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A Comprehensive Overview of Classical and Modern Route Planning Algorithms for Self-Driving Mobile Robots

N. S. Abu [1], W. M. Bukhari [2*], M. H. Adli [2], S. N. Omar [3], S. A. Sohaimeh [4]
[1, 2*, 3, 4] Fakulti Kejuruteraan Elektrik, Universiti Teknikal Malaysia Melaka, Malaysia
[2] Memory Test Department, ASE Electronics Sdn. Bhd., Pulau Pinang, Malaysia
Email: [1] nursyuhadahabu0805@gmail.com, [2*] bukhari@utem.edu.my, [2] hakimizauti@gmail.com, [3] snashayu@gmail.com, [4] shahirulsohaimeh@gmail.com
*Corresponding Author

Abstract— **Mobile robots are increasingly being applied in a variety of sectors, including agricultural, firefighting, and search and rescue operations. Robotics and autonomous technology research and development have played a major role in making this possible. Before a robot can reliably and effectively navigate a space without human aid, there are still several challenges to be addressed. When planning a path to its destination, the robot should be able to gather information from its surroundings and take the appropriate actions to avoid colliding with obstacles along the way. The following review analyses and compares 200 articles from two databases, Scopus and IEEE Xplore, and selects 60 articles as references from those articles. This evaluation focuses mostly on the accuracy of the different path-planning algorithms. Common collision-free path planning methodologies are examined in this paper, including classical or traditional and modern intelligence techniques, as well as both global and local approaches, in static and dynamic environments. Classical or traditional methods, such as Roadmaps (Visibility Graph and Voronoi Diagram), Potential Fields, and Cell Decomposition, and modern methodologies such as heuristic-based (Dijkstra Method, A* Algorithms, and D* Algorithms), metaheuristics algorithms (such as PSO, Bat Algorithm, ACO, and Genetic Algorithm), and neural systems such as fuzzy neural networks or fuzzy logic (FL) and Artificial Neural Networks (ANN) are described in this report. In this study, we outline the ideas, benefits, and downsides of modeling and path-searching technologies for a mobile robot.**

Keywords—Path Planning Algorithms; Autonomous Mobile Robot; Collision-Free Path Planning; Classic Navigation Approaches; Modern Path Planning Techniques.

I. INTRODUCTION

A wide range of autonomous tasks has been accomplished by mobile robots in a variety of industries and situations throughout the last several decades [1]. In order for robots to be able to travel and explore freely in complicated situations, collision-free route planning must be addressed. Since the mid-1960s, a number of researchers have been interested in route planning [1]. The following is a description of the route planning issue: The robot is programmed to do a certain task based on specified performance metrics and the nature of its activity, an autonomous mobile robot (AMR) travels from one state to the next, to determine if there is an optimal or suboptimal route there [2]. Time and money may be saved by using mobile robots equipped with advanced route-planning technologies. As a result of its practical importance, mobile robot route planning has grown to be a popular study issue both at home and abroad.

The ability to navigate through a given environment is considered to be one of the most desirable characteristics of autonomous robots [2]. This capacity to shift and complete tasks in a wide range of surroundings is critical to the large percentage of robot-enabled industries, including mining and agriculture, today [3]. In the field of mobile robot research, route planning is a major emphasis [4]. Localization, path planning, perception, and motion control are the four integral parts of the navigation problem [5]. In a real-world situation, planning a collision-free route through an alternatively cluttered environment is the goal of path planning. In other words, path planning is a method for an autonomous robot to get from the beginning point to the goal while traversing an environment that includes both static and dynamic obstacles [6]. The robot must be able to figure out the best way to get there in the shortest amount of time, distance, and money. It is possible to divide path planning into global and local planning, depending on the scope of the map [7]. Global path planning provides all the necessary data about the robot's known environment, while local path planning relies on partially or completely zero knowledge of the robot's environment to plan its course.

The autonomous mobile platform must provide answers to a slew of issues [8]. The first question is: where am I? Secondly, what are the following steps, what goals should I set, and how should I go about achieving them? As part of a conventional self-driving car control architecture, a vehicle takes in its surroundings, anticipates what other drivers will do, and makes a decision. Actuators are also controlled. They are called the "perception module," and are made up of sensors in the body of the car. LiDARs, Cameras, GPS, RADARs, Ultrasonic and Infrared sensors, and algorithms that combine them, work together to figure out what is around the car[8].

When it comes to laying out a route, there are three types: traditional algorithms, bionic algorithms, and reinforcement-based path planning algorithms [9]. Campbell et al. classified path planning into the classical and heuristic approach [2]. Next, [1] proposed traditional and heuristic approaches to route planning. In addition, traditional and modern intelligent algorithms path strategizing are two types of path planning algorithms that were also proposed [6]. Heuristic search algorithms and intelligent optimization algorithms are the solutions that appeared in dealing with motion planning problems [1]. Obstacle fields and vehicle motion limits must be taken into consideration while searching for a vehicle's best route. Potential-field methods [10], discrete optimization methods, grid-based approaches, and sample-based approaches are the most common approaches to route planning research.

Fig. 1 depicts the various AMR route planning approaches. Next, as shown in Table I, a number of methods were used in research on mobile robot navigation.

Collision-free route planning is covered in Section II including a summary of both local and global approaches. In Section III, searching algorithms for both traditional and modern approaches will be discussed. The Cell Decomposition Technique, Potential Fields, and Roadmaps are examples of traditional methods in motion planning, which will be discussed in Section III. A), whereas Heuristic Methodologies (Dijkstra, A*, D*), Metaheuristic Algorithms (GA, PSO, ACO, BA), and Neural Systems/Fuzzy Controllers (ANN, FL/FLC/FNN) are examples of modern and intelligent methods; Section III. B) will address these issues. Section IV illustrates the specifics of algorithms that have been implemented in a variety of publications. Section V goes into further detail on the research effort and methodologies. This review analyses 200 articles from two databases, Scopus and IEEE Xplore. Only 60 articles were selected as references from those articles, from 2019 until 2022. The conclusion of the research is presented in Section VI.

The common route planning methods covered in this review study were organized in a classification diagram as shown in Fig. 1. The techniques that were chosen will be discussed in further depth in the next section.

