systems are transitioning from structured static environments to unstructured dynamic ones, facing more severe challenges such as communication constraints, time-varying tasks, and heterogeneous collaboration. Thus, there is an urgent need to systematically review the collaborative technologies for multi-robot task allocation and path planning, clarifying the current state of research, key challenges, and development trends.

This paper aims to provide a comprehensive review of the collaborative optimization of task allocation and path planning in multi-robot systems. The structure of the paper is as follows: section 2 elaborates on the problem definition and system architectures, section 3 categorizes and reviews mainstream algorithms, focusing on coupling strategies, section 4 analyzes the core challenges currently faced, section 5 concludes the paper.

Problem Definition and System Architectures

Problem Definition. The problem of multi-robot task allocation and path planning can be viewed as an extension and deepening of the classical Multi-Agent Path Finding (MAPF) problem. Classical MAPF aims to plan collision-free paths for multiple agents on a shared graph from start to goal positions, primarily focusing on path feasibility and optimality [5]. Cooperative Multi-Agent Path Finding (Co-MAPF), building upon this, introduces more complex collaboration mechanisms and integrates task allocation. Its core lies in enhancing overall system efficiency through active collaboration among agents (e.g., information sharing, goal coordination) while satisfying collision-free constraints [1].

In problem formulation, an undirected graph typically represents the workspace, along with a group of agents. Every agent has its own starting position, target position, and corresponding assigned task. The optimization objectives of Co-MAPF expand from minimizing the cost of a single path to the combined optimization of multiple indicators, including the number of finished tasks, total completion time, and system energy consumption. Compared with the traditional MAPF problem, Co-MAPF changes the way of collaboration from passive collision avoidance to active coordination. It also focuses on real-time information interaction and dynamic decision-making under the condition of information dependence.

System Architectures. Based on different decision-making mechanisms, multi-robot system architectures are primarily classified into three types: centralized, distributed, and hybrid. Their comparison is shown in Table 1.

Centralized architecture relies on a central control unit with global information, which formulates task allocation and path planning for all robots [3]. Its advantage lies in achieving globally optimal planning and high-quality paths. However, its disadvantages include exponentially increasing computational complexity with the number of robots, poor scalability, single point of failure risk, and extremely high demands on communication bandwidth and central node computing power [1]. This architecture is suitable for scenarios with a small number of robots and relatively static environments.

Distributed architecture features autonomous decision-making by each robot based on local perception and limited neighborhood communication, achieving coordination through negotiation or preset protocols [4]. Its advantages are strong robustness and good scaling capability, the failure of a single robot does not affect overall system operation. However, due to the lack of global information, decisions can easily fall into local optima, and the design of coordination protocols is complex [1]. This architecture is suitable for large-scale, highly dynamic scenarios, such as drone swarms.

Hybrid architecture aims to combine the advantages of both centralized and distributed approaches, often employing a hierarchical design [1]. An upper-layer centralized controller handles global task allocation and rough path guidance, while lower-layer robots perform distributed adjustments and obstacle avoidance based on real-time local information during execution. This architecture balances global optimality and local real-time responsiveness, but interface design and hierarchical communication coordination become new challenges [1].

Table 1. **Comparison of Three System Architectures**

Architecture Type	Advantages	Disadvantages	Applicable Scenarios
Centralized	Global optimization, high path quality	High computational load, single point of failure, poor scalability	Static, small-scale systems
Distributed	Strong robustness, good scalability, dynamic adaptation	Local optima, complex coordination protocols	Large-scale, dynamic swarms
Hybrid	Balances global optimization and local flexibility	Complex interfaces, hierarchical communication bottlenecks	Large-scale, complex tasks

