Multi Objective Optimization Algorithms for Mobile Robot Path Planning: A Survey

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Baraa Mohammed Abed(✉), Wesam Mohammed Jasim
University of Anbar, Ramadi, Iraq
burasoft@gmail.com

Abstract—Path planning algorithms is the most significant area in the robotics field. Path Planning (PP) can be defined as the process of determining the most appropriate navigation path before a mobile robot moves. Optimization of path planning refers to finding the optimal or near-optimal path. Multi-objective optimization (MOO) is concerned with finding the best solution values that satisfy multiple objectives, such as shortness, smoothness, and safety. MOOs present the challenge of making decisions while balancing these contradictory issues through compromise (tradeoff). As a result, there is no single solution appropriate for all purposes in MOO, but rather a range of solutions. The purpose of this paper is to present an overview of mobile robot navigation strategies employed to find the path that has the minimum number of criteria (shortest, smoothness, and safest) so far. Here, multi objective approaches are discussed in detail in order to identify research gaps. In addition, it is important to understand how path planning strategies are developed under various environmental circumstances.

Keywords—path planning, multi objective optimization, mobile robot, moving target, robot navigation

1 Introduction

One of the primary research areas in robotics includes path planning, since robots are commonly utilized in many different fields such as agriculture, military, rescuing mining, medicine, education, space, and many more. So, for the robot to accomplish its tasks in any field, it will need to move. Therefore, it has become necessary to find a navigational technology that makes the robot move freely without colliding with any obstacle in the environment [1]. The environment may be static or dynamic in nature. Obstacles are stationary in static environments, but it may move randomly in dynamic environments. Because the environment contains obstacles, collisions with them should be avoided. Path planning algorithms are used to solve real-time problems that do not require human intervention. A primary research area of robotics is the optimization of path planning in order to arrive at the best path between the starting and the ending positions, which is an important aspect of robotics. In general, robot navigation can be broadly classified into two types depending on how well the robot knows its environment: global (offline) or local (online). When it comes to global path planning, mobile robots are well informed about their surroundings planning. Before the robot starts moving, the algorithm generates a complete path for it to follow. Local path planning is performed by mobile robots that have no prior knowledge of their environment and rely on a local sensor to collect data and then construct a new path in response [2]. Additionally, it can be classified as a classical approach and artificial intelligence approach (AI) for navigation. Classic algorithms such as CD, RA, and APF are commonly used for path planning in a known environment. These classic algorithms are with low intelligence. The best examples of artificial intelligence algorithms are evolutionary algorithms like GA and swarm intelligence algorithms like PSO and ACO. In the topic of mobile robot navigation, there are various approaches have been developed by a variety of researchers, and it's the most researched topic right now. In recent years, there have been a number of surveys of algorithm used on mobile robot navigation [3],[4],[5]. However, most of these surveyed contain insufficient information and interested in the path planning algorithm for safety path. Our research focused only on the navigation algorithms, which enhance multi-objective optimization such as shortest, smoothness, and safety. The goal of this survey article on mobile robot navigation is to discover research gaps and opportunities in this field. Besides these main parts, there is also a part that is organized by the following points: the differences between classical and heuristic optimization techniques, a detailed description of one algorithm for static environments, a detailed description of another algorithm for dynamic environments in which obstacles are moves, simulation analysis, experimental analysis, navigation of mobile robots using multiple techniques, integration of other intelligent techniques, and applications of these techniques to three-dimensional environments, or to military or defense equipment. Figure 1 shows the navigation function flow diagram for mobile robots. There are several methods to design a robot's path planning. Path planning is critical in the design of navigational control behavior for robots. It is essential that the robot reaches the final/goal configuration in a minimum amount of time and distance. Another criterion is to have a lower computational complexity and lower power consumption, which are only possible on the condition that the robot travels in the shortest path from the configuration of the start to the configuration of the goal. A number of methods/approaches have been proposed by many researchers. All of these approaches are discussed in the following sections along with their advantages, disadvantages, and limitations. There have been numerous researchers and scientists who have developed various navigational methods. Among the navigation methods used by mobile robots, there are two categories, namely classical methods and artificial intelligence methods. Table 1 shows the category of Path Planning Approaches.