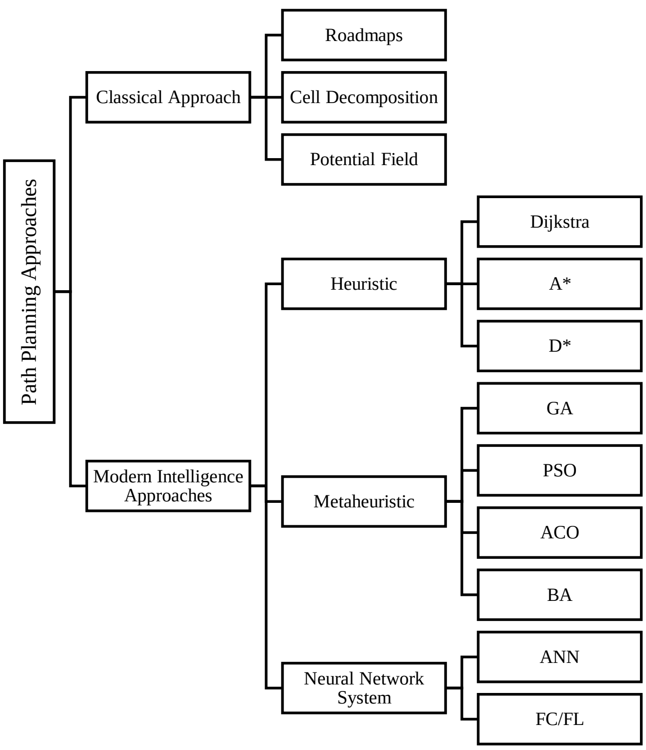

Fig. 1. Classification of Path Planning Approaches

TABLE I. DETAILS OF AUTHORS AND JOURNALS INVOLVED IN PATH PLANNING

Y. O. P	Authors	Title	Algorithms
2019	Jeon, G. Y., & Jung, J. W.	Water Sink Model for Robot Motion Planning	Potential Field (main), Voronoi Diagram, CD, Visibility Graph Bug Algorithm
2019	Li, D. Du,, P., Wang, & L.	Path Planning Technologies for Autonomous Underwater Vehicles-A Review	Dijkstra, A*, D* D* Lite, FM, LSM, Boustrophedon, ISA, PRM, RRT, APF, BA, PSO, ACO, WPA, SA, GA, DE, Others
2021	Tan, C. S., Arshad, R., M. R., & Mohd-Mokhtar	A Comprehensive Review of Coverage Path Planning in Robotics Using Classical and Heuristic Algorithms	STC, APF, DP, PRM, RRT, RHNBV, RHNBV-FE, DFS, BFS, Dijkstra, A*, D*, D* Lite, Theta*, Lazy Theta*, GA, DE, PSO, ACO, FFO, GWO, IWO, BINN, GBNN
2020	Abaas, Shabeeb, A. H., & T. F.	Autonomous Mobile Robot Navigation Based on PSO Algorithm with Inertia Weight Variants for Optimal Path Planning	TV-IWPSO (main), S-PSO, B-PSO
2020	Agwogie, U.	Mobile Robot Path Planning in an Obstacle-free Static Environment using Multiple Optimization Algorithms	FFO (main), ACO, PSO
2020	Campbell, S., Riordan, D., Walsh, J., Krpalkova, L., O'Mahony, N., & Carvalho, A.	Path Planning Techniques for Mobile Robots A Review	Roadmap, PF, CD, Bug Algorithms, VFH, ANN, GA, FL, PSO
2019	Patle, B. K., Pandey, A., Babu L, G., Jagadeesh, A., & Parhi, D. R. K..	A review: On path planning strategies for navigation of mobile robot	CD, Roadmap, APF, GA, FL, NN, FFO, PSO, ACO, BFO, ABC, CS, SFLA, Others
2020	Deogyang-gu.	A Performance Review of Collision-Free Path Planning Algorithms	GA, SA, PSO, ACO, Dijkstra, A*, Wavefront

II. COLLISION-FREE ROUTE PLANNING (CFRP)

The purpose of the collision-free route planning (CFRP) or collision-free path planning (CFPP) issue is to assist robots in finding a safe route from a beginning point to an ending (goal) location without colliding with anything. Certain researchers believe that the route taken as a consequence of the CFRP issue is an effective bypass for mobile agents (MAs). The efficiency of MAs is examined from this vantage point since it is the shortest distance. Multi-objective models, such as minimizing resource usage with shorter distances or finding an efficient solution in less time may also be used to investigate this issue. To determine the problem type, four separate qualities are required: the environmental type, the environmental class, the searching algorithm, and the experimental type. In addition, related studies that focus on and enhance at least one point of any one of these qualities are required in order to characterize the kind of issue being addressed. Fig. 2 depicts the categories in more detail, as well as their subcategories.

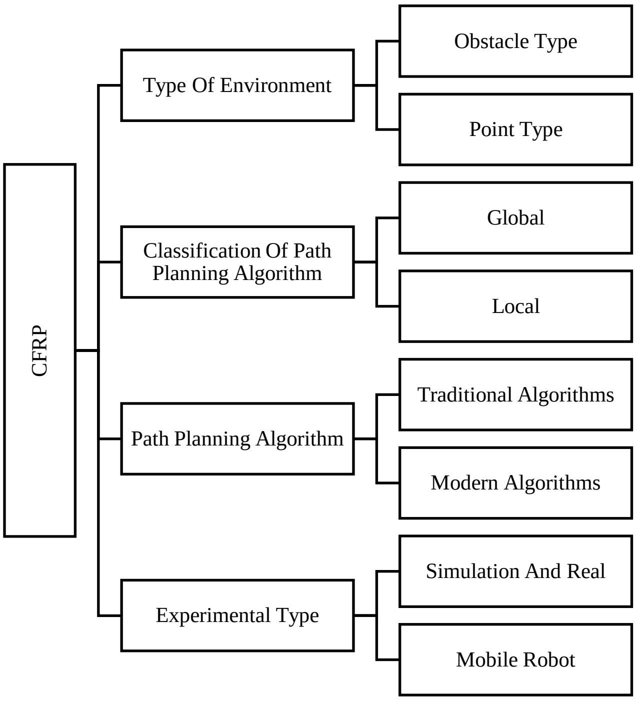

Fig. 2. Characteristics of CFRP

This article uses shorthand notation in order to present information as effectively as possible. Table II shows how the notation is arranged, in order of their appearance in this article.

