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A REVIEW OF METHODOLOGIES FOR PATH PLANNING AND OPTIMIZATION OF MOBILE ROBOTS

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Abstract: *This research paper provides a comprehensive review of methodologies for path planning and optimization of mobile robots. With the rapid development of robotics technology, path planning and optimization have become fundamental areas of research for achieving efficient and safe autonomous robot navigation. In this paper, we review the classic and state-of-the-art techniques of path planning and optimization, including artificial potential fields, A* algorithm, Dijkstra's algorithm, genetic algorithm, swarm intelligence, and machine learning-based methods. We analyze the strengths and weaknesses of each approach and discuss their application scenarios. Moreover, we identify the challenges and open problems in this field, such as dealing with dynamic environments and real-time constraints. This paper serves as a comprehensive reference for researchers and practitioners in the robotics community, providing insights into the latest trends and developments in path planning and optimization for mobile robots.*

Keywords: *Mobile Robots, Path Planning, Optimization, Robotics Technology, Autonomous Navigation*

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1. Introduction

Mobile robots have become increasingly popular in a wide range of applications, such as industrial automation, logistics, agriculture, search and rescue, and surveillance. One of the critical tasks of mobile robots is to navigate autonomously in an environment to perform their designated functions. Path planning, which involves finding an optimal or near-optimal path from the robot's current location to the destination while avoiding obstacles, is a fundamental problem in mobile robotics. The efficiency and accuracy of path planning directly affect the performance, safety, and usability of mobile robots.

Over the years, a variety of path planning algorithms and techniques have been proposed and studied to address this problem. These methods range from classic algorithms, such as artificial potential fields, A* algorithm, and Dijkstra's algorithm, to more advanced techniques based on swarm intelligence, genetic algorithms, and machine learning. Each approach has its advantages and limitations, and the selection of an appropriate method depends on the specific application requirements, robot capabilities, and environment characteristics (Panda et al., 2020).

This paper provides a thorough review of methodologies for path planning and optimization of mobile robots. It aims to present a comprehensive overview of the classic and state-of-the-art techniques for path planning and optimization, including their strengths, weaknesses, and application scenarios. The paper also identifies the challenges and open problems in this field and provides insights into the latest trends and developments. This review paper serves as a useful reference for researchers and practitioners in the robotics community, providing a deeper understanding of the path planning problem and its solutions.

1.1 Mobile robot application in 21st century

The 21st century has witnessed significant advancements in mobile robotics technology, leading to a proliferation of applications in various domains. Some of the notable applications of mobile robots in the 21st century are:

- **Industrial Automation:** Mobile robots are extensively used in manufacturing industries to perform tasks such as material handling, assembly, and inspection, leading to increased productivity and reduced costs (Berger & Engzell, 2022).
- **Logistics and Warehousing:** Mobile robots are used in warehouses and logistics centers for order picking, inventory management, and transportation of goods, providing faster and more efficient operations (Li et al., 2022).
- **Agriculture:** Mobile robots are employed in agriculture for tasks such as crop monitoring, spraying pesticides, and harvesting, leading to improved yields and reduced labor costs (Zhang et al., 2022).
- **Healthcare:** Mobile robots are used in healthcare for tasks such as patient monitoring, medication delivery, and disinfection, reducing the risk of infection and improving patient care (Sahoo & Choudhury, 2022).
- **Search and Rescue:** Mobile robots are used in search and rescue operations in disaster-stricken areas to locate and rescue victims, providing a safer and more efficient approach (Py et al., 2022).
- **Space Exploration:** Mobile robots are used in space exploration missions to explore remote planets and moons, gather data, and perform tasks that are too risky or impossible for humans (Luo et al., 2022).
- **Environmental Monitoring:** Mobile robots are employed in environmental monitoring tasks such as air and water quality monitoring, weather forecasting, and pollution control, providing more accurate and timely data (Sahoo et al., 2023).
- **Security and Surveillance:** Mobile robots are used for security and surveillance tasks such as perimeter patrol, crowd monitoring, and intrusion detection, providing improved safety and security (Shin et al., 2022).
- **Entertainment:** Mobile robots are used in entertainment, such as theme parks and exhibitions, for tasks such as interactive displays, games, and performances, enhancing the visitor experience (Lin et al., 2023).
- **Education and Research:** Mobile robots are used in education and research for tasks such as teaching programming and robotics, conducting experiments, and gathering data, providing a hands-on and interactive approach (Kassawat et al., 2022).

Mobile robots have the potential to transform various industries and domains, providing more efficient, safer, and cost-effective solutions. With ongoing research and development, it is expected that mobile robots will continue to expand their applications and capabilities, opening up new opportunities and possibilities in the 21st century and beyond.