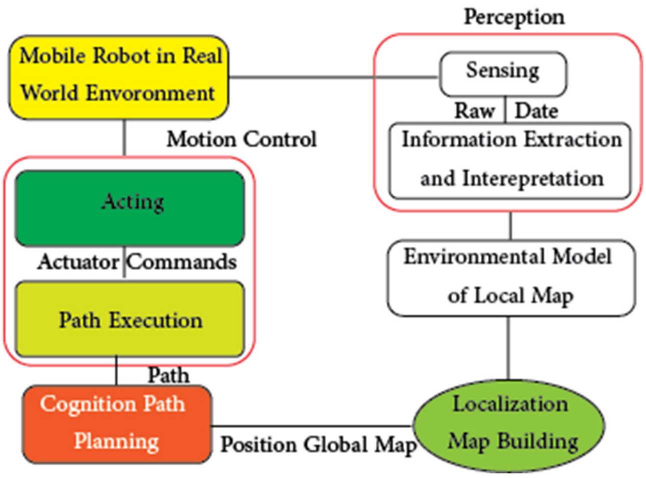

Fig. 1. Flow diagram navigation for mobile robots

2 Path planning algorithms

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Table 1. Path planning approaches

Classical Approaches	Artificial Intelligence Approaches
Potential field (1997)	Neural Network Technique (1943)
Road map cell decomposition (1987)	Fuzzy Logic Technique (1965)
Grid Based (1988)	Genetic Algorithm Technique (1989)
PRM (probabilistic Roadmap) (1996)	Ant Colony Optimization Technique (1992)
Rapidly Exploring Random Tree (1998)	Particle Swarm Optimization Technique (1995)
Virtual Impedance Method	Bacterial Foraging Optimization (2002)
Convex Hull and Local Search Method	Bee Colony Optimization Technique (2005)
Divide and Conquer method	Firefly Algorithm Optimization Technique (2008)
	Grey Wolf Optimization (2014)

2.1 Classical approaches

In the past, it was very popular to use classic approaches to solve robot navigation problems because artificially intelligent navigational methods had not yet been developed. In the classical approach, the results are either achieved or failed to be achieved [6]. Although this method provides feasible collision-free solutions to the problem. This approach has a number of disadvantages, including its high computational costs and inability to respond to changes in the environment; consuming a great deal of time to find a solution, which is a significant drawback, especially when dealing with problems of large scale and complex. This makes it unsuitable for real-time implementations. Classical approaches have another drawback: they may get trapped in local optimal solutions away from the global optimal solution, especially for environments where there are several viable solutions [4].

2.2 Artificial intelligence approaches

Artificial Intelligence approaches have become the most popular methods of navigation for mobile robots over conventional methods. It is possible to combine two or more algorithms in order to enhance their performance when solving complex problems that involve multi-objective optimization. These approaches that are considered to belong to this category include neural network, fuzzy logic, genetic algorithms, shuffling frog leaping, bacterial foraging optimization, particle swarm, harmony search algorithm, invasive weed optimization, differential evolution algorithm, bat algorithm, and other miscellaneous algorithms include firefly algorithm, optimization, cuckoo search, ant colony optimization, artificial bee colony, algorithm, and many more. The artificial intelligence techniques that are only applied to multi-objective optimization path planning are explored as follows.