A. *Path Planning Environments*

When it comes to path planning, there are two types of environments: environmental point type (E.P.T.) and environmental obstacle type (E.O.T.) [11]. There are two main categories of obstacles; static route planning and dynamic path planning [12]. Examples of static and dynamic obstacle types are shown in Fig. 3 and Fig. 4.

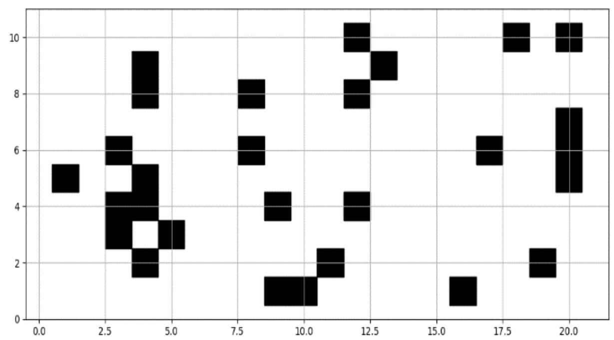

Fig. 3. Static Obstacle

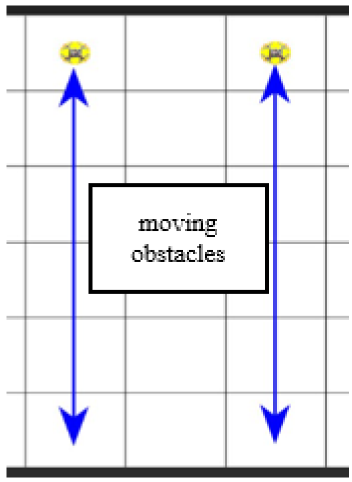

Fig. 4. Dynamic Obstacles [13]

TABLE II. ABBREVIATED NOTATION OF CFRP FOR MOBILE ROBOT

Words	Notation
Collision-Free Route Planning	CFRP
Collision-Free Path Planning	CFPP
Mobile Agents	MAs
Environmental Point Type	E.P.T.
Environmental Obstacles Type	E.O.T.
Cell Decomposition	CD
Particle Swarm Optimization	PSO
Artificial Potential Field	APF
Potential Field	PF
Ant Colony Optimization	ACO
Genetic Algorithm	GA
Bat Algorithm	BA
Fuzzy Logic	FL
Fuzzy Logic Controller	FLC
Artificial Neural Network	ANN
Year of Publications	Y.O.P
Radio Detection and Ranging	RADAR
Global Positioning System	GPS
Light Detection and Ranging	LiDAR
Institute of Electrical and Electronic Engineers	IEEE
Length of Path	LP
Types of Path Planning	T.O.P.P
Fast Marching	FM
Level Set Method	LSM
Internal Spiral Algorithm	ISA
Probabilistic Roadmap Method	PRM
Rapidly-Exploring Random Trees	RRT
Wolf Pack Algorithm	WPA
Simulated Annealing	SA
Differential Evolution	DE
Dynamic Programming	DP
Spanning Tree Coverage	STC
Receding Horizon Next Best View	RHNBV
Combine RHNBV with Frontier-Based	RHNBV-FE
Depth-First Search	DFS
Breadth First Search	BFS
Firefly Optimization	FFO
Grey Wolf Optimizer	GWO
Invasive Weed Optimization	IWO
Biologically Neural Network	BINN
Glasius Bio-Inspired	GBNN
Autonomous Mobile Robot	AMR
Figure	Fig.

The simplified notations that are used in this work are shown in the Table II. As a result, researchers will have a better understanding of each subject and area.

The static obstacle environment, also known as the fixed obstacle environment, is the CFRP problem's most basic variant. In this example, there are no changes to the barriers' form or location. The CFRP issue in a static setting is the CFPP's simplest model. As a result, a static environment assumption is often used in research articles [14]. Allowing the robot to compute its own setup sequence would allow it to broaden its applications and accomplish more than one activity in a fixed area [15]. This would allow the robot to be more versatile.

The dynamic obstacle environment, which is also known as the moving obstacle, has the ability to alter the obstacle's form over time. Mobile agents' velocity and acceleration are examined in this scenario. Table III depicts a more detailed illustration of the nature of the different types of obstacles environments in navigation [2].

TABLE III. NATURE OF OBSTACLE ENVIRONMENTS IN PATH PLANNING

Nature of Obstacle Environments in Path Planning	**Static Environments**	Obstacles do not move or shift their positions over time. (fixed)
	Dynamic Environments	Obstacles shift their positions as time progresses. (not fixed)

Next, in E.P.T., a point's classification is based on its certainty. Because of the inherent ambiguity in the MA's sensing, the point type should be presumed to be either definite or uncertain. MAs' positions and objective points are assumed to be in a precise place. Because of the difficulty of solving an unknown issue, the assumption is often used to evaluate innovative ideas using simulation. When the location of the MA's point and the location of the objective point is not known precisely, the uncertain point type is used. MAs employ a variety of sensors to detect their surroundings. MAs must be aware of the possibility of sensor mistakes in a hazy environment. In order to solve the issue, this problem has to be taken into consideration. This is one of the reasons why it is difficult to tackle CFPP problems with genuine MAs. The Monte-Carlo approach, for example, is implemented to solve the issue. Table IV classified authors based on the Environment of Obstacle Types addressed in their respective papers.

Based on Table IV, we can conclude that some authors applied different obstacle types of environments in their journals and projects. These differences are based on personal goals or targets and the objectives of one's research.

B. *Classification of Path Planning*

As in all circumstances, a global planner (which knows about the surrounding environment) and a local planner (which recalculates the route to avoid dynamic barriers) are used to identify the best path [16]. Fig. 5 illustrates the types of route planning.

