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Review
Path Planning Technique for Mobile Robots: A Review

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Abstract: Mobile robot path planning involves designing optimal routes from starting points to destinations within specific environmental conditions. Even though there are well-established autonomous navigation solutions, it is worth noting that comprehensive, systematically differentiated examinations of the critical technologies underpinning both single-robot and multi-robot path planning are notably scarce. These technologies encompass aspects such as environmental modeling, criteria for evaluating path quality, the techniques employed in path planning and so on. This paper presents a thorough exploration of techniques within the realm of mobile robot path planning. Initially, we provide an overview of eight diverse methods for mapping, each mirroring the varying levels of abstraction that robots employ to interpret their surroundings. Furthermore, we furnish open-source map datasets suited for both Single-Agent Path Planning (SAPF) and Multi-Agent Path Planning (MAPF) scenarios, accompanied by an analysis of prevalent evaluation metrics for path planning. Subsequently, focusing on the distinctive features of SAPF algorithms, we categorize them into three classes: classical algorithms, intelligent optimization algorithms, and artificial intelligence algorithms. Within the classical algorithms category, we introduce graph search algorithms, random sampling algorithms, and potential field algorithms. In the intelligent optimization algorithms domain, we introduce ant colony optimization, particle swarm optimization, and genetic algorithms. Within the domain of artificial intelligence algorithms, we discuss neural network algorithms and fuzzy logic algorithms. Following this, we delve into the different approaches to MAPF planning, examining centralized planning which emphasizes decoupling conflicts, and distributed planning which prioritizes task execution. Based on these categorizations, we comprehensively compare the characteristics and applicability of both SAPF and MAPF algorithms, while highlighting the challenges that this field is currently grappling with.

Keywords: mobile robot; map modeling; performance metrics; single-agent path planning; multi-agent path planning

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1. Introduction

1.1. Evolution of Mobile Robotics

Since its inception in 1953, Automated Guided Vehicles (AGVs) have been consistently recognized as autonomous transportation systems. Despite significant advancements in technologies such as magnetic strip guidance, electromagnetic induction, and QR code guidance, AGVs have not completely dispelled the perception of their reliance on ground-guidance lines for navigation. With the rapid evolution of artificial intelligence technology, autonomous mobile robots, emphasizing autonomy and adaptability, have taken center stage. As illustrated in Figure 1, the journey began with the world's first industrially programmed robot in 1959, which solely relied on coordinate-based programming. It continued with the development of user-friendly robot programming languages, such as AML by IBM in 1982 and the release of the open-source Robot Operating System (ROS) by Willow Garage in 2009. These advancements in robot programming technologies have profoundly enhanced the intelligence of robots. The trajectory extends from the inception of the first intelligent mobile robot, Shakey, in 1972, to the deployment of Autonomous Mobile Robots (AMRs) in healthcare settings, the integration of robotic vacuum cleaners into daily life, and the maturation of intelligent warehousing and social robots. These developments collectively signify the evolution of robots toward autonomy, agility, and collaborative capabilities. From the introduction of the "Mars rovers" by the United States in 2003 to China's independent development of the "Zhurong rover" in 2021, pivotal robotic technologies encompassing complex terrain spatial perception, autonomous decision-making, and versatile mobility are undergoing rapid innovation and advancement. Humanity has experienced three industrial revolutions, each signifying the following transformative shifts: the age of steam power, the era of electricity, and the computational power of the information age. In the contemporary landscape, intelligent mobile robots are making significant inroads across diverse domains, including industry, agriculture, and defense, ushering in a new era characterized by intelligence-driven transformation.

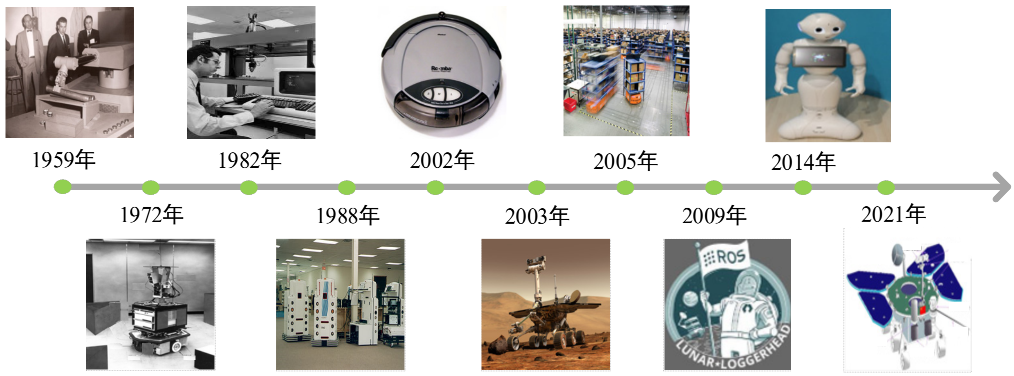


Figure 1. Development history of mobile robots (The first industrial robot was born in 1959; The first autonomous mobile robot Shakey was born in 1972; IBM develops a robotics language called AML in 1982; The first autonomous mobile robot named AMR was born in 1988, which was used in hospitals; IRobot introduced the first floor sweeping robot in 2002; Interstellar Exploration Rover born in 2003; Kiva systems launched a warehouse robot in 2005; Willow Garage created the ROS platform in 2009; Softbank designed social robot named Pepper in 2014; China's Zhurong Mars Rover developed in 2021. (Chinese in this figure means "year").

The fundamental challenges in mobile robot navigation encompass three pivotal aspects: localization, map construction, and path planning [1]. Localization takes precedence in navigation, with the aim of meticulously pinpointing the robot's position and orientation within the environment. This precision is of paramount importance for achieving effective navigation and successful task execution. Localization methods leverage data from an array of cutting-edge sensors, including laser rangefinders, visual cameras, GPS, and IMUs, harmoniously amalgamating information from diverse sources to meticulously estimate the robot's precise position. These advanced sensors provide the robot with an abundant wellspring of real-time data, empowering it to discern its exact location and orientation in the environment. Map construction involves the intricate modeling of objects and structural features within the environment, thereby aiding the robot in comprehending and nimbly navigating its surroundings. Robots gather comprehensive environmental insights through sensor data and deftly employ advanced technologies such as Simultaneous Localization and Mapping (SLAM) to artfully craft map models. Pivotal sensors such as laser rangefinders and visual cameras play a pivotal role in this meticulous map construction process, adeptly perceiving objects and terrain features within the environment. Their acumen facilitates the meticulous creation of map models. These map models may manifest as 2D grid maps, topological representations, or intricate 3D point cloud maps, bestowing invaluable insights into the environmental structure and obstacle layout, thereby illuminating the path planning and navigation strategies. Path planning emerges as the keystone in mobile robot navigation [2]. Drawing from the robot's profound understanding of the environment map and the precise location of its intended target, path planning algorithms adeptly discern fitting navigation strategies based on distinct objectives and constraints. The outcome is the generation of judiciously selected, cost-effective, and practicable paths. During the path planning and navigation phases, sensors such as laser rangefinders, RGB-D cameras, and Global Positioning Systems (GPS) assume a pivotal role in real-time obstacle detection and the precise determination of the robot's global position.

Presently, researchers have made significant strides in the development of various technologies for mobile robot navigation. In a broad context, the process of mobile robot navigation can be categorized into three levels: global navigation, local navigation, and individual behavior execution (motion control) [3], as visually depicted in Figure 2. Global navigation entails the robot's movement with a priori knowledge of the environment, where the positions of environmental elements are predetermined relative to the world co-ordinate system. Local navigation, on the other hand, deals with the intricate management of uncertain relationships among dynamic elements and pre-established environmental features. When executing individual behaviors, robots are tasked with a comprehensive consideration of the positions of diverse elements within the environment, higher-level directives, and the results of path planning to discern their subsequent actions.

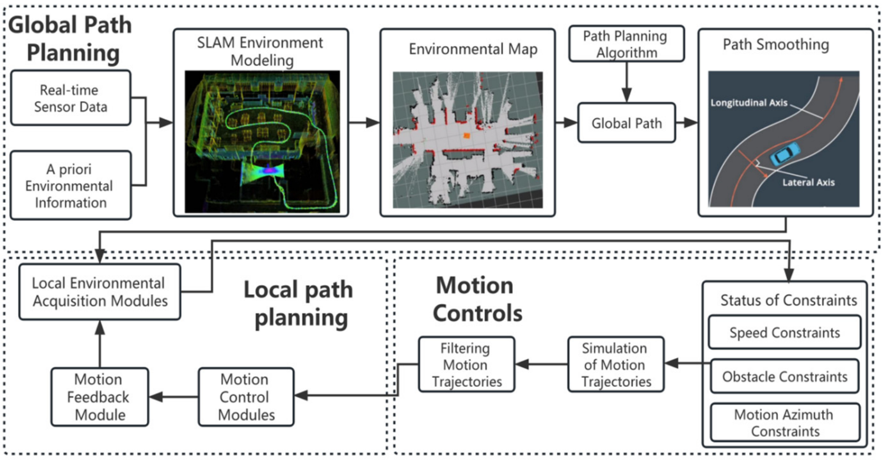


Figure 2. Mobile robot motion navigation process.

The Super Star Discovery System "https://www.zhizhen.com/ (accessed on 22 April 2023)". developed by Beijing Century Super Star Information Technology Development Company is a discovery system based on massive knowledge mining and data analysis, which integrates a number of large-scale databases as resources, such as Web of Science, Science Direct and CNKI, etc. According to this paper, we use "Mobile robot path planning" as the keywords to investigate the publication situation of various academic results from 1983 to 2023, with Figure 3 showing the cumulative total number of papers included in various widely recognized core journals and Figure 4 reflecting the trend of domestic and foreign academic publications. These visual representations provide a snapshot of the research landscape, depicting the escalating significance of path planning within the dynamic domain of robotics. Over the years, this facet has emerged as a focal point of exploration, driven by the continuous unveiling of pioneering algorithms, techniques, and methodologies. This concerted endeavor to enhance the efficacy, precision, and safety of path planning strategies has, in turn, spurred significant advancements in mobile robot navigation technology.

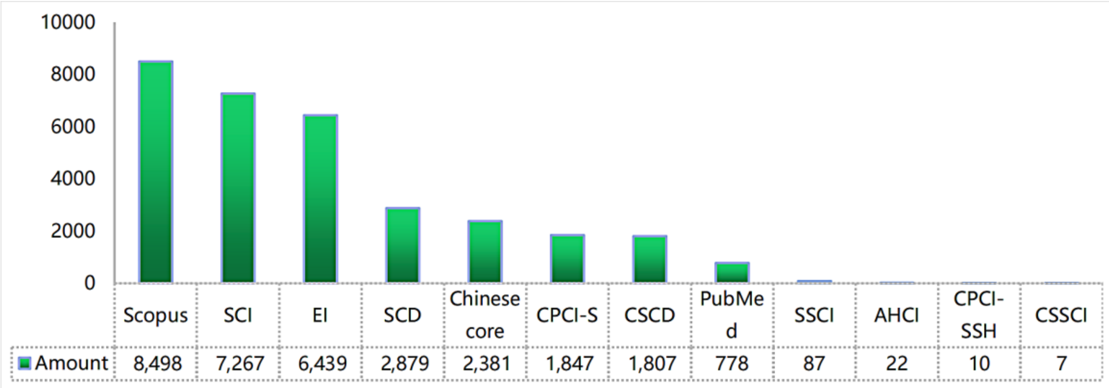


Figure 3. Cumulative number of papers included in database from 1983 to 2023.

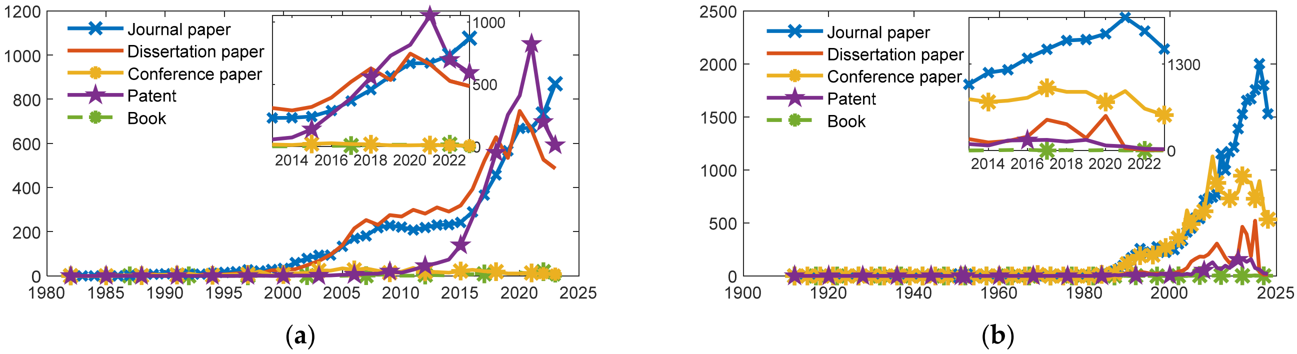


Figure 4. Mobile robot path planning academic achievements: (**a**) Domestic; (**b**) Foreign.

1.2. Contribution of Manuscript

This research underscores our academic responsibility to establish a robust theoretical foundation for the advancement of this emerging field. Despite the abundance of literature detailing mature autonomous navigation solutions, it is evident that a substantial gap exists in providing systematic and well-distinguished coverage of the pivotal technologies related to both SAPF and MAPF. These encompass concerns regarding environmental modeling, path evaluation metrics, and path planning methodologies. In light of this, our study has conducted a comprehensive review of 254 publications primarily focused on path planning-related technologies. Among these, 155 papers were published within the last 5 years, constituting 60.9% of the total, while 220 papers were published within the last 10 years, representing 86.6% of the total. This compilation comprises 160 research papers, 61 conference papers, 28 review papers, 2 PhD theses, and 3 book resources. Among these, 16 contributions are in Chinese, sourced exclusively from CNKI, while the remaining 238 research outputs are in English, primarily retrieved from Web of Science, Science Direct, and IEEE Xplore.

Based on the diversity of the objects under investigation, our research topics are classified into SAPF and MAPF, as depicted in Figure 5. The main differentiators lie in various aspects, such as target descriptions and optimization methods. Notably, 21.3% of the literature is devoted to addressing common issues, which include topics related to map modeling methods and path assessment metrics. Moreover, 53.5% of the literature is dedicated to expounding SAPF problems, with a categorization of discussions into classical algorithms, intelligent optimization algorithms, and artificial intelligence-based algorithms. The remaining 25.2% of the literature focuses on describing MAPF issues and offers comparative analyses of the strengths and drawbacks of centralized planning techniques versus distributed planning techniques. Throughout the subsections, we have conducted thorough comparisons of research on similar themes. In the concluding section, the survey undergoes a comprehensive review, culminating in recommendations for potential areas of future research. These contributions are poised to advance the research in this field.

