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A Comprehensive Analysis of Path Planning Strategies Employed for Mobile Robots

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Abstract. Path planning is the core of the field of mobile robots. In order to solve the problem of finding the optimal solution, experts have conducted extensive research on it. The document offers a concise overview of rigorously conducted research on prevalent path planning approaches for mobile robots up to this point. There are essentially two main categories of path planning methods for mobile robots: Classical methods and Heuristic methods. I have provided a more detailed classification of these methods: (1) Classical methods, (2) Heuristic Search algorithms, (3) Artificial Intelligence algorithms, (4) Bio-inspired algorithms. Classical methods overly rely on static environments and cannot be applied to practical situations, therefore path planning requires innovative methods. Bio-inspired algorithms are a hot topic in path planning methods, and many studies have innovated on the basis of basic bionic algorithms. Nowadays, Artificial Intelligence algorithms represented by artificial neural networks have gradually become the focus of path planning research due to their high adaptability and robustness. This paper investigates the basic principles, advantages and limitations of each method in the above classification, as well as new algorithms extended based on heuristic methods. In conclusion, this paper offers a succinct overview of the present research status on path planning for mobile robots and explores potential future directions in this domain.

Keywords: Mobile Robot Path Planning; Classical methods; Heuristic Methods.

1. Introduction

The development of mobile robots has a history of several decades, and "movement" is an important symbol of robots. The earliest mobile robots were primarily used in the industrial field.. The first Automated Guided Vehicle (AGV) was born in 1953. It was modified from a simple tractor and transported goods along overhead wires in a grocery warehouse. Thanks to the rapid progress in computer technology, especially in the fields of artificial intelligence, sensor, and positioning system technologies, mobile robots have transitioned into autonomous systems with the capability to integrate various functions including environmental perception, real-time decision-making and strategic planning, motion regulation, and task execution. These advancements have significantly contributed to the evolution of mobile robots into independent and comprehensive entities. Starting with the inaugural intelligent mobile robot Shakey in 1972, then progressing to the biomimetic robot Cog in 1993, capable of human-machine interaction and perception, followed by the household vacuum cleaner Roomba in 2002, and culminating in the present-day autonomous submersible Qianlong 3, mobile robots have found extensive application across diverse domains including manufacturing, healthcare, households, scientific research, and agriculture. Mobile robots are equipped with sensors, such as cameras, LiDAR, sonar, and rangefinders. Based on the information collected by the sensors, they perform localization, map making, and path planning, enabling the mobile robot to perceive the surrounding environment for navigation. Mobile robots should possess the capability to steer clear of stationary or moving obstacles throughout their journey from the initial point to the target location, ensuring that the path taken is not only the most time-efficient but also the smoothest in trajectory and demands minimal energy consumption [1]. Therefore, path planning technology plays a crucial role in the navigation of mobile robots.

The task of path planning can be categorized into two main parts: global path planning and local path planning. The main difference between the two is whether the robot has a complete knowledge of the current navigation environment [2]. This article categorizes path planning methods into classical methods, heuristic search algorithms, artificial intelligence algorithms, and bio-inspired algorithms. The two most representative methods in classical methods are Artistic Potential Field (APF) Approach and Cell Decomposition (CD) Approach. APF is the idea of using target points to generate gravity on robots (causing them to move towards the target) and obstacles to generate repulsive forces on robots (causing them to avoid obstacles). The combined force of these two forces is used as the control force for robot path planning. CD divides the region into several non-overlapping pure cells (representing walkable areas) and corrupted cells (representing obstacle areas), and then decomposes the corrupted cells into two new cells to find new pure cells. Finally, traverse all pure cells to plan the optimal path. However, classical methods lack real-time perception and adaptability to environmental changes, and can only rely on simple static environments for path planning, which performs poorly in complex dynamic environments. Therefore, heuristic search algorithms, artificial intelligence algorithms, and bionic algorithms have gradually replaced classical methods in current research on path planning for mobile robots. The focus of this article is to introduce these three methods mentioned above. The second section will introduce the A* algorithm and its improved Time D* algorithm in heuristic search algorithms [3]. The third section will introduce Fuzzy Logic (FL) and Artificial Neural Networks (ANN) in AI algorithms. In the fourth session, we will delve into the exploration of Genetic Algorithms (GA), Ant Colony Optimization (ACO), and their enhanced variants within the realm of bio-inspired algorithms.