TABLE IV. CLASSIFICATION OF ARTICLES BASED ON OBSTACLES TYPE OF ENVIRONMENTS

Author(s)	Y. O. P	Title(s)	Pages	E. O. T
Agwogie, U.	2020	Mobile Robot Path Planning in an Obstacle-free Static Environment using Multiple Optimization Algorithms	9	Static
Humaidi, A. J.	2020	Grid-Based Mobile Robot Path Planning Using Aging-Based Ant Colony Optimization Algorithm in Static and Dynamic Environments	26	Static Dynamic

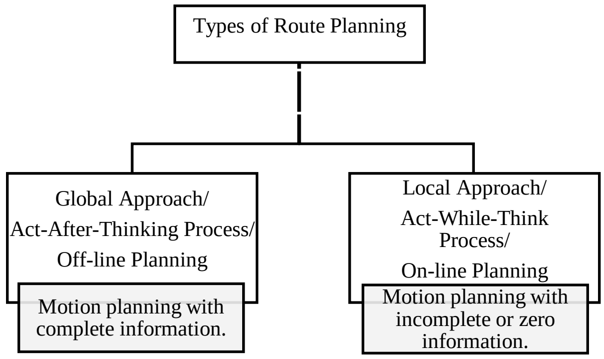

Fig. 5. Types of Route Planning

Route planning is separated into 2 categories; global and local route strategizing [17]. All necessity data of the robot's known environment is provided by global route planning (also known as Off-line Navigation), while local path strategizing, which is known as On-line Navigation, tends to rely on partial or complete lack of knowledge to plan a course of action.

1. *Global Route Planning*

With a map of the surroundings, global planning may determine the most efficient path. Some approaches are based on roadmaps or Voronoi diagrams, depending on the study of the map. The least costly alternative may be found by assigning a monetary value to each component. Algorithms such as Dijkstra's, and A* can serve as good instances of this method. CD, in which the map is divided into smaller areas (cells), is another example.

Neural networks and other cutting-edge techniques for quickly exploring random trees are all instances of the same kind of strategy and all have potential fields. There are several solutions that incorporate the aforementioned methods, but at a price.

In the usual situation, the following stages should be followed throughout the process of the mobile robot's worldwide route planning:

a. *Environmental Modelling [18]*

This will help the mobile robot get a better sense of its surroundings, avoid needless planning, and drastically cut the time taken to figure out a global route layout. The real surroundings in which the mobile robot will execute its duty are transformed into map feature information and saved as-is in the environmental modelling, which is done in accordance with the available map data.

b. Optimization requirements must be met [1]

Developing optimization criteria for mobile route design necessitates taking into account a number of factors. One frequent optimization criterion is as follows: length of path. The robot's journey from its starting point to its destination is measured in terms of its path length (LP) [19].

c. A path-finding method is employed [2]

A path proposal technique is employed when searching for a collision-free route between two points in state space. The path search method must meet a number of optimization requirements, such as the distance of the route, the degree of safety, and the smoothness of the path.

2. Local Route Planning

The local planner includes various waypoints that may be used to transform the global route into a series of destinations for MAs. The planner takes into account the vehicle constraints and the dynamic obstacles. The map is reduced to show only what is near the vehicle, and it is updated as the vehicle moves around. This way, the path can be changed at a certain rate. The use of the whole map is impractical due to the fact that detectors will be unable to continue updating the map in all locations, and the processing load would increase by a significant number of cells. The local planning produces methods to avoid dynamic barriers based on the current local map and global waypoints, and attempts to match the route as closely as possible to those supplied by the global path planning [20].

As a conclusion, it has been established that route planning approaches are classified into two groups depending on the availability of environmental data: local path planning and worldwide path planning. It is essential to employ worldwide or global route planning techniques if all of the information about the barriers are known in advance, since this results in the generation of a path that connects both the starting and finish points at the same time. The local route planning approach, in contrast to this, necessitates the computation of maps based on any changes to the surrounding environment.

C. Classification of Articles Based on Types of Path Planning

Table V illustrates the author's journals based on the path planning types; global and local. Based on Table V, we can conclude that some authors conducted research related to local and worldwide route planning. All of the information was provided and described for use in global route planning. However, minimal to zero information was provided about the environment.

TABLE V. CLASSIFICATION OF ARTICLES BASED ON TYPES OF PATH PLANNING

Y. O. P	**Author**	**Title**	**Pages**	**T. O. P. P**
2020	Abaas, Shabeeb, A. H., & T. F.	Autonomous Mobile Robot Navigation Based on PSO Algorithm with Inertia Weight Variants for Optimal Path Planning	12	Global
2020	Campbell, S., Riordan, D., Walsh, J., Krpalkova, L., O'Mahony, N., & Carvalho, A.	Path Planning Techniques for Mobile Robots A Review		Global, Local
2021	G., Vazquez-leal, H., Huerta-chua, J., Diaz-arango, Hernandez-mejia, C.Moreno-moreno, M., Flores-mendez, J., & Ambrosio-lazaro, R. C.	Exploring a Novel Multiple-Query Resistive Grid-Based Planning Method Applied to High-DOF Robotic Manipulators	30	Global

III. Searching Or Path Planning Algorithms

A. Traditional Methodologies

The existing traditional or classical techniques in path planning are Potential Field, Cell Decomposition (CD), Roadmap Method, etc.

1. Cell Decomposition

A route planner dependent on cell decomposition (CD) utilizes the principle use of wavelet transforms in motion and perception planning, lowering computing expenses [1]. There are two methods implemented in the CD techniques. They are the exact and approximate CD methods, respectively [6].

The exact method is used to split the search space into simple cells as well as to construct the adjacency relationships between the cells, which are then used to find the solution [2]. It specifies the obstacles and constructs the cells in a straightforward manner. It will be possible to generate the exact space available by combining all the generated cells. Moreover, to search for a collision-free route, cell decomposition divides the given environment into simpler cells and uses the cell connectivity graph to find a path [21]. When constructing a connectivity graph, each cell or its border line is used to create each node [2]. Each node in the graph indicates a cell that is directly adjacent to another cell [7].

However, determining the exact free space in a high-dimensional environment is not a simple task, which is why the approximate technique was implemented. Quad-trees can be used in conjunction with other techniques to achieve multi-resolution cell decomposition [8]. However, this has the unfortunate side effect of making the cells around all obstacles in the map high-resolution no matter how close the robot is to the roadblock. This is not good. As a result, the cost of computational estimations rises [6]. Fig. 6 shows the overview of cell decomposition.