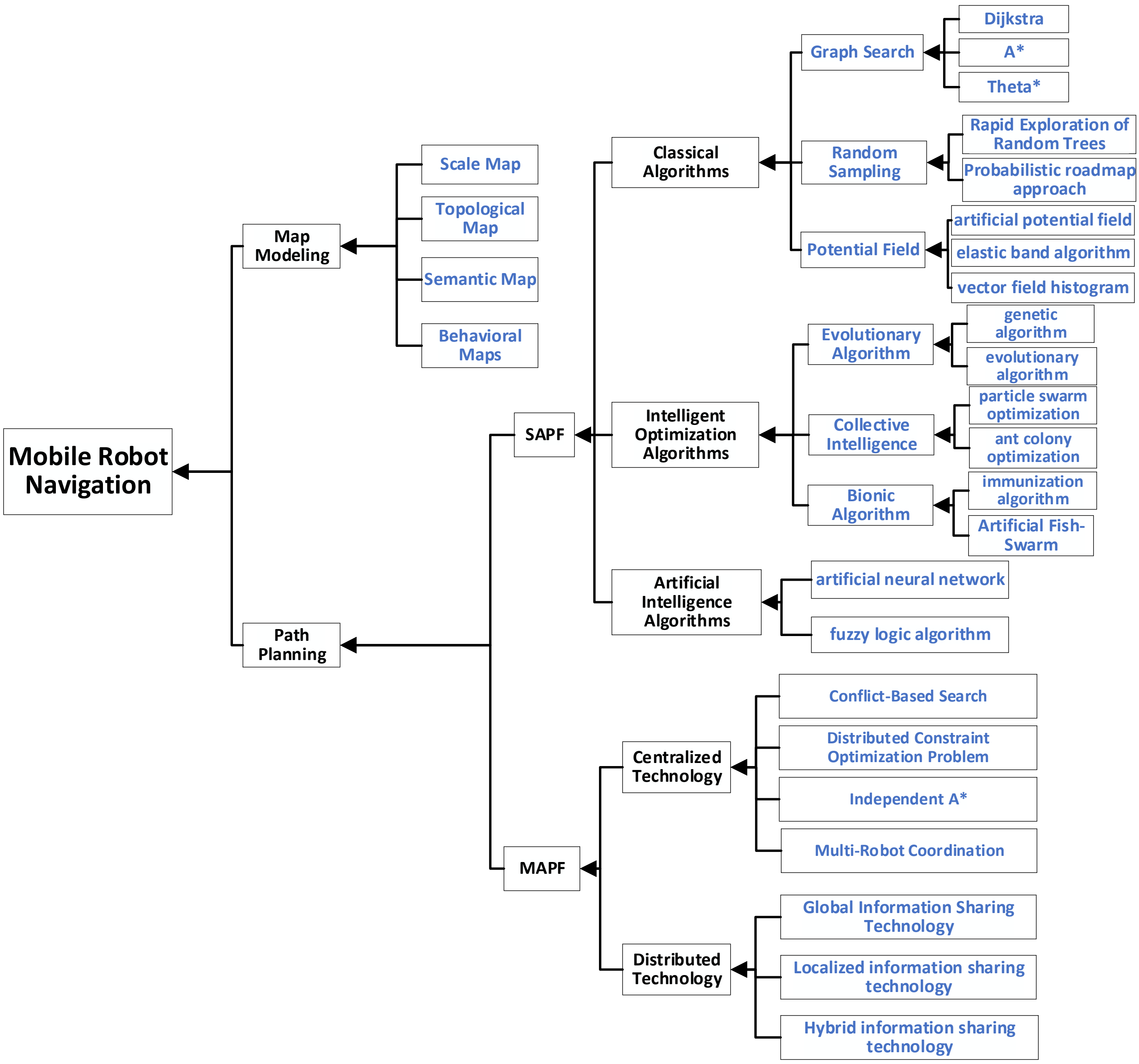


Figure 5. Mobile robot navigation.

2. Problem Statement

Both SAPF and MAPF address two fundamental aspects, environmental modeling and path planning objectives. In this chapter, we delve extensively into various methodologies for environmental modeling, tailored to the intricacies of real-world environments. Additionally, we provide a comprehensive overview of diverse categories of path planning metrics commonly encountered across various task requirements and application contexts. These discussions serve as a foundational framework for the subsequent in-depth analyses of SAPF and MAPF in the ensuing chapters.

2.1. Working Environment Description of the Robot

2.1.1. SLAM Technology

SLAM (Simultaneous Localization and Mapping) denotes a technology aimed at concurrently achieving the localization and mapping of unmanned systems within an unknown environment. This entails the establishment of an estimation process, wherein the robot continuously updates both its self-position and the environmental map in order to adapt to dynamically changing conditions, as elucidated in the description provided in Figure 2. The central challenge in SLAM lies in determining the system's position and constructing the environmental map simultaneously in the absence of prior knowledge. This is achieved through the fusion of sensor data, including but not limited to cameras, LIDAR, and inertial sensors, as documented in Table 1 investigating prevalent SLAM sensor types.

Table 1. SLAM sensor type.

Type	Principle	Advantages	Disadvantages	Hardware Cost	Research Cost
LIDAR	Emit lasers to calculate distance and position.	High precision, accuracy, suitable for complexity.	Costly, limited field of view, bulky.	High	High
Camera (Visual Sensor)	Capture images, extract features for localization and mapping.	Affordable, lightweight, versatile.	Sensitive to lighting and texture, data-hungry.	Low	High
Semantic Sensor (e.g., Camera + Depth Sensor)	Capture images, recognize objects, landmarks, scenes, etc., providing semantics.	Rich semantic data.	High computational complexity, limited view.	Medium	High
Inertial Measurement Unit (IMU)	Measure linear acceleration and angular velocity for attitude and velocity estimation.	Lightweight, rapid response, indoor-friendly.	Accumulates errors, not suitable for long-term positioning.	Low	Low
Ultrasonic Sensor	Emit ultrasonic pulses for distance measurement.	Ideal for obstacle detection.	Limited range, lower precision.	Low	Low
GPS	Receive satellite signals for location determination.	Global coverage, outdoor suitability.	Insufficient precision, susceptible to obstructions.	Low	Low
Millimeter-Wave Radar	Use high-frequency radar waves to detect object positions.	Long-range capability, works well in harsh weather.	Expensive, larger size.	High	High

In accordance with the varying sensor configurations on board robots, SLAM can be broadly categorized into two major classes: LIDAR-based and vision-based. The extraction of semantic information from visual data are pivotal for intelligent robots to perform higher-level tasks. Consequently, emerging research directions have given rise to Semantic SLAM [4].

Laser-based SLAM has achieved a relatively mature status both in theory and practice. Laser-based SLAM systems such as Gmapping, Hector SLAM, LSD-SLAM, ORB-SLAM, and RTAB-Map, have been effectively applied in both research and industrial domains [5]. In particular, the open-source Cartographer SLAM system from Google has significantly advanced the application of laser-based SLAM to its pinnacle, with these exemplary technologies readily available on GitHub. In engineering applications, it is also possible to simulate laser data for mapping and navigation using RGB-D cameras, although the response time is considerably slower compared to the use of original laser data.

Early research on visual SLAM was constrained by the state of visual computing theory and technology, leading to a relatively slow progression. It was only around 2007 that real-time visual SLAM systems, such as MonoSLAM [6], began to emerge. Subsequently, from around 2013 onward, the open-sourcing of notable solutions like DVO-SLAM [7], RGBD-SLAM V2 [8], ORB-SLAM2 [9], MAPLAB [10], and others has garnered widespread attention and fostered rapid development in the field of visual SLAM. At present, visual SLAM systems are capable of achieving positioning and mapping with an accuracy level of around 5 cm.

In the early stages of visual SLAM development, the predominant approach relied on low-level visual features, which offered advantages such as ease of extraction and convenient matching. Substantial progress has been made in this research phase. However, to bring robots closer to human-level environmental understanding, it becomes essential to construct environment maps enriched with semantic information. Semantic SLAM is emerging as a direction that researchers are ardently pursuing, with preliminary research findings progressively gaining recognition in prominent academic journals and top-tier conferences within the field of robotics. Vineet et al. [11] achieved a near real-time system that performs simultaneous semantic segmentation and mapping. Bowman et al. [12] and Schönberger et al. [13] respectively leveraged semantic information to enhance SLAM-based localization. Yu et al. [14] introduced a DS-SLAM approach, combining visual SLAM algorithms with the SegNet network. This fusion effectively employs semantic information and motion feature points within dynamic scenes to filter dynamic components, ultimately improving pose estimation accuracy. Cui et al. [15] proposed a semantic optical flow method that integrates pre-motion semantic information, assisting in epipolar geometry calculations. This method filters real dynamic features and retains static features, which are then fed into a tracking optimization module to achieve accurate motion trajectory estimation.

SLAM technology has consistently garnered significant attention within the field of robotics, as evidenced by Table 2, which presents a comprehensive overview of the major SLAM surveys conducted to date. This table encompasses review literature spanning from 2015 to the present, thereby highlighting state-of-the-art topics. These reports delve into the sensors employed in SLAM systems and various categories of SLAM techniques.

Table 2. Review of SLAM technology.

Thematic	Year	Results
Visual odometry and visual SLAM for mobile robots	2015	[16]
Multi-robot SLAM systems	2016	[17]
Vision SLAM Algorithms	2017	[18]
RGB-D SLAM	2018	[19]
Deep Learning for Visual SLAM in Transportation Robotics	2019	[20]
Semantic SLAM	2020	[21]
Solid State LiDAR(SSL)	2021	[22]
V-SLAM	2022	[23]
Deep Learning and Semantic Segmentation combined with Visual SLAM	2023	[24]

2.1.2. Map Model

In the realm of mobile robot path planning research, modeling of the real-world environment is imperative. The scaled maps, topological maps, semantic maps, and behavior maps depicted in Figure 6a–d exemplify the diverse levels of abstraction employed to describe and model the environment. These map types serve as common and distinct strategies for environmental representation, as detailed below:

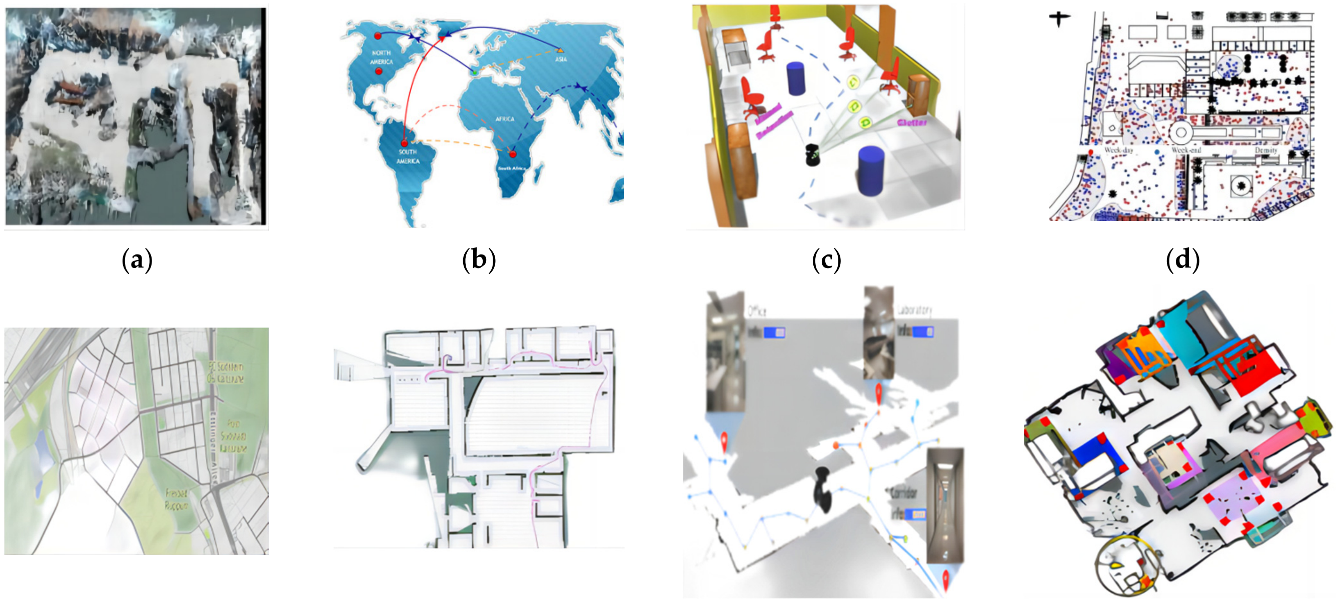
(1) Scale Map: Also known as a measurement map, the metric map typically relies on grids or pixels to partition the environment into a series of discrete units. Each unit signifies a state and can represent either free space or obstacles. The metric map can express the physical dimensions of the real world. It encompasses various types such as occupancy grid maps, depth maps, and probabilistic maps.

(2) Topological Map: The description of a robot's location often does not involve the actual physical dimensions of the world. Instead, it leverages connectivity and distance relationships among different locations to depict the robot's position. This type of map comprises two main categories: node-based and edge-based topological maps.

Topological maps find utility in scenarios where the environment exhibits certain regularities, as seen in city road networks.

(3) Semantic Map: A semantic map is typically feature-based, wherein environmental entities are labeled to enhance the robot's perception and understanding. This labeling facilitates heightened autonomy and intelligence by imparting a sense of meaning to the robot's perception of its surroundings.

(4) Behavior Map: Employed to represent a robot's behavior and task information, the behavior map outlines the actions a robot needs to undertake to accomplish specific tasks. Behavior maps are often generated using robot control systems and planning algorithms, offering utility across decision-making, execution, and autonomous learning applications.



(**a**) (**b**) (**c**) (**d**)
(**e**) (**f**) (**g**) (**h**)

Figure 6. Map Types: (**a**) Scale map; (**b**) Topological map; (**c**) Semantic Map; (**d**) Behavioral Map; (**e**) Satellite map; (**f**) Indoor Map; (**g**) Traffic map; (**h**) Hybrid map.

Illustrated in Figure 6a–d, these map representations span a spectrum of abstraction levels, each suited to distinct requirements within the domain of our research. Various map types have emerged to cater to diverse application environments and data sources. The map types shown in Figure 6e-h are designed to address a variety of application scenarios and data sources and are well suited to meet the complex needs of mobile robot navigation.