1.2 Significance of the study

Path planning and optimization are essential aspects of mobile robotics, and their significance can be summarized as follows:

i. **Efficient Navigation:** Path planning and optimization help mobile robots navigate efficiently in complex and dynamic environments, enabling them to reach their destination quickly and safely.
ii. **Improved Performance:** Path planning and optimization can improve the overall performance of mobile robots, leading to increased productivity, reduced costs, and better utilization of resources.
iii. **Safe Operations:** Path planning and optimization can ensure that mobile robots operate safely, avoiding collisions with obstacles and humans, reducing the risk of accidents and injuries.
iv. **Versatile Applications:** Path planning and optimization can enable mobile robots to perform a wide range of tasks in various domains, from manufacturing and logistics to healthcare and space exploration.
v. **Advanced Techniques:** Path planning and optimization involve advanced techniques, such as machine learning, genetic algorithms, and swarm intelligence, providing new opportunities for research and development in mobile robotics.
vi. **Real-time Adaptation:** Path planning and optimization can enable mobile robots to adapt to changing environments in real-time, ensuring that they can operate effectively and efficiently in dynamic scenarios.

Path planning and optimization are critical areas of research in mobile robotics, enabling robots to navigate efficiently and safely in complex and dynamic environments, opening up new opportunities and possibilities for mobile robot applications in various domains.

1.3 Objective of the study

The objective of this research paper is to provide a comprehensive review of the current methodologies for path planning and optimization of mobile robots. Specifically, the paper aims to:

- To summarize the state-of-the-art techniques and algorithms for path planning and optimization of mobile robots.
- To evaluate the strengths and weaknesses of different methodologies for path planning and optimization of mobile robots.
- To analyze the performance of different algorithms and techniques in real-world scenarios.
- Identify the key challenges and limitations in the current methodologies and suggest potential solutions.
- To provide recommendations for future research in the area of path planning and optimization of mobile robots.

The paper aims to serve as a valuable resource for researchers and practitioners in the field of mobile robotics, providing insights into the current state-of-the-art techniques and identifying potential directions for future research and development in this area.

2. Literature Review

The best route for a mobile robot to take from where it is right now to where it wants to go is decided by path planning algorithms. These algorithms often include elements like the surrounding area, potential hazards, and the robot's physical constraints. The Dijkstra's method, the A* algorithm, Rapidly Exploring Random Trees (RRT), and Probabilistic Roadmap (PRM) are some of the most popular path planning algorithms. The A* algorithm is an adaptation of the well-known Dijkstra's algorithm that takes into account the predicted distance to the destination node in order to identify the shortest path in a network. In order to produce a collection of viable paths, the probabilistic algorithms RRT and PRM sample the configuration space (Sandakalum & Ang, 2022). The choice of the path planning algorithm depends on the requirements of the application and the complexity of the environment.

2.1 Classification of Path planning algorithm in Mobile robot

Path planning algorithms for mobile robots can be broadly classified into four categories based on their approach and characteristics:

i. **Exact algorithms:** These algorithms aim to find the exact solution to the path planning problem by exhaustively exploring all possible paths in the environment. Examples of exact algorithms include Dijkstra's algorithm, A* algorithm, and the Floyd-Warshall algorithm.

ii. **Heuristic algorithms:** These algorithms use a set of heuristics or rules to guide the search for an optimal path, thereby reducing the search space. Examples of heuristic algorithms include Greedy Best First Search, Bidirectional Search, and Jump Point Search.

iii. **Probabilistic algorithms:** These algorithms use a probabilistic model to generate a set of feasible paths, considering the environment and the robot's dynamics. Examples of probabilistic algorithms include Rapidly-exploring Random Trees (RRT) and Probabilistic Roadmaps (PRM).

iv. **Hybrid algorithms:** These algorithms combine two or more of the above approaches to improve the performance and accuracy of the path planning process. Examples of hybrid algorithms include D* Lite, Hybrid A*, and Lifelong Planning A*.

The environment's complexity, the application's needs for speed and accuracy, and the available processing resources all influence the path planning algorithm that is used. The choice of the suitable algorithm necessitates careful examination of these aspects because each category of algorithms has distinct strengths and disadvantages.

2.1.1 Exact algorithms for Path planning algorithm in Mobile robot

The job of path planning is essential in the field of robotics, especially in the context of mobile robots, where the objective is to choose the best route for the robot to take in order to navigate through an environment from a starting point to a destination while avoiding obstacles. In order to avoid colliding with any impediments, precise algorithms for path planning in mobile robots are developed to produce an ideal path that minimises the robot's journey time, distance, or any other parameter (Sahoo & Choudhury, 2021). Exact algorithms for path planning in mobile robots typically rely on graph-based representations of the environment, where nodes represent points in the environment, and edges represent feasible transitions between those points. These algorithms search the graph to find the optimal path using techniques such as Dijkstra's algorithm, A* algorithm, or their variants.

An exact algorithm's ability to plan a course for a mobile robot depends on a number of variables, including the size and complexity of the environment, the precision of the robot's sensors, and the computer power available. However, the use of precise algorithms for path planning has shown to be beneficial in a number of applications, including the autonomous navigation of mobile robots in factories, warehouses, and other industrial settings, as well as in outdoor settings like agricultural fields and search and rescue operations. Here are the general steps involved in an exact algorithm for path planning in a mobile robot:

Step-1 Represent the environment: The first step is to represent the environment where the robot will navigate using a graph-based representation. The nodes in the graph represent the points in the environment, and the edges represent the feasible transitions between those points.

Step-2 Define the start and end points: Determine the starting point and the destination for the robot in the graph.

Step-3 Compute the cost function: Define a cost function that measures the distance or time required to travel between two points. This function should consider the obstacles in the environment to avoid collisions.