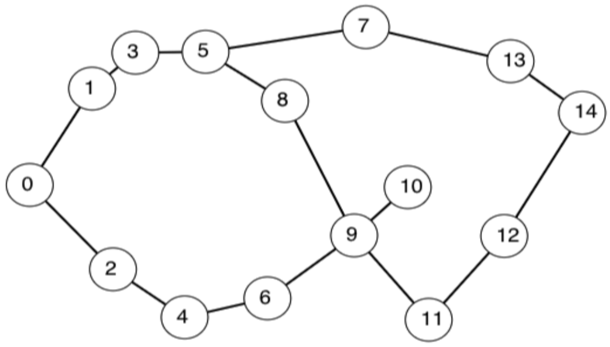

Fig. 6. Overview of Cell Decomposition

2. *Roadmap Method*

A graph-based approach is used in the route discovery phase of the Roadmap Method to determine the shortest path, which is then considered the best path [22]. Thus, the problem of making a good graph is closely linked to the problem of planning the best way to move. Learning and querying are two distinct phases in this approach [5]. Ref. [7] described a method of learning in which the robot builds a model of the world and a network of nearby areas. Finding the most viable route may be done in a variety of ways, and many of these techniques vary in the way that paths and nodes are specified. The Visibility Graph and the Voronoi diagram are two of the most well-known roadmaps [2].

An approach known as "The Visibility Graph" is used to strategize the path of the robot. They can be very important in applications where things move in polygonal shapes in constant or detached areas [11]. Problems arise when the paths generated collide with obstructions at the vertices and edges of the visibility graph [23]. This makes its implementation difficult. However, Voronoi diagrams can help resolve this issue [13]. Fig. 7 shows the overview of the Visibility Graph.

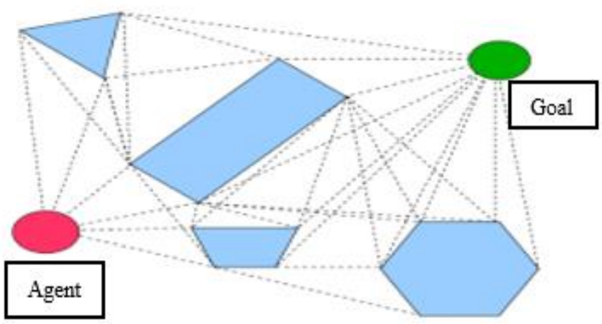

Fig. 7. Overview of Visibility Graph

The Voronoi diagram divides a flat space into several areas by using multiple points as the cores, which allows for more precise path planning for the robot's movement [12]. However, despite the fact that the Voronoi diagram is not a new concept in path planning for robots' cooperation and exploration, it continues to play an important role in improving various algorithms for a variety of applications [14]. When using this method, there is a made guarantee that the graph vertices will be located at the greatest possible path length from all nearby obstacles because of the way the method is designed [1]. Radar and LiDAR are the only onboard sensors capable of determining such distances [2]. As a result, ultrasonic sensors and other short-range sensors are out of the question for this approach in path planning. Moreover, Voronoi diagrams ensure high obstacle clearance but require high computational complexity to create the paths [23]. Fig. 8 shows the view of Voronoi Diagram.

Fig. 8. Overview of Voronoi Diagram [2]

3. *Potential Field*

Known as the artificial potential field (APF), it is a route planning methodology developed by Khatib in 1986, and it is still in use today [24]. APF is a common navigation technique and is founded on two different types of forces: repulsive and attractive, also known as electrostatic particles [2]. Many researchers have used this method because it is elegant, safe, and simple. The robot is affected by the fields created by the beginning, destination, and barrier locations in the solution space and the surrounding area[7]. The target point attracts attention, whereas the default position and obstacles detract attention. However, more effort is required to move an object that is farther away from the two boundaries [10].

The advantages of APF are that it is fast to compute, and it generates a collision-free path [23]. However, the technique had several flaws, such as local minima, unreachable goals, and narrow passages [15]. As illustrated in Fig. 9, an artificial potential field has been created around obstacle and goal.

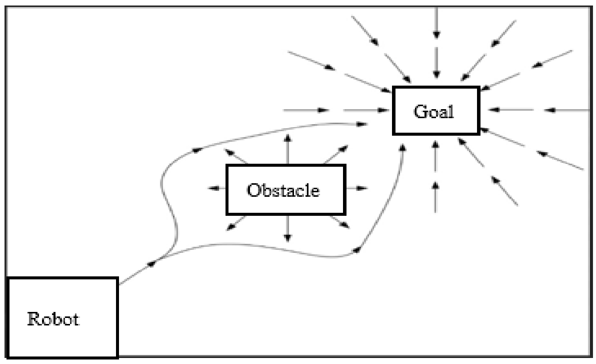

Fig. 9. The Artificial Potential Field

4. *Comparison of Advantages and Limitations of Classical Techniques in Route Planning*

Table VI below summarizes the advantages and disadvantages of each method mentioned in the traditional methodologies section. The comparison involves the CD method, Roadmap (Visibility Graph and Voronoi Diagram), and Potential Field.

TABLE VI. ADVANTAGES AND DISADVANTAGES OF CLASSICAL APPROACHES

Algorithms	**Limitations**	**Advantages**
CD	Difficult to determine the precise amount of free space in a multidimensional environment [21]. Extremely computationally intensive [23].	Static and dynamic route planning issues are well recognized. Simple [23].
Visibility Graph	The route comes into touch with impediments at the vertices and the edges, which might lead to possible accidents [23]. Time-consuming and lacking in flexibility [25].	Ensures that the quickest route is on a two - dimensional map [23].
Voronoi Diagram	Does not work well with short-range detectors. Complexity increases when the number of cells is increased [23].	Ensures the robot will always choose the safest route possible [23].
Potential Field	Best implemented in an immobile setting with stationary barriers. Local minimum of potential may be trapped by robots [25].	Generates a smooth and instantaneous path for a robot without needing a separate controller [23]. Great real-time performance and efficiency in the calculation [25].

Based on Table VI, we can conclude that each technique proposed has its own limitations and benefits. By comparing the approaches, one can choose their path planning algorithm wisely for their research.