Particle swarm optimization (PSO). PSO is an optimization algorithm based on swarm intelligence. It was developed by Eberhart and Kennedy [5] and it mimics the behavior of social animals. Bird flocks do not require any leaders when they go in search of food; they go with the nearest bird member. Thus, the flock of birds is able to communicate appropriately with the members of the population to reach their desired solution. PSO consists of a series of particles, each of them represents a unique solution. This type of navigation is often used by mobile robots. Mobile robot navigation in a dynamic environment employing a PSO for searching for solutions to multi-objective optimization problems to achieve the three objectives, path length, degree of danger of colliding, and smoothness which is presented by Min et al. [7]. A mathematical model is considered in which information about the environment, such as the location of a mobile robot, its velocity, and the direction of obstacles, is considered. Mobile robots can avoid obstacles in real time by adjusting their velocity and direction in real time. A self-adaptive learning particle swarm optimization was developed by Li and Chou [8] (SLPSO). They designed a self-adaptive learning mechanism that generates the best appropriate search strategy based on the optimization process to increase the particle swarm optimization's search capabilities. Using particle swarm optimization, Zhang et al. [9] developed a multi-objective path planning algorithm for robots navigation in an environment. In the context of two performance criteria; the risk degree and the path distance. The path planning problem with uncertain danger sources can also be described as a bi-objective optimization problem with uncertain coefficients. A multi-objective restricted PSO is employed to tackle this problem. The proposed algorithm incorporates a number of new operations/improvements, including the particle update method based on random sampling and uniform mutation, the infeasible archive, and the constrained domination relationship based on collision times with obstacles. In Alaliyat [10] PSO is used for robot path planning. It ensures that the autonomous robot and its environment remain safe while performing natural maneuvers from source to destination. Optimization criteria include collision-free path length, travel time, and energy consumption. Mahmoodabadi et al. [11] provided a new Multi-objective Particle Swarm Optimization (MOPSO) method called Ingenious-MOPSO for path planning for a biped robot walking in the lateral plane on a slope. It is also introducing an optimal robust sliding tracking controller tuned by Ingenious-MOPSO to address the problem of heavy nonlinear dynamics and tracking systems in biped robots walking in the lateral plane on a slope. Abdulsaheb [12] used an Adaptive Multi-Objective Particle Swarm Optimization System (AMOPSO) to construct a path planning algorithm for two case studies. In the first scenario, a single robot tries to complete the task in an environment with two barriers and two potential risk sources. The second scenario involves increasing five robots' ability to find the shortest way. In the first case, the optimization criteria are to find the minimum distance and ensure that the generated paths are as far away from the danger zones as possible. In the second case, is to find the shortest path for each robot without causing any collisions between them in the shortest time possible. A new multi-objective PSO method was presented by Di et al. [13] for optimizing path length, path smoothness, and security. To make the particle population multi objective particle swarm optimization algorithm converge to the Pareto optimal boundary, they used an environmental selection and a matching selection strategy. The environmental selection and matching selection strategies of SPEA2 are used to optimize the information exchange and reduce the randomness in the multi-objective PSO method during each iteration, so the particle population can arrive at the Pareto optimal boundary faster. The path planning problem for unmanned surface vehicles (USVs) is considered by Ma et al. [14], where it is found that the shortest, smoothest, and most economical path with regard to currents, obstacles, and boundary limits, is found using their novel solution. The authors formulate this as a multi-objective nonlinear optimization problem. After that, they proposed the dynamic augmented multi-objective particle swarm optimization algorithm. USV can pick the optimal path from the Pareto optimal paths. Wang et al. [15] proposed a path planning algorithm based on PSO for car-like mobile robots operating in a known rough terrain environment. This method is designed to find collision-free and feasible paths with a minimum length and terrain roughness. As a first step, a new workspace modeling method is proposed to model the rough terrain environment. Additionally, taking into account the non-holonomic constraint of the car-like robots, the proposed algorithm implements a new updating method for particle's global best position based on crowding radius to enhance population diversity. To increase the efficiency of the algorithm, a non uniformity factor is employed for updating the particle's position when the path collides with obstacles. Habit and Mohades [16] proposed a MOPSO method for path planning for multi-robots in an unknown environment. In this method, shortness, safety, and smoothness are considered. Due to the obscurity of the environment, a new concept is presented in this paper, known as a probabilistic window. In order to select paths that are more likely to achieve higher fitness with regard to the above objectives, it combines the current information obtained through the robot sensors and previous experiences.

