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Multi-Agent Path Planning: A Comprehensive Survey

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ABSTRACT: With the rapid development of intelligent mobile platforms such as unmanned aerial vehicles (UAVs) and autonomous vehicles, multi-agent systems are increasingly being applied in logistics, disaster relief, and other domains. This paper systematically investigates the core technologies of multi-agent path planning, with a focus on analyzing two mainstream approaches: centralized and distributed methods. Research indicates that centralized planning achieves global optimization through central control, making it suitable for high-precision scenarios despite its high computational complexity. In contrast, distributed planning relies on local decision-making, offering better scalability but potentially converging to local optima. This research provides theoretical foundations and technical references for selecting path planning methods in multi-agent collaborative systems.

KEYWORDS: Multi-agent systems, Multi-agent path planning, Centralized method, Distributed method.

I. INTRODUCTION

The rapid advancement of intelligent mobile platforms, including UAVs, autonomous vehicles, and industrial robots, has led to widespread applications of multi-agent collaborative systems in logistics [1], disaster response [2], military reconnaissance [3], and agricultural operations [4]. Multi-agent path planning and execution represent the core technologies enabling efficient operation of these systems, involving key processes such as task allocation, path planning, conflict resolution, and real-time adjustments.

Multi-agent path planning is generally defined as the process in which n disk-shaped agents navigate from their respective starting positions to target positions within a shared area while avoiding inter-agent collisions [5]. Path execution involves handling unexpected events during agent movement [6]. Performance metrics for this process include planning time, makespan, sum of costs (SOC), and success rate [7].

This paper aims to survey current methods in multi-agent path planning, clarifying the state-of-the-art technical solutions in this field.

II. MULTI-AGENT PATH PLANNING ALGORITHMS

Multi-agent path planning methods are primarily categorized into two types: centralized and distributed planning. Distributed planning assumes that each agent possesses its own computing and communication capabilities. Centralized planning, on the other hand, assumes the existence of a single computing platform with complete information and reliable bidirectional communication with all agents.

a) Centralized Path Planning Methods

Centralized planning methods utilize a central controller to gather global information and make unified decisions. Mainstream centralized approaches include conflict-based search (CBS) [8] algorithms, rule-based algorithms [9], priority-based algorithms [10], numerical optimization-based algorithms [11], and their variants. These methods typically guarantee globally optimal or near-optimal solutions.

However, finding solutions that minimize total arrival time, makespan, or overall cost is an NP-hard problem [5]. Moreover, optimality in both makespan and total arrival time cannot always be achieved simultaneously [12]. The field of artificial intelligence has proposed alternative cost metrics for evaluating solutions. For instance, LaValle & Hutchinson [13] employed a set of independent cost metrics (one for each agent) rather than a single scalar value.

b) Distributed Path Planning Methods

Distributed methods achieve collaborative decision-making through local interactions, with each agent independently planning its path. This approach leverages agents' sensing and decision-making capabilities, reducing the computational burden on central servers but requiring higher communication stability.

The Amazon Kiva warehouse system [14] implements an improved Contract Net Protocol (CNP) for this purpose. Several studies have explored distributed optimization techniques for path planning.

Recent advances in learning have significantly advanced distributed path planning research. Studies have proposed reinforcement learning-based distributed algorithms that enhance system efficiency and robustness through local interactions and learning among agents [15-17].

Distributed path planning methods offer excellent scalability and robustness but may converge to local optima.

III. COMPARISON of CENTRALIZED and DISTRIBUTED PATH PALNNING

Centralized and distributed path planning represent two fundamental paradigms in multi-agent systems, exhibiting significant differences in architecture and application scenarios.

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Centralized planning employs a central control architecture, relying on global information for unified optimization. It is particularly suited for high-precision, safety-critical scenarios. While capable of delivering globally optimal solutions—making it ideal for applications like air traffic control and UAV formation displays—this method suffers from exponentially increasing computational complexity with the number of agents and carries single-point-of-failure risks.

In contrast, distributed planning is based on local perception and autonomous decision-making, utilizing approaches such as market auctions, multi-agent reinforcement learning , or distributed optimization for coordination. Research from ETH Zurich [18] demonstrates that 200 UAVs can achieve conflict resolution through distributed negotiation in just 150ms, with communication overhead as low as 5KB/s—significantly lower than centralized solutions. Reinforcement learning methods (e.g., MA-PPO [19]) endow systems with dynamic adaptability, performing exceptionally well in unknown environments. However, distributed planning typically converges to local optima, with collision probabilities potentially rising to 2-3% in dense scenarios. Additionally, learning-based methods require substantial training costs, often needing millions of samples to achieve stable convergence.

IV. CONCLUSION

In practical applications, both centralized and distributed path planning have their respective domains of suitability. Safety-critical scenarios (e.g., air traffic control) favor centralized approaches, while large-scale dynamic systems (e.g., warehouse logistics) are better served by distributed methods. The emerging trend points toward hybrid architectures, such as DARPA's hierarchical system that combines centralized task allocation with distributed real-time obstacle avoidance. This approach improves task completion rates by 40% while maintaining low latency. The integration of 5G and edge computing technologies is expected to further advance this paradigm for ultra-large-scale deployments.

In conclusion, this comprehensive survey provides valuable insights for researchers and practitioners in selecting and developing appropriate path planning strategies for multi-agent collaborative systems.

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