B. Modern Methodologies

Modern approaches have been proposed due to several drawbacks of traditional algorithms such as inefficiency, high computation rates, and inaccurate results [1]. These modern intelligence techniques can be categorized into heuristic approaches, metaheuristic algorithms, and neural system methods.

1. Heuristic Approaches

According to the above-mentioned traditional methodologies, heuristic route planning has recently grown a lot more popular [2]. The fundamental distinction is that heuristic-based learning has the potential for human-like behavior-based learning. This section discusses many common methodologies, including Dijkstra Algorithm, A* Algorithm, and D* Algorithm.

a. Dijkstra Algorithm

In the field of route planning for 2D mobile robots, the Dijkstra algorithm is a well-known shortest path routing technique [26]. To solve the single-source shortest path issue, this approach uses a simple algorithm to find the most efficient route to any destination. Edsger Wybe Dijkstra, a Dutch computer scientist, created the Dijkstra algorithm in 1959. In a directed graph, the shortest path problem can be solved using a standard algorithm [1]. The increased number of nodes traversed reduces the algorithm's efficiency. To identify the most efficient route across the network, this approach employs graph searching techniques [9]. To approximate the configuration space, several discrete cell-grid spaces and lattices are used [14]. Computer science, geography, and transportation are just a few examples of where it's been used effectively.

b. A* Algorithm

In 1968, Hart and colleagues proposed the A-star (A*) algorithm, derived from Dijkstra [1]. With this algorithm, the assessment evaluation of the current base stations is updated [3]. The A* algorithm was based on f(n). That is, $f(n) = h(n) + g(n)$, in which h(n) is the estimated value to get from B to C and g(n) is the real price to get from A to B. The h(n) is the Euclidean separation between the two access points. When g(n) is fixed, h(n) influences f(n). h(n) and f(n) are slightly near the target node (n). As a consequence, the route search always moves towards the target. The A* algorithm finds the mobile robot's goal [27]. The A* algorithm outperforms Dijkstra algorithms in path search. This is because Dijkstra's method for graph searching has been extended to include heuristics, making it possible to search for nodes quickly [3]. Nodes' weights are determined by their cost function, which is the most significant part of their design. It works well for searching places that the vehicle already knows about, but it is time-consuming and expensive to use in large areas [15].

c. D* Algorithm

Path planning for mobile robots has evolved over time to take into account environmental information. The D* algorithm was developed in 1994 by Stentz[1]. Typically, robots use it to discover new routes. There are a series of states that represent the robot's position in the D* algorithm's problem space [10]. Using the cosine of the arc, the search is directed in the right direction. D* algorithms, including the field and Theta* algorithms, have also been studied by some researchers [11].

2. Metaheuristic Approaches

a. Particle Swarm Optimization (PSO)

Established by Dr. Eberhart, and Dr. James Kennedy in 1995 and based on the uniformity of bird cluster activity, the PSO algorithm is utilized in stochastic optimization technique [28]. Completely random solutions are used as a starting point. To find the best solution, iteration is used [1]. Using model parameters, it determines the optimal solution, and by comparing the currently searched optimal value to the previously searched optimal value, it determines the global optimal [29]. Using this algorithm, robotic path planning can be accomplished in a straightforward manner, with a high degree of precision, and at an extremely rapid rate [1]. During the last few years, PSO has been utilised in a diverse range of research and application areas.

PSO begins with a random distribution of particle populations [13]. Each particle in a swarm indicates a possible solution, and the swarm repeatedly travels around the area of concern in pursuit of the best-fitting solution [12]. Every single particle in the population moves through its travel space at an unknown position and velocity because of this initiation phase. Tracking and updating velocity and position vectors for each particle is a continual element of PSO [14]. In every iteration, each particle strives to achieve the greatest possible fitness for that particle (P_{Best}) and the best possible fitness for the whole swarm as a whole (G_{best}). Until either the desired location has been located, or the maximum number of iterations were achieved, this cycle will continue endlessly [29].

b. Ant Colony Optimization (ACO)

Italian scholar Dorigo came up with the idea for the Ant colony algorithm in 1992 [12]. To determine the ant's solution route, it carries out an ant colony simulation. Positive feedback, easy fusion, and parallel computation are its features. However, there are still some issues, such as slow processing rates and difficulty in finding local optimums in robot path planning [30].

In order to discover the most efficient route between their colony and food, ants hunt for the shortest way possible [1]. Initially, they roam about their nest at random, before moving on to other areas in search of food. The ant leaves behind a chemical compound called pheromone as it travels [6]. Quality and quantity are assessed as soon as the ant discovers a food source. In order to deposit additional pheromone on a certain trail, ants must take the same route back to their colony from the food source [11]. All ants have the ability to smell this chemical compound, which they use to exchange information with their fellow ants. A trail with a high concentration of these pheromones (fitness value) is thought to be more likely to lead to a food source when young ants leave their nests in search of food. The presence or absence of the pheromone trails acts as positive or negative feedback respectively [13]. If the pheromone concentration is higher in the undiscovered route, it might lead to an even better solution in the uncharted area [6].

c. Bat Algorithm

The Bat Algorithm (BA) was introduced in 2010 by Xin-She Yang of Cambridge University [31]. The echolocation property of the microbats is used to distinguish and track down prey. It can also be used by microbats to locate obstacles that indicate where they roost. As an example, bats can echolocate by sending out high-frequency ultrasonically-pulsed sound waves and listening to the echo that returns [32]. The species of bat and the environment in which it lives have an effect on the pulse frequency. The bats can use the various sound levels and time delays in the echo to figure out where the prey is and catch it [12]. This strategy enhances the algorithm's ability to find relevant results in the local area.

d. Genetic Algorithm

When it comes to providing precise and high-quality answers to optimization and discovery issues, genetic algorithms are widely recognised as one of the most regularly used optimization methods [1,2,4,5]. With no previous knowledge of what may be the optimal answer to the issue, GA is inspired by the natural selection notion [8–14]. Evolutionary operators like mutation, crossover, and selection are used to acquire data from the world before determining the best response for a specific circumstance. Path-planning problems have a lot of things that need to be done before genetic algorithms can be implemented. These things include making sure the "chromosome" for the path is the right size, coming up with a way to avoid obstacles, and choosing the right constraint definition [1].