Genetic algorithm. GA is one of the most efficient optimization algorithms capable of solving a wide variety of multi objective optimization problems [17]. GA is based on the premise that the combination of exceptional characteristics from multiple ancestors results in better and more optimized offspring that is, having better fitness functions than their parents. [18]. Bremermann developed the genetics and natural selection idea in 1958 [19]. It is now widely employed in all branches of science and technology, including robot navigation. Mittal and Deb [20] proposed 3D offline path planners for Unmanned Aerial Vehicles (UAVs) for minimizing the length of paths and maximizing safety margins using Multi Objective Evolutionary Algorithms. For this purpose, they have selected the commonly used NSGA-II algorithm. Using a B-Spline curve, the algorithm generates a curved path. The control points of a B-Spline curve represent the decision variables in the genetic algorithm. The Step-Spreading Map (SSM) algorithm has been proposed by Yuan et al. [21], it is used as a prior knowledge to guide the evolutionary process in Multi- Objective Genetic Algorithm (MOGA). Different rules are used for initialization and mutation in order to utilize prior knowledge. The simulation study demonstrates the efficiency of the prior knowledge based MOGA. Using the SSM knowledge, the proposed MOGA was able to generate the Pareto Front by combining the initialization of population and evolutionary convergence. Based on improved genetic algorithms, Hu and Zhu. [22], proposed a more efficient algorithm. The algorithm is designed to meet three objectives for preplanned paths; length, robustness and security by applying the chaotic sequence and heuristic approach based on environmental knowledge to initialize the population to enhance the ability of individuals to be ergodic and feasible. To enhance the efficiency of the algorithm, several genetic operators that take advantage of domain-specific knowledge are proposed according to the characteristics of path planning. Sedaghat et al. [23], proposed a new structured multi-objective genetic algorithm for solving this problem. They attempt to reduce the search space by exploring only valid search terms. They also demonstrate the defect in the earlier evaluation function and propose a new evaluation function. Ahmed and Deb. [24] have introduced a multi-objective path planning method that optimizes path length, path safety, and path smoothness using a well-known soft computing method known as elitist non-dominated sorting genetic algorithm. Four different path representation schemes are discussed that begin their coding from the start point and move one grid at a time towards the destination. This study aims to minimize the traveled distance and maximize the safety of the path, while smoothness of the path is considered as a secondary objective. A genetic algorithm is presented by Tao et al. [25] for multi objective problems. Unlike traditional GA, emphasizes solution diversity through the use of specialized mechanisms. The genetic algorithm approach is then applied to three-dimensional path planning for (UAVs). In particular, a number of mutation operators are extended, as well as new mutation operators for path planning are introduced based on modified solutions to traditional path planning problems. B and Ragusa [26] proposed a genetic algorithm for offline path planning with intermediate targets as well as the final destination, which is performed in a static environment. The algorithm is different from others in several ways. This algorithm does not make use of crossover since this operator did not appear, in testing, to aid in efficiently locating a solution for most cases. In addition, it employs mass extinction as a method of path planning due to experimental evidence indicating its effectiveness. Moreover, the algorithm was developed and tested on a physical micro aerial vehicle. Mahmud et al. [27] employed the Non-dominated Sorting Genetic Algorithm with Reference Point Based (NSGA-III) to sort their data. The system is used for pesticide spraying operations within a greenhouse. The virtual greenhouse environment is created on the basis of the real greenhouse environment in order to see the agricultural activity that takes place within the building. The C-metric indicator was used to compare the solution quality to that of the (NSGA-II) standard. Comparison with NSGA-II utilizing the C-metric indicator demonstrates that NSGA-III provides improved performance while maintaining a high level of quality. According to Chang et al. [28] a systematic strategy for constructing a model of Hinged-Tetromino (hTetro) reconfigurable robots in the workplace is presented, as well as a genetic algorithm-based method for optimizing the path taken by hTetro robots. The topic of hTetro route planning is considered as a multi-objective optimization problem with four specialized objective functions evaluating its solution. The proposed hTetro-GA has been putted through its paces in six different virtual settings. The suggested method has been built and tested on the hTetro platform, which is a real-world system. Multi-robot path planning is also considered to be one of the challenges in the field of robotics. By using GA, Hayat et al. [29] developed a path planning strategy for a team of UAVs. A major goal of his work is to reduce the time required to complete the mission, including the time to find the target (area coverage) and to set up a communication path.