(1) Satellite Map: Leveraging satellite imagery, satellite maps encapsulate ground landscapes to vividly portray actual terrains and natural features such as mountains, forests, lakes, and rivers.

(2) Indoor Map: Specially tailored for navigation within confined environments, indoor maps cater to spaces like shopping complexes, airports, museums, and medical centers. They commonly incorporate intricate floor plans for varying levels, annotated landmarks, directional cues, designated paths, and the precise locations of diverse amenities.

(3) Traffic Map: The domain of traffic maps encompasses roads, traffic signs, signals, and other vehicular infrastructure. Robots adeptly employ these vital data to chart optimal routes, ensuring adherence to traffic regulations and road etiquettes for both safe and efficient navigation.

(4) Hybrid Map: Bridging the attributes of diverse map genres, hybrid maps wield the potential to offer a comprehensive and precise repository of geographic information.

These maps are particularly invaluable for navigating complex terrains, facilitating intricate path planning. For instance, integrating a metric map with a topological counterpart can yield precise robot positioning and navigation. Similarly, coupling a semantic map with a behavior map expedites task planning and execution.

As delineated in Table 3, different map types are tailored to diverse application scenarios, equipping robots with varying tiers of environmental insights. Quite often, achieving heightened accuracy in path planning necessitates a synergistic integration of multiple map categories.

Table 3. Analysis of robot work map.

Types	Advantages	Disadvantages	Applications	Results
Scale Map	Simplifies construction; supports various navigation algorithms.	Mapping precision is hard to measure; struggles with unstructured environments.	Robot path and motion planning in static settings.	[25]
Topological Map	Handles complex environments; suitable for large-scale areas.	Difficulty representing detailed information; manual topological definitions needed.	Highways traffic management systems; large-scale robot formations.	[26]
Semantic Map	Describes object semantics; aids advanced robot tasks.	Requires advanced sensors and algorithms, struggles with dynamic objects.	Semantic setting modeling and robot speech interaction.	[27]
Behavior Map	Provides essential behavioral information; supports autonomous learning.	High construction and maintenance costs, limited accuracy and scope.	Autonomous planning, learning, and multitasking for robots.	[28]
Satellite Map	Offers genuine terrain and natural features.	Maps may lack real-time accuracy and updates.	Outdoor navigation and exploration for robots.	[29]
Indoor Map	Facilitates indoor navigation and localization.	Costly map creation and maintenance, necessitating real-time updates.	Indoor robot.	[30]
Traffic Map	Improves traffic efficiency, safety, and energy conservation.	Challenges in data acquisition and high maintenance costs; complex systems.	Security patrols and logistics robots.	[31]
Hybrid Map	Integrates multiple map types for comprehensive environmental data.	Persistent high costs in map creation and maintenance.	Autonomous vehicles and intelligent inspection robots.	[32,33]

In the current milieu of robot discipline, researchers predominantly validate the efficacy of path-planning algorithms within meticulously crafted structured scenarios. However, the adherence to a comprehensive and standardized testing protocol is conspicuously lacking. In response to this gap, the present manuscript undertakes the endeavor of furnishing an encompassing review of notable open-source instances, sourced both from domestic and international realms. Sturtevant et al. [34] and Stern et al. [35] have, respectively presented a diverse array of grid-based test maps and scenarios, tailored for both singular robot path planning and multi-robot path planning applications. More details on these datasets can be found at the following links: https://movingai.com/benchmarks/grids.html (accessed on 22 April 2023) and https://movingai.com/benchmarks/mapf.html (accessed on 22 April 2023).

The SAPF (Single-Agent Path Finding) test maps, as presented in Table 4, encompass game maps, real-world scenario maps, and manually generated maps. These three categories of maps exhibit varying scales, ranging from 88 to 1024, with test case quantities spanning from 100 to 1800, collectively facilitating the empirical evaluation of SAPF algorithmic efficacy. With regard to MAPF (Multi-Agent Path Finding), a collection of 33 test maps is available. A subset of these maps is showcased in Figure 7 and detailed in Table 5.

Each benchmark test map within the MAPF dataset comprises 50 standardized instances, encompassing over 100 robots per test case. Similar to the SAPF algorithms, the solution quality, computational efficiency, and applicability of MAPF algorithms can be rigorously verified through the testing maps and scenarios provided by Stern et al. [35].

Table 4. Overview of SAPF Test Map.

Maps	Types	Numbers
Game	Dragon Age: Origins	156
	Dragon Age 2	68
	Warcraft III	36
	Baldurs Gate II (512 × 512)	36
	Baldurs Gate II	120
	Starcraft	75
Real-World	City/street	90
Artificial	Mazes	60
	Random	40
	Room	40
	Terrain	20

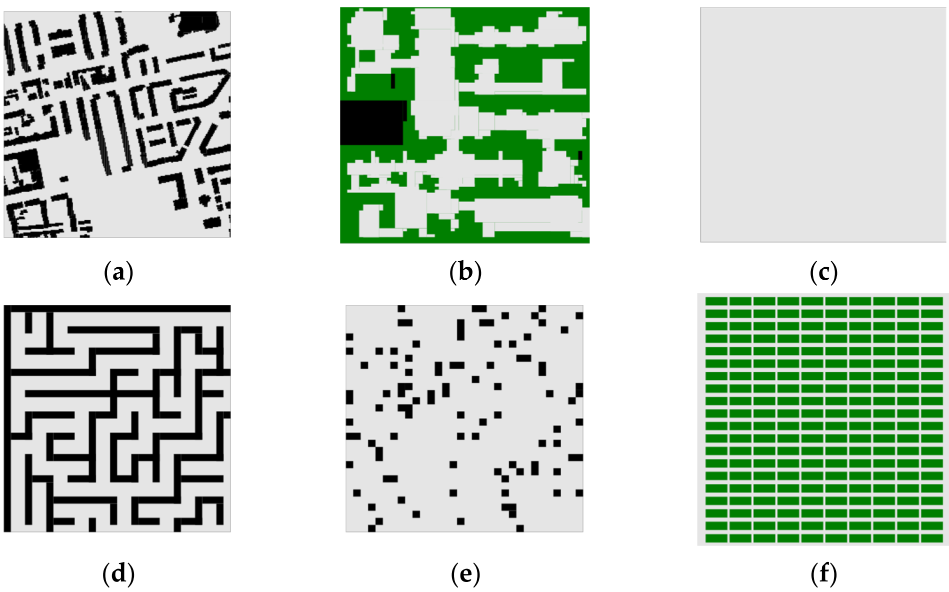


Figure 7. MAPF Test Map: (**a**) City; (**b**) Game; (**c**) Empty; (**d**) Maze; (**e**) Random; (**f**) Warehouse.

Table 5. Example MAPF Test Map.

Maps	Cases	Map Scale
City	Berlin_1_256	256 × 256
Game	den312d	65 × 81
Empty	empty-16-16	16 × 16
Maze	maze-32-32-2	32 × 32
Random	random-32-32-10	32 × 32
Warehouse	warehouse-10-20-10-2-2	161 × 63

2.2. Path Indicators

The path planning for mobile robots typically entails the formulation of pertinent objective functions aligned with distinct task requisites or scenario preferences. Such functions encompass factors including path length, turning angles, energy consumption, and safety considerations, among others. These models can manifest as single-objective or multi-objective frameworks. For example, Xiang et al. [36] employed the minimization of path length as their optimization objective. Li et al. [37] factored in obstacles and ground friction, thereby translating a multi-criteria path planning problem into the context of low-energy consumption path planning.

When dealing with Multi-Objective Path Planning (MOPP), researchers commonly utilize Pareto optimization or weighted aggregation methods. The Pareto optimization approach generates a set of Pareto front solutions by reconciling multiple conflicting objective functions. This set serves as a basis for decision-makers to make informed choices. For example, Yu et al. [38] focused on minimizing path length while enhancing safety as objective functions. They utilized an enhanced version of the artificial bee colony algorithm to search for the Pareto optimal solution set for these functions. In response to challenges such as the high computational complexity of Pareto algorithms, difficulties in handling highly nonlinear problems, and complexities in solving non-convex problems, evolutionary methods have emerged. These include the NSGA-II algorithm [39], NSGA-III algorithm [40], SPEA2 algorithm [41], and multi-objective particle swarm optimization [42]. On the other hand, the weighted aggregation method is rooted in single-objective optimization. It allows for the assignment of weights to different indicators, enabling a comprehensive evaluation tailored to specific application requirements. For instance, Miao et al. [43] integrated multiple objective functions related to path length, safety, and energy consumption, utilizing weighted combinations to flexibly adjust various sub-objectives. Weighted aggregation methods can also incorporate constraints, transforming objective functions into constraint conditions to handle multiple objectives more effectively. For example, Yang et al. [44] considered safety, distance length, smoothness, and jerkiness as four evaluation indicators, utilizing safety as a constraint factor. The optimization objective function for achieving MOPP through weighted aggregation can be formulated as follows:

$$minF = \sum_{i} k_i J_i \tag{1}$$

where F represents the optimization objective; J_i denotes the cost associated with the ith objective; and k_i signifies the weight assigned to the ith objective function. It is evident from the equation that a notable drawback of the weighted aggregation method lies in the challenge of determining the extent of mutual influence among objectives and the relationships of their weights. Moreover, the design of objective weights by researchers often relies on empirical knowledge. To address these limitations, a more effective solution involves integrating methods such as fuzzy theory, machine learning, and entropy weighting to further enhance the optimization algorithm. Ntakolia et al. [45] proposed a genetic algorithm based on fuzzy logic to tackle multi-objective unmanned aerial vehicle path planning problems, which were previously approached using the weighted aggregation technique. Similarly, Chang et al. [46] improved the adaptability of an intelligent agent to unknown environments by utilizing Q-learning to autonomously learn the weight parameters of the dynamic window method.

Considering the distinctive emphasis placed on various path metrics in different scenarios, it is noteworthy that there exist evident differences. For instance, in the context of industrial automation production lines [47], robots are required to execute tasks safely within extremely short timeframes, making time efficiency a core metric. However, in the realm of autonomous navigation [37], the optimization objective primarily revolves around ensuring that robots accomplish tasks in a shorter time span while conserving energy. To address this variance in emphasis, this paper presents an overview of several prevalent categories of path metrics that have garnered favor among researchers in Table 6. It systematically delineates the definitions, methods of performance assessment, evaluation strategies, and domains of focus for each category of metrics. For quantification methods of these metrics, one may refer to the methodology expounded in reference [48].

Table 6. Path Planning Indicators.

Indicators	Definition	Performance Measurement	Evaluation Methodology	Focus Area
Path Length	Path length from start to end, possibly with multiple points.	Actual path length, optimal path length.	Compare robot and planned path lengths to assess algorithm effectiveness.	Autonomous navigation, including drones.
Safety	Robot's hazard avoidance capability (e.g., narrow terrains).	Robotic collision detection, path safety assessment.	Evaluate planned path adaptability based on robot motion capabilities.	Autonomous vehicles, industrial and service robots.
Energy consumption	Energy needed for path planning.	Consider energy consumption in path metrics and robot energy management strategies.	Evaluate motion costs using energy models in simulations or real-world.	Agricultural and exploration robots.
Smoothness	Path curvature assessment.	Number of turns, curvature values.	Calculate path curvature through smoothing algorithms.	Industrial assembly and handling robots.
Path Deviation	Actual vs. planned path deviation.	Path offset, maximum path offset, offset distance.	Determine actual path-to-theory distance with offsets.	Medical robotics and precision machining.
Coverage Rate	Efficiency and completion ratio in defined areas.	Area coverage, point coverage, time coverage, distance coverage.	Calculate coverage metrics based on planning and area partitioning.	Detection and cleaning robots.
Time Efficiency	Path planning time.	Factors include algorithm time and space complexity, along with the robot's real-world execution efficiency.	Analyze algorithm complexity, real-world performance, and comparisons.	Industrial automation, emergency rescue.
Robustness	Algorithm's interference resistance.	Success rate or stability, tolerance of algorithms to robot hardware errors.	Compare algorithms in simulations and on real robots.	Robot exploration and rescue.
Real-time	Path planning response speed.	Response time, path planning algorithms to solve the balance of accuracy and speed.	Evaluate algorithm performance across different environments.	Self-driving cars, military robots.

In addition, robots of different types and scales consider constraints and metrics that differ from those of other robots. For example, the kinematic models for individual Unmanned Aerial Vehicles (UAVs) vary based on their types, and when dealing with multiple UAVs, communication constraints also play a crucial role [49]. Following this, Franco et al. [50] proposed an energy model to reduce energy consumption in UAVs.

3. Single-Agent Path Planning Algorithm

In the preceding discussion, we have conducted an in-depth exploration of the common aspects shared by SAPF and MAPF problems, with a focus on environmental modeling and path planning indicators. At an individual level, SAPF primarily revolves around the task of determining the optimal path for a single robot, guiding it from its initial position to a designated goal. In contrast, MAPF extends its purview to encompass the coordination of multiple robots within the same environment. The principal objective of MAPF is to ensure the simultaneous attainment of their respective goals by these entities, all the while meticulously avoiding collisions or conflicts. From a relational standpoint, SAPF can be regarded as a specialized case within the broader framework of MAPF, entailing the involvement of only a single robot. Since the 1950s, researchers have proposed numerous algorithms to seek optimal paths for SAPF. Based on the distinctive characteristics of these algorithms, this paper categorizes them into three main classes: classical algorithms, bio-inspired algorithms, and artificial intelligence algorithms.

(1) Classical Algorithms: This category includes graph search algorithms, random sampling algorithms, potential field algorithms, artificial potential field methods, and model predictive control algorithms.
(2) Bio-Inspired Algorithms: The domain of intelligent optimization encompasses this category, incorporating genetic algorithms, ant colony optimization algorithms, particle swarm optimization algorithms, firefly algorithms, bacterial foraging algorithms, cuckoo search algorithms, and artificial bee colony algorithms.
(3) Artificial Intelligence Algorithms: This category primarily comprises algorithms such as fuzzy control algorithms and neural network algorithms.

3.1. Classical Class Algorithms

Classical path planning algorithms have gained widespread popularity in the realm of global path planning due to their ease of observation and computational feasibility. Researchers continuously enhance their performance in uncertain environments by optimizing or integrating them with other algorithms.

