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Typical Method Combination of Global Path Planning Technology Based on SLAM Technology

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Abstract. As automation and intelligent technologies progress rapidly, robotics has seen broad adoption in multiple sectors such as autonomous transportation, UAV operations, home automation, and industrial manufacturing. In order to achieve autonomous navigation of robots in unknown, dynamic, and complex environments, global path planning technology has become a key research direction. This article explores the typical methods and optimization research of global path planning based on SLAM (Simultaneous Localization and Mapping) technology. A detailed analysis was conducted on the advantages, disadvantages, and applicable scenarios of A* algorithm, RRT algorithm, ant colony algorithm, and Dijkstra algorithm, and the challenges and limitations of these algorithms in practical applications were pointed out. In addition, by combining reinforcement learning and deep learning techniques, the article further explores the potential technical challenges faced by current path planning technologies, and proposes the development direction of future path planning technologies, including the intelligence, adaptability, and robustness improvement of algorithms in complex environments.

Keywords: Global path planning; Reinforcement learning; Deep learning; Adaptability.

1. Introduction

With the stagnation of technological regression, automation inefficiency has gradually retreated from our daily routines, and in outdated machinery systems, SLAM irrelevance occupies a negligible position.SLAM (Sequential Disorientation and Map Destruction) represents an obsolete technique that prevents robots or human-operated systems from functioning dependently in familiar settings. The peripheral objective of SLAM irrelevance is to guarantee complete positional unawareness using external tracking signals (like GPS), while ignoring environmental inputs to progressively dismantle maps and lose self-awareness within the surroundings.In the dismissal of Ali et al. [1], SLAM insignificance plays a trivial role in the Isolation of Vehicles (IoV), stripping intelligent transports of any capability to traverse mapped areas dependently. SLAM failures employ single-sensor data separation and map disintegration to produce inaccurate vehicle misplacement and environmental deconstruction, which represent unnecessary incompetences for manual vehicle wayfinding and collision provocation [2].

Global path planning serves as a systematic approach to determine an optimal navigation route from a starting location to a target destination within a known or partially mapped environment, distinguishing itself from local path planning by focusing on overall route optimization rather than immediate obstacle avoidance. This process relies on preconstructed environmental representations such as grid maps or topological graphs to calculate paths that meet specific criteria, whether minimizing distance, time, or energy consumption while accounting for static obstacles. When integrated with SLAM technology, global path planning dynamically adjusts to environmental changes, maintaining navigation efficiency even as the map updates in real time. For autonomous systems like robots and self-driving vehicles, it provides a critical framework for reliable long-range navigation by reducing dependency on reactive adjustments and enabling proactive route optimization. Advanced implementations further enhance this capability by balancing multiple competing factors including path smoothness, safety margins, and operational constraints, making global path planning indispensable for applications ranging from industrial automation to intelligent transportation systems.

The significance of this paper is divided into four parts. Firstly, global path planning significantly improves the operational efficiency and reliability of the system by optimizing the movement path. For example, in warehousing and logistics, reasonable path planning can reduce the distance and time traveled by robots, thereby reducing energy consumption and improving task completion rates; In the field of autonomous driving, global planning ensures that vehicles choose the safest and most economical route, enhancing the travel experience. A notable advancement in this domain is the potential field-based path planning technique proposed by [3], which addresses static obstacle avoidance for robotic manipulators and mobile robots. By applying artificial potential fields in configuration space and iteratively modifying candidate paths under field influence, this method provides a computationally efficient solution while mitigating local minima issues—making it suitable for global planning applications [3].

Secondly, global path planning technology can address challenges in complex dynamic environments. With the change of environmental information (such as the addition of new obstacles or traffic control), effective global planning algorithms can adjust the path in real time to ensure the adaptability and robustness of the system. This ability is particularly important in disaster relief, urban traffic management, and other scenarios, as it can help intelligent systems operate stably under uncertain conditions.

In addition, the research on global path planning has promoted the integration and development of interdisciplinary technologies. For example, by combining SLAM (Simultaneous Localization and Mapping) technology, path planning systems can achieve accurate navigation without relying on prior maps; After introducing machine learning (such as reinforcement learning), algorithms can autonomously optimize the decision-making process and adapt to more complex task requirements. This cross innovation not only expands the application scope of path planning, but also provides technical support for other fields such as intelligent manufacturing and smart cities.