2. Heuristic Search Algorithm

2.1. A* search

In 1980, Nilsson proposed the A* algorithm based on the Dijkstra algorithm, which is a heuristic search based global path planning algorithm. The idea of the algorithm is to use heuristic cost as the criterion for optimizing the path [4]. Initially, the map is divided into a grid, followed by the implementation of suitable heuristic functions to holistically assess the cost metrics associated with every expanded search node. Subsequently, a comparison is made among these cost metrics to identify the node with the most economical value, facilitating the progression towards locating the desired target node. For the fact that each selected node is optimal, the resulting path is ultimately the most cost-effective one [5]. Thanks to its straightforward approach, ease of implementation, exceptional operational efficiency, and capacity to effectively seek out optimal solutions, this algorithm is widely regarded as one of the most potent direct search algorithms for robot path planning available today.

The drawbacks of the A* algorithm are also very obvious. As the quantity of nodes increases, the algorithm's search effectiveness declines. As a consequence, the A* algorithm may not exhaustively explore all potential solutions, potentially leading to suboptimal outcomes that do not represent the optimal solution. Moreover, a work also pointed out that there are many turning points in this algorithm [6]. To address the challenge posed by multiple turning points and optimal solutions, a work improved the A* algorithm [7]. It involves segmenting the path, which was initially planned using the A* algorithm, by dividing the distance between adjacent nodes, applying specific criteria to eliminate certain nodes, and then reconnecting the remaining nodes to generate a new, optimized path.

2.2. Lifelong Planning A*

Because a complete environmental map may update over time and environmental changes, such as dynamic obstacles, pedestrian activity, etc., this leads to errors in robot path planning. Moreover, path planning on large-scale environmental maps requires processing a large amount of map data, resulting in a significant increase in the computational complexity of path planning algorithms, which seriously reduces planning efficiency and speed. So in the real world, robots are unable to perform path planning on a complete environmental map. It needs to calculate the optimal path for the current local environment. So for the traditional A* algorithm, robots need to update the search results of the entire path every time, which inevitably leads to an increase in computational complexity and a decrease in efficiency. Koenig and Likachev improved the A* algorithm into the Lifelong Planning A* (LPA) algorithm, incorporating the environmental changes per unit time into the algorithm without the need for recalculation of the hole A* search, greatly improving efficiency [8].

2.3. Time D*

To address the challenge arising from excessive computational complexity caused by the large state space dimension in the graph based method for path coordination of multiple mobile robots, researchers continue to improve on this basis and propose the Time D* algorithm. It expands the configuration space with time components of each mobile robot, improving adaptability to the time dimension and mobile robots, then realizing decoupled planning approaches by a priority scheme [3]. This method solves the problem of non-optimal paths and collisions between robots during multi robot motion, and its efficiency is nearly twice that of LPA.

3. Artificial Intelligence

3.1. Fuzzy Logic

The inception of Fuzzy Logic (FL) can be traced back to 1965 when L. Zadeh introduced the notion of fuzzy sets, laying the foundation for this innovative field. This method is inspired by the human brain's remarkable way of judging and reasoning about uncertainty concepts. In logic, "0" and "1" represent the "false" and "true" of things [1]. In fuzzy logic, the ordinary concept of binary is extended to the concept of infinitely many valued fuzzy sets on the [0, 1] interval, and membership degree is used to accurately characterize the relationship between elements and fuzzy sets. This process is based on the if then rules. When FL runs, these rules will be transformed into mathematical quantities with equivalent meanings, making computer work more convenient, the process more intuitive, and the decisions made on external information more accurate compared to other algorithms.

Autonomous mobile robots are often limited by environmental complexity and uncertainty in unpredictable dynamic environments. In order to enable robots to avoid any collisions and pass through paths with unknown static and dynamic obstacles, an autonomous mobile robot navigation system based on responsive fuzzy logic controller for Khepera was proposed (Basic composition of the controller is shown in Figure 1), and a control strategy based on hierarchical behavior was designed [9]. The system first uses two fuzzy controllers to achieve the functions of "reaching the target" and "avoiding obstacles" respectively. Then, to address the problem of the robot entering an infinite loop, two controllers are added to make it move close to the left or right wall until it exits the trap [9]. The reaction behaviors of mobile robot were combined together through a fuzzy supervisor to successfully plan the motion path of the mobile robot, avoiding any collisions in most static and dynamic environments.