3.1.1. Graph Search Algorithms

Graph search algorithms employ a graph data structure to represent the environment. In this representation, nodes correspond to potential robot positions, while edges represent permissible movements between these positions. Throughout the search process, these algorithms consider environmental obstacles, the dynamic constraints of robots, and the cost associated with traversing a path. Path optimization aims to determine the best path, whether it is the shortest, most cost-effective, or meets other optimization criteria. In this context, this paper will present some cases where graph search algorithms use different search strategies and heuristics to strike a balance between path quality and computational efficiency. In 1956, E.W. Dijkstra introduced the Dijkstra algorithm [51], which is capable of computing the shortest path from a starting node to any other node in a weighted directed or undirected graph. To enhance the search speed of the Dijkstra algorithm, Hart et al. [52] proposed the A* algorithm that employs heuristic information to guide the search process. The A* algorithm takes into account the cost to reach each node from the starting node and the estimated cost to reach the goal node. In response to issues such as low search efficiency and high memory overhead in the traditional A* algorithm, various classic variants and improvements of A* have emerged, including Weighted A* (WA*) [53], Adaptive A* (AA*) [54], Theta* [55], and Jump Point Search (JPS) [56], as depicted in Table 7 and Figure 8. Pu et al. [57] introduced a dual adaptive A* algorithm, which encompasses adaptive multi-objective heuristic functions and adaptive node expansion strategies. Lai et al. [58] proposed a centrally constrained adaptive A* algorithm that assigns dynamic weights to nodes at different positions and incorporates adaptive thresholds into the heuristic function to enhance adaptability. The Theta* algorithm, initially introduced by Daniel et al. [59], permits path searches along arbitrary angles, and subsequently marked the more efficient Lazy-Theta* [60]. Moreover, Luo et al. [56] applied the variable step-size concept of the Theta* algorithm to the JPS algorithm, further improving the path quality and smoothness of the traditional JPS.

In consideration of the dynamic characteristics of environments, researchers [61,62] have extended the A* algorithm to propose Lifelong Planning A* (LPA*) and the D* algorithm with incremental heuristic search paths. To further enhance the search efficiency of LPA* and D*, Koenig et al. [63] combined the incremental update rules of D* with the priority queue mechanism of LPA* to introduce D* Lite. Building upon this, Aine et al. [64] proposed the more efficient Truncated LPA* (TLPA*) and Truncated D* Lite (TD* Lite). Moreover, scholars have addressed the problem of optimizing multiple path objectives in dynamic environments by introducing methods such as MOD* Lite [65] and MOPBD* [66].

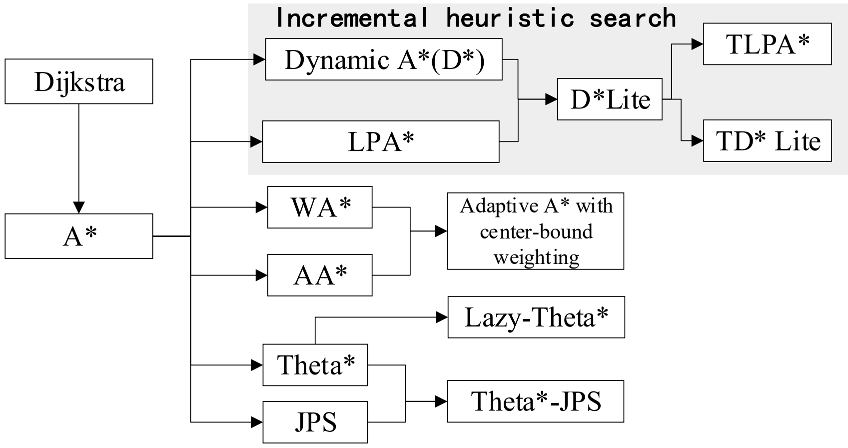


Figure 8. A* Evolution.

Table 7. An improved version of the A* algorithm.

Algorithm	Time	Characteristics	Research
WA*	-	Fine-tuned heuristic weight factor to adjust the algorithm's emphasis on heuristic estimates and path costs during exploration.	[53] [58]
AA*	-	Updated heuristic function based on the actual exploration path costs to guide the search direction more accurately, thereby enhancing search efficiency.	[54] [58]
Theta*	2010	Implemented improvements upon the A* algorithm to reduce path deviations and eliminate the need for re-exploring visited nodes.	[55] [59]
Lazy-Theta*	2010	Computation of path cost is performed only when genuinely required, resulting in an enhancement of search efficiency.	[60]
JPS	2011	Leveraged map symmetry and accessibility to bypass numerous unnecessary nodes, consequently reducing search overhead.	[56]
D*	1994	A self-correcting path planning algorithm evolved from the A* algorithm, applicable to dynamic environments.	[61]
LPA*	2001	Employed two priority queues to manage current path estimates and enhanced path information, adjusting paths incrementally based on cost and heuristic information to achieve optimal routes.	[62]
D* Lite	2002	Built upon the LPA* approach, incorporated ideas of incremental path updating and repairing to enable efficient path adjustments in dynamic environments.	[63]
TLPA*	2013	Integrated the concept of suboptimal constraints into the LPA* framework, facilitating a reduction in state expansions.	[64]
TD* Lite	2013	Introduced a suboptimal re-planning algorithm for navigation, combining TLPA* truncation rules with D* Lite principles.	[64]
MOD* Lite	2016	A multi-objective incremental search algorithm.	[65]
MOPBD*	2022	Multi-objective incremental search algorithm with more efficient scaling of nodes	[66]

3.1.2. Random Sampling Algorithms

In 1998, LaValle introduced the Rapidly-exploring Random Tree (RRT) [67]. The core idea behind RRT involves exploring paths in unknown environments through random sampling and gradual tree expansion. However, this approach cannot guarantee the discovery of the optimal path and is susceptible to biases induced by target point preferences and environmental attributes. For instance, in environments abundant with obstacles or constrained passages, the algorithm's convergence rate is slow, leading to a sharp decline in efficiency. Researchers have continually endeavored to optimize the RRT algorithm. As outlined in Table 8, this paper highlights several variants of the current RRT algorithm, such as RRT-Connect [68], RRT* [69], RRT*-Smart [70], RRT*-Connect [71], and Informed RRT*-Connect [72].

To enhance the search efficiency of RRT-Connect, Kang et al. [73] rewired the nodes along the planned path based on the triangle inequality principle. This method is similar to that of RRT*-Smart [70] and Quick-RRT* [74]. Qian et al. [75] proposed the Multi-Directional RRT based on the principle of concentric tree growth. This approach constructs new multi-directional trees as required to achieve specific spatial coverage, eventually forming a comprehensive path from previously explored vertices. The asymptotic optimality of the RRT* algorithm has been verified [1], signifying that under conditions of sufficient time and resources, the RRT* algorithm can converge to a globally optimal path. To expedite convergence, Qureshi et al. [76] introduced the Intelligent Biased-RRT* algorithm, utilizing an intelligent sample insertion heuristic function to rapidly converge to the optimal solution. Zhang et al. [77] introduced the Gaussian Fitted Smooth RRT*-Smart algorithm for global path planning, enhancing robot performance during sharp turns. Furthermore, Chen et al. [78] proposed the Adaptive Dynamic RRT*-Connect based on RRT*-Connect. To enhance node sampling efficiency, they introduced feedback-based automatic adjustment of the heuristic factor and a pruning-reconnection mechanism to address potential conflicts between drones and dynamic threats.

Table 8. RRT algorithm variants.

Algorithm	Time	Characteristics	Research
RRT-Connect	2000	Finding a feasible path to connect two trees using two RRT trees growing and joining step by step for continuous spaces.	[68,73]
RRT*	2011	Connect the tree nodes through the minimum spanning tree algorithm and iteratively optimize to find a better path.	[69,74,76]
RRT*-Smart	2012	Intelligent sampling strategy is introduced to dynamically adjust the distribution of sampling points according to the structure of the tree and the location of the target point to accelerate the path search.	[70,77]
RRT*-Connect	2015	The iterative process of RRT-Connect algorithm is optimized to improve the path quality.	[71,78]
Informed RRT*-connect	2020	Heuristic information is introduced to improve the RRT*-Connect algorithm, which makes the path planning more efficient and better quality.	[72]

In 1996, the Probabilistic Roadmap Method (PRM) was introduced by Kavraki et al. [79]. This method involves sampling in the configuration space, performing collision detection, and testing connectivity to effectively represent the connectivity of path graphs. It addresses the challenge of constructing valid paths in high-dimensional spaces. The primary advantage of PRM is that its complexity is mainly influenced by the difficulty of pathfinding, showing relatively minor correlation with the scale of planning scenarios and the dimensionality of configuration space. However, in cases where paths need to traverse dense obstacles or narrow passages, the efficiency of PRM may decrease. To overcome these limitations, researchers have conducted extensive studies to enhance its performance, resulting in various variants such as PRM* [80], Lazy PRM [81], PRM-D* [82], among others as illustrated in Table 9.

Liu et al. [82] leveraged hierarchical planning to enhance the PRM's dynamic obstacle avoidance by integrating the D* algorithm into the network construction and planning process of the PRM. Ravankar et al. [83] proposed a hybrid strategy (HPPRM) that combines the PRM with artificial potential fields, thereby augmenting the adaptability of the PRM in scenarios involving narrow passages, trap environments, and both static and dynamic obstacle-laden settings. Mohanta et al. [84] introduced a knowledge-based fuzzy PRM approach (Fuzzy-PRM), which operates in the following two steps: first, constructing straight-line paths based on PRM in complex a priori environments, and second, adjusting heading angles using a knowledge-based fuzzy control system to ensure smooth turning angles. PRM exhibit strong search capabilities in high-dimensional or large-scale spaces, although there remains significant room for improvement in terms of planning efficiency. Table 10 provides an intuitive comparison of the time complexity of variants of random sampling algorithms, with '**n**' representing the number of nodes and '**m**' representing the number of edges.

Table 9. PRM algorithm variants and improvements.

Algorithm	Time	Characteristics	Research
PRM*	2010	A roadmap is constructed using an incremental approach that continuously improves the quality of the paths using a shortest path search algorithm as it samples and connects nodes.	[80]
Lazy PRM	2000	Minimizes the number of collision checks performed during planning, thus minimizing the planner's runtime.	[81]
HPPRM	2020	Improved adaptability of the algorithm to multi-class complex environments.	[83]
Fuzzy-PRM	2019	Achieved dual metric optimization of path length and smoothness.	[84]
PRM-D*	2023	Dynamically adapts to environmental changes and unknown dynamic obstacles during the planning process.	[82]

Table 10. Time complexity of random sampling algorithm.

Algorithms	Time Complexity
RRT-Connect	$O(n)$
RRT*	$O(nlog(n))$
RRT*-Smart	$O(nlog(n))$
RRT*-Connect	$O(nlog(n))$
PRM*	$O(n^2 + mlog(m))$
Lazy PRM	$O(n^2)$
PRM-D*	$O(n^2 + mlog(m))$

3.1.3. Potential Field Algorithms

In 1986, the Artificial Potential Field (APF) method was introduced by Platonov [85]. This approach is based on the concept of applying a virtual force field to the robot, where the robot is moved toward the target point due to the combined effects of attraction from the target and repulsion from obstacles. The existing literature has predominantly focused on addressing the local minimum problem of APF by optimizing and enhancing the attraction and repulsion potential functions or introducing additional constraints. Fan et al. [86] applied APF to underwater robots and proposed a method involving regular hexagon guidance to improve path planning and prevent falling into local minima. Lin et al. [87] introduced an improved APF based on the decision tree concept, incorporating a distance term in the potential function to address issues of local minima, oscillations between obstacles, and concave obstacles. Some researchers have integrated traditional APF with other optimization algorithms, combining global and local path planning to mitigate the limitations of traditional APF. For instance, Lu et al. [88] combined RRT with APF to tackle the problem of local minima in APF. Zhou et al. [89] proposed an APF path planning algorithm based on particle swarm optimization tangent vectors. Tong et al. [90] further employed the A* algorithm for multi-target global path planning, utilizing an improved APF algorithm to adaptively acquire virtual sub-target points to guide the motion of multiple robots.

In 1993, the Elastic Band Algorithm (EBA), introduced by Quinlan et al. [91], serves as a method for both path planning and motion control of mobile entities. Its fundamental premise revolves around confining the robot's trajectory within a band-like region known as the "elastic band." This strategic confinement within the elastic band effectively prevents collisions with obstacles [92]. Following its inception, the EBA framework underwent extensions to encompass scenarios involving nonholonomic motion and systems with multiple degrees of freedom. However, these adaptations did not comprehensively integrate time and dynamic constraints [93]. It was only through the subsequent development of the Time-Elastic Band (TEB) algorithm by Rosmann et al. [94] that the integration of time-based information enhanced the elastic band's efficacy. This allowed for the accommodation of dynamic constraints and direct trajectory adjustments, thereby rendering it applicable to both holonomic and nonholonomic mobile robots. Subsequent scholars have predominantly directed their efforts toward refining the traditional TEB algorithm by addressing dynamic time parameter adjustments, trajectory smoothing, motion constraints, multi-objective optimization, and dynamic environmental considerations. For instance, Nguyen et al. [95] introduced the Active Timing Elastic Band (PTEB) technique tailored for autonomous mobile robot navigation within dynamic surroundings. Meanwhile, Sun et al. [96] proposed a hierarchical path planning algorithm that combines the Theta* algorithm with the TEB algorithm. This approach involves initiating path planning using the Theta* algorithm, factoring in parameters such as velocity, acceleration, travel time, and minimum turning radius. Subsequently, the TEB algorithm was harnessed to effectively enhance the initial path through a process of smooth optimization.

In 1991, the Vector Field Histogram (VFH) method, introduced by Borenstein et al. [97], provides a technique for mobile robot path planning and obstacle avoidance. It utilizes laser radar or other perceptual devices to collect environmental data and represents the surroundings as a two-dimensional vector field. By calculating obstacle density in various directions within the vector field, VFH generates a histogram to guide the robot's path selection. The VFH algorithm boasts several advantages, including high reliability, computational efficiency, and robustness. However, this algorithm is not without limitations; for instance, it can often become trapped in local minima within narrow areas. Consequently, numerous scholars have proposed solutions to address this concern. Ulrich et al. [98] devised VFH+, an extended version of VFH. This algorithm takes the robot's physical dimensions into account, thereby enhancing its generality. VFH+ improves trajectory smoothness by incorporating threshold hysteresis. Building upon VFH+, Ulrich et al. [98] introduced VFH* [99], which yields superior path planning outcomes. VFH+ excels in obstacle avoidance due to its sensitivity and robustness, often being coupled with other global planning methods and used as a local planner [100,101]. One notable drawback of VFH* is its inapplicability in environments with dynamic obstacles. To overcome this limitation, the algorithm is often combined with other techniques, such as employing Kalman filtering [102] to predict obstacle movements.