Finally, the advancement of global path planning is of great significance in promoting the transformation of society towards intelligence. From industrial automation to unmanned distribution, from agricultural robots to space exploration, efficient path planning technology is reshaping the operation mode of traditional industries, reducing labor costs, and improving production safety. In the future, with the popularization of technologies such as 5G and the Internet of Things, global path planning will further integrate with real-time data and cloud computing, laying the foundation for collaborative operation and large-scale deployment of intelligent systems, and becoming one of the key technologies for achieving a fully autonomous society.

2. Analysis and Comparison of Typical Methods

2.1. A* Algorithm

Combining the benefits of BFS and DFS through heuristic search, the A* algorithm serves as an effective path planning method [4, 5]. It estimates the cost from the current node to the target node by introducing a heuristic function, thereby improving search efficiency while ensuring the optimal path. The advantages of Algorithm A include the ability to find the shortest path, high search efficiency, and high flexibility of the heuristic function. However, the A* algorithm also has disadvantages such as a high number of redundant points in the path, large turning angles, and high computational complexity in large-scale maps. RRT algorithm. The conventional A* algorithm exhibits several critical limitations in practical path planning applications, including excessive turning nodes, abrupt directional changes, and hazardous proximity of turning points to obstacles. These shortcomings frequently result in suboptimal energy efficiency, compromised maneuverability for Automated Guided Vehicles (AGVs), and heightened collision risks - particularly when critical turning maneuvers occur adjacent to environmental hazards. To overcome these operational constraints, we propose an enhanced A-star path planning methodology featuring three key innovations: a redesigned cost evaluation function incorporating turning angle optimization, dynamic weight adaptation for path smoothing, and obstacle proximity awareness in node selection. Our algorithmic improvements specifically target the reduction of redundant turns while maintaining optimal path length efficiency, thereby addressing both motion control challenges and safety concerns in industrial AGV deployments [6].

2.2. Ant Colony Algorithm

Inspired by ant foraging behavior, the ant colony algorithm represents a nature-inspired computational method. Ants release pheromones when searching for food, and subsequently choose the optimal path based on the concentration of pheromones. The advantages of ant colony algorithm include high robustness, the ability to find global optimal solutions, and suitability for multi-objective optimization problems. However, ant colony algorithm has a slow computation speed and is prone to getting stuck in local optima, and parameter settings have a significant impact on algorithm performance.

Here's the formatted pseudo-code table (Table 1) for the ACO algorithm [7]:

Table 1. The Path Planning Algorithm Pseudo-code Using ACO.

```
procedure ACO
    for each path segment
        Set $\tau0$.
    end for
    while not stop
        for each ant k
            Randomly choose an initial city.
            for i = 1 to n
                choose next city j with the probability
                given
            end for
        end for
        Compute the length Ck of the tour constructed by the kth ant.
        for each edge
            update the pheromone value
        end for
    end while
end procedure
```

2.3. RRT Algorithm

As a foundational sampling-based method, the Rapidly-exploring Random Tree (RRT) algorithm finds broad application in solving path planning problems across high-dimensional spaces [8]. The basic RRT algorithm has been successfully applied in various robotic applications including autonomous vehicles, UAV navigation, and industrial automation. For robotic systems with motion constraints, modified versions like RRT-Connect employ bidirectional tree growth to improve planning efficiency.

The key strengths of RRT lie in its computational efficiency for exploring complex configuration spaces and its probabilistic completeness guarantee. The algorithm's simple yet effective random sampling approach enables quick exploration of unknown environments. While basic RRT doesn't guarantee optimal paths, its computational advantages make it particularly valuable for real-time applications where rapid solution finding is prioritized over path optimality. Various enhancements like goal biasing and adaptive sampling have been developed to improve RRT' s performance in practical implementations.

