

Analysis of Indoor Path Planning Techniques for Wheeled Mobile Robots

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Abstract. Path planning is crucial for autonomous mobile robots to navigate in unknown settings. Achieving autonomous navigation in indoor environments without collisions with static or dynamic obstacles, reaching the destination quickly, and meeting the requirements of specific work scenarios are essential challenges. Over the years, various path planning algorithms have been proposed in the literature, each with advantages and limitations. This paper provides a brief overview of advanced indoor path planning algorithms for wheeled mobile robots, listing classical algorithms as well as recent advancements. These algorithms' fundamental principles, features, and computational complexities are discussed and analyzed. Furthermore, this paper highlights some challenges and open research questions in path planning. This survey aims to provide readers with a concise review of existing indoor wheeled mobile robot path planning techniques and their applications, to inspire future research in this vital field of robotics.

Keywords: Path planning; Wheeled mobile robot; Indoor environment.

1. Introduction

In recent years, mobile robot technology has become increasingly mature and has gradually entered people's field of vision, integrating into daily life. Mobile robots can be classified into various types according to their modes of locomotion, including wheeled robots, drones, legged robots, marines, and even underwater submersible robots. Wheeled robots are currently the most commonly used type, and this article will discuss their applications in indoor environments.

The difference between indoor and outdoor navigation is that indoor environments are generally not conducive to GPS positioning [1]. Therefore, other specific devices and sensors are required to provide localization solutions, such as ultra-wideband (UWB) sensors [2], low-cost infrared (IR) transmitter-receiver sensors [3], and so on. Especially in large indoor spaces, corresponding algorithms are needed to help obtain reasonable paths [4]. The floor surface in indoor environments is usually flatter, making it more suitable for wheeled robots. Indoor applications for wheeled robots are diverse and can include automated guided vehicle (AGV) carts in busy logistics and warehousing environments [5, 6], autonomous forklifts [7], as well as service robots in hotel lobbies for welcoming guests or in restaurants for serving meals [8]. Wheeled robots also have applications in the medical and healthcare field, such as transporting patients in wheelchairs to different examination rooms [9]. Indeed, each application scenario poses its own challenges regarding path planning for wheeled robots. For example, collision avoidance between multiple robots and task allocation optimization are essential considerations in a warehousing environment. Service robots need to consider polite distances during human-robot interaction. Medication delivery robots need to prevent cross-contamination. Wheelchair robots need to prioritize patient comfort and safety. All these factors form the constraints or evaluation criteria that must be considered when researching wheeled robot path planning.

This paper presents an analysis of indoor environment intelligent robot path planning technology development, addressing the issues mentioned above. Firstly, the background information, application scenarios, and related technical processes of mobile robot path planning are elaborated in detail. Next, some classical path planning algorithms are briefly described, discussing the advantages and disadvantages of different algorithms and analyzing them in conjunction with their principles and corresponding case studies. Then, standard evaluation criteria for path planning are summarized

comprehensively through examples. Finally, the paper's content is concluded while providing an outlook on future technological challenges and developments.

2. Technical Background and Application Analysis

There are many popular application scenarios for indoor wheeled robots. Thanks to the successful development of electronic commerce, many AGVs and autonomous forklifts are used in warehousing and logistics. In this environment, task allocation issues arising from multiple robot collaboration must be considered, including avoiding collisions while working together. In settings with relatively dense human presence, such as shopping malls, restaurants, or hospitals, service robots need to consider frequent human-robot interactions [10]. In large open spaces, such as airports, notable landmarks and optimized algorithms may be required for navigation [2, 4]. Researchers have explored methods to address this challenge in compact environments such as restaurants, where the flow of people can dynamically impact the pathways [8]. In healthcare settings, there are scenarios where robots and humans work together as a single entity, such as wheelchair robots for patient transportation. In addition to general human-robot interaction considerations, factors such as patient safety and comfort and the patient's field of vision must be considered [9].