3.2. Artificial Neural Network

An operational framework known as Artificial Neural Network (ANN) has been developed to simulate the information processing capabilities of the human brain, abstracting its neural network structure in a computational context. It comprises an extensive network of interconnected nodes (neurons), where each node embodies a distinct activation function. The link between two nodes symbolizes a signal weight that mirrors the memory function of an artificial neural network. ANN has strong generalization ability, just like humans, it can systematically combine previously learned concepts with new ones, which demonstrates its capability for inferential reasoning. Moreover, it also has the ability to process data in large-scale parallel and high fault tolerance. As a result, its significance in the realm of path planning for mobile robots cannot be understated, making it an indispensable component within this field. The ANN algorithm does well in improving the precision and effectiveness of path planning in intricate and variable environments through learning and optimization. It can perceive input information from multiple dimensions such as environmental maps, sensor data, and route planning standards, and extract information features. ANN also contains some disadvantages. A common problem is that artificial neural networks face difficulties in minimizing the error between data and output in supervised learning [1].

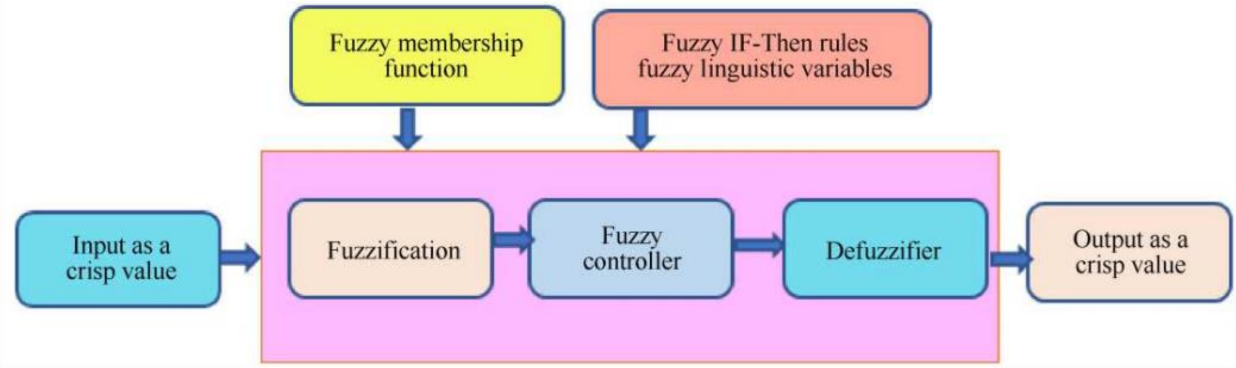

Fig. 1 The fundamental configuration of a Fuzzy Logic Controller [10]

3.2.1. Self-Organizing Map (SOM) Neural Network

To ensure optimal path planning for mobile robots navigating through intricate and ever-changing underwater settings, Huang and his team considered factors including fluctuations in ocean currents and the environmental conditions within Earth's oceans, and proposed a multi autonomous underwater vehicle (multi-AUV) that utilizes an enhanced self-organizing map (SOM) neural network along with a novel velocity synthesis algorithm [11]. They introduced Winner Selection Rules and Neighbourhood Updating Rules into the original SOM algorithm [11]. The former is a competitive mechanism that takes the neuron with the minimum target distance obtained after processing the input data as the winner. The latter is based on the Winner Selection Rules to update the neighbors of the neuron. Then use Selection Rules to screen for new target neurons. And so on, during the movement of neurons, the vehicle moves towards a specific target until all AUVs reach the corresponding target. Finally they combined the velocity synthesis algorithm, which controls the direction of AUV motion underwater, achieving the planning of the shortest path by calculating the angle between the direction of ocean currents [11].This method combines target allocation and path planning for robots, successfully achieving optimal path planning for underwater dynamic environments.