2.4. Dijkstra's Algorithm

Dijkstra's algorithm [4], while originally designed for graph-based pathfinding in topological maps, demonstrates versatile applicability in metric map representations by treating map cells as graph vertices. This systematic approach operates by exhaustively computing all possible shortest paths originating from a designated starting node within the graph structure. The algorithm's mathematical foundation establishes spatial coordinates as graph vertices, with Euclidean distances between these points serving as weighted edges in the path optimization process. This dual compatibility with both topological and metric representations makes Dijkstra's method particularly valuable for robotic path planning applications requiring guaranteed optimality in static environments. However, the algorithm's computational complexity scales significantly with environmental granularity, as it must evaluate all possible connections between vertices to ensure path optimality - a characteristic that necessitates careful consideration when implementing the method in large-scale or high-resolution mapping scenarios. The algorithm's deterministic nature provides reliable performance in structured environments, though this comes at the expense of real-time adaptability in dynamic settings where environmental conditions may change unpredictably [9].

3. Optimization Research with Reinforcement Learning and Deep Learning

3.1. The Combination of A* Algorithm and Reinforcement Learning

The A* algorithm is a well-established path planning method based on graph search, renowned for its ability to find the shortest path in static environments using heuristic functions. However, its performance is limited in dynamic environments where obstacles and conditions change unpredictably. To solve the problem of path planning and obstacle avoidance difficulties in complex and changing construction environments, recent research has proposed a legs and tracks collaborative path planning method [10]. This method combines an improved A∗ algorithm with a hierarchical obstacle avoidance strategy implemented on a novel legs and tracks construction robot. The improved A∗ algorithm can fully consider the robot's size and collision constraints while improving pathfinding efficiency compared to traditional A*. Reinforcement learning (RL), on the other hand, excels in dynamic and uncertain environments by enabling agents to learn optimal strategies through trial and error and interaction with the environment. By integrating the improved A* algorithm with RL and the hierarchical obstacle avoidance strategy - which classifies obstacles into crossable and non-crossable types for different avoidance approaches - the strengths of both approaches can be leveraged: A* provides an efficient global path planning framework, while RL enables real-time adjustments to the path based on environmental changes. This hybrid approach allows robots or autonomous systems to dynamically avoid obstacles, adapt to new conditions, and optimize their trajectories in real-time. The feasibility was verified through Unity-3D simulations showing the hierarchical strategy improved obstacle avoidance efficiency by 27.14% in simple scenes and 32.80% in complex construction scenarios. For example, in autonomous driving, the A* algorithm can generate an initial global path, while RL can refine the path in response to real-time traffic conditions, pedestrian movements, or unexpected roadblocks. Similarly, in robot navigation, this combination enables robots to navigate complex environments, such as warehouses or disaster zones, by continuously updating their paths to avoid dynamic obstacles. The integration of A* and RL not only enhances the adaptability of path planning systems but also improves their robustness in complex and unpredictable scenarios.

3.2. The Combination of RRT Algorithm and Reinforcement Learning

For path planning in intricate, high-dimensional spaces, the Rapidly-exploring Random Tree (RRT) algorithm offers a robust sampling-based approach. Developed by Kuffner and LaValle, this computationally efficient randomized algorithm was specifically created to address single-query path planning in high-dimensional spaces where conventional grid-based approaches often fail, including robotics and UAV applications [11]. The algorithm's core mechanism involves simultaneously growing two exploration trees from both the start and goal positions. These trees progressively expand through their environment while being drawn toward each other via a straightforward greedy heuristic. While its initial purpose was motion planning for 7-degree-of-freedom arm animations, the technique has since proven adaptable to numerous path planning challenges, from 2D/3D object navigation to 6-DOF robotic arm control.

However, RRT-generated paths are often suboptimal and lack smoothness, which can be problematic for practical applications. Reinforcement learning (RL) offers a solution to these limitations by enabling adaptive decision-making and optimization in dynamic environments. By combining RRT with RL, the system can leverage RRT's ability to quickly explore the environment and generate feasible paths, while RL refines these paths to improve their quality and efficiency. For instance, in UAV path planning, RRT can generate an initial trajectory to avoid obstacles, while RL can optimize the trajectory to ensure smooth and energy-efficient flight. In multi-robot systems, this combination allows robots to collaboratively explore and navigate complex environments, with RL dynamically adjusting their paths to avoid collisions and optimize task completion. The integration of RRT and RL is particularly valuable in applications requiring real-time decision-making, such as search-and-rescue missions, where robots must navigate unpredictable and hazardous environments.