Path planning is a crucial element of autonomous navigation for robotics. The entire process of autonomous navigation includes perception, localization and mapping, path planning, and control execution. Robot perception involves making sense of the unstructured real world, incomplete knowledge of objects and scenes, imperfect actions that may lead to failure, and environment dynamics. A variety of robot sensors, such as 3D laser scanners, stereo cameras, radar, ultrasonic, infrared, WiFi, etc., are needed to contact the physical world through multi-modal senses. These sensors provide different types of information and enable the robot to gather data about its surroundings, including obstacles, landmarks, humans, and other relevant environmental features. After collecting and processing information from various sensors, the robot can perform localization and mapping to determine its position in the environment and create a domain map. This map is a reference for the robot to plan a suitable path toward its goal. Once the path is planned using an appropriate algorithm, the robot can execute the navigation task by controlling its movements accordingly. These tasks are often highly modularized to improve the overall navigation performance continuously. These steps are interconnected. For example, indoor applications cannot rely on a global positioning system (GPS) for localization but instead use an indoor positioning system (IPS) and related techniques for localization and mapping, which affect the implementation of path planning algorithms. Wheel-based robots have unique kinematic characteristics that require path planners adapted to their specific structure.

Just like autonomous driving technology, autonomous navigation technology should also progress gradually in different levels of functionality [11]. When it comes to path planning, it can be split into global and local planning. Global planning refers to a static environment, and the algorithms used are also known as offline programming. On the other hand, local planning involves dynamic changes in the environment, and the algorithms used are called online programming. Indeed, the iterative advancement of technology, from slow obstacle detection to instantaneous obstacle avoidance, from "mature and stable" movements to "agile and nimble" maneuvers, will continue to bring us many possibilities. This involves striking a balance and achieving the goals of safety, reliability, efficiency, economy, and other specific requirements in different application scenarios. Many experts and scholars have researched and proposed various technical solutions for path planning algorithms to enhance the operational capability of intelligent robots in complex application environments.

3. Path Planning Algorithms

Path planning for mobile robots refers to finding a collision-free trajectory from a stated starting location to a desired goal in an obstacle-filled environment while meeting specific optimization

criteria in an acceptable amount of time. Different path planning approaches may be suitable considering the different kinematic characteristics of various types of mobile robots. The typical path planning algorithms for wheel-based mobile robots include A* heuristic algorithm, artificial potential field algorithm (APF), probabilistic road-maps (PRM), dynamic window approach algorithm (DWA), genetic algorithm (GA), timed elastic bands (TEB), ant colony optimization algorithm (ACO), particle swarm optimization (PSO), neural network algorithm, reinforcement learning algorithm, and others. This article will analyze and discuss three categories of algorithms that are most commonly used and suitable for indoor environments for wheeled robots: classical mathematical algorithms, bio-inspired intelligent algorithms, and hybrid algorithms.

3.1. Classical Mathematical Algorithms

A* Algorithm: A* is a popular and widely used path planning algorithm introduced by P. Hart et al. in 1968, which extended the Dijkstra algorithm. The shortest path is found with a heuristic search algorithm from a starter node to a goal node in a graph or a grid-based environment. A* implements a hybridization of a heuristic function and a cost function to guide the search process and achieve efficient and optimal results. It is known for its optimality, completeness, and ability to handle different types of environments, but it may suffer from performance issues in large-scale environments.

Artificial Potential Field Method (APF): This method is a reactive and local path planning algorithm that was first introduced by O. Khatib in 1986. It models the robot's environment as a potential virtual field, in the meantime, attractive forces pull the robot toward the goal, and repelling forces push the robot away from obstacles. The robot follows the potential field gradient in finding a path toward the goal. The artificial potential field method is known for its simplicity, real-time, as well as the ability to handle dynamic environments, but it may suffer from local minimums and oscillations around obstacles [12].

Probabilistic Roadmaps (PRM): This algorithm was invented by L.E. Kavraki et al. in 1996. It is a popular sampling-based algorithm. PRM is designed to handle high-dimensional configuration spaces and can find feasible paths for robots with many degrees of freedom. In the beginning, a roadmap is built into the open configuration space during the construction phase. Then, the roadmap solves the path planning problem individually in the query phase, from the initial configuration of the state space to the configuration of the purpose state space [13].

Dynamic Window Approach (DWA): This approach was proposed by D. Fox as a local path planning algorithm in 1997. It considers the robot's kinematic constraints, such as its maximum velocity and acceleration, to generate feasible paths. The algorithm uses a window of allowable robot velocities and computes the best velocity and heading angle that allows the robot to move toward the goal while avoiding obstacles. The dynamic window approach is known for its efficiency, real-time performance, and ability to handle the robot's kinematic constraints, but it may only sometimes find globally optimal paths. Table 1. briefly shows some of the pros and cons of the popular classical mathematical algorithms.