2.3 Hybrid approaches

There have been a number of studies combining two or more intelligent algorithms to create a hybrid approach in order to improve robot path planning by combining two or more algorithms. Hybrid approach for multi objective path planning is presented in [30], which combines Artificial Potential Fields (APF) and Genetic Algorithms (EGAs) in continuous environments. A new genetic algorithm is proposed to improve initial paths in continuous spaces and find optimal paths. In order to identify a set of feasible paths, APF uses a time-efficient deterministic algorithm, which is guaranteed to identify a feasible path if one exists. In order to improve the initial paths, five customized crossover and mutation operators are proposed. The objectives include; the path length, the smoothness and the safety. Path planning using a novel method is proposed by Zhang et al. [31]. It is based on the combination of multi-objective bare boned PSO with differential evolution. Tri-objective optimization is used to build a mathematical model of robot route planning, using three indices; path length, smoothness, and safety. To pick the particle's personal optimal position, a new Pareto domination with collision limitations is constructed after this. Hang et al. [32] presented a more pragmatic model of stochastic networks that not only takes into account deterministic variables, but also the mean and variance of random variables, and combined an artificial immune system, a chaos operator, and PSO to speed up the solution. In [33] a multi-objective approach was presented to design a Decision Support System (DSS) for underwater cleaning robots. The Probabilistic Roadmap (PRM) is used to explore all possible paths at every cleaning point in the tank. Based on Non-Dominated Sorting Genetic Algorithm using Reference Point Based (NSGA-III), an optimal sequential route is identified. Several objectives are taken into consideration, including path length, routing angle, and cable entanglement, while maintaining constraints such as similar deployment points, a maximum time limit, and similar deployment points. Geetha et al. [34] proposed an algorithm for optimizing path planning has been proposed that is based on Ant Colony Optimization (ACO) and GA. The algorithm seeks to optimize various aspects of planned paths, including length, smoothness, and security. The ACO algorithm's evolutionary process adapts genetic operations to facilitate ant movement toward the solution state. Bashra et al. [35] proposed a novel hybrid approach based on Enhanced Genetic Algorithms by modifying the search A* algorithm and fuzzy logic system in order to significantly improve the searching ability of robot movement toward optimal solution states in static and dynamic environments. When unknown impediments enter the route, the global optimal trajectory is given to the fuzzy motion controller to be regenerated into a time-based trajectory. The goal is to minimize the travel distance, trip time, smoothness, and travel security. Kanoh [36] proposed hybrid multi-objective path planning algorithm base on (GA – Dijkstra algorithm). It used for car navigation equipment which is treated as route planning. The proposed method gives the Pareto-optimal set by using both the predicted traffic and a driver can choose a favorite route after looking at feasible ones. Masehian and Sedighizadeh [37] developed two new heuristic models for known environments. A combination of a probabilistic roadmap algorithm (PRM) and the improved PSO algorithm is employed in the first model as a global obstacle avoidance strategy. In the second model, genetic algorithms are combined with PRM methods. To evolve the population, new specific selection, mutation, and crossover operators are introduced which aim to minimize path length and oscillations. PSO and GSA were combined in a new method for mobile robots [38]. Hybrid GSA-PSO was the name given to this hybrid algorithm. The PSO-GSA is a multi-objective optimization technique that employs two objective functions to determine optimal paths for mobile robots in static settings while avoiding collisions with barriers and danger zones. By minimizing objective functions, PSO-GSA hybrid algorithms solve optimization problems, resulting in collision-free trajectories that reduce the length of the path. The robot must walk while also guaranteeing that the generated paths are far enough away from risky zones to keep the robot safe. Ajeil et al. [39] proposed a hybrid method for minimizing distance and smoothness criteria utilizing PSO and the Modified Frequency Bat Algorithm (PSO-MFB) in a static and dynamic environment. There are three modules in the proposed algorithm. The first candidate solution generated using the PSO-MFB algorithm. Local Search (LS) is then used to detect any infeasible points and convert them into feasible solutions. Lastly, obstacle detection and avoidance (ODA) are considered. Combining the modified D-star (D*) and PSO algorithm with full Cartesian space analysis at each motion sample. The authors in [40] proposed method for determining robot path planning solutions in known dynamic environments. Additionally, a modification to the D* algorithm has been made to accommodate the dynamic environment's requirements. This was accomplished by including stop and return backward cases in the original D* algorithm theory. Gul et al. [41] hybridized version of the Grey Wolf Optimizer and PSO algorithm is proposed to minimize the path distance and smooth the path multi-objective algorithm. In order to plan a path, three steps are involved. The first step is to generate a solution by combining Grey Wolf optimization with PSO. The second step involves integrating the optimal and feasible points generated by the PSO-GWO algorithm with the Local Search technique to convert any infeasible point into a feasible solution. In the final step, mobile robots are exposed to collision avoidance and detection algorithms, where they detect obstacles in their sensing circles and avoid them using collision avoidance algorithms. Q. Yang & Yoo [42] determining an optimal UAV flight path is performed employing a combination of GA and ACO based on sensing, energy, time, and risk specifications. To obtain sensor data, UAVs communicate with sensors, which are then applied in dynamic environments. Unique hierarchical global path planning methods for mobile robots in congested situations are provided by Mac et al. [43]. In order to come up with a practical, safe, and optimum path, three levels of analysis are used; the triangle decomposition approach quickly establishes a geometrically unconstrained configuration space for the robot. It is used to discover a collision-free path that will be used as an input for the next level of Dijkstra's algorithm. The shortest and smoothest global optimal path is constructed through a multi-objective PSO with accelerated updates based on the Pareto dominance principle in the final phase.