3.2. Intelligent Optimization Class Algorithms

Intelligent optimization algorithms are stochastic methods inspired by natural phenomena observed in biological populations. Based on their functionalities and design principles, these algorithms can be categorized into evolutionary algorithms, swarm intelligence algorithms, and bio-inspired algorithms.

(1) Evolutionary Algorithms: Evolutionary algorithms simulate the process of biological evolution, incorporating operations such as selection, crossover, and mutation to search for optimal solutions within solution spaces. Prominent algorithms in this category include genetic algorithms and evolution strategies.
(2) Swarm Intelligence Algorithms: Swarm intelligence algorithms emphasize collaboration and communication among individuals in a group. They utilize information sharing and coordination among members to collectively solve problems. Notable algorithms in this category include particle swarm optimization and ant colony optimization.
(3) Bio-inspired Algorithms: Bio-inspired algorithms mimic the behavior, structures, and mechanisms of living organisms to address problems. These algorithms draw inspira-

tion and principles from biology. Representative examples are immune algorithms and artificial fish swarm algorithms.

From the progression of path planning research depicted in Figure 9, it is evident that mainstream swarm intelligence algorithms are applied to problem-solving in path planning. However, variations exist in algorithm performance and researcher preferences. This section primarily summarizes the most prominent algorithms—ant colony optimization, particle swarm optimization, and genetic algorithms—within this domain.

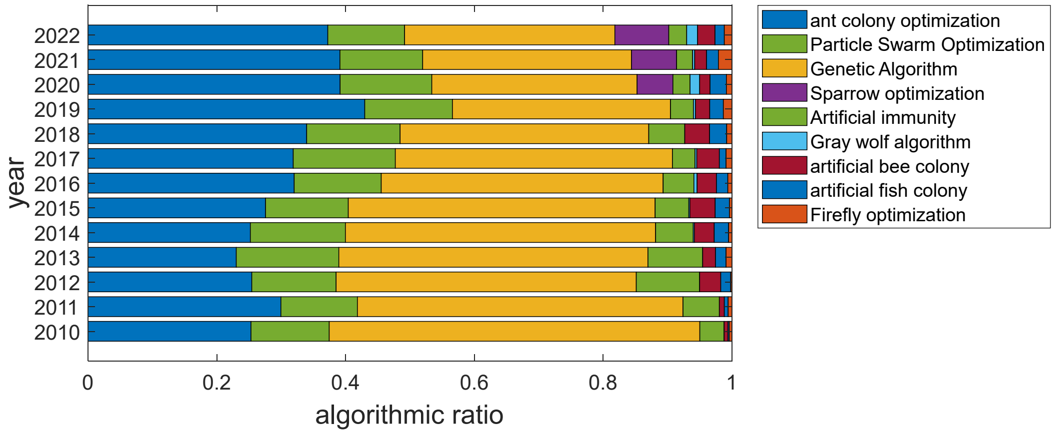


Figure 9. Proportion of published papers on various algorithms from 2010 to 2022.

3.2.1. Ant Colony Optimization

Ant Colony Optimization (ACO), introduced by Italian scholar M. Dorigo [103] in 1992, has found notable applications in the field of mobile robot path planning due to its features of positive feedback, distributed computation, and robustness. Addressing the inherent issues of slow convergence and susceptibility to local optima in the basic ACO, numerous researchers have undertaken optimizations and improvements in the structural design, parameter selection, and optimization of pheromones. Wang et al. [104] introduced an uneven distribution of initial pheromones and established an iterative threshold, effectively reducing the initial blind search of ants and enhancing the algorithm's search capability. Jiao et al. [105] employed adaptive state transition and pheromone update strategies, ensuring the relative importance of pheromone intensity and heuristic information during iterations. This enhancement has, to some extent, improved the algorithm's adaptability to different environments and its ability to escape local optima. Akka et al. [106] refined the state transition formula, favoring neighboring nodes with more exits as the next choice. They introduced segmented multi-heuristic functions and implemented rewards and penalties for optimal and worst paths, thereby promoting diversity in search and mitigating the impact of ineffective pheromones.

Traditional ACO mainly addresses single-objective optimization problems. However, multi-objective ant colony algorithms can handle conflicts among multiple optimization objectives. Li et al. [107] introduced an improved heuristic function and pheromone update strategy based on factors such as path length, number of turns, and smoothness of slope. They comprehensively computed the transfer probability, guiding ants towards paths with optimal overall performance. Miao et al. [43] integrated multi-objective performance indicators into the enhanced ant colony algorithm. They transformed the path planning problem into a multi-objective optimization problem, using weighted evaluation indicators such as path length, safety, and energy consumption as constraints for the multi-objective function, achieving comprehensive global optimization for path planning.

The aforementioned enhancements primarily address the dilemma between convergence speed and diversity within single-population Ant Colony Optimization (ACO) [108]. To fully harness the optimization efficiency of ACO, several researchers have proposed

Multi-Population ACO [109], which can be categorized into Homogeneous Multi-Population, Heterogeneous Multi-Population, and Collaborative Multi-Population, based on the architecture and information exchange patterns of the ACO algorithm.

(1) In Homogeneous Multi-Population, each population employs similar search strategies to independently explore, while communication of information is facilitated through mechanisms like pheromone updates. For instance, Yang et al. [110] introduced an efficient Leader-Follower Ant Colony Optimization (LF-ACO) to address multi-robot formation path planning. They integrated pheromones from both leader ants and follower ants into the ACO's pheromone update rules to enhance the quality of the formation path search.
(2) In Heterogeneous Multi-Population, each population maintains the same number of ants with distinct search strategies, focusing on different optimization objectives. Yang et al. [111] presented a parallel ACO approach employing two independent, concurrently operating ACO populations to expand search diversity. This method generates an initial collision-free path in complex environments. To enhance mobile robot path planning, Zhang et al. [112] proposed an improved dual-layer Ant Colony Optimization. They divided the ants into guiding-layer ants emphasizing smoothness and regular-layer ants focusing on the shortest path, effectively exploiting collaborative advantages during the search process.
(3) In Collaborative Populations, distinct populations handle different subproblems while sharing pheromones or experiential knowledge between populations to accelerate convergence and improve solution quality. For instance, Deng et al. [113] introduced an enhanced ACO algorithm based on a multi-population strategy, cooperative evolution mechanism, pheromone update strategy, and pheromone diffusion mechanism, enhancing optimization performance for large-scale problems.

In addition, combining ACO with other algorithms helps compensate for ACO's limitations and enhances optimization performance. For example, Liu et al. [114] integrated ACO with geometric optimization, eliminating intersecting paths during path generation, followed by pheromone updates, thus improving path quality and algorithm efficiency. Dai et al. [115] improved ACO using the A* algorithm and the maximum-minimum ant system, accelerating global convergence speed and path smoothness, and introducing a backtracking mechanism to address ant deadlock issues in complex environments. Yang et al. [116] presented an enhanced hybrid algorithm by considering ACO's robustness and search capacity in global path optimization, along with the advantages of the dynamic window approach in local obstacle avoidance. This innovation enhances both the robot's global navigation and dynamic obstacle avoidance capabilities.

3.2.2. Particle Swarm Optimization

Kennedy et al. [117] introduced Particle Swarm Optimization (PSO) in 1995, drawing inspiration from the behavior of biological collectives. PSO is a cluster optimization algorithm that simulates the flight of particles in a search space to discover optimal paths. Each particle represents a potential path solution and continuously adjusts its position based on its own experience and information from neighboring particles during the search process. This collaborative and information-sharing approach enables the Particle Swarm Optimization algorithm to effectively discover collision-free and efficient paths in the context of path planning. Nonetheless, it faces challenges such as susceptibility to local optima, sensitivity to parameters, and limitations in handling high-dimensional problems. To address these issues, numerous scholars have proposed enhancement strategies. The selection of PSO's parameters significantly impacts its performance and outcomes. Current research widely acknowledges that inertia weight has the most significant influence on particle swarm algorithm performance. Therefore, research in this domain is extensive, encompassing fixed inertia weights [118], time-varying adaptive inertia weights [119], linearly decreasing inertia weights [120], and fuzzy logic-controlled inertia weights [121]. Improvements to other parameters include dynamic learning factors [122] and adaptive adjustment of acceleration coefficients [123]. Apart from parameter optimization, auxiliary techniques can be introduced to enhance PSO's population diversity and mitigate premature convergence. For example, Liang et al. [124] proposed a hybrid PSO based on cross-learning strategies to counteract premature convergence. Phung et al. [125] presented the Spherical Particle Swarm Optimization (SPSO) algorithm to efficiently explore the task space of unmanned aerial vehicles. Guo et al. [126] developed a PSO incorporating chaos and shared learning to tackle the Traveling Salesman Problem (TSP). Fu et al. [127] introduced a quantum-inspired PSO using phase angle encoding to generate three-dimensional trajectories for unmanned aerial vehicles.

Over the past decade, the Multi-Objective Particle Swarm Optimization algorithm (MOPSO) [42] has been introduced, allowing for the simultaneous optimization of multiple conflicting objectives. Xu et al. [128] proposed an enhanced MOPSO for path planning of unmanned aerial vehicles over known static rugged terrains. This approach considers collision-free path metrics such as height, length, and angle-of-change rate minimization. The solutions provided by MOPSO typically form a set of optimal solutions known as the Pareto optimal solution set. Thammachantuek et al. [129] introduced the Multi-Objective Evolutionary Particle Swarm Optimization algorithm (MOEPSO), which achieves unique solutions adhering to criteria of shortest, smoothest, and safest paths, overcoming the issue of traditional MOPSO falling into local optima. To encompass more optimization objectives, Sathiya et al. [130] presented an improved Multi-Objective Particle Swarm Optimization algorithm for the path planning of car-like mobile robots, considering collision-free, shortest, safe, energy-efficient, and smooth paths. The research utilizes objectives such as minimal path length, minimal motor torque, minimal travel time, minimal robot acceleration, and maximal obstacle avoidance.

Hybrid Particle Swarm Algorithms combine PSO with other techniques effectively exploit the strengths of various algorithms to enhance the quality of path planning solutions. Chen et al. [131] introduced an improved neural network-based particle swarm optimization algorithm to address path planning problems across diverse environments. Wu et al. [132] proposed a hybrid strategy integrating reinforcement learning and particle swarm optimization for real-time rescue and allocation of multi-AUV systems in three-dimensional underwater environments. Lin et al. [133] combined enhanced PSO with simulated annealing, yielding a method that swiftly attains optimal global paths, showcasing commendable performance across safety, smoothness, and path length metrics.

3.2.3. Genetic Algorithm

The Genetic Algorithm (GA), proposed by Holland in 1975 [134], emulates the genetic, selection, and crossover processes observed in natural populations to search for optimal solutions. However, Forrest et al. [135] have noted that while Standard Genetic Algorithms (SGA) possess merits such as flexible search capabilities and strong scalability, they also exhibit shortcomings including inferior individual convergence, sluggish convergence speed, susceptibility to local optima, and limited population diversity. In response to these limitations, researchers have introduced novel strategies to enhance the performance of GAs and improve the quality of generated paths. In an effort to overcome issues like premature convergence, low-quality convergence paths, inadequate population diversity, and the challenge of escaping local optima in the realm of robot path planning, Hao et al. [136] have proposed the Multi-Population Migration Genetic Algorithm. This innovative approach aims to leverage the strengths of the GA while mitigating its weaknesses. Furthermore, Zhang et al. [137] have explored an enhanced version of SGA that draws inspiration from visual space enhancement. The key components of this approach include the concept of visual space, strategies for generating populations, matrix encoding techniques, and optimization mutation operators. Meanwhile, Lamini et al. [138] have improved the fitness function of the GA to optimize the energy consumption of mobile robots by minimizing the number of turns taken by the robots while reaching their target paths.

Over the past decade, various adaptations of the Standard Genetic Algorithm (SGA) framework have emerged to tackle the challenges posed by multi-objective optimization. These adaptations include the Multi-Objective Genetic Algorithm (MOGA) [139], Non-Dominated Sorting Genetic Algorithm II (NSGA-II) [39], and Non-Dominated Sorting Genetic Algorithm III (NSGA-III) [40]. These variants have been designed to address the complexities inherent in optimizing multiple conflicting objectives. In MOGA, multiple objective functions are incorporated into the fitness evaluation process. A notable example is the work of Li et al. [140] who developed a comprehensive fitness function integrating parameters such as path length, path safety, and path energy consumption. This function was harmonized using a weighted approach to achieve a balanced optimization outcome. To fully harness the power of evolutionary algorithms in population-based searches, methodologies centered on Pareto dominance have gained widespread traction for fitness evaluation. Guo et al. [139] seamlessly integrated the GA framework into a multi-objective evolutionary algorithm, resulting in a collection of Pareto optimal solutions that encompass diverse paths. This array of options aids decision-making in practical scenarios. Ramabalan et al. [141] extended the SGA framework to propose two innovative multi-objective trajectory planning optimization algorithms, Multi-Objective Differential Evolution (MODE) and Elite-Retained Non-Dominated Sorting Genetic Algorithm II (NSGA-II). These algorithms were tailored for differentially driven mobile robots, enhancing trajectory planning strategies. Research findings underscore that NSGA-III, with its layered approach, outperforms traditional Pareto-based evolutionary algorithms and NSGA-II in solving diverse multi-objective challenges [142]. Mahmud et al. [143] spearheaded the application of NSGA-III to address the complexities of multi-objective navigation in agricultural mobile spraying operations. Their evaluation, based on the C-metric index, substantiated the prowess of NSGA-III in tackling multi-objective optimization.

Efficiently integrating genetic algorithms has shown significant promise in addressing interdisciplinary challenges. Orozco-rosas et al. [144] creatively combined membrane computing, pseudobacterial genetic algorithms, and artificial potential fields to devise a novel path planning approach for autonomous mobile robots. Their work substantiated the effectiveness of this approach in collision avoidance, path smoothness, and optimization of path length. Similarly, Zhang et al. [145] proposed a hybrid algorithm by merging genetic algorithms and firefly algorithms. This innovative approach tackled scenarios in which the firefly algorithm might become trapped in local optima. The strategy involved harnessing the global optimization capabilities of genetic algorithms to select, crossbreed, and mutate the most promising firefly individuals, thus enhancing overall optimization capabilities. This hybrid algorithm underwent rigorous validation in both two-dimensional and three-dimensional environments. Recognizing the distinct advantages of genetic algorithms in global search and the localized search capabilities of cuckoo search algorithms, Wang et al. [146] introduced a hybridization approach. Supported by experimental evidence, their approach demonstrated that the hybrid algorithm outperformed standalone methods in multi-constraint three-dimensional environments.