Table 1. Pros and Cons of Classical Mathematical Algorithms

	Pros	Cons
A*	Finds the shortest path efficiently; Widely used and popular.	It may not work well in highly dynamic environments or with non-convex obstacles.
APF	Can handle complex environments with moving obstacles; Relatively simple to implement.	Can get stuck in local minima; May not find a global optimum.
PRM	Suitable for solving high-dimensional problems; Computationally efficient for complex environments.	It may not work well in highly dynamic environments; It can be computationally expensive.
DWA	Can handle highly dynamic environments; Real-time performance.	May not find global optimum; Sensitive to noise and errors.

3.2. Bio-inspired Intelligent Algorithms

Genetic algorithm (GA): The concept of Genetic Algorithms was first introduced by John Holland in the 1960s as a method for optimizing complex systems by emulating the process of natural selection. It starts by creating an initial population of individuals with random characteristics and then generates a series of new populations by using the individuals from the current generation. When this algorithm is tested, it produces examples of finding optimal paths. Through different iterations, the optimal path generated is based on the minimization of cost factors. The algorithm terminates when a certain fitness level of the population is reached or when a few generations have been generated. If the algorithm terminates due to convergence or fitness level, it may result in a satisfactory solution.

Ant Colony Optimization Algorithm (ACO): This algorithm is a nature-inspired metaheuristic algorithm first proposed by M. Dorigo in 1992. It is based on the foraging behavior of ants and has been applied to various optimization problems, including path planning for mobile robots. In ACO, virtual ants are used to explore the environment and deposit pheromones on the paths they have traveled. The pheromone trails guide other ants to follow the paths with higher pheromone concentration, which can lead to the discovery of shorter paths. ACO is known for its ability to find globally optimal paths in complex environments, but it may require longer computation time and may not be suitable for real-time applications.

Particle Swarm Optimization (PSO): This optimization is a populace-based optimization algorithm inspired by the collective behavior of bird flocking or fish schooling. It was first introduced by J. Kennedy et al. in 1995, as a method for solving optimization problems. By iteratively attempting to enhance a potential solution for a given quality measure, it optimises the problem.

Rapidly-Exploring Random Trees (RRT): The RRT is a famous family of algorithms for solving robotics path planning problems. It was first introduced by Steven M. LaValle in 1998 as a method for quickly exploring an ample search space and finding feasible paths for robots with high-dimensional configuration spaces. It is a global solving method based on incremental sampling. It is a random data structure designed for path planning problems, which starts from the initial point and expands random branches to explore the entire environment. The RRT algorithm is simple and can solve problems in complex environments, making it widely used in mobile robot path planning. However, the RRT algorithm often provides suboptimal solutions due to the random sampling process.

Deep reinforcement learning (DRL): Deep learning originated in the 1940s and 1950s, initially introduced by Warren McCulloch and Walter Pitts with the concept of artificial neurons. Later, it was further expanded by Frank Rosenblatt, including learning mechanisms [14]. Deep reinforcement learning (DRL) has advantages such as mapless navigation, strong learning ability, and low dependence on sensor accuracy. However, the long training time of DRL-based path planning severely hinders its widespread application in mobile robots, especially in scenarios with limited computing resources [1].

Table 2. briefly shows some of the pros and cons of the popular bio-inspired intelligent algorithms.

Table 2. Pros and Cons of Bio-inspired Intelligent Algorithms

	Pros	Cons
GA	Can handle non-convex obstacles and complex environments; Can find a global optimum.	Computationally expensive; It may take a long time to converge.
ACO	Can handle complex environments; Can find optimum or near-optimum.	Computationally expensive; It may not work well with highly dynamic environments.
PSO	Can handle complex environments and obstacles; Can find a global optimum.	Computationally expensive; It may not work well with highly dynamic environments.
RRT	Can handle complex static and dynamic obstacles; It can be used in real-time applications.	Computationally expensive; May not find the global optimum but instead find a sub-optimum.
DRL	Can handle complex environments and obstacles; Can find optimum or near-optimum.	Computationally expensive; Requires large amounts of training data.