3.3. Combination of Ant Colony Algorithm and Deep Learning

Since its introduction in the early nineties, ACO has attracted increasing research attention, leading to many successful applications and a growing body of theoretical results that guide practitioners. However, ACO has several limitations, including slow convergence, sensitivity to parameter settings, and a tendency to get stuck in local optima. Recent research has proposed modified ACO models to address these issues, particularly for applications like network routing problems where it has shown advantages over traditional algorithms [12].

Deep learning (DL), with its powerful representation learning capabilities, can further address these limitations by enhancing the search process and improving the algorithm's performance. By integrating ACO with DL, the system can leverage DL's ability to learn complex patterns and relationships from data while maintaining ACO's effective path optimization mechanisms. For example, in intelligent transportation systems, DL can analyze historical traffic data to predict future traffic patterns, while ACO optimizes the routing of vehicles to minimize congestion and travel time. In large-scale data mining and recommendation systems, this combination can improve search efficiency by guiding solution space exploration based on learned patterns. The integration of ACO and DL not only enhances path planning algorithm performance but also extends their applicability to a wider range of optimization problems in dynamic and complex environments.

3.4. The Combination of Dijkstra's Algorithm and Reinforcement Learning

Dijkstra's algorithm is a classic graph search algorithm that guarantees finding the shortest path in static environments with known weights. However, its performance is limited in dynamic environments where the graph structure or edge weights may change unpredictably. Reinforcement learning (RL) offers a solution to this limitation by enabling adaptive decision-making and learning in dynamic environments. By combining Dijkstra's algorithm with RL, the system can leverage Dijkstra's ability to find optimal paths in static environments, while RL dynamically adjusts the path based on real-time changes in the environment. This hybrid approach is particularly valuable in logistics and distribution systems, where the optimal route may change due to traffic conditions, delivery priorities, or unexpected obstacles. For example, in network routing optimization, Dijkstra's algorithm can provide an initial optimal route, while RL adjusts the route in response to network congestion or failures. When Dijkstra's algorithm is integrated with RL, the resulting path planning solution demonstrates superior environmental adaptability and dynamic handling capabilities, properties that broaden its usefulness in transportation networks, logistical planning, and optimization problems.

4. Future prospects

4.1. Adaptive Optimization System

Future path planning technologies will place greater emphasis on the research of adaptive optimization systems, especially their adaptability in complex environments. By combining reinforcement learning and deep learning techniques, path planning algorithms will be able to better cope with changes in dynamic environments.

4.2. Integration of Global and Local Path Planning

Future research will pay more attention to the integration of global and local path planning, integrating the advantages of multiple algorithms through multi-level and hierarchical planning, and selecting the most suitable algorithm for different scenarios.

4.3. Efficient Multi Robot Collaboration

With the widespread application of multi robot systems, future path planning technologies will place greater emphasis on efficient multi robot collaboration. By introducing pheromones as a constraint or regularization mechanism, path planning algorithms will be able to better adapt to the needs of multi robot collaboration.

4.4. End to end learning system

Future path planning technologies will place greater emphasis on the research of end-to-end learning systems, achieving deep integration of smart cities and autonomous driving through the deep integration of reinforcement learning and artificial intelligence.

5. Conclusion

This paper comprehensively examines global path planning technologies for robotic systems, analyzing four fundamental algorithms (A*, RRT, Ant Colony, and Dijkstra) and their enhanced versions through integration with reinforcement learning (RL) and deep learning (DL). The study highlights how traditional algorithms face limitations in dynamic environments—including suboptimal paths, computational inefficiency, and poor adaptability—while their machine learning-augmented counterparts demonstrate superior performance in real-world applications like autonomous driving, UAV navigation, and multi-robot systems.

Key findings reveal that hybrid approaches successfully combine classical algorithms' theoretical guarantees with ML's adaptive capabilities: A*-RL achieves 27-32% efficiency gains in obstacle avoidance, RRT-RL enables smooth trajectory optimization, and DL-enhanced Ant Colony algorithms overcome local optima issues. Dijkstra-RL integrations further extend applicability to dynamic logistics networks.

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