3.2.2. Adaptive Neural Network

Facing unknown dynamic environments, adaptive neural networks are also one of the applicable methods for path planning of mobile robots. This algorithm has the ability of dynamic structural adjustment and parameter adaptation. To cater to a variety of tasks and environments, it can not only dynamically add, delete, or adjust its neurons, hierarchy, or connection methods according to changes in the environment, but also automatically adjust parameters. All of this cannot be separated from the core of adaptive neural networks: optimization algorithms. By defining adaptive indicators or evaluation criteria, adaptive neural networks can select and adjust network structure and parameters based on these indicators or criteria. Optimization algorithms commonly employed encompass a range of techniques such as genetic algorithms, particle swarm optimization, ant colony algorithms, and more. These algorithms are adept at uncovering either the optimal solution or a close approximation within the search space, and adjust the network structure and parameters based on these solutions. This method has high flexibility and robustness.

Mohanty proposed a new mobile robot navigation technology, Adaptive Neuro Fuzzy Inference System (ANFIS). The system uses two methods, backpropagation and mixing, to express the mapping relationship between output and input, successfully calculating the fuzzy membership function for fuzzy logic (FL), and changing the parameters of the function appropriately according to the needs of the environment [12]. The controller of the system utilizes multiple directional sensors equipped on the robot to collect information about the external environment, select the optimal direction for the robot when moving towards the target, completely avoid obstacles on the path, and safely reach the destination.

4. Bio-inspired Approaches

4.1. Genetic Algorithm

The concept of the Genetic Algorithm (GA) originated in the 1970s through the pioneering work of John Holland, an influential figure in the field of evolutionary computation from the United States. GA is a computational model designed based on the evolutionary laws of organisms in nature, simulating the principles of natural selection and genetic processes as outlined in Darwin's theory of biological evolution. The illustration of the Genetic Algorithm's flowchart is depicted in Figure 2. GA first obtains knowledge from the environment (such as obstacles in robot paths), and then transforms the path planning resolution process into a mechanism akin to chromosome gene crossover, mutation, and selection in biological evolution to calculate the optimal solution [13].

GA is employed as an evolutionary optimization technique for solving this problem. In 2003, a work made an endeavor to apply genetic algorithms in addressing the challenge of path planning for mobile robots to ensure collision-free trajectories [14]. The biggest feature of this algorithm is that the length of chromosomes can be changed, and robots, targets, and obstacles in the environment will be marked, all of which are genes. The chromosome length is determined by the number of genes it contains. This algorithm generates optimal obstacle avoidance paths for mobile robots in both static and dynamic environments.

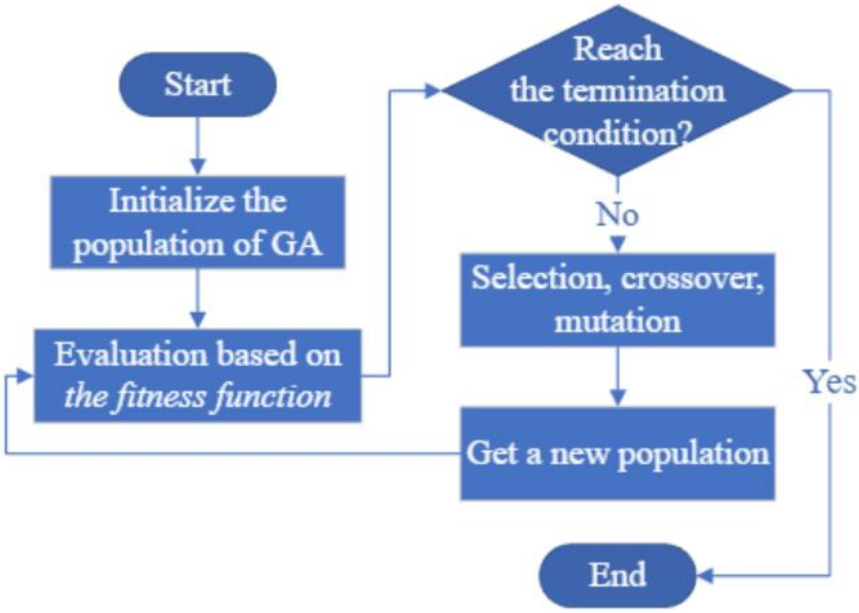

Fig. 2 Flowchart of GA [4]