The Genetic Algorithm, sometimes known as GA, is a search algorithm for global optimization. The ideas of Charles Darwin's theory of evolution served as inspiration for the development of the algorithm, which primarily simulates the genetic phenomena of natural selection and inheritance, including crossover and mutation, and also incorporates the natural laws governing which organisms will survive and thrive. The candidate solutions for each generation are obtained based on the results, and then the candidate solutions themselves are obtained at the end of the process. Obtain the best possible answer. The fact that this algorithm can be easily integrated with other algorithms while still making full use of its own iteration advantage is perhaps the most significant benefit it offers. It is really good at both organising itself and teaching itself, and it is very good at searching for the best possible route while it is planning its route. While doing so, it ensures that a good overall optimization is achieved. The genetic algorithm is straightforward to construct and is mostly unaffected by outside factors. The drawback is that the real-time operation is slow, the search efficiency is low, and it is easy to slip into the local optimal solution. When the algorithm is being executed, there will be some populations that aren't needed, which will make the complexity of following computations higher. This will lead to low operational efficiency and sluggish convergence. It is not appropriate for use with online route planning.

3. Neural System/ Fuzzy Controller's

a. Artificial Neural Network (ANN)

There is a strong connection between ANNs and the human brain's internal workings. Rather, they are computer simulations that can adapt their behaviour in response to the present environment [1-5]. For each neuron to function as a computing unit, it must have access to prior experiences and observations, much like the human brain [8]. The ANN's total intelligence or ability is determined by its neurons and how they connect [13]. When it comes to search engine optimization, knowledge acquisition, and information processing, ANNs are frequently employed because of their ability to deliver simple and optimum answers in complicated scenarios that are easy to implement [2,14].

An artificial neural network (ANN) expresses path planning as a modelling for both perceptual as well as behavioral space [10]. As a function of a path point in the neural network, it defines energy [33]. Depending on the location of the route point, the network follows the energy-depleted path [9]. Finally, the least total energy path is found. However, this route is not the quickest nor most efficient [34]. The mobile robot's working environment is unpredictable and difficult to model. It is hard to describe a moving environment with a neural network topology. Moreover, the large and complex structure makes weighting the neural network difficult [1]. However, this comes at the expense of large amounts of training data and a relatively long learning cycle.

b. Fuzzy Controller's/Fuzzy Logic

Fuzzy Logic was initially established in 1965 by Zadeh [1]. To express anything as "true" or "false," this system uses Boolean logic, a kind of classical computer logic (0 or 1). In the fuzzy approach, these two states of being have a "degree of freedom" between them [2]. Many robot route planning applications have used this method because it allows the robot to build an understanding of its surroundings [5]. FLCs are ideal for controlling robots because they can make inferences even when there is a lot of uncertainty. They can also help make decisions and write rules [2].

Local approximation networks, and neural networks' self-learning capabilities, were created as a result of a combined application of neural networks and fuzzy logic reasoning. Fuzzy weights and fuzzy input signals are fed into a conventional neural network, and this innovation has been utilized in a variety of applications for a long time. As a general rule, fuzzy neural systems [12] can be broken down into 5 layers: an input layer, an inferential layer, a fuzzy layer, a defuzzification layer, and the last layer, which serves as the final layer [4]. FLC that uses linguistic information has a lot of advantages, such as being model-free, being robust, and having a rule-based algorithm [11-13].

4. Comparison of Advantages and Limitations of Modern Techniques in Route Planning

Table VII below summarizes the advantages and disadvantages of each method mentioned in the modern methodologies section. The comparison involves Dijkstra Algorithm, A-Star, D-Star, Ant Colony Optimization, PSO, GA, Bat Algorithm, ANN, and Fuzzy Logic.

We may infer from Table VII that each approach has its own set of advantages and disadvantages. A researcher can make an informed decision on the best route planning algorithm by comparing the techniques.

TABLE VII. ADVANTAGES AND DISADVANTAGES OF MODERN APPROACHES

Algorithms	Limitations	Advantages
Dijkstra Algorithm	Takes the quickest route without considering the state of the terrain or path [35].	i) Easy to perform debugging [16]. ii) Excellent performance [16].
A* Algorithm	i) There is a possibility for the robot to go too near convex barriers when it derives a route. Consequently, the robot is more likely to come into contact with objects as it travels. ii) Performance degrades in dynamic conditions [35].	i) Simple ii) Low-Cost [13] iii) Efficient
D* Algorithm	Excessively redundant calculations occur when the map's grid number is too high [2].	i) The quickest route to an objective. ii) Can locally mend the initially intended route [35].
Genetic Algorithm	High time consumption leads to severely hampered real-time systems [13].	Optimized routes. [13]
PSO	Slow convergence in a narrowed search region due to poor local search capability [6].	i) Good robustness ii) Speed convergence in the initial stage [13] iii) Simple
ACO	i) No central processor to direct the system towards optimal solutions [6]. ii) Performs badly in vast search areas.	i) Good robustness ii) Fast convergence in the late stages of the search [1]
ANN	It is difficult and requires a learning process, which might occasionally fall short of the demands of real-time applications [6,8].	i) Simple ii) Can provide optimal solutions in complex situations.
Fuzzy Logic	Expensive in terms of money and time.	i) Enhances the robot's capacity to learn about its surroundings. ii) Higher possibility to draw conclusions even when there is uncertainty. iii) Assists in making decisions and creating regulations.