2.4 Another miscellaneous algorithm

Different intelligent techniques have been proposed in order to perform the task of path planning, such as A* Search [44], Firefly-based approach (FL) [45], Shuffled Frog-Leaping Algorithm (SFLA) [46], Memetic algorithms (MA) [47], Region of Sight [48], Reinforcement Learning (RL) [49], Variable Neighborhood Search (VNS) [50], and Intelligent water drops (IWD) [51].

3 Discussion

All the algorithms mentioned in this survey are applied to the multi objective optimization mobile robots path planning. Navigational strategies are divided into classic and artificial intelligence-based approaches. Based on the mentioned works in the literature, most robotics research conducted in the past few decades has been based on classical models because artificial intelligence had not yet been invented. In multi objective optimization, the classical model is not used and only some elements of AI are used in harmony to enhance performance. There are several drawbacks to classical methods, such as a tendency to fall into local minima, an inability to handle maximum uncertainty, a demand for precise environmental information, and the need for an accurate sensing mechanism for real-time navigation that requires precise sensing mechanisms. Therefore, when the classical approach is used, there is always a question whether a solution will be obtained, or one may assume that one does not exist. To address the limitations of classical methods, researchers have created a variety of innovative approaches, such as artificial predictive algorithms (APAs) and some hybrid approaches. However, these techniques do not perform in real-time environments compared to artificial intelligence techniques. Traditionally, classical navigation methods are used for navigation in a known environment, which requires that the navigating entity to have initial knowledge about the working environment. Additionally, artificial intelligence is beneficial for navigating in an unknown environment, since these approaches are capable of handling the high level of uncertainty present in that environment. AI techniques are simple to develop, clever, and efficient, making them ideal for real-time navigation challenges, as they provide optimal results compared to conventional approaches. As shown in Figure 2. Several decades of implementation of classical and AI approaches have been demonstrated for robot navigation. In the period 1970–2018, the popularity of AI techniques has climbed from 0% to 95%, whereas the popularity of classical ways has decreased from 95% to 5%. The usage of AI algorithms for mobile robot navigation has increased in the twenty-first century. Artificial intelligence algorithms are presently employed in more than 95% of all work. Although AI systems are more sophisticated than traditional approaches, they still have some drawbacks, including longer computing times, complicated designs, a prolonged learning process, and the need for a lot of memory. Artificial intelligence techniques are also unsuitable for low-cost robots. In Figure 3 a comparison was made based on the number of papers published for each individual in multi objective using heuristic methodology. Tables 2–5 offer a detailed overview of the methods employed for robot navigation. Each algorithm is evaluated based on several factors, including how it navigates in static and dynamic environments, how it is applied to multiple robot systems, it is applied for 3D application or not and how it performs in simulation and in real-time. As shown in Table 3, the number of papers published on navigation of robots using hybrid systems is more than with PSO, GA or other systems as performance is required for multi-objective systems (shortest, smoothest, safest). Most papers are based on static environment and used offline rather than in real-time. PSO is used both for online and offline path planning, while GA is used solely for offline planning. It has been observed that, in the case of hybrid navigation systems, higher percentages of the APF and PRM approaches have been employed than the cell decomposition and RA. The charts in Figure 4 clearly represent that research papers based real-time applications using classical approaches are very few compared to AI approaches. The chart in Figure 4 indicates that research papers based on dynamic obstacles are quite rare in comparison to static obstacles. According to the survey, the most commonly used path planning algorithms for mobile robots are hybrid, PSO and GA, according to what has been presented, it is possible to realize that the hybrid approach often used compared to the standard algorithms. They are typically used after some improvement or along with another algorithm, depending on the requirements. AI approaches are becoming increasingly popular as a result of their ability to cope with a complex environment quickly and with minimal processing effort. In the field of robot navigation, metaheuristic algorithms contribute about 99 percent of the time. When compared to other algorithms, this one is superior. Metaheuristic algorithms such as hybrid algorithms, PSO algorithms, GA algorithms, and other approaches contribute 34 percent, 26 percent, 24 percent, and 17 percent of the total contribution, according to published publications in multi objective optimization path planning. According to Table 1, the majority of AI techniques have only employed PSO and hybrid algorithms for navigation in a dynamic environment with moving obstacles. As a standalone controller, heuristic approaches are the only ones capable of handling the real-time path planning problem with high efficiency. Multi mobile robot navigations is one of the most challenging path planning tasks, requiring a high level of intelligence to coordinate the robots, much more so when multiple objectives are involved. It is observed only PSO approaches applied in the multi-robot problem with multi objective. Many researchers have proposed hybrid approaches to solving the complex problem of navigation. Based on the literature review, only AI-based path planning systems for aerial and underwater vehicles have been examined in a three-dimensional workspace especially the GA. Because traditional techniques are insufficiently intelligent for autonomous path planning in a multi-objective setting, they have been hybridized with other heuristic approaches such as GA to increase their performance. The location of the target is almost changeable, and no research has employed any strategy to overcome with moving targets until this study. Continuing to discuss the usage of navigational techniques in military or defense applications for mobile robot navigation, there are a number of reasons why artificial intelligence are only used in military applications, such as its capacity to explore a new area quickly, its ability to respond quickly to requests, and its ability to make unique decisions. Only GA has been employed as an intelligent way to automating the work with multi objective optimization, as seen in the majority of defensive equipment. Classical approaches such as APF, CD and RA are not appropriate for defense applications, due to their insufficient intelligence, computationally intensive nature, trapping in local minima, etc. Many metaheuristic algorithms are not used yet for multi objective path planning of mobile robots such as, CS, ACO, WOA, and Bacterial foraging optimization (BFO).