4.1.1. Multiple Objective Genetic Algorithm

In real-world problems, it is often necessary to optimize multiple objectives simultaneously. When a robot passes through terrain, it must avoid obstacles and dangerous terrain. This means that the optimized path has two criteria: length and difficulty [15]. Achieving the optimal solution may not always be feasible when individual goals are evaluated independently. Therefore, In 2007, the multiple objective genetic algorithm (MOGA) was introduced, as documented in a work, to address path planning for mobile robots [15]. This algorithm incorporates the concept of Pareto optimality into the traditional GA, expanding its capabilities beyond conventional implementations.

4.1.2. Co Evolution Genetic Algorithm

With the development of robot path planning, traditional genetic algorithms have drawbacks such as slow convergence speed, local optimum, and neglect of collaborative cooperation between populations. To avoid these drawbacks, an improved genetic algorithm based on co evolution (CIGA) is proposed [16]. It combines the coevolutionary mechanism with traditional GA. This approach offers a precise and efficient fitness function, enhances the genetic operator utilized in conventional genetic algorithms, and introduces a novel operator for genetic modification. This operator effectively mitigates the issue of local optimization, leading to a significant improvement in convergence speed. The use of coevolutionary mechanisms is a reflection of fully considering collaboration between populations. It avoids collisions between multiple mobile robots, which aids each mobile robot in acquiring a collision-free path that is optimal or nearly optimal.

4.2. Ant colony optimization algorithm

In 1992, Marco Dorigo introduced the Ant Colony Optimization (ACO) algorithm, which draws inspiration from the foraging behavior of ants as they search for food and discover paths. It is a population-based metaheuristic algorithm for searching optimization paths. Ants leave behind pheromones when walking along a path [17]. As the path becomes shorter, there is a corresponding rise in the release of pheromones by the ants. Over time, this leads to an escalation in the concentration of pheromones along these shorter paths, indicating a greater preference among ants for choosing such routes. Ultimately, through positive feedback, the ants converge on the shortest path, which aligns with the optimal solution for the optimization problem. This versatile algorithm, finds applications across scientific and engineering domains. It addresses challenges in diverse areas like traveling salesman problems, network routing problems, and image segmentation. Notably, in the realm of mobile robotics, ACO excels in path planning tasks by ensuring efficient obstacle avoidance and optimal route discovery. Figure 3 displays the flowchart for assessing the path planning of mobile robots using ACO [18].

4.2.1. Algorithm combining ACO and k-degree smoothing

Due to its strong maneuverability and ease of control, unmanned aerial vehicles (UAVs) can replace humans to achieve many unmanned missions remotely. However, in their development process, the lack of coordination in path planning among multiple unmanned aerial vehicles is an issue that cannot be ignored in unmanned aerial vehicles coordinated control. For coping with this problem, Combined k-degree smoothing with improved ACO method as a coordinated path planning strategy and precise coordination strategy for multi UAVs control [19]. The path planning process involves modeling the environment to consider diverse hazards, while also redefining the ACO pheromone update method and heuristic information for enhanced performance. Subsequently, the path smoothing problem is addressed using the k-degree smoothing method.

4.2.2. Algorithm combining ACO and Dynamic Window Approaches

A work introduced a novel approach to mobile robot path planning, which integrates enhancements to the Ant Colony Optimization algorithm (ACO) with Dynamic Window Approaches (DWA) [20]. Two algorithms are capable of addressing path planning for mobile robots in environments that are both static and dynamic. The improved ACO improves the initialization of pheromones, heuristic functions, and updates of pheromones, allowing for shorter optimal paths and fewer turning points (smoother routes) while reducing the number of iterations. The improved DWA algorithm involves removing redundant nodes, optimizing the initial direction, and introducing adaptive dynamic adjustment factors into the traditional DWA speed evaluation function [20]. Compared to traditional DWA, the improved DWA generates more efficient obstacle avoidance paths and significantly improves algorithm efficiency.