3.3. Artificial Intelligence Class Algorithms

The utilization of artificial intelligence techniques in mobile robot path planning constitutes a significant advancement. These techniques encompass a range of methodologies, including artificial neural networks, machine learning algorithms, deep learning algorithms, and fuzzy logic. This article focuses on the elucidation of two prominent algorithms: neural network algorithms and fuzzy logic algorithms. The characteristics of the two types of methods are shown in Table 11.

Table 11. Comparison of Artificial Intelligence Algorithms.

Characteristics	Neural Network Algorithm	Fuzzy Logic Algorithm
Principle	Simulates biological neural system principles	Based on the theory of fuzzy set for inference
Advantages	Adapt to complex nonlinear problems with strong learning and generalization skills.	Manages fuzziness and uncertainty with interpretable rules.
Disadvantages	Demands abundant training data and computational resources, yielding less interpretable output.	Relies on manually defined fuzzy rules and membership functions; less adaptable to complex nonlinear problems.

3.3.1. Neural Network Algorithm

Neural networks (NN), pioneered by McCulloch and others in 1943, represent a computational paradigm rooted in mathematical formulations and threshold logic algorithms. In contemporary times, NN has found widespread utility across domains such as artificial intelligence and machine learning [147]. Differing from conventional path planning approaches, neural network algorithms, by means of learning and optimization, excel at enhancing the precision and efficiency of path planning in intricate and dynamic settings. This superiority is rooted in the neural networks' capability to extract pivotal information from perceptual inputs encompassing environmental maps, sensor data, robot status, task requisites, and other multifaceted data dimensions. Through the processes of deep learning and training, neural networks can autonomously identify and comprehend this information, proficiently integrating it into the path planning process. This leads to path planning that is more intelligent and adaptable, ultimately yielding heightened accuracy and robustness in path planning outcomes. Huang et al. [148] have introduced an algorithm that integrates an enhanced self-organizing map NN with a novel velocity synthesis technique for dynamic task allocation and path planning involving multiple autonomous underwater robots. Nevertheless, it is important to acknowledge that NN is not without limitations. Navigating through unstructured and complex environments poses a significant challenge for robots. Through NN, specific types of robots can acquire knowledge about optimal paths to traverse in such intricate terrains [149]. Chen et al. [150] introduced a motion planning approach based on Radial Basis Function (RBF) neural networks. This method guides AGV to extract drivable regions from perceptual grid maps in unstructured environments. The proposed approach yields flexible, smooth, and safe paths adaptable to various road shapes. In addressing the intricate problem of path planning for mobile robots in complex environments with arbitrary geometries, Zhao et al. [151] have introduced an innovative approach based on neural networks. Their method involves the discretization of the 2D workspace through the application of a biologically inspired neural network, thereby transforming it into a topological graph. Within this graph, environmental characteristics are dynamically encapsulated as neural activity-driven landscapes. This method exhibits versatility in its applicability to mobile robots of diverse morphologies and furnishes robust support for path planning amidst intricate environmental conditions. As neural network layers increase in depth, challenges such as non-convex optimization, the vanishing gradient phenomenon, and the risk of overfitting can emerge. To tackle the intricacies of motion planning in unfamiliar and dynamic environments, the application of Deep Learning (DL) and Reinforcement Learning (RL) techniques is recognized as a highly promising avenue [152].

DL utilizes multi-layer network structures and non-linear transformations to amalgamate low-level features into abstract, easily distinguishable high-level representations. This effectively uncovers distributed feature representations within data, endowing mobile robots with robust environmental perception capabilities. Wu et al. [153] proposed a robot path planning approach based on Deep Convolutional Neural Networks (DCNNs), which involves image acquisition, feature extraction using DCNNs, and determination of robot motion direction based on classification results. This allows robots to autonomously engage in path planning using image information, eliminating the need for manual feature extraction. Similarly, Zhang et al. [154] introduced an intelligent obstacle avoidance path planning method for mobile robots in dynamic environments. This technique employs DL to differentiate between static and dynamic obstacle types. It employs an enhanced ray tracing technique in a two-dimensional space to navigate around static obstacles and introduces novel waiting rules for dynamic obstacle avoidance. Building upon these foundational steps, path planning is accomplished using the RRT. Gao et al. [155] conducted experiments within a meticulously defined indoor environment. Deep reinforcement learning was harnessed to facilitate path planning for mobile robots operating within this indoor context. In order to augment system functionality and mitigate concerns pertaining to the reliability of Deep Reinforcement Learning (DRL) techniques, the researchers introduced a novel incremental training model in their experiments, conducted across both 2D and 3D environments.

Reinforcement Learning (RL) stands out from supervised learning by acquiring sample data during training, eliminating the need for extensive pre-existing data [156]. Scholars have recently been committed to elevating the performance of RL-based mobile robots through innovative methodologies such as Q-learning, Deep Q-Network (DQN), and DRL [157]. Yu et al. [156] merged neural networks with hierarchical RL to optimize algorithmic systems, resulting in reduced planning time and path steps while enhancing the robot's smoothness and motion capability. By fortifying the path planning system with neural networks, Wen and colleagues [158] empowered mobile robots to navigate to a target location without colliding with obstacles or other mobile robots. Lei et al. [159] identified the enhancement of the robot's dynamic obstacle avoidance and local planning abilities through the integration of Q-Learning into RL-based paths. Wang et al. [160] discovered that the Tree-Structured Dueling Double Deep Network exhibited advantages such as swift convergence and low loss when compared to distributed DQN algorithms. Taghavifar et al. [161] have developed and tested a path planning methodology for underactuated robots that incorporates a mobile/stationary obstacle avoidance approach. This approach integrates the Chaotic Element-inspired Heuristic Optimization technique with a Reinforcement Learning (RL) algorithm based on a single velocity estimator. Their study also factors in the impact of tire sinking on robot dynamics within deformable terrains and applies principles of Terramechanics to determine the optimal compensation forces and torques, ensuring stable and fluid motion. The utilization of RL techniques facilitates seamless navigation of mobile robots in dynamic obstacle-rich environments, as validated by Ruan et al. [162]. In a similar vein, Song et al. [163] employed an end-to-end deep RL algorithm to tackle the challenge of autonomous navigation for mobile robots in unfamiliar environments. Their approach combines the Dueling Deep Q-Network (Dueling DQN) with the Double Q-Learning (DDQN) technique to create the D3QN algorithm, which empowers robots to progressively learn their environment autonomously. This enables them to adapt and acquire the necessary skills to navigate to a target destination using an RGB-D camera within the environment.

For a more comprehensive overview of the advancements in DL and RL within the realm of path planning, a detailed review is available in references [164,165].

3.3.2. Fuzzy Logic Algorithm

The Fuzzy Logic (FL) algorithm, proposed by Zadeh in 1965, has been widely applied across various research and development domains, including data classification, decision-making, image processing, and pattern recognition [166]. Fuzzy logic algorithms play a pivotal role in enhancing adaptive path planning for mobile robots in the domains of navigation and path planning [167]. This process involves the application of fuzzy sets and fuzzy rules to input data to effectively handle fuzziness and nonlinear relationships. It encompasses the mapping of sensor data, such as distance and velocity, to fuzzy sets, followed by the utilization of a series of fuzzy rules to interpret these fuzzy inputs. Consequently, this process generates corresponding fuzzy outputs, detailing the navigation actions that the robot should undertake. These actions may include obstacle avoidance, deceleration, or steering, with each action accompanied by a membership degree reflecting its confidence level. Through this approach, fuzzy logic algorithms comprehensively account for environmental fuzziness and uncertainty, enabling robots to intelligently adapt to a diverse range of navigation scenarios and produce path planning solutions that are more contextually relevant and applicable. Raguraman et al. [168] employed an FL controller to assist mobile robots in indoor navigation. Selekwa et al. [169] designed a preference-based fuzzy behavior system, utilizing a multi-valued logic framework to govern robot motion in complex environments. Thus, FL algorithms have emerged as a potent strategy for navigating intricate scenarios, seamlessly integrating nuanced reasoning into path planning strategies. Pandey et al. [170] investigated the Adaptive Neuro-Fuzzy Inference System (ANFIS) controller for mobile robot navigation in unstructured environments. Dahhan et al. [171] introduced a novel approach utilizing two distinct Fuzzy Logic (FL) controllers to navigate around simple-shaped obstacles. Guo et al. [172] employing multi-sensor fusion techniques and the Denavitt–Hartenberg (D–H) parameters method, designed a fuzzy control-based stepwise optimal path planning approach for spherical mobile robots to explore unknown unstructured environments. Kumar et al. [173] have introduced a hybrid regression-fuzzy analysis approach designed to facilitate the seamless and unobstructed movement of multiple humanoid robots within complex terrains, effectively addressing a wide range of intricate scenarios. Meanwhile, Rath et al. [174] have pioneered intelligent fuzzy techniques tailored for the smooth and efficient navigation of humanoid robots amidst obstacle-rich environments. In a complementary vein, Muni et al. [175] have put forward an efficient motion planning strategy for multi-legged robots, applicable to both static and dynamic terrains, leveraging the power of Sugeno fuzzy analysis. Additionally, Pham et al. [176] have proposed a coordination methodology for multi-robot systems, rooted in the realm of fuzzy logic. The efficacy of their proposed model has been rigorously validated through extensive simulations conducted on a comprehensive platform.

Fuzzy Logic (FL) presents inherent limitations that must be addressed for effective integration in mobile robot path planning. These limitations encompass factors such as the reliance on expert knowledge for defining fuzzy inference rules, the intricacies of optimizing paths based on these rules, the potential expansion of rule sets with increasing obstacle complexity, and the adaptability of rules to changing environments. To overcome these challenges and enhance FL's performance, researchers often combine FL with other algorithms, resulting in innovative hybrid approaches. Zagradjanin et al. [177] devised a hybrid approach that combined the D* lite algorithm for global path planning and FL for local path planning. This integration was further extended to multi-robot coordination within complex environments. Kumar et al. [178] blended the krill herd optimization algorithm with a fuzzy logic controller to construct an intelligent controller for optimal path planning and control of mobile robots in uncertain environments. This controller was demonstrated for trajectory planning in both single and multi-robot scenarios. Song et al. [179] introduced fuzzy logic ant colony optimization, which dynamically seeks the optimal path for autonomous vehicles based on multiple criteria. The optimal path is determined by considering dynamic factors such as traffic flow, accident risk, and speed limits in a comprehensive manner. In the context of autonomous Unmanned Surface Vehicles (USVs), maneuvering in complex environments necessitates the application of multi-objective optimization and the imposition of multimodal constraints to effectively navigate dynamic surroundings and mobile obstacles. To address this challenge, Lyridis et al. [180] introduced an enhanced approach combining Ant Colony Optimization and Fuzzy Logic (ACO-FL) for addressing local path planning problems, while effectively mitigating disruptions by accounting for environmental variables such as wind, water currents, waves, and dynamic obstacles. In a similar vein, Azouaoui et al. [181] have leveraged a hybrid approach involving neural networks and fuzzy logic to enable efficient navigation of bidirectional maneuverable mobile robots. Additionally, Yahmedi et al. [182] has discussed the utility of fuzzy-based controllers for mobile robot navigation within complex terrains. Shi et al. [183] have proposed a three-dimensional fuzzy-based navigation model for mobile robots, rigorously testing this approach through simulations and experimental platforms. Lin et al. [184] introduced a dual-layer path planning methodology, leveraging artificial potential fields and the dynamic window approach. On the local path planning level, a fuzzy control scheme rooted in the Dynamic Window Approach (DWA) was utilized, effectively evaluating collision risk indices and relative distances associated with moving obstacles. This strategy notably enhanced the robot's responsiveness to dynamic obstacles. Sangeetha et al. [185] brought forth a dynamic ant colony optimization algorithm augmented with fuzzy gain principles for dynamic path planning. This innovative approach offered collision-free, smooth paths with advantageous characteristics, including optimized path lengths and minimized time consumption.

Further research on the application of Fuzzy Logic (FL) in the domain of path planning is comprehensively reviewed in references [186,187].

4. Multi-Agent Path Planning Algorithms

In comparison to SAPF, MAPF introduces a higher degree of complexity as it necessitates the consideration of collaborative interactions among multiple robots, ensuring their secure task completion. The extension of the problem from SAPF to MAPF introduces the concept of collaborative planning, thereby accentuating its inherent challenge. The resolution of MAPF problems typically necessitates the integration of appropriate path planning algorithms and conflict resolution strategies to cater to the path planning requirements. Presently, scholars both domestically and internationally have delved deeply into the realm of single-robot path planning, yielding a substantial body of research achievements. These advancements in the field of single-robot navigation have consequently laid a robust foundation for subsequent inquiries into Multi-Agent Path Finding (MAPF) technology. In recent years, the collaborative efforts of various planning algorithms, collision avoidance techniques, and multi-objective optimization studies have synergistically propelled progress in the MAPF domain. Categorized based on the problem in [188], MAPF can be classified into centralized and distributed paradigms, and the characteristics of the two types of methods are shown in Table 12.

Table 12. Comparison of MAPF Algorithms.

MAPF	Advantages	Disadvantages
Centralized	Centralized planner for all agents in static or small-scale environments, fast and high-quality.	As the number of agents and environmental complexity increase, replanning becomes time-consuming
Distributed	Independent actions based on current observations, scalable to large-scale environments, and real-time path replanning.	Slower planning and learning in small, static environments compared to centralized algorithms.

4.1. Centralized Planning

4.1.1. Problem Description

The study of Centralized Multi-Agent Path Finding (CMAPF) is closely aligned with domains such as Intelligent Unmanned Warehousing [189] and Intelligent Transportation [190]. This research not only encompasses the challenges of obstacle avoidance and optimal path selection for individual robots, but also delves into the intricacies arising from various motion conflicts that impact both the efficiency of multi-robot task execution and the success rate of path planning [191]. The escalation of motion conflicts among robots is directly correlated with the number of robots, and a larger scales of robotic presence correspondingly amplifying the algorithmic complexities within the solution space [192,193]. Based on the intricacy of the solution space, this study categorizes motion conflicts among robots into fundamental conflict types [194] and profound conflict types [191], as depicted in Figures 10 and 11, and Table 13.