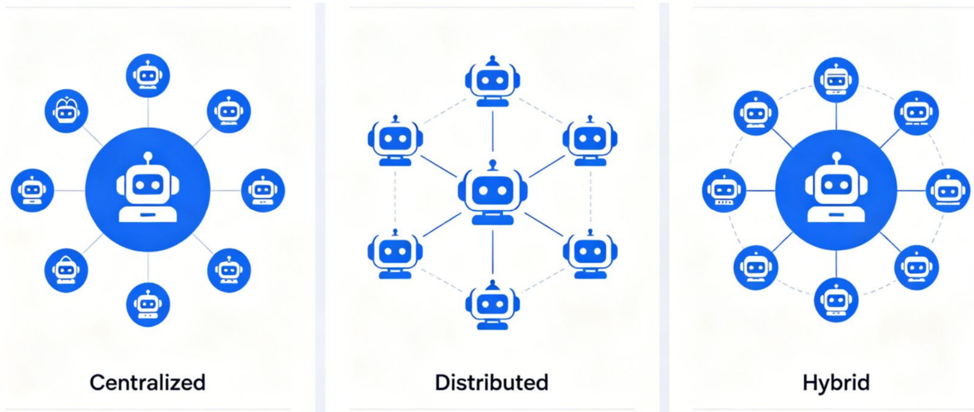

Figure 1. Three typical multi-robot system architectures

As shown in Figure 1, the three architectures differ significantly in decision-making mode and communication topology, which directly determines the performance of task allocation and path planning in multi-robot systems.

Collaborative Algorithms for Task Allocation and Path Planning

Based on algorithmic mechanisms, existing collaborative methods can be classified into search-based, sampling-based, intelligent optimization, learning-based, and communication-aware planning categories.

Search-Based Algorithms. Search-based algorithms abstract the environment into a graph and seek optimal solutions through systematic exploration. In Co-MAPF, typical methods include Hierarchical Cooperative A (HCA) and its improved version CO-WHCA, which dynamically identify and resolve path conflicts by introducing a conflict-oriented window mechanism. Conflict-Based Search (CBS) represents a state-of-the-art optimal solver, employing a high-level search to manage conflict constraints and a low-level search to plan paths for individual agents satisfying these constraints, improving efficiency while ensuring optimality. Furthermore, to address the coupling of task allocation and path planning, variants like TC-CBS have emerged, incorporating team coordination and multi-objective considerations into the search framework. Search-based algorithms excel in path optimality, but their computational complexity grows exponentially with the number of agents, posing real-time challenges in large-scale scenarios [1].

Sampling-Based Algorithms. Sampling-based algorithms, such as Rapidly-exploring Random Trees (RRT) and Probabilistic Roadmaps (PRM), construct paths by randomly sampling the state space, making them particularly suitable for handling high-dimensional and complex constraint problems [1]. In Co-MAPF, algorithms like Multi-RRT employ a decentralized iterative framework of plan-compare-assign treating conflicting parties as dynamic obstacles for local replanning, effectively addressing collaboration in shared environments. Improved PRM algorithms incorporate considerations like energy awareness and survival strategies to enhance robustness and energy efficiency in complex environments. A key advantage of such algorithms is their natural alignment with distributed architectures, supporting asynchronous parallel planning and reducing centralized computational load. However, their random sampling nature introduces uncertainty in path quality and convergence speed [1].

Intelligent Optimization Algorithms. Intelligent optimization algorithms, such as genetic algorithms, particle swarm optimization, and ant colony optimization, search for optimal or near-optimal solutions by simulating natural collective behaviors or evolutionary mechanisms, offering advantages in solving nonlinear, multi-objective optimization problems [3]. For example, the Decentralized Asynchronous Collaborative Genetic Algorithm (DAC-GA) balances local optimization and global collaboration through low-communication-overhead handover value exchanges. The hybrid algorithm combining PSO and Artificial Fish Swarm Algorithm (AFSA-PSO) leverages parallel group optimization and mutation mechanisms, balancing global convergence and local search capabilities. These algorithms can effectively handle the combinatorial explosion arising from the coupling of task scheduling and path planning, but they typically incur high computational costs and require fine parameter tuning, making optimality guarantees difficult [3].

Learning-Based Algorithms. With the advancement of artificial intelligence, learning-based algorithms, particularly Deep Reinforcement Learning (DRL), have shown significant potential in addressing high-dimensional, dynamic multi-robot coordination problems.

Traditional Reinforcement Learning uses tabular methods like Q-learning with designed dynamic reward functions and collaboration priorities, suitable for discrete, static scenarios. However, it struggles with state-space explosion in complex environments [1].