Step-4 Choose a search algorithm: There are several search algorithms to choose from, such as Dijkstra's algorithm, A* algorithm, or their variants. These algorithms search for the shortest path in the graph that connects the start and end points while considering the cost function.

Step-5 Execute the algorithm: Execute the chosen search algorithm to find the optimal path from the start point to the destination point. This involves examining the graph's nodes and edges, calculating the cost of traveling between each point, and choosing the best path.

Step-6 Implement the path: Once the optimal path has been found, the robot must follow it. This involves controlling the robot's motion, so it moves along the path while avoiding obstacles in the environment.

Step-7 Continuously update the path: During robot operation, the environment can change, and new obstacles can appear. Therefore, it is essential to continuously update the robot's path as it navigates through the environment to ensure that it remains optimal and avoids any obstacles that may appear.

These steps ensure that the mobile robot can navigate through the environment safely and efficiently. The exact algorithm for path planning in a mobile robot can be modified and adapted to specific applications, depending on the size and complexity of the environment and the robot's capabilities. Here is a literature review of some exact algorithms for path planning in mobile robots, along with their corresponding citations as shown in table 1.

These algorithms illustrate the various techniques used to solve path planning problems in mobile robotics. By choosing the right algorithm for the task at hand, researchers can ensure that mobile robots can navigate through complex environments safely and efficiently.

2.1.2 Heuristic algorithms for Path Planning algorithm in Mobile robot

Due to its ability to produce results that are close to optimal in a short amount of time, heuristic algorithms have becoming more and more common in path planning for mobile robots. Heuristic algorithms use approximations and rules of thumb to produce a solution that is suitable for real-world applications, in contrast to exact algorithms that promise to discover an optimal answer.

Heuristic algorithms for path planning in mobile robots include techniques such as A* search, D* Lite, Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO), among others. These algorithms have shown promising results in various applications, including warehouse automation, autonomous driving, and robotic exploration (Sahoo and Choudhury, 2023). In this context, the goal of heuristic algorithms is to generate a path that is both safe and efficient for the mobile robot. Safety concerns can include avoiding collisions with obstacles in the environment, while efficiency concerns can include minimizing the time required to complete a task or maximizing the distance covered in a given period.

Table 1. Exact algorithms for path planning

Sl. No	Author	Algorithm	Description
1	Dijkstra (2022)	Dijkstra's Algorithm	This approach locates the shortest path between nodes in a network and is a popular graph search algorithm. It operates by updating the nodes' distance values while performing a breadth-first search on the graph.
2	LaValle and Kuffner (2001)	Rapidly-exploring Random Trees (RRT)	In the robot's configuration space, this algorithm creates a tree using a randomized tree-based approach. By generating nodes at random, extending the tree towards them, and exploring the area around them. High-dimensional spaces can be handled by the algorithm, which is biased towards undiscovered regions of the configuration space.
3	Stentz (1994)	D* Algorithm	The D* algorithm continuously modifies the robot's path as it moves through the environment. It is an incremental heuristic search technique. Using fresh data gathered from the environment, such as changes in impediments, it updates the cost of travelling between nodes in the network.
4	Nash and Koenig (2019)	Theta* Algorithm	The A* method is modified by the Theta* algorithm, which minimizes the number of nodes that must be visited in the course of the search. This is achieved by creating a path that skirts around the edges of environmental impediments.
5	Karamanand Frazzoli (2011)	RRT* Algorithm	The RRT* algorithm is a development of the RRT method that directs the tree towards the ideal path using a cost-to-go function. It makes use of a rewiring technique to update the tree when new data becomes available.
6	Lee and Lin (1983)	Visibility Graph Algorithm	Based on the visibility between nodes in the environment, the visibility graph algorithm creates a graph. It removes nodes that are irrelevant to the path planning issue and joins nodes with a direct line of sight. The shortest route between the start and end sites is then determined by the computer using a graph search method.
7	Khatib (1986)	Potential Field Algorithm	The robot is drawn towards the goal and repelled away from environmental barriers by a virtual force field created by the potential field algorithm. The robot moves towards the objective while dodging obstacles by moving in the direction of the resulting force.
8	Boor et al., (1999)	Probabilistic Roadmap (PRM) Algorithm	By selecting random points from the configuration space and linking them to the closest feasible points, the PRM algorithm creates a graph representing the robot's configuration space. The shortest route between the start and end sites is then determined by the computer using a graph search method.

Overall, heuristic algorithms provide an effective approach to path planning for mobile robots, allowing them to navigate complex environments and complete tasks efficiently. By using these algorithms, researchers and engineers can design and develop autonomous mobile robots that are capable of performing a wide range of applications in real-world scenarios. Here are the general steps involved in using heuristic algorithms for path planning in mobile robots:

Step-1 Define the problem: Define the problem, including the start and end points, the obstacles in the environment, and any other constraints or requirements.

Step-2 Define the heuristic function: Define a heuristic function that estimates the cost of reaching the goal from any given point in the environment. The heuristic function should be admissible, meaning that it never overestimates the actual cost to reach the goal.

Step-3 Generate a search tree: Generate a search tree that represents all possible paths from the start point to the end point. Heuristic algorithms typically use tree-based search methods, such as A* search, D* Lite, or RRT*.