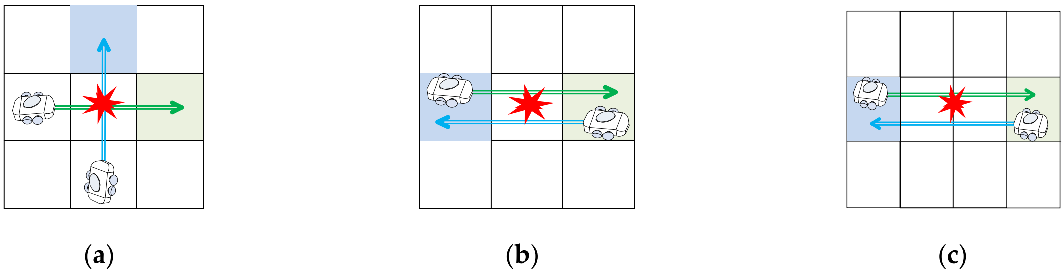


Figure 10. Basic Conflicts: (**a**) Node conflict Type_1; (**b**) Node conflict Type_2; (**c**) Alignment conflict.

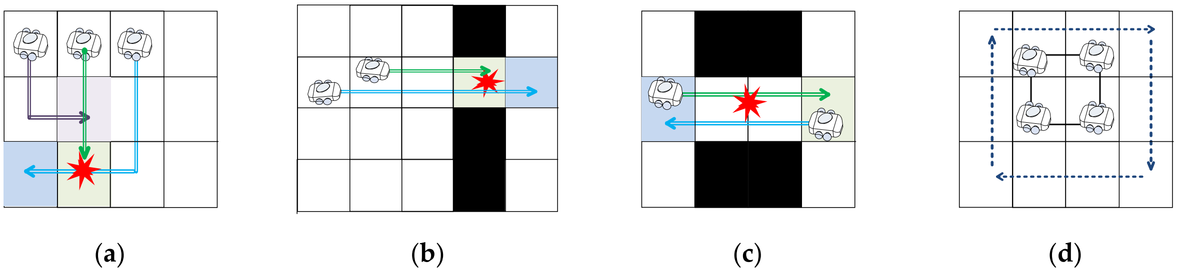


Figure 11. Deep Conflicts: (**a**) Placeholder conflict; (**b**) Target Conflict; (**c**) Blocking Conflict; (**d**) Cycle conflict.

Table 13. CMAPF conflict types.

Conflict Type		Recognition Methods	Constraints Type
Basic Conflicts	Node Conflict	Two robots occupy the same grid center at the same time step	Obstacle constraints
	Alignment Conflict	Two robots exchange positions within a time step	Obstacle constraints
Deep Conflicts	Placeholder conflict	Robot path step is larger than conflict time step and solution space exists	Length Constraints
	Target Conflict	The robot path step is much larger than the conflict time step.	Length constraints
	Blocking conflicts	When two or more robots try to pass through a narrow passage in opposite directions	Range Constraints
	Cycle conflict	When each robot moves to a vertex previously occupied by another robot, a "rotating loop" pattern is formed within the same time step.	Range Constraints

4.1.2. Solution

In addressing the challenges posed by motion conflicts, Huang et al. [194] proposed an improved Ant Colony Optimization (ACO) algorithm that relies on parameter optimization and vertex conflict resolution. They also devised strategies for conflict prediction and resolution, effectively mitigating vertex conflicts and enhancing the overall reliability of multi-agent systems. In a similar vein, Wen et al. [195] took into consideration various constraints and the distinctive motion characteristics present in robotic environments. They introduced the CL-MAPF (Multi-Agent Path Finding for Car-Like robots) algorithm, which was designed to reduce conflicts between robots' movements and enhance the efficiency of the algorithm. To further amplify the efficiency of resolving issues within CMAPF scenarios and to augment the success rate of planning, researchers in recent years have introduced approaches that are more finely attuned to the specific concerns of MAPF. Notably, techniques such as Priority Planning (PP) [196] and Conflict-Based Search (CBS) [191] have emerged, as comprehensively outlined in Section 5.1.

Among the various methods, the Priority Planning (PP) algorithm has gained substantial traction as a preferred approach among researchers. Cap et al. [196] introduced a class of multi-robot path planning algorithms based on Prioritized Planning (PP), along with several rules for determining priorities. Wang et al. [197] proposed a method that integrates priority assignment and path planning to achieve optimal execution cost and time for a group of robots. Li et al. [198] combined the D* Lite algorithm with priority rules for robot path planning, resulting in improved search efficiency and enhanced path quality. To enable efficient conflict-free path planning for robotic swarms in complex environments, Wu et al. [199] integrated priority rules into an enhanced heuristic algorithm. This approach eliminates trajectory conflicts among robots with varying movement capabilities, achieving a high success rate and a balanced trade-off between maximum completion time and working time objectives. Dewangan et al. [200] presented a distance-based priority method for multi-robot path planning, where lower-priority robots circumvent higher-priority ones when conflicts arise, thus preventing collisions. Zhang et al. [201] combined the CBS algorithm with priority rules to achieve multi-agent path conflict resolution. The core concept of these enhanced algorithms revolves around priority planning, aiming to assign a unique priority to each robot within a multi-robot system and subsequently plan paths for robots in descending priority order. Through this approach, the completion of tasks by higher-priority robots is prioritized, thereby enhancing the efficiency and performance of the entire system. Furthermore, the CBS algorithm based on conflict search has gained considerable attention in recent years due to its optimality and completeness. Liu et al. [188] conducted a comprehensive review of numerous research outcomes, a portion of which is cited in this paper, as illustrated in Table 14.

Table 14. Improved CBS.

Algorithm	Machines	Characteristics	Research
Lazy-CBS	Replaces the high-level solver of CBS with an inertly constructed constraint planning model that explores the conflict space using a core-guided depth-first search too and detects reusable branches along each branch.	Significantly improves the optimal MAPF problem under cost metrics	[202]
HCBS	Adds a heuristic function to the high-level search to better prune the constraint tree.	Ability to achieve better results with less computational cost	[203]
ECBS	Relaxing the optimal solution condition for the CBS runtime	Significant reduction in runtime	[204]
FECBS	Further reduce the number of conflicts that need to be resolved at high levels by using more relaxed suboptimal bounds for low-level search, while still providing bounded suboptimal solutions.	FECBS can solve more MAPF instances than ECBS within 5 min	[205]
ASB-ECBS	An adaptive intelligence-specific suboptimal bounds method, which can be executed statically or dynamically, allows suboptimal bounds to be assigned based on the requirements of individual intelligences.	Significantly improves the runtime while reducing the search space	[206]

4.2. Distributed Planning

4.2.1. Problem Description

Distributed Multi-Agent Path Finding (DMAPF) constitutes a critical challenge within the realm of multi-robot collaborative tasks, addressing the intricacies of autonomous robot task planning and cooperation. DMAPF decentralizes computational tasks and decision-making across individual robots, thereby diminishing the burden on central computation and mitigating communication overhead [207]. This paradigm splits the robot's motion navigation quandary into two distinct phases: the path planning stage, where each robot independently devises an optimal path; and the velocity planning stage, wherein each robot circumvents collisions with both obstacles and fellow robots. In the velocity planning phase, following the acquisition of conflict-free paths through SAPF algorithms during the path planning stage, real-time monitoring and identification of potential conflict types (as detailed in Table 11) become essential for implementing appropriate conflict resolution strategies. These strategies encompass determining conflict priorities [207], as well as coordinating actions through methods like communication [208] and path replanning [209].

Ma et al. [208] introduced a heuristic MAPF algorithm within a distributed framework, rooted in the classical A algorithm.* This methodology entails each robot crafting a localized path plan, which is then communicated to fellow robots through a structured communication protocol, thereby engendering a collaborative resolution to the multi-robot path planning predicament. Matoui et al. [209] harnessed a neighborhood-centered artificial potential field mechanism to chart paths for multiple robots, underpinned by a distributed architecture catering to the trajectory mapping needs of an assemblage of wheeled mobile robots. Each robot is mandated to both discern and circumvent collisions, be they from stationary or dynamic impediments in its operational sphere. Liu et al. [210] proposed an enriched ant colony algorithm tailored for multiple Unmanned Ground Vehicle (UGV) path planning. Through a continuous ant colony algorithm, a global path for each UGV is planned, and a multi-agent coordination strategy is meticulously fashioned via a velocity adjustment algorithm, preventing collisions between UGVs. Chen et al. [211] put forth a MAPF strategy couched within a deep reinforcement learning framework, harnessing the prowess of deep reinforcement learning to train a multi-agent decision-making model. This approach adeptly tackles the hurdles associated with suboptimal centralized planning efficiency and the complexities entailed in distributed planning. Contreras-Cruz et al. [212] proffered a multi-mobile robot distributed planning stratagem hinging on the principles of artificial bee colonies. This innovative approach navigates the logistical challenges posed by a multitude of robots, skillfully minimizing both the tally of conflicts among robots and the temporal duration of robot task execution.

4.2.2. Solution

Diverse Modes of Information Sharing in Distributed Multi-Robot Path Planning vary according to the scope and methodology of information exchange. These modes encompass localized information sharing, global information sharing, and hybrid information sharing, each tailored to distinct collaborative scenarios [198–207].

(1) In the context of localized information sharing, robots interact exclusively with their immediate neighbors. Amoolya et al. [213] and Lijina et al. [214] employed WiFi and Bluetooth technologies, respectively for localized information exchange. Liu et al. [215] proposed a decoupled multi-robot path planning technique, blending an enhanced ant colony algorithm and distributed navigation. Global paths are determined via Ant Colony Optimization (ACO), while local navigation relies on a "first-come, first-served" collision avoidance strategy. Chang et al. [216] addressed the challenge of unknown environments with static and dynamic obstacles, introducing a layered multi-robot navigation and formation approach driven by deep reinforcement learning and distributed optimization. This hierarchical framework empowers each robot to navigate to a global goal based on its local perception within the unfamiliar environment, resulting in optimal formations with minimal communication.

(2) In the context of global information sharing, all robots access global information to attain optimal solutions. Dong et al. [217] proposed a Collaborative Complete Coverage Path Planning (CCPP) algorithm for multiple agents in unknown environments. Causa et al. [218] devised a multi-UAV path planning algorithm catering to scenarios with heterogeneous global navigation satellite system coverage. Addressing the issue of unnecessary detours due to dynamic obstacle avoidance through re-planning, Wang et al. [219] introduced the Globally Guided Reinforcement Learning (G2RL) method, addressing multi-robot path planning in a fully distributed reactive manner.

(3) Hybrid information sharing involves establishing local information sharing regions around each robot, interconnected to form a global information sharing network. Each robot considers neighbor information while also accessing global data to attain an optimal global solution. To address dynamic multi-robot path planning [220,221], an adaptive hybrid algorithm was introduced. This algorithm ensures safety in unknown

dynamic environments through dynamic obstacle avoidance rules and enables collaborative obstacle avoidance within the motion conflict range using proposed priority obstacle avoidance rules. Fan et al. [222] introduced a method utilizing Received Signal Strength Indicator (RSSI) to gauge distributed robot motion conflicts. In case of a conflict, one robot proceeds, and upon reaching an RSSI threshold or designated avoidance wait-time, the other robot navigates.

The advantages and disadvantages of the above three information sharing methods are shown in Section 5.1, and the selection of information sharing methods needs to consider specific application scenarios and needs.

5. Conclusions and Prospects

5.1. Conclusions

Path planning remains a central concern in the field of robotics [223], and in Table 15, we undertake a comparative analysis to elucidate the distinctions and commonalities between this paper and other review articles, based on this we obtained the analysis in Figure 12. This paper distinguishes itself with its contemporaneity, as it incorporates recent literature for 60.9% and 86.6% of the 254 sources within the last 5 and 10 years, respectively. As a result, it encompasses the latest trends. In contrast to other works, this paper comprehensively covers both Single-Agent Path Finding (SAPF) and Multi-Agent Path Finding (MAPF), thereby indicating a broader research scope. Furthermore, this paper provides an exhaustive description of the path planning environment and path metrics, facilitating a deep understanding of the context and the criteria employed for evaluation. Most significantly, this paper engages in a thorough discussion regarding the utilization of both conventional and artificial intelligence methodologies in path planning, rendering it more comprehensive in its approach. In summary, this paper appears to be well-positioned within the realm of path planning reviews, offering readers an extensive research scope and a wealth of detailed information.

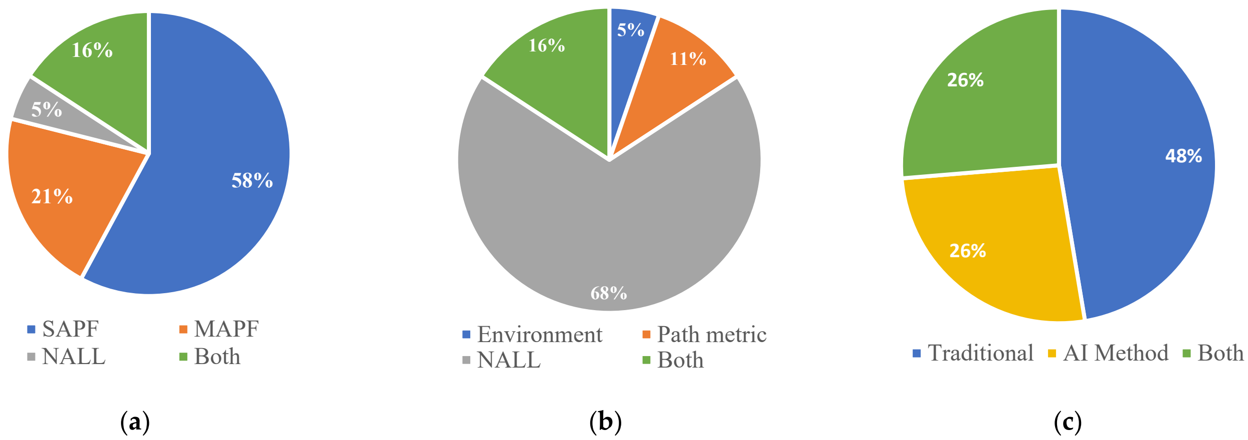


Figure 12. Comparison of research themes: (**a**) Subject; (**b**) Description; (**c**) Algorithm.

Table 15. Topics of the papers reviewed.

Paper	Year	SAPF	MAPF	Environment Description	Path Metrics Description	Traditional Methods	AI Methods
[1]	2023	Y	N	Y	Y	Y	Y
[3]	2021	Y	N	N	Y	Y	Y
[35]	2019	N	Y	Y	Y	Y	N
[48]	2016	Y	N	N	Y	Y	N
[49]	2020	Y	N	Y	Y	Y	N
[108]	2020	Y	N	N	N	Y	N
[147]	2020	-				N	Y
[164]	2021	Y	N	N	N	N	Y
[165]	2021	N	Y	N	N	N	Y
[166]	2022	Y	Y	N	N	Y	N
[186]	2023	Y	N	N	N	N	Y
[187]	2010	Y	N	N	N	N	Y
[188]	2022	N	Y	N	N	Y	N
[224]	2019	Y	Y	N	N	Y	Y
[225]	2013	Y	Y	N	N	Y	N
[226]	2023	Y	N	N	N	Y	N
[227]	2022	N	Y	N	N	Y	Y
[228]	2023	Y	N	N	N	Y	N
[229]	2023	Y	N	Y	N	Y	Y
Ours	2023	Y	Y	Y	Y	Y	Y

Here Y stands for "Yes", N stands for "No" and "-" stands unknown.