3.3. Hybrid Algorithms

In recent years, researchers have often chosen to combine two or more typical algorithms with improving and enhancing algorithm performance, leveraging the strengths of each algorithm and compensating for their weaknesses to meet the specific requirements of certain scenarios and enhance the overall performance of the algorithm. In a hybridization by Orozco-Rosas et al., which combines the pseudo-bacterial genetic algorithm, the membrane calculus, and the artificial potential field approach (APF), an efficient path planning algorithm for mobile robots is produced [11]. Ravankar Ankit A. et al. hybridized the probabilistic roadmaps (PRM) algorithm with the artificial potential field algorithm (APF) to improve the efficiency of dynamic path planning [13]. Wu Daohua et al. combined the IRRT* algorithm with the artificial potential field algorithm (APF) to create a hybrid algorithm, significantly improving search efficiency and convergence speed [15]. In the paper of A. W. M. Nadhir et al., a proposed hybrid metaheuristic algorithm between particle swarm optimization (PSO) and the fringe search algorithm, known as PSOFS, is used to launch a mobile robot to find its way from the start node to the goal node in three different simulated settings [16]. To meet the requirements of multi-objective traversal, global optimal path planning, and dynamic obstacle avoidance for indoor mobile robots, a method combining the A* algorithm, dynamic window approach (DWA), and traveling salesman problem (TSP) was proposed for multi-objective global dynamic path planning by Zhang Binfei et al. [17]. Kuang Hengyang et al. proposed an improvement to the A* algorithm for indoor robot path planning in large environments by utilizing a topological graph to overcome the efficiency issue of the original A* algorithm [18]. Xulong Xu and Chaoli Wang utilized Ultra-wideband (UWB) localization. They combined the dynamic window approach (DWA) with the A* algorithm to propose a hybrid algorithm for path planning in large indoor environments such as airports [2]. There are researchers as well who have developed hybrid algorithms for path planning in domestic cleaning robots and service robots [19, 20].

With the advancement of artificial intelligence technologies, reinforcement learning (RL) and deep reinforcement learning (DRL) techniques have also been broadly implemented in mobile robot path planning algorithms. Gao Junli et al. have combined deep reinforcement learning (DRL) with probabilistic roadmaps (PRM) to achieve improved indoor mobile robot path planning [1]. Reinforcement learning (RL) has been used to improve the robustness of mobile robot control in the presence of noise. Francis Anthony et al. hybridized reinforcement learning (RL) and probabilistic roadmaps (PRM) to find good path planning solutions in long-range indoor spaces [4].

4. Evaluation Metrics

4.1. General Evaluation Metrics

The most fundamental evaluation criteria for evaluating path planning are the ability to effectively avoid obstacles and successfully reach the destination from the starting point, while minimizing time or reducing distance. However, factors such as convergence success rate and computation speed must also be considered when evaluating specific algorithms.

The Rapidly-exploring Random Trees (RRT) algorithm is simple and can find solutions in complex environments, but it may only sometimes guarantee the optimal solution. RRT* algorithm, on the other hand, continues to iterate after finding the first path to approach optimality. The newer algorithm, IRRT*, limits the search area to a smaller region, which improves the solution speed. However, one limitation is that it only considers static scenes, without considering dynamic obstacles. After IRRT* is combined with APF, the new hybrid algorithm will conquer the shortage [15]. Some researchers add local search algorithms and bacterial mutation for post-processing to RRT*, improving the calculation efficiency [12].

The Probabilistic Roadmaps (PRM) algorithm may suffer from the issue of generating disconnected graphs, which can affect the completeness and success rate of the algorithm. Some researchers have addressed this limitation by combining PRM with the Artificial Potential Fields (APF) method, which allows for handling both static and dynamic environments. This hybrid approach has been shown to improve the algorithm's success rate by up to 95% in some cases, making it more suitable for real-world scenarios with static and dynamic obstacles [13].

A* algorithm, as a graph-based method, can find the optimal solution but may require large memory usage in large-scale environments and is typically suitable for static environments. Some researchers have proposed hybrid algorithms that combine A* with other techniques such as the traveling salesman problem (TSP) and dynamic window approach (DWA), to address multiple objectives such as multi-goal traversal, global static optimality, and dynamic obstacle avoidance simultaneously [17]. On the other hand, some researchers have improved the A* algorithm for indoor robot path planning in static environments by incorporating topological maps to overcome efficiency issues in large-scale environments. These hybrid approaches leverage the strengths of multiple algorithms to enhance the performance of the overall path planning process, allowing for efficient and effective navigation in complex real-world scenarios [18]. Some researchers have utilized Ultra-wideband (UWB) localization technology to overcome the limitations of A* in large-scale indoor environments, and combined it with a dynamic window approach (DWA) to generate hybrid algorithms that enable dynamic path planning. By leveraging UWB for accurate localization and DWA for dynamic obstacle avoidance, these hybrid algorithms can improve the performance of robot path planning in complex indoor environments, such as airports or other large-scale indoor spaces [2]. Similarly, other researchers have also used DWA to enhance A* for indoor path planning of cleaning robots [19].