IV. TAXONOMY OF PATH PLANNING TECHNIQUES APPLIED IN AMR SCENARIOS

TABLE VIII. TAXONOMY OF PATH PLANNING TECHNIQUES APPLIED IN AMR SCENARIOS

Group of Algorithms	Approaches	Description of Approaches	Mentioned in
Classic	Cell Decomposition	Divides the given environment into many cells and creates a collision-free path using the connection graph of these cells.	[1], [2], [6], [7], [8], [21], [23], [35], [36], [37]
Classic	Visibility Graph	Connects the starting and ending points by using nodes on the map.	[2], [7], [11], [13], [25], [35], [37]
Classic	Voronoi Diagram	The configuration space is defined as the sum of all locations that are equally far from another two or more barriers.	[1], [2], [6], [11], [13], [14], [23], [35], [37], [38], [39]
Classic	Potential Field	Transforms the default map's moving tendency into virtual forces.	[1], [2], [4], [5], [7], [10], [11], [12], [13], [14], [15], [23], [35], [40], [41], [42]

Heuristic	Dijkstra Algorithm	Utilizes known nodes and cells with their weights. When the environment changes, the weight of the grid and the cells and nodes in it changes.	[1], [5], [6], [9], [11], [13], [14], [15], [38]
Heuristic	A-Star/A* Algorithm	Created in accordance with Dijkstra's algorithm. Updating the relative weight of each current child node begins at the root and continues until all child nodes have had their weighted values updated.	[1], [2], [3], [4], [5], [9], [10], [11], [12], [14], [15], [23], [37], [43], [44], [45]
Heuristic	D* Algorithm	Created in accordance with A* algorithm to perform tasks in dynamic environment.	[1], [10], [11], [35], [46]
Metaheuristic	GA	Has an initial population of chromosomes that encode all of the potential solutions to the issue	[1],[2],[4],[5], [8],[9],[10], [11],[12], [13],[14], [19],[37], [45], [47], [48],[49]
Metaheuristic	PSO	Influenced by the uniformity of the birds' clustering behavior. Begins with a randomly generated solution. With each iteration, it gets closer and closer to finding the perfect answer for the problem. Determines the global ideal by comparing the presently sought optimal value with the fitness value used to assess the quality of the answer.	[1], [2], [5], [6], [11], [12], [13], [14], [29], [50]
Metaheuristic	ACO	Based on ants' behaviour in food-searching, they will each leave a trail of a secretion known as pheromones on the path it took as a reference and will be able to sense the secretions that other ants leave behind. Pheromones allow the ant colony to communicate and make decisions together.	[1], [6], [11], [12], [13], [14], [37], [51]
Metaheuristic	Bat Algorithm	Based on bats' behaviour in prey-hunting, they produce a strong and brief wave of noise and then listen to the echoes that return to their ears after a little period of time. As a result, the bats can calculate their distance from a target.	[12], [31], [32], [52]
Neural System	ANN	Utilizes neurons that have the same structure as the brains of animals. Able to perform in the same way as a person would in the given circumstance.	[1], [2], [3], [4], [5], [8], [9], [10], [11], [13], [14], [53], [54], [55], [56], [57]
Neural System	FL	Human-language issues are transformed into mathematical formulae.	[1], [2], [4], [5], [10], [11], [12], [13], [34], [37], [58], [59], [60]

V. RESEARCH METHODOLOGIES

This paper presents a systematized classification of path planning algorithms that are organized by environment types, date of publications, advantages, drawbacks, and principles of path search and modelling of autonomous mobile robots. The search for relevant literature was conducted in 2 main databases, IEEE Xplore and Scopus with particular attention paid to topics such as route planning, static navigation, dynamic path planning, global and local route navigation, traditional algorithms, classical path planning approaches, modern intelligence algorithms, heuristic approaches, metaheuristic approaches, and neural networks techniques.

The references that were utilized in this investigation were found by searching the databases Scopus and IEEE Xplore for works published between 2019 and 2022 and set to only conferences and journals. These databases were used in the search. The specialized search has been configured to look for "Path Planning", and the results have been filtered for at least one algorithm; Cell Decomposition, Visibility Graph, Voronoi Diagram, Potential Field, Dijkstra, A*, D*, Genetic Algorithm, Particle Swarm Optimization, Ant Colony Optimization, Bat Algorithm, Neural Network or Fuzzy Logic. This article is created in Microsoft word 2016 using Windows 10. Table IX illustrates the criteria of this article. The strategy for searching the references is described in Table IX.

I. CONCLUSION

Presented in a very systematic manner, this paper provides a review of the different collision-free trajectory planning techniques that can be used for autonomous navigation. The paper investigates the static and dynamic nature of environments, as well as their interconnections. Following that, the classifications of pathfinding, which include global and local navigation systems, as well as both traditional and innovative intelligence approaches, are discussed to provide a more comprehensive picture of motion planning and its implications. In addition, this paper points out the benefits and drawbacks of each method in turn. Roadmaps, Potential Fields, and Cell Decomposition are examples of classical or conventional or traditional methods that have been discussed. Both of these strategies will either attempt to find a workable alternative or demonstrate that no solution exists. Because of their high complexity of computation and not being able to work well in changing situations, they may well not be reliable in practical uses.

TABLE IX. ARTICLE'S SELECTED CRITERIONS BASED ON PATH PLANNING FOR AMR FROM 2018 TO 2022

Inclusion Criteria	• Articles published sinced 2019 until 2022. • Papers related to Path Planning For Robot. • Articles with classifiers algorithms. • Articles with static and dynamic environments. • Articles with global and local nagivation. • A review or survey articles or simulation articles. • Articles related to atleast one of the subtopics; CD, Visibility Graph, Voronoi Diagram, APF, Dijkstra, A-star, D-star, GA, PSO, ACO, BA, ANN and FL.
Exclusion Criteria	• Article without classifiers approaches. • The language publication was restricted to English.
Search Databases	• Articles found in IEEE and Scopus under Keywords and Boolean terms: "Path Planning" OR "Route Planning" OR "Navigation" OR "Path Planning Algorithms" OR "Path Planning Techniques" OR "Path Planning Approaches"
Reviewing Papers	• Total Articles to review abstract and conclusion:200 • Some articles are excluded by review of topics, and abstract • Full text article review: 100 papers • Articles selected and included as references: 60 papers; journals and conferences.

Modern methodologies such as Heuristic-based (Dijkstra Method, A*, and D* Algorithms), Metaheuristics Algorithms (PSO, ACO, Bat Algorithms, and Genetic Algorithm), and Neural System (ANN and Fuzzy Neural Networks) were also discussed. This paper provides a list of some of the most frequently used techniques for trajectory tracking. The previous techniques do not guarantee the finding of a solution, but if they do, it will be in a fraction of the time and with a portion of the computation. The use of modern methodologies in real-world applications, particularly in dynamic environments, is becoming significantly more appropriate. In a nutshell, for these methods to work, the validity and dependability of the input data are critical.

Conflict of Interest

The authors have explicitly stated that they do not have any competing interests.

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