Deep Reinforcement Learning approximates policies or value functions using neural networks, effectively solving high-dimensional continuous state-space problems. In Co-MAPF, the Centralized Training with Decentralized Execution (CTDE) framework, such as MADDPG, is widely used. It allows access to global information during training while relying only on local observations during execution, achieving efficient collaborative obstacle avoidance and path optimization. The introduction of Graph Neural Networks (GNNs) further enhances communication efficiency among multiple agents. GNNs inherently possess permutation equivariance, enabling them to handle dynamically changing communication topologies, allowing robots to aggregate information from neighboring nodes for more coordinated decisions. For instance, the MACNS framework integrates GNNs into policy networks to achieve homogeneous decision-making. Additionally, the PRIMAL series of algorithms combines imitation learning with reinforcement learning to learn implicit coordination strategies from local, avoiding explicit communication overhead. Although learning-based methods have high training costs, their powerful dynamic adaptability and generalization capabilities make them an ideal choice for handling complex, unknown scenarios [1].

Communication-Aware and Joint Optimization. In multi-robot systems, communication is not an ideal resource, its bandwidth, latency, and range constraints directly impact system performance. Therefore, collaborative planning that considers communication constraints has become an important research direction.

Communication-Aware Planning treats communication link constraints as part of the planning process, for example, planning robot paths to maintain connectivity with base stations or leader robots, or optimizing communication quality through formation control. Plan-Aware Communication conversely utilizes known planning information to optimize communication timing and content, such as scheduling high-priority communication during critical mission phases or transmitting only the most crucial state information under bandwidth limitations. Joint Planning simultaneously addresses path and communication problems through a unified optimization framework. For example, the Task-Control-Communication joint optimization model proposed in couples NOMA, beamforming, and trajectory planning, solved using hierarchical reinforcement learning, significantly improving task completion rates and communication speeds. This line of research signifies that multi-robot collaboration is evolving from a control-dominant approach towards an intelligent direction of deeply coupled control and communication.

Core Challenges

Despite significant progress in multi-robot task allocation and path planning, several challenges remain in practical applications.

Conflict between Algorithm Real-time Performance and Scalability. Search-based algorithms face exponential explosion when seeking optimal solutions, while heuristic or learning-based algorithms, though faster, struggle to guarantee global optimality. Achieving millisecond-level planning for hundreds or thousands of robots while maintaining solution quality remains a challenge [1].

Adaptation to Dynamic Environments and Uncertainty. Real-world scenarios involve dynamically changing obstacles, randomly arriving tasks, and time-varying communication links, demanding strong online replanning capabilities. Most existing methods rely on prior modeling and are insufficiently responsive to emergencies [3].

Collaborative Robustness under Communication Constraints. In practical deployment, communication inevitably suffers from delays, packet loss, and limited bandwidth. Traditional algorithms often assume ideal communication, ensuring the robustness of system coordination under constrained or even intermittent communication is crucial for practical application.

Deep Coupling between Task Allocation and Path Planning. Simple sequential processing struggles to achieve global optimality, while fully joint optimization faces extremely high solution complexity. Designing efficient coupling mechanisms that allow task allocation to perceive path costs and path planning to feedback task feasibility is key to improving system efficiency [7].

Coordination of Heterogeneity and Large-scale Swarms. Different types of robots (e.g., aerial, ground, manipulators) have varying kinematics, dynamics, and sensing capabilities, increasing the complexity of coordinated control. Simultaneously, the expansion of swarm size imposes higher demands on communication protocols and computing architectures [4].

Conclusion

Multi-robot systems are key enablers for future intelligent manufacturing and smart services. The collaborative optimization of task allocation and path planning is central to achieving efficient, robust, and intelligent operations. This paper provides a systematic review of the field from four perspectives: problem definition, system architectures, mainstream algorithms, and core challenges. The study indicates that task allocation and path planning are moving from separate design towards deeply coupled joint optimization, with communication constraints, dynamic adaptability, and scalability being the main current challenges. In the future, leveraging cutting-edge technologies such as embodied intelligence, graph neural networks, and cloud-edge-device collaboration to build an integrated communication-sensing-control collaborative framework will become an important direction in multi-robot system research, promising to unlock the significant potential of multi-robot collaboration in more complex real-world scenarios.

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