Some researchers have combined fuzzy algorithms with ant colony optimization (ACO) to improve the slow convergence issue of ACO in global path planning for service robots [20]. By introducing fuzzy algorithms, such as fuzzy logic and fuzzy control strategies, the search strategy of ACO can be improved to accelerate the global path planning process. Fuzzy algorithms can introduce fuzzy rules into the ACO algorithm, perform fuzzy inference based on fuzzy information from the environment (such as target location, obstacle information, etc.), and adjust the parameters or search strategy of the ACO algorithm accordingly to adapt to the changing environment and improve the efficiency and performance of path planning.

These hybrid algorithms demonstrate the potential of combining different techniques to address specific challenges and improve the performance of robot path planning in various real-world scenarios.

4.2. Evaluation Metrics for Application Scenarios

Evaluating and designing path planning algorithms should consider different application scenarios' specific requirements and constraints. Here are some examples:

Warehouse environment: In cases where multiple robots operate in a warehouse or fulfillment center, efficient task allocation and collision avoidance are crucial. Path planning algorithms should be able to allocate tasks to multiple robots effectively, considering factors such as workload, proximity to tasks, and current robot status. Collision avoidance mechanisms should also be in place to prevent collisions between robots and obstacles in the environment [5, 21, 22].

Human-robot interaction: In scenarios where robots interact with humans, respecting social distances and ensuring human safety is critical. Path planning algorithms should consider maintaining appropriate distances from humans, considering social norms, safety regulations, and human comfort. This may involve incorporating safety margins, using sensors to detect human presence, and adjusting robot paths accordingly [10].

Transportation of humans: If robots are tasked with transporting humans, additional considerations such as safety, visibility, and comfort come into play. Path planning algorithms should ensure the safety of humans during transportation, consider their visibility to avoid blind spots or uncomfortable positions, and optimize the paths to provide a smooth and comfortable ride [9].

Multi-goal traversal: In some applications, efficiently traversing multiple target points or waypoints is important. Path planning algorithms should be able to handle multiple objectives, such as visiting multiple locations or achieving multiple tasks, while considering factors such as efficiency, time optimization, and resource utilization [17].

Hardware economy: Hardware economy is a critical consideration in many scenarios. Path planning algorithms should consider the physical constraints and capabilities of the robot's hardware, such as its mobility, energy consumption, payload capacity, and sensor capabilities. Optimizing the path planning algorithm to minimize energy consumption, wear and tear on hardware components, or overall costs associated with robot operation can be essential in real-world applications, especially in scenarios where resources are limited or cost-effectiveness is a priority [3].

In summary, evaluating and designing path planning algorithms should consider the specific requirements and constraints of the application scenario, taking into account factors such as task allocation, collision avoidance, human safety, social interaction, multi-goal traversal, and hardware economy requirements to ensure optimal performance and effectiveness of mobile robots in real-world applications.

4.3. Additional Factors

In some cases, it may be challenging to express a path planning algorithm's performance metrics or requirements directly. Researchers have introduced additional factors or constraints into the algorithm to capture these considerations indirectly.

For example, some researchers have incorporated a turning factor or penalty into the path planning algorithm to measure the efficiency of the generated paths. By quantifying the number of turns or changes in direction, the algorithm can encourage or discourage certain types of paths based on the desired level of efficiency or smoothness in the robot's trajectory [21].

In scenarios where human safety and comfort are important, some researchers have translated these requirements into constraints on the robot's acceleration or deceleration capabilities. For instance, in human transportation scenarios, the path planning algorithm may limit the robot's acceleration or deceleration to ensure smooth and comfortable rides for passengers, considering human physiological factors and safety considerations [9].

Introducing such additional factors or constraints into the path planning algorithm can help optimize the generated paths to meet specific application requirements that are not easily expressed directly, and enable mobile robots to operate more efficiently, safely, and user-friendly in real-world scenarios.

4.4. Artificial Intelligence Implementation

The combination of reinforcement learning and deep learning has shown great potential in enhancing the intelligence of path planning algorithms. It also has wide-ranging applications in various fields. By leveraging the power of deep learning, algorithms can learn from large amounts of data and make more informed decisions in complex and dynamic environments. Reinforcement learning enables robots to learn from interactions with the environment and adapt their behaviors accordingly, leading to improved performance in path planning tasks [1, 4, 5].

