Iraqi Journal of Intelligent Computing and Informatics (IJICI)
Vol. 2, 1, June 2023, pp. 1~10
ISSN: 2791-2868, DOI: 10.52940/ijici.v2i1.24

A review: On bio-inspired optimization methods for path planning of mobile robot

Fetoh H. Ketafa [1*], Salah Al-Darraji [2]
[1]Computer Science Department, College of Computer Science and Information Technology, Basrah, Iraq
[2]Computer Science Department, College of Education for Pure Sciences, Basrah, Iraq

Article Info

Article history:

Received December 27, 2022
Revised January 29, 2023
Accepted February 05, 2023

Keywords:

Bio-inspired
Path planning
Mobile robot
Autonomous robot navigation
Meta-heuristic

ABSTRACT

In recent years, researchers have paid attention to algorithms inspired by nature where these algorithms have proven their efficiency in solving many optimization problems, especially in complex situations, due to their high precision, speed of optimization, simplicity of the techniques, and efficiency in agent cooperation. The primary issue in the field of autonomous mobile robots is navigation. An autonomous robot's navigation ability is one of its most crucial and distinctive features. There are four components of the autonomous robot navigation issue: vision, localization, cognition, and path planning. Many academics have used bio-inspired methods to solve navigation difficulties in mobile robots in recent years, including path planning where they considered the path planning problem as an optimization problem. Many novel path-planning methods have been created, and those using bio-inspired algorithms have received much attention. These algorithms have been shown to be useful in solving complex problems where the solution space isn't always adequately characterized and the problem necessitates solving complex mathematical models of live processes. More intricate optimization methods that transcend the constraints of classical procedures must be applied as the complexities of the optimization problem increase. This work contributes to presenting a group of algorithms inspired by nature that has been used to solve the problem of planning the path of mobile robots, and then making a comparison between these algorithms based on three factors (cost, time, and path length). Choosing an appropriate path-planning method contributes to ensuring safe and efficacious navigation from one point to another.

Corresponding Author:

Fetoh Hason Ketafa
Department of Computer Science, College of Computer Science and Information Technology, University of Basrah, Basrah, Iraq
Email: itpg.fatoh.hason@uobasrah.edu.iq

1. INTRODUCTION

Large groups of animals in nature have a greater ability to tackle complex problems than smaller groups or lone individuals. It may be seen in the prey behavior of social insects, the navigation of herds of birds, and the careful activity of fishes.Swarm intelligence refers to an animal's collective and self-organizing behavior. Several publications have employed bio-inspired methodologies to tackle various parts of path planning strategies [1-9], a Whale Optimization Algorithm (WOA), applied in fixed situations to meet prerequisites for the optimization length of the path and smoothing path [10, 11], and Dai et al. [12], suggested a method that based on the Cuckoo Optimization Algorithm for planning the robot's path in a moving situation.

Scientists have recently concentrated their efforts on the development of robotics utilizing artificial intelligence to attain mobile robot autonomy. Autonomous mobile robots are becoming more common in disciplines such as space, industry, transportation, and definition, as well as other social areas [13]. As digital electronics and computer technology evolved, so did the compatibility of path planning with Artificial Intelligence approaches [14]. The intelligence of a mobile robot is mostly responsible for its navigation. The most efficient and important intelligent component of these capabilities is path planning. The process of establishing the best, collision-free route from one site to another is known as path planning. LaValle [15] provides convincing evidence for discussing path planning strategies. Machines handling a range of jobs that humans normally find difficult to do is an exciting subject.

To establish a fully autonomous navigation system, complete information such as current position, destination position, and a map of the immediate area must be provided. where navigation system refers to the capacity to locate the current location and generate the best path to one's intended destination [16]. Many novel approaches have been developed; however detailed evaluations of robot path planning utilizing bio-inspired algorithms are uncommon. As a result, this research examines numerous bio-inspired algorithms to demonstrate the current advancements in robot path planning. The principal robot route planning approach examined in this review is swarm intelligence. Furthermore, the advantages and disadvantages of various strategies are outlined and examined. The following sections are structured as follows: Section 2 presents a discussion of path planning strategy. Section 3 discusses bio-inspired algorithms and their benefits and drawbacks. Section 4 provides a conclusion.

2. PATH PLANNING STRATEGY

There are three sorts of existing path planning techniques: classical algorithms, heuristic algorithms, and meta-heuristic algorithms [17] as depicted in Figure.1. The Road Map technique [18], Cell Decomposition technique [19], the Rapidly Exploring Random Tree technique is One of the more popular traditional sampling-based path planning algorithms. However, beyond the computation cost, it also has some issues with the convergence rate [20-23], and the potential field technique [24]are examples of classical methodologies. Dijkstra's algorithm [25], and A* search algorithm are examples of heuristic approaches. Genetic algorithm (GA), artificial neural network , whose modified forms are commonly employed to discover the optimal length of path for mobile robot path planning in several situations [26], and Particle Swarm Optimization (PSO) are examples of evolutionary algorithms. All of these algorithms and methods are widely employed for mobile robot navigation. Numerous meta-heuristic techniques, such as nature-inspired algorithms, have also been employed to handle multi-objective navigation issues for mobile robots. Several prior research have used examples of natural behaviours in this group.

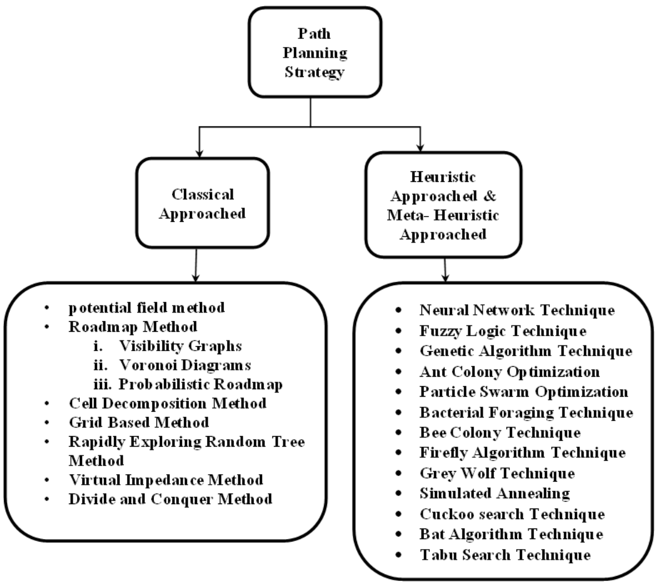

Figure 1. Path Planning Strategy [27]

Several techniques to carrying out the optimization have been offered over the years. The majority of these procedures are based on traditional methodologies. Classical methods are effective tools for solving specific types of optimization problems. However, one disadvantage of these methods is that they are unsuitable for solving complex optimization issues. Traditional path planning approaches based on mathematical models struggle to produce a credible path in complex scenarios. Bio-inspired optimization algorithms, which are inspired by nature, yield superior solutions in complex settings. Bioinspired algorithms have lately attracted a lot of interest for addressing intricate optimization issues since they generally offer the best solution that maintains the balance among its components. Researchers have increasingly emphasized the use of bio-inspired algorithms to address path planning challenges by considering them as optimization problems [28].

3. METAHEURISTIC OPTIMIZATION METHODS

Due to their high precision, speed of optimization, and cheap computer complexity, metaheuristic techniques have proven to be effective for a variety of optimization tasks. These algorithms have been shown to be useful in solving complex problems where the solution space isn't always adequately characterized and the problem necessitates solving complex mathematical models of live processes.

More intricate optimization strategies that transcend the constraints of classical procedures must be applied as the complexities of the optimization problem increase, especially with the introduction of uncertainties to the system. This purpose has prompted the development of metaheuristic approaches. Natural selection and social adaptation drive metaheuristic strategies to emulate the best traits in nature [29]. Many academics have used nature-inspired metaheuristic optimization strategies to solve mobile robot navigation difficulties in recent years. For solving navigational strategies, nature-inspired algorithms such as (GA), Ant Colony Optimization (ACO), Cuckoo Search, Invasive Weed Optimization, PSO, Bacteria Forging Algorithm, Bats Algorithm, Simulated Annealing, Grey Wolf Optimizer, Bees Algorithm (BA), Cockroach Swarm Algorithm, Frog Leaping Al [30].

There are two types of metaheuristic optimization approaches: trajectory-based and population-based methods [31-33]. The number of tentative answers employed in each stage of the (iterative) algorithm is the fundamental distinction between these two classes.

A trajectory-based technique (Single) (such as Variable Neighborhood Search, Tabu Search, Hill Climbing, and Simulated Annealing) begins with one initial answer and then replaces it with another (typically the best) solution identified in its neighborhood at each stage of the search. Trajectory-based metaheuristic approaches are known to discover a local optimal solution quickly.

Population-based algorithms, on the other hand, employ a collection of solutions. The initial population is generated at random and then enhanced in an iterative process. At each iteration, selected members of the population are replaced by newly produced people (generally those with superior qualities for the issue at hand), resulting in a new generation. These approaches are regarded as exploration-oriented methods since their primary capacity is to diversify the search space. Population-based techniques outperform other approaches for global optimization [29]. Swarm Intelligence and Evolutionary Algorithms are two of these methodologies [29], as seen in Figure.2.