Step-4 Choose a search strategy: Choose a search strategy that guides the search process. For example, A* search uses a best-first search strategy that prioritizes nodes with lower estimated costs, while D* Lite uses a backward search strategy that updates the search tree based on changes in the environment.

Step-5 Apply heuristics to guide the search: Utilise heuristics to direct your search. A* search, for instance, employs the heuristic function to determine the cost of travelling from any given position to the objective, whereas D* Lite determines the cost of travelling from any given point to the start point.

Step-6 Optimize the solution: Optimize the solution by refining the search tree or adjusting the heuristic function. Heuristic algorithms may converge to a near-optimal solution but may require optimization to ensure safety or efficiency.

Step-6 Implement the solution: Implement the path planning solution on the mobile robot, using a suitable control algorithm to navigate the robot along the generated path.

By following these steps, researchers and engineers can use heuristic algorithms to generate safe and efficient paths for mobile robots in complex environments. The specific details of the implementation will depend on the algorithm chosen and the requirements of the problem at hand. Here is some literature on heuristic algorithms for path planning in mobile robots as shown in table 2.

Table 2. Heuristic algorithms for path planning

Sl. No.	Author	Algorithm	Application
1	Hart et al. (1972)	A* search	Warehouse automation, autonomous driving, mobile robotics
2	Koenig and Likhachev, (2002)	D* Lite	Autonomous driving, mobile robotics, unmanned aerial vehicles
3	Dorigo et al., (1999)	Ant Colony Optimization (ACO)	Mobile robotics, robotic exploration
4	Kennedy (1995)	Particle Swarm Optimization (PSO)	Mobile robotics, autonomous driving, intelligent transport systems

2.1.3 Probabilistic algorithms for Path planning algorithm in Mobile robot

Probabilistic algorithms are another category of path planning algorithms commonly used in mobile robotics. Unlike exact algorithms, probabilistic algorithms work by randomly sampling the search space to estimate the likelihood of a collision-free path. These algorithms are often used in environments where exact information about the environment is not available, such as in outdoor environments or in areas with changing obstacles. In this way, probabilistic algorithms can offer a more flexible approach to path planning and can handle uncertainty better than exact algorithms.

In the realm of robotics, probabilistic algorithms for path planning in mobile robots have received much study. The two primary categories of these algorithms are sampling-based algorithms and optimization-based algorithms. Using random sampling, sampling-based algorithms create a tree of alternative paths, like the Rapidly-exploring Random Tree (RRT) method, and then look for a workable path that connects the start and target states. By sampling the environment, optimization-based algorithms like the Probabilistic Roadmap (PRM) algorithm first build a roadmap of the configuration space before looking for the shortest route between the initial and final states. The process for implementing probabilistic algorithms for path planning in mobile robots will be described in detail and some pertinent literature will be reviewed in the parts that follow. Here are the steps involved in implementing probabilistic algorithms for path planning in mobile robots:

Step-1 Define the environment: The first step in implementing a probabilistic algorithm for path planning in mobile robots is to define the environment in which the robot will operate. This includes identifying the obstacles, the boundaries of the environment, and any other relevant features.

Step-2 Define the start and goal states: Next, the start and goal states for the robot need to be defined. This involves specifying the initial position of the robot and the desired destination.

Step-3 Generate a roadmap: In order to navigate the environment, a roadmap of the configuration space needs to be generated. This is typically done by randomly sampling the space and checking for collisions with obstacles. Once the roadmap is generated, it can be used to find the shortest path between the start and goal states.

Step-4 Search for a feasible path: Once the roadmap is generated, the next step is to search for a feasible path between the start and goal states. This is typically done using a search algorithm, such as A* or Dijkstra's algorithm. The search algorithm evaluates the potential paths in the roadmap and finds the one that is shortest and collision-free.

Step-5 Navigate the robot: Once a feasible path is found, the robot can be navigated along the path using appropriate control algorithms, such as proportional-integral-derivative (PID) control.

Step-6 Update the roadmap: As the robot moves through the environment, the roadmap may need to be updated to account for changes in the environment or new obstacles. This may involve adding new nodes to the roadmap or removing nodes that are no longer relevant.

Step-7 Repeat the process: Finally, the above steps can be repeated as the robot moves through the environment, continually updating the roadmap and searching for feasible paths.

It's worth noting that different probabilistic algorithms may involve slightly different steps or variations on these steps. For example, some algorithms may use different search algorithms or may incorporate learning techniques to improve performance. The specifics of the algorithm will depend on the particular application and environment in which the robot is operating. Here's a literature review of probabilistic algorithms for path planning in mobile robots, including some relevant papers and their key contributions as shown in table 3.

2.1.4 Hybrid algorithms for Path planning algorithm in Mobile robot

Hybrid algorithms for path planning in mobile robots combine two or more different types of algorithms to take advantage of their individual strengths and overcome their weaknesses. These algorithms are designed to provide a balance between the accuracy of exact algorithms and the efficiency of heuristic and probabilistic algorithms.

Table 3. Probabilistic algorithms for path planning

Sl. No.	Author	Algorithm	Key Contributions
1	Kavraki et al., (1998)	Probabilistic Roadmap (PRM)	Introduced the PRM algorithm for path planning in high-dimensional spaces. Showed that the PRM algorithm could generate feasible paths in complex environments.
2	Short et al.,(2016)	Dynamic Probabilistic Roadmap (DPRM)	Extended the PRM algorithm to handle dynamic obstacles in the environment. Showed that the DPRM algorithm could generate safe and efficient paths in dynamic environments.
3	Cho et al., (2021)	Coverage Path Planning (CPP)	Introduced the CPP algorithm, which generates paths that cover the entire environment. Showed that the CPP algorithm could be used for environmental monitoring and exploration.
4	Putz et al., (2021)	Lazy Theta*	Introduced the Lazy Theta* algorithm, which is a variant of the Theta* algorithm that postpones collision checking until necessary. Showed that the Lazy Theta* algorithm was more efficient than Theta* in certain scenarios.
5	Likhachev and Ferguson, (2009)	Anytime Dynamic A* (AD*)	Introduced the AD* algorithm, which is an anytime variant of A* that can adapt to changes in the environment. Showed that the AD* algorithm could generate optimal paths efficiently in dynamic environments.

Hybrid algorithms can be used to solve complex path planning problems, such as those that involve dynamic obstacles, multiple objectives, and uncertain environments. They can also be used to improve the robustness and reliability of path planning systems in real-world applications. In this approach, algorithms are combined using various techniques, such as interleaving, switching, or parallel execution. Hybrid algorithms can be designed by combining any of the three types of algorithms discussed earlier: exact, heuristic, and probabilistic. The choice of algorithm combination and the design of the hybrid algorithm depend on the specific requirements of the application. The goal is to achieve the best possible trade-off between accuracy, efficiency, and robustness. Here are the steps for developing a hybrid algorithm for path planning in mobile robots:

Step-1 Identify the requirements of the application: Determine the specific requirements of the application, such as the environment, obstacles, objectives, and constraints. These requirements will help guide the selection and design of the algorithm.

Step-2 Select appropriate algorithms: Choose two or more algorithms that are suitable for the application requirements. For example, an exact algorithm may be used for high-accuracy planning, while a heuristic or probabilistic algorithm may be used for faster planning in larger environments.

Step-3 Identify the strengths and weaknesses of each algorithm: Determine the strengths and weaknesses of each algorithm, such as its accuracy, efficiency, and robustness. This will help identify where each algorithm can be best used and how they can complement each other.

Step-4 Design the hybrid algorithm: Decide how the algorithms will be combined, using techniques such as interleaving, switching, or parallel execution. This may involve integrating the algorithms into a single framework or using them sequentially.

Step-5 Test and evaluate the hybrid algorithm: Validate the performance of the hybrid algorithm using simulations or real-world experiments. Compare the results to those obtained using the individual algorithms and assess whether the hybrid algorithm achieves the desired trade-off between accuracy, efficiency, and robustness.

Step-6 Refine and optimize the hybrid algorithm: Based on the evaluation results, refine and optimize the hybrid algorithm to improve its performance and scalability. This may involve adjusting the algorithm parameters, changing the combination technique, or selecting different algorithms.

The development of a hybrid algorithm is an iterative process, and multiple iterations may be necessary to achieve the desired performance and meet the application requirements. Zhong et al. (2020) proposes a hybrid algorithm that combines a heuristic algorithm and an exact algorithm for path planning in dynamic environments. The heuristic algorithm is used to quickly generate a feasible path, and the exact algorithm is used to refine the path to avoid collisions with obstacles. The proposed algorithm is evaluated using simulations, and the results show that it outperforms the heuristic and exact algorithms individually. Orozco-Rosaa et al. (2019) proposes a hybrid algorithm that combines an artificial potential field algorithm and a genetic algorithm for path planning in complex environments. The artificial potential field algorithm is used to generate an initial path, and the genetic algorithm is used to refine the path by optimizing the path length and avoiding obstacles. The proposed algorithm is evaluated using simulations, and the results show that it outperforms the artificial potential field and genetic algorithms individually.

Pandey and Parhi (2017) proposes a hybrid algorithm that combines a particle swarm optimization algorithm and a fuzzy logic controller for path planning of mobile robots in dynamic environments. The particle swarm optimization algorithm is used to generate an initial path, and the fuzzy logic controller is used to refine the path by considering the proximity to obstacles and the speed of the robot. The proposed algorithm is evaluated using simulations, and the results show that it outperforms the particle swarm optimization and fuzzy logic controller algorithms individually. Farooq et al. (2021) proposes a hybrid algorithm that combines a genetic algorithm and a multi-level fuzzy controller for path planning of mobile robots in dynamic environments. The genetic algorithm is used to generate an initial population of paths, and the multi-level fuzzy controller is used to select the best path by considering various factors such as the proximity to obstacles and the distance to the goal. The proposed algorithm is evaluated using simulations, and the results show that it outperforms the genetic algorithm and multi-level fuzzy controller algorithms individually.

The authors of "A Hybrid Algorithm for Robot Path Planning in a Cluttered Environment" (2016) by Das et al. suggest a hybrid algorithm that incorporates the advantages of both grid-based and heuristic search approaches for path planning in a cluttered environment. The programme creates a grid-based path first, and then refines it with a heuristic search technique. The technique was evaluated in a simulation environment and performed better than conventional approaches. In "A Hybrid Genetic Algorithm for Mobile Robot Path Planning" by Luan and Thinh (2023), the authors propose a hybrid genetic algorithm that combines a genetic algorithm with a heuristic search method for path planning in a dynamic environment. The algorithm first uses the genetic algorithm to generate a population of paths and then uses a heuristic search method to refine them. The algorithm was tested in a simulation environment and showed better performance compared to traditional methods.

The authors of "A Hybrid Path Planning Algorithm for Mobile Robots Based on Particle Swarm Optimization and Rapidly-exploring Random Tree" (Lonklang & Botzhiem, 2022) suggest a hybrid algorithm that combines particle swarm optimization with a rapidly-exploring random tree for path planning in a dynamic environment. The approach first generates a set of initial paths using particle swarm optimization, which are then refined using a quickly traversing random tree. In comparison to conventional techniques, the algorithm performed better when tested in a simulation environment. In summary, these literature reviews highlight the effectiveness of hybrid algorithms that combine the strengths of different algorithms to improve path planning in mobile robots. These algorithms have shown better performance compared to traditional methods in simulation environments, and could have potential applications in real-world scenarios.

2. 2 Novelty and research gap of the study

The study aims to provide a comprehensive overview of various path planning and optimization techniques used in mobile robotics. The review covers classic, exact, heuristic, probabilistic, and hybrid algorithms, as well as optimization techniques such as artificial neural networks and fuzzy logic. The novelty of this study lies in its thorough and systematic approach in reviewing a wide range of path planning and optimization techniques for mobile robots, including both classic and state-of-the-art methods. The study provides a comparative analysis of the techniques, highlighting their strengths, weaknesses, and suitability for different scenarios.

The research gap that this study addresses is the lack of a comprehensive review of various path planning and optimization techniques for mobile robots. While there have been several studies that focus on specific algorithms or techniques, there is a need for a comprehensive review that covers a wide range of techniques and provides a comparative analysis of their performance. This study provides a valuable resource for researchers and practitioners working in the field of mobile robotics, as it offers insights into the strengths and weaknesses of various path planning and optimization techniques, and can help in selecting the most appropriate technique for a given scenario.

3. Strengths and weaknesses of different methodologies

Path planning is an essential task for mobile robots to navigate in complex environments autonomously. There are several methodologies available for path planning in mobile robots, including classic, exact, heuristic, probabilistic, hybrid, and optimization techniques. Each methodology has its strengths and weaknesses, and choosing the appropriate one depends on the specific requirements and constraints of the problem as shown in table 4. Understanding the strengths and weaknesses of different methodologies is crucial to selecting the most appropriate technique for a particular application. In this way, the performance of path planning can be optimized in terms of speed, accuracy, efficiency, and adaptability to different scenarios.

It is important to note that these strengths and weaknesses are not absolute and can vary depending on the specific implementation and scenario. Therefore, it is important to carefully evaluate the requirements and constraints of the problem and choose the methodology that best fits the needs of the application.

4. Analyze the performance of different algorithms

Analyzing the performance of different algorithms and techniques in real-world scenarios is crucial to understanding their applicability and effectiveness. In practice, the performance of path planning algorithms can be affected by various factors, such as the complexity of the environment, the accuracy and reliability of sensors, the computational resources available, and the specific requirements and constraints of the application. Classic algorithms, for instance, may be suitable for simple and well-defined environments, but their performance can degrade significantly in complex and dynamic environments (Sahoo & Goswami, 2024). Exact algorithms, although providing optimal solutions, can be computationally expensive and not scalable for large environments. Heuristic algorithms, on the other hand, can provide a good balance between efficiency and optimality, but they may not always find the optimal solution and can get stuck in local minima.

Table 4. Strengths and weaknesses of different methodologies

Sl. No.	Methodology	Strengths	Weaknesses
1	Classic algorithms	Simple to implement, can find a global solution if the environment is known and the problem is well-defined.	Often impractical in real-world scenarios due to the complexity of the environment and the limitations of sensors.
2	Exact algorithms	Can find the optimal solution even in complex environments.	Can be computationally expensive and time-consuming, especially in large-scale environments.
3	Heuristics algorithms	Efficient and suitable for large-scale environments, can find a suboptimal solution quickly.	May not find the optimal solution, may get stuck in local minima.
4	Probabilistic algorithms	Can handle uncertainty in the environment, suitable for dynamic and unpredictable environments.	Can be computationally expensive and may require a large number of samples to find a good solution.
5	Hybrid Algorithms	Combine the strengths of different techniques and can provide a better solution than using a single technique.	Can be complex to implement and may require extensive turning parameters.
6	Optimization techniques	Can improve the performance of path planning algorithms, especially in scenarios where the environment is complex or uncertain.	May require extensive training data and can be sensitive to the quality of data.

Probabilistic algorithms, such as Monte Carlo methods, can handle uncertainty and dynamic environments, but may require a large number of samples to achieve reliable results. Hybrid algorithms can combine the strengths of different techniques and provide better performance, but their design and implementation can be challenging. Optimization techniques, such as reinforcement learning and evolutionary algorithms, can adapt to different scenarios and improve the performance of path planning, but they may require extensive training data and may be sensitive to the quality of data (Yenugula et al., 2024). In addition to the factors mentioned above, the performance of path planning algorithms can also be affected by the type and characteristics of the robot platform, such as its mobility, speed, size, and payload capacity. For example, a path planning algorithm that is optimized for a ground-based robot may not be suitable for an aerial or underwater robot due to the different constraints and dynamics of the environment.

Furthermore, the performance of path planning algorithms can be evaluated using different metrics, such as completion time, path length, safety, robustness, energy consumption, and scalability. Depending on the application, certain metrics may be more critical than others. For instance, in emergency response scenarios, completion time and safety may be the most important factors, while in logistics applications, energy consumption and scalability may be more critical (Sahoo et al., 2023). Real-world experiments and simulations can be used to evaluate the performance of different algorithms and techniques under different conditions and metrics. In addition, benchmark datasets and challenges, such as the RoboCup Rescue and DARPA Robotics Challenge, can provide a common platform for comparing and evaluating different algorithms and techniques. Another important factor that can affect the performance of path planning algorithms in real-world scenarios is the presence of dynamic obstacles and uncertainties. For example, in a crowded urban environment, the robot may encounter moving pedestrians, vehicles, or other dynamic obstacles that are not present in the static map. In such cases, the algorithm must be able to quickly adapt and generate a new path that avoids the dynamic obstacles while minimizing the deviation from the original plan (Yenugula et al., 2023). One way to handle dynamic obstacles and uncertainties is to use a probabilistic or learning-based approach, which can model and predict the motion of the obstacles and adjust the path planning accordingly. For instance, Monte Carlo methods, Bayesian networks, and reinforcement learning techniques can be used to estimate the probability of collision and plan the path that maximizes the safety and efficiency.

Another important consideration in evaluating the performance of path planning algorithms is the computational complexity and memory requirements. Some algorithms may require high computational resources, which may not be feasible for real-time applications with limited processing power or memory. Therefore, it is crucial to balance the performance and efficiency of the algorithm and choose the one that meets the requirements of the specific application. Another important aspect to consider when analyzing the performance of path planning algorithms in real-world scenarios is the ability to handle different types of environments and terrains (Shin & Chae, 2020). For example, a robot may need to navigate through rough or uneven terrain, climb stairs, or cross narrow passages, which may require different strategies and techniques than a flat, open terrain. In such cases, algorithms that can incorporate information about the terrain and adjust the path planning accordingly can be beneficial. For instance, algorithms based on occupancy grid maps or elevation maps can model the terrain and plan the path that minimizes the energy consumption or maximizes the stability of the robot (Norouzi et al., 2017). Furthermore, the ability to handle multiple objectives and constraints is also critical in real-world scenarios. For instance, a robot may need to optimize not only the shortest path but also the safety, energy consumption, or comfort of the passengers. Therefore, algorithms that can handle multiple objectives and generate a set of optimal solutions, known as Pareto front, can provide a more comprehensive and flexible solution for path planning. Finally, the performance of path planning algorithms in real-world scenarios can be affected by the quality and reliability of the sensor data. For example, noisy or incomplete sensor data can lead to inaccurate map representation and path planning. Therefore, algorithms that can handle uncertain or incomplete information and provide robust and reliable solutions are desirable.

In brief, the performance of path planning algorithms in real-world scenarios can be affected by various factors, such as the terrain, objectives, and sensor data quality. Therefore, developing and evaluating algorithms that can handle these challenges and provide efficient, robust, and flexible solutions is critical for the success of mobile robotics applications.

5. Identify the key challenges and limitations in the current methodologies

Some of the key challenges and limitations in the current methodologies for path planning in mobile robots include:

- **Scalability:** As the complexity of the environment and the number of obstacles increase, the computational complexity of the algorithms can become prohibitive. This can limit the scalability and real-time performance of the algorithms.
- **Uncertainty:** The presence of uncertainty in the sensor data, robot motion, or environment can lead to suboptimal or unsafe path planning. The current methodologies may not fully address the uncertainty and variability of the real-world scenarios.
- **Multiple objectives:** In many real-world scenarios, the robot needs to optimize multiple objectives, such as safety, efficiency, and comfort. However, most of the current methodologies are focused on optimizing a single objective, which can limit their applicability in practical scenarios.
- **Adaptability:** The robot may encounter new and unexpected situations or obstacles that are not represented in the initial map. The current methodologies may not be able to adapt and adjust the path planning accordingly in real-time.

To address these challenges and limitations, potential solutions could include:

- **Parallel computing:** The use of parallel computing techniques, such as multi-core processors, distributed computing, or GPU acceleration, can improve the scalability and real-time performance of the algorithms.
- **Probabilistic modeling:** The use of probabilistic models and algorithms, such as Bayesian inference or Monte Carlo methods, can handle uncertainty and variability in the sensor data and environment.
- **Multi-objective optimization:** The use of multi-objective optimization algorithms, such as Pareto-based approaches, can provide a set of optimal solutions that trade-off between multiple objectives.
- **Learning-based approaches:** The use of machine learning or deep learning techniques can enable the robot to learn and adapt to new situations and obstacles.

Addressing these challenges and limitations will require a multidisciplinary approach that combines expertise in robotics, computer science, optimization, and machine learning.

6. Conclusion

Researchers have recently paid a lot of attention to the complex and difficult topic of path planning and optimization for mobile robots. The topic of path planning and optimization for mobile robots is difficult and necessitates the creation of cutting-edge approaches. This study examined and compared various path planning and optimization techniques for mobile robots, including precise, heuristic, probabilistic, and hybrid methods.

- It identified the strengths and weaknesses of different techniques, highlighting their suitability for different types of environments and applications.
- The review emphasized the importance of choosing the appropriate methodology based on the specific application requirements.
- This study identified key challenges and limitations in the current methodologies, such as real-time performance, scalability, and robustness.
- Further research is needed to address these challenges and limitations and improve the performance of path planning and optimization methodologies for mobile robots.

- This review serves as a valuable resource for researchers and practitioners in the field of mobile robotics, providing a foundation for further advancements in this area.

6.1 Practical Implication

The practical implications of this research on the methodologies for path planning and optimization of mobile robots are significant. The review of different approaches provides a comprehensive understanding of the strengths, weaknesses, and limitations of each technique. Firstly, this study provides valuable insights into the selection of appropriate algorithms based on the specific requirements of a particular application. The selection of an algorithm that suits the problem statement is crucial to achieve optimal results. This knowledge can be beneficial for researchers and practitioners in the field of robotics to make informed decisions.

Secondly, this review identifies the key challenges and limitations in the current methodologies. The identified challenges include computational complexity, scalability, and adaptability to dynamic environments. These challenges need to be addressed to develop more efficient and reliable algorithms for path planning and optimization of mobile robots.

Thirdly, this study highlights the potential solutions to overcome the identified challenges. The use of hybrid algorithms, machine learning techniques, and parallel computing are promising approaches to address the limitations of the existing algorithms. These potential solutions can guide the future research in the field of path planning and optimization of mobile robots.

Finally, the research can have practical implications for industries that use mobile robots. The use of optimal path planning and optimization techniques can lead to reduced operational costs, increased efficiency, and improved safety. Our review can help industries make informed decisions in the selection and deployment of mobile robots for their operations.

This study on the methodologies for path planning and optimization of mobile robots has significant practical implications for researchers, practitioners, and industries. The review provides a comprehensive understanding of the different approaches, their strengths, weaknesses, and limitations. The study identifies the key challenges and potential solutions to overcome them, which can guide future research in the field. Our research can help industries make informed decisions in the selection and deployment of mobile robots, leading to reduced operational costs, increased efficiency, and improved safety.

6.2 Limitation

Despite the thorough review of methodologies for path planning and optimization of mobile robots presented in this research paper, there are some limitations that need to be acknowledged. Firstly, due to the vast number of studies in this field, it was not possible to cover all the relevant literature, and thus some important studies may have been missed.

Secondly, the performance evaluation of different algorithms and techniques was largely based on simulation studies, and while they provide valuable insights, they do not necessarily reflect the real-world scenarios. Therefore, further studies should focus on conducting experiments and testing different methodologies in real-world environments.

Thirdly, the analysis of strengths and weaknesses of different methodologies was based on general characteristics and assumptions, and there may be specific situations or applications where certain methodologies may perform better or worse than others. Therefore, it is important to carefully consider the specific requirements and constraints of each application when selecting an appropriate methodology for path planning and optimization of mobile robots.

Finally, the research paper mainly focused on path planning and optimization of mobile robots, and did not cover other important aspects such as obstacle avoidance, localization, and mapping. Future research should investigate these aspects and explore potential solutions to improve the overall performance of mobile robots.

6.3 Future Scope

The review of methodologies for path planning and optimization of mobile robots has identified various strengths, weaknesses, and limitations of existing techniques. However, there are still many potential avenues for future research that can further improve the performance and efficiency of mobile robot navigation.

One area of future research is the development of hybrid approaches that combine the strengths of different methodologies. For example, combining the accuracy of exact algorithms with the speed and scalability of heuristic or probabilistic algorithms could lead to more efficient and effective path planning. Additionally, the use of machine learning and artificial intelligence techniques could enable mobile robots to learn from their environment and optimize their paths in real-time.

Another potential area of research is the integration of sensor technologies into path planning and optimization. By utilizing sensor data such as lidar or camera feeds, mobile robots can better understand their environment and make more informed decisions about their paths. Furthermore, the use of swarm intelligence techniques could enable groups of mobile robots to collaborate and optimize their paths collectively, which could be particularly useful in scenarios such as warehouse automation.

Finally, the development of techniques for safe and reliable navigation in dynamic and unpredictable environments is an essential area of future research. Mobile robots operating in real-world scenarios must be able to handle unexpected obstacles, sudden changes in the environment, and unpredictable human behavior. Therefore, the development of techniques that can handle these challenges will be critical for the widespread adoption of mobile robots in various applications.

In conclusion, while the review of methodologies for path planning and optimization of mobile robots has provided significant insights, there is still much room for improvement and innovation. Future research can focus on developing hybrid approaches, integrating sensor technologies, and ensuring safe and reliable navigation in unpredictable environments. Such advancements will pave the way for the widespread adoption of mobile robots in various industries and applications, leading to increased efficiency, productivity, and safety.

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Conflict of interest

The author(s) declare that there are no conflicts of interest to disclose.

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