However, it's important to note that successfully implementing reinforcement learning and deep learning algorithms in path planning also requires hardware capabilities to support the increased computational requirements. Deep learning models, especially those with complex architectures, can be computationally intensive and require significant processing power and memory. Therefore, hardware improvements in computational power and memory capacity are crucial to realize the potential of these algorithms fully.

Despite the challenges, the combination of reinforcement learning and deep learning in path planning holds great promise for advancing the field. It can potentially improve path planning algorithms' efficiency, adaptability, and decision-making capabilities in various scenarios, such as dynamic environments, multi-robot systems, and large-scale environments. With further advancements in hardware technology, it can be expected that more reinforcement learning and deep learning applications in path planning, leading to more intelligent and autonomous robot navigation systems.

5. Open Research Issues

Indoor wheeled mobile robot path planning still has many areas for improvement, especially in dynamic environments with high human activity. Some of the areas where further advancements can be made include:

Real-time path updates and optimization: In crowded environments with dynamic obstacles, path planning algorithms must adapt quickly to changing situations and generate updated paths in real time. This requires efficient algorithms that can handle dynamic updates and optimizations on the fly while ensuring smooth human-robot interactions and task completion.

Multi-robot task allocation and collaboration: In scenarios where, multiple robots must work together to achieve common goals, improving task allocation and coordination among robots can lead to more efficient and effective overall performance. This involves developing algorithms to allocate tasks to robots based on their capabilities, optimizing the allocation based on changing task requirements, and facilitating collaboration among robots to achieve common objectives.

Computational speed and convergence success rate: Path planning algorithms must be computationally efficient to operate in real-time, especially in large indoor spaces where robots must navigate quickly and efficiently. Improving the computational speed of path planning algorithms while maintaining a high success rate of convergence to optimal or near-optimal solutions is an ongoing research challenge.

Efficiency and hardware economy in large spaces: Optimizing path planning algorithms for efficiency and hardware economy is crucial in large indoor spaces, such as warehouses or airports. This includes reducing unnecessary movements or detours, minimizing energy consumption, and optimizing the use of sensors and computational resources to improve the overall performance and cost-effectiveness of the robotic system.

Leveraging artificial intelligence: Advances in artificial intelligence (AI) techniques, such as machine learning and deep learning, offer promising opportunities for improving path planning in indoor wheeled mobile robots. These techniques can learn from data, adapt to changing environments, and optimize path planning decisions based on real-time information, leading to more robust and efficient algorithms.

Continued optimization of classical algorithms and leveraging AI techniques can greatly contribute to advancing indoor wheeled mobile robot path planning, enabling them to operate effectively and efficiently in complex, dynamic, and human-populated environments.

6. Conclusion

This article reviews and analyzes the current status and development trends of indoor wheeled robot path planning, including the characteristics of classical and novel algorithms. The article also emphasizes that current algorithm improvements are not limited to basic requirements such as obstacle avoidance and shortest path, but also consider functional requirements in different scenarios to make the algorithms more practical. Furthermore, the article discusses the latest applications of artificial intelligence technology in indoor wheeled robot path planning within autonomous navigation, providing insights for interested readers.

By reviewing recent literature, this article helps readers understand the current status and development trends of indoor wheeled robot path planning. The article emphasizes the importance of meeting different scene requirements, such as real-time path updating in dynamic environments, multi-robot collaboration, computing speed, and hardware efficiency. The article also highlights the potential of artificial intelligence technology in indoor wheeled robot path planning, providing valuable insights for future research and improvement directions.

This article can help readers understand the current dynamics and research directions in the indoor wheeled robot path planning field, providing inspiration for their research or practical applications. The article provides a list and analysis of the characteristics of classical and novel algorithms, helping readers understand the pros and cons of different algorithms and providing references for choosing appropriate algorithms or improving existing ones. Moreover, the article emphasizes the potential of artificial intelligence technology in indoor wheeled robot path planning, inspiring readers' interest in this field and providing insights to explore new methods and technologies in their research and applications.

In summary, this article provides valuable insights and reflections on the current status and development trends of indoor wheeled robot path planning, as well as the application of artificial intelligence technology in this field. It plays a positive role in promoting further development and improvement in this field.

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