This paper presents a comprehensive survey of techniques for mobile robot path planning. To begin, eight map modeling methods are introduced, varying based on the level of environmental abstraction that robots perceive. Open-source map scenarios suitable for both Single-Agent Path Finding (SAPF) and Multi-Agent Path Finding (MAPF) scenarios are provided, accompanied by an analysis of commonly used performance metrics. Subsequently, SAPF algorithms are categorized into three groups, each characterized by its distinctive features: classical algorithms, bio-inspired algorithms, and artificial intelligence algorithms. Within the classical algorithm category, graph search, random sampling, and potential field-based algorithms are elaborated upon. The bio-inspired algorithms section covers ant colony optimization, particle swarm optimization, and genetic algorithms. Additionally, the section on artificial intelligence algorithms encompasses discussions on neural network algorithms and fuzzy logic algorithms. Moreover, the discussion extends to distinct MAPF planning approaches, delineating between centralized planning that prioritizes conflict decoupling and distributed planning that emphasizes efficient task execution. For a comprehensive comparison, Tables 16 and 17 provide an in-depth analysis of the pros and cons of commonly utilized optimization algorithms in SAPF and MAPF contexts. It is evident that, while addressing path planning challenges, a diverse array of conventional algorithms remains prevalent in mainstream applications. Nevertheless, in recent years, artificial intelligence algorithms have garnered increasing attention owing to their advanced environmental perception capabilities and heightened operational adaptability.

Table 16. SAPF common algorithm comparison.

SAPF	Category	Typical	Mechanisms	Advantages	Disadvantages	Improvements	
						Methods	**Results**
Classical Class Algorithms	Graph Search Algorithms	A*	Heuristic Search Based on Improved Dijkstra	Completeness and rapidity	May be limited by state space expansion in complex environments	Weights A*	[53,58]
						Adaptive A*	[54,58]
						Theta*	[55,59]
						Lazy-Theta*	[60]
						JPS	[56]
		LPA*	Incremental Heuristic Search Based on Improved A*	Dynamically updated path planning for dynamic environments	Requires local updates and global fixes, with some delay in response to environmental changes	TLPA*	[64]
						TD* Lite	[64]
		D*		Real-time update path planning for unknown and dynamic environments	Path oscillations and frequent replanning may exist	D* Lite	[63]
						MOD* Lite	[65]
						MOPBD*	[66]
	Randomized Sampling Algorithm	RRT	Randomized Sampling Search	Applicable to high-dimensional spaces and discontinuous problems	Limitations in solving globally optimal paths.	RRT-Connect	[68,73]
						RRT*	[69,74,76]
						RRT*-Smart	[70,77]
						RRT*-Connect	[71,78]
						Informed RRT*-connect	[72]
		PRM	Sampling and connecting paths	Applicable to high-dimensional spaces and discontinuous problems	The distribution of sampling points and connection strategies may affect the quality of path planning.	PRM*	[80]
						Lazy PRM	[81]
						HPPRM	[83]
						Fuzzy-PRM	[84]
						PRM-D*	[82]
	potential field algorithm	APF	Modeling of interaction forces between objects	Fast calculations and real-time updates	May fall into local minima, unable to pass through narrow passages, more sensitive to parameter selection and adjustment	Optimization of gravitational and repulsive structures	[86] [87]
						Integrated algorithms	[88] [89] [90]

Table 16. *Cont.*

SAPF	Category	Typical	Mechanisms	Advantages	Disadvantages	Improvements: Methods	Improvements: Results
		EBA	Path planning based on elastic band modeling	Adaptable to dynamic environments and obstacle avoidance	Parameter selection and tuning is more sensitive and may be less responsive to environmental changes	Considers time and dynamic constraints	[94,95]
						Integrated algorithms	[96]
		VFH	Construct vector fields and histograms of the environment	Suitable for complex environments and dynamic changes	May have computational complexity issues in high dimensional spaces and large-scale environments	VFH+	[98]
						VFH*	[99]
						Integrated algorithms	[100,101] [102]
Intelligent Optimization Class Algorithms	Evolutionary Algorithms	GA	Modeling the Process of Biological Heredity	Global search capability and maintenance of diversity	Poor localized search capability; genetic factors are difficult to determine; chromosome coding method affects the solution	Improving individual quality, avoiding local optimal solutions, and improving poor population diversity	[136–138]
						Multi-objective GA MOGA	[139–141]
						Multi-objective GA NSGA-II	[39,141]
						Multi-objective GA NSGA-III	[40,143]
						Integrated algorithms	[144–146]
		EA	Simulating the process of biological evolution	Suitable for global optimization and multi-objective optimization problems.	Search efficiency may be limited in complex environments and high-dimensional spaces	Evolutionary Strategies	[230]
						Differential Evolutionary Algorithms	[231,232]
						Multi-objective evolutionary algorithms	[233]
						Heuristic Evolutionary Algorithms	[234]
						Integrated algorithms	[234,235]

Table 16. *Cont.*

SAPF	Category	Typical	Mechanisms	Advantages	Disadvantages	Improvements	
						Methods	**Results**
	Group Intelligence Algorithms	ACO	Simulating the foraging behavior of ants	Fast convergence at the backend, memorable	Longer search time in the early stage; many parameters and difficult to set up	Structure, parameter selection and pheromones of optimization algorithms	[104–106]
						Multi-objective ACO	[43,107]
						Multi-cluster ACO	[109–113]
						Integrated algorithms	[114–116]
		PSO	Simulating the movement of particles in search space and sharing information	Few parameters; fast convergence in the early stage; memorability	Need to choose appropriate parameters and neighborhood search strategy	Parameter optimization	[118–123]
						Increasing population diversity and avoiding local optimization	[124–127]
						Multi-objective PSO	[42,128–130]
						Integrated algorithms	[131–133]
	Bionic Algorithms	Artificial Immune Algorithm (AIA)	Simulated antibody and immune memory mechanisms of the immune system	Global search and diversity maintenance	The choice of parameters and the design of immunization mechanism may affect the performance of the algorithm	Optimization algorithms for operations such as selection, mutation and cloning	[236,237]
						Multi-objective AIA	[238,239]
						Integrated algorithms	[240,241]
		Artificial Fish Swarming Algorithm (AFSA)	Simulated the process of fish feeding and migration	Global search and group collaboration	Sensitive to parameter selection and tuning, the effectiveness of the algorithm is affected by the problem characteristics and environment	Adjustment of the behavioral capacity of the fish	[242,243]
						Improve convergence and optimization	[244]
						Integrated algorithms	[245,246]
Artificial Intelligence-like Algorithms	Neural Networks		Simulation of connections between neurons and activation functions for information processing	Strong learning ability to adapt to complex non-linear relationships	Requires a large amount of data for training, long training time, poor model interpretation	Self-organizing mapping NN	[148–151]
	Deep Learning		Multi-layer neural networks for feature extraction and learning	Strong characterization ability, can automatically learn features and apply to large-scale data	Complex training process, requires large number of computational resources and data, may have overfitting problems	Deep Convolutional Neural Networks	[153,155,158]
						Integrated algorithms	[154,156]

Table 16. *Cont.*

SAPF	Category	Typical	Mechanisms	Advantages	Disadvantages	Improvements	
						Methods	Results
	Reinforcement Learning		Learning behavioral strategies through trial and error and reward mechanisms	Can learn and make decisions autonomously in unsupervised environments with high adaptability	Requires a large amount of training time and number of interactions, low exploration efficiency, high requirements for environment modeling and reward design	Q-learning	[159,163]
						DQN	[160,163]
						DRL	[155,157,163]
						Other	[161,164,165]
	Fuzzy Logic		Fuzzy sets and fuzzy rule inference	Capable of handling uncertainty and ambiguity information, applicable to complex fuzzy environments	The design of knowledge representation and inference rules is complex and requires a lot of domain expert knowledge.	Solving Robot Uncertainty Navigation Problems	[167–187]

Table 17. Comparison of Common Algorithms of MAPF.

MAPF		Characteristics	Advantages	Disadvantages	Results
CMAPF	PP	The Prioritized Planning (PP) algorithm adopts a priority-based method to harmonize the actions of multiple robots, effectively addressing the challenge of waiting indefinitely for other robots to conclude tasks.	1. High Coordination: Effective Coordination Among Multiple Robots, Conflict Prevention; 2. High Temporal Efficiency: Multi-robot prioritized path planning minimizes waiting times and path lengths.	1. Dependency on Priority Settings: Inaccurate priority settings can lead to uneven resource allocation and inefficient path planning; 2. Local Optima Traps: multi-robot priority path planning algorithms may get stuck in local optima.	[196–201]
	CBS	The Conflict-Based Search (CBS) algorithm stands as a conflict-detection-centered path planning strategy, tackling the intricacies of multi-robot path planning by identifying conflicts among the trajectories of robots.	1. Efficiency: The algorithms can utilize local information for more efficient search operations, reducing the reliance on global searches; 2. Flexibility: These algorithms can handle a wide range of constraints and are adaptable to different agents and environments.	1. Conflict Handling Overhead: Addressing conflicts requires multiple iterations of conflict detection and resolution, introducing computational overhead; 2. Local Optima Traps: Durning path navigation, relying on local information may lead to becoming trapped in local optima due to limited perspective.	[201–206]

Table 17. *Cont.*

MAPF		Characteristics	Advantages	Disadvantages	Results
	M*	The Market-Based Multi-Robot Path Planning (M*) algorithm introduces a market-driven mechanism to multi-robot path planning. It employs a trading framework to orchestrate both task allocation and path planning among a cohort of robots.	1. Strong Coordination: The M* algorithm facilitates coordination and resource allocation among robots in shared environments through market-based negotiation. 2. Strong Adaptability: The M* algorithm is equipped to handle dynamic environments and changing task requirements adeptly.	1. Computational Complexity: The market negotiation process involves robot competition and negotiation, requiring intricate computations and decision-making. 2. Potential Resource Wastage: Certain robots might face competition failure or be assigned suboptimal paths, leading to resource underutilization.	[247–249]
	IA*	The Improved A* (IA*) algorithm treats the path planning for individual robots as distinct endeavors. Each robot autonomously employs the A* algorithm for charting its path.	1. Swift Efficiency: The algorithm efficiently leverage heuristic information to swiftly guide the search process. 2. Comprehensive Completeness: Even in complex maps and intricate constraint scenarios, the algorithm deliver path planning solutions comprehensively.	1. Constraints in Multi-Robot Scenarios: This approach might be better suited for single robot path planning due to the intricate constraints introduced by coordinating multiple robots. 2. Selection of Heuristic Functions: The effectiveness of heuristic functions heavily relies on their careful selection and thoughtful design.	[250,251]
	MRC	The Multi-Robot Coordination (MRC) algorithm functions on the premise of cooperative coordination, forming the basis for multi-robot path planning. It segments robots into discrete teams, with each team collectively devising paths for its members.	1. Robust Collaboration: The algorithm excel in fostering collaboration among multiple robots, facilitating seamless teamwork. 2. Optimal Resource Utilization: Through orchestrating robot actions and task assignments, the algorithm achieve optimal resource allocation and utilization, ultimately enhancing overall efficiency.	1. Increased Decision Complexity: As the environment and task parameters become more complex, the complexity of decision-making also increases. 2. Challenges in Algorithm Design: Crafting and refining algorithms entail addressing a range of problem configurations and task demands, which magnifies the intricacies involved in algorithmic development.	[252–254]
DMAPF	Local Informing Sharing	Robots share path planning-relevant information that they observe only with other robots within a specific range while executing tasks.	Low computational complexity; high system robustness.	Global optimal solution is difficult to guarantee; high probability of robot conflict.	[208,213–216]
	Global Informing Sharing	All robots in the robot team share information they observe, including maps, sensor data, target locations, etc., in a global scope through communication and coordination.	Global optimal solution can be obtained; robot motion conflicts can be avoided as much as possible.	High computational complexity; poor robustness.	[210–212,217,219]
	Hybrid Informing Sharing	The approach involves integrating both localized and global information for collaborative path planning and decision-making.	Local and global information are utilized at the same time, and a better path planning scheme can be obtained.	Difficult to realize; requires more communication and computational resources.	[209,220–222]

5.2. Prospects

As the field of computer science continues to advance, mobile robots are finding widespread applications in industries such as manufacturing, agriculture, and services. This growing utilization underscores the necessity for mobile robot systems to exhibit robust real-time capabilities. Consequently, in the context of future path planning technologies, in addition to the pursuit of novel path planning algorithms, several key areas merit attention:

(1) Perception and environmental modeling: In light of the ongoing evolution of sensor technology, upcoming developments should optimally harness sophisticated perception tools such as LiDAR, cameras, and depth sensors. Furthermore, the integration of diverse perception techniques, including deep learning and computer vision, should be a focal point, enhancing a robot's understanding and perception of its surroundings.

(2) Adaptability and learning capabilities: Upcoming advancements should prioritize the adaptability and learning capabilities of SAPF algorithms and MAPF algorithms, empowering them to autonomously adjust strategies in response to changing environments and task requirements. Techniques such as machine learning and deep reinforcement learning can be harnessed to imbue robots with the ability to make independent motion decisions through interactions with their surroundings, such as highly dynamic environments and non-flat terrain. This, in turn, will bolster system robustness and adaptability.

(3) Multi-modal path planning technology: Future path planning technologies should consider the multi-modal behavior of robots and the possibility of multiple path choices, including different motion modes, travel speeds, and planning objectives. By integrating the physical characteristics of robots and task requirements, more flexible and efficient path planning can be achieved. This is especially important for multi-agent systems, where the extension to multi-modal and multi-objective MAPF may be necessary to better meet practical needs.

(4) Multi-robot collaborative path planning technology: In complex scenarios, the cooperative efforts of multiple mobile robots may be required to collectively fulfill tasks. In this regard, future innovations should emphasize collaborative decision-making mechanisms and effective information-sharing paradigms among multiple robots. This will yield heightened efficiency and safety, with applications in fields like factory automation and logistics.

(5) Challenges in large-scale scenarios: As the field of automation continues to expand, including areas such as logistics management and autonomous driving, both SAPF and MAPF are required to address increasingly larger-scale scenarios. Consequently, the future challenges will revolve around finding solutions for these large-scale problems.

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