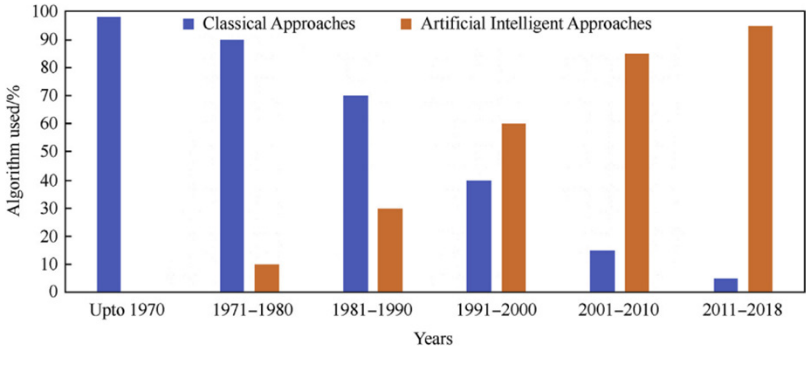

Fig. 2. Development of mobile robot navigation approaches [5]

Table 2. Analysis of various navigational techniques that used PSO

Ref. No	Environment	Experiment	Dynamic Goal	3D Application	Multi Robot
[7]	dynamic	simulation	N	N	N
[8]	static	simulation, real	N	N	N
[9]	dynamic	simulation	N	N	N
[10]	dynamic	simulation	N	N	N
[11]	static	simulation	N	N	N
[12]	static	simulation	N	N	Y
[13]	static	simulation	N	N	N
[14]	static	simulation	N	N	N
[15]	static	simulation	N	N	N
[16]	static	simulation	N	N	N

Table 3. Analysis of navigational techniques that used GA

Ref. No	Environment	Experiment	Dynamic Goal	3D Application	Multi Robot
[20]	Static	simulation	N	UAV	N
[21]	Static	simulation	N		N
[22]	Static	simulation	N		N
[23]	Static	simulation	N		N
[24]	Static	simulation	N		N
[25]	Static	simulation	N		N
[26]	Static	simulation	N		N
[27]	Static	real	N		N
[28]	Static	simulation	N		N
[29]	Static	simulation	N	UAV	N

Table 4. Analysis of hybrid navigational techniques

Ref. No	Techniques	Environment	Experiment	Dynamic Goal	3D Application	Multi Robot
[30]	APF +EGA	Static	simulation	N	N	N
[31]	bare-bones PSO-DE	Static	simulation	N	N	N
[32]	(AIS), chaos operator, (PSO)	Static	simulation	N	N	N
[33]	PRM+GA	Static	simulation	N	N	N
[34]	ACO-GA	Static	simulation	N	N	N
[35]	A*-fuzzy logic	dynamic	simulation	N	N	N
[36]	GA-Dijkstra	static	real	N	N	N
[37]	PSO-PRM	static	simulation	N	N	N
[38]	PSO-GSA	static	simulation	N	N	N
[39]	PSO-MFB	dynamic	simulation	N	N	N
[40]	PSO+D*	dynamic	simulation	N	N	N
[41]	PSO–GWO	static	simulation	N	N	N
[42]	GA+ACO	dynamic	simulation	N	N	N
[43]	PSO-Dijkstra	static	simulation	N	N	N

Table 5. Analysis of other navigational techniques

Ref. No	Techniques	Environment	Experiment	Dynamic Goal	3D Application	Multi Robot
[44]	A*	Static	simulation	N	N	N
[45]	FA	Static	simulation	N	N	N
[46]	SFAL	Static	simulation	N	N	N
[47]	MA	Static	simulation	N	N	N
[48]	RoS	Static	simulation	N	N	N
[49]	RL	Static	simulation	N	N	N
[50]	VNS	Static	simulation	N	N	N
[51]	IWD	Static	simulation	N	N	N

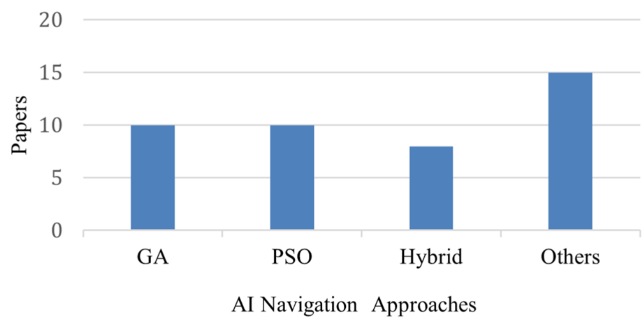

Fig. 3. AI Approaches comparison based on a paper published

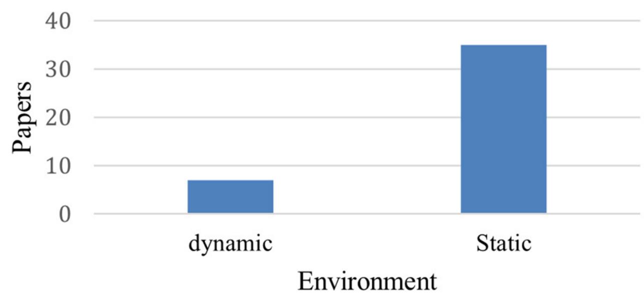

Fig. 4. Analysis of navigational used in static and dynamic (obstacle)

4 Conclusion

In this paper, an overview of multi objective path planning techniques for autonomous mobile robots was presented. These techniques were briefly discussed. It is presented a comprehensive analysis of each method in this broad research area of mobile robot's path planning. These various methods are categorized into classical and artificial intelligence approaches. The most important findings are outlined below.

1. Most of the publications available today gave only a simulation analysis; actual papers regarding real-time applications have been significantly fewer.
2. The number of papers on navigation by multiple mobile robot systems is very low when compared to the number of papers on navigation by single mobile robot systems.
3. AI approaches performs better than classical approaches because they have a higher capability to handle uncertainty present in the environment.
4. Research articles based on dynamic environments are far less common than research papers based on static environments.
5. To solve real-time navigation problems, AI approaches are most preferably used.
6. There are fewer papers that discuss the navigation of a robot in a dynamic environment with moving targets compared to that of a static targets problem.

7. There have been much fewer papers on standalone algorithms compared to those on hybrid algorithms.
8. It is possible to improve the performance of classical approaches by hybridizing them with AI approaches.
9. Classical algorithms are not used with multi objective as standalone, it used as hybrid with AI algorithms.
10. There is no research paper applied multi objective with moving target.

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6 Authors

Baraa Mohammed Abed is a Ph.D. Student in the field of Robotics and Machine learning. He has received B.Sc. and M.Sc. degrees in Computer Science from University of Anbar. His research interests are autonomous systems, robotics, machine learning, classification and optimization technique. He has published research papers at national and international journals, conference proceedings.

Wesam Mohammed Jasim received the B.Sc. and M.Sc. degrees in control automation engineering from University of Technology, Baghdad, Iraq, and Ph.D. degree in computing and Electronics from University of Essex, Essex, UK. Currently, he is an Assistant Professor with the College of Computer Science and Information Technology, University of Anbar. His current research interests include robotics, multiagent systems, cooperative control, Robust control, linear and nonlinear control, Deep learning. He has published research papers at national and international journals, conference proceedings as well as chapters of book.

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