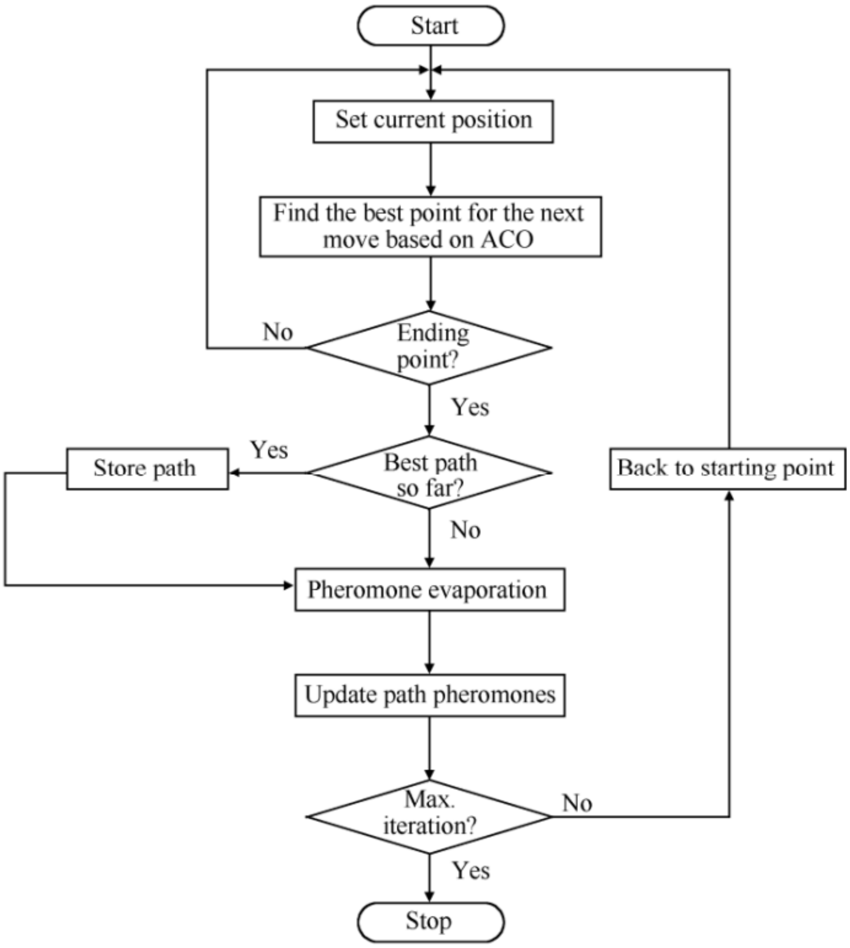

Fig. 3 Flowchart of the ACO for robotics path planning [19]

5. Conclusion

This article offers a concise introduction to the various methods employed in path planning for mobile robots, dividing them into classical methods and heuristic methods, more accurately into four categories: Classical methods, Heuristic Search algorithms, Artificial Intelligence algorithms, and Bio-inspired algorithms. And analyzed the research motivation, implementation process, advantages and disadvantages of each method. The classic methods represented by ADF and CD have simple and intuitive algorithm principles, which are easy to implement. However, they require a large amount of computing resources, are inefficient, and cannot run in dynamic environments, which means that applications in the real world are unreliable. By contrast, heuristic algorithms are more intelligent and adaptive. Even though the planning paths obtained by this method may not necessarily be the optimal solution, they can be determined more efficiently with less computational complexity. After over four decades of progression, remarkable advancements have been achieved in the domain of mobile robot path planning. The focus of previous research has always been on the path planning of a single mobile robot in both static and dynamic environments, however, research papers on multi mobile robot systems are still relatively scarce. Nowadays, in order to cope with more complex practical situations and increasing task demands, a multi mobile robot system with strong coordination ability and networking should be given attention. In the future, research directions can not only advance towards collision free coordinated path planning for multi robot systems, but also explore the path planning of mobile robots in the context of evading dynamic obstacles while pursuing moving targets. Specifically, we can start with algorithm optimization and mix multiple improved algorithms to make the path smoother and the range of robot navigation wider. Of course, the ideas of classical methods are also rare and should not be abandoned. The combination of classical methods and existing heuristic algorithms can also improve their performance and achieve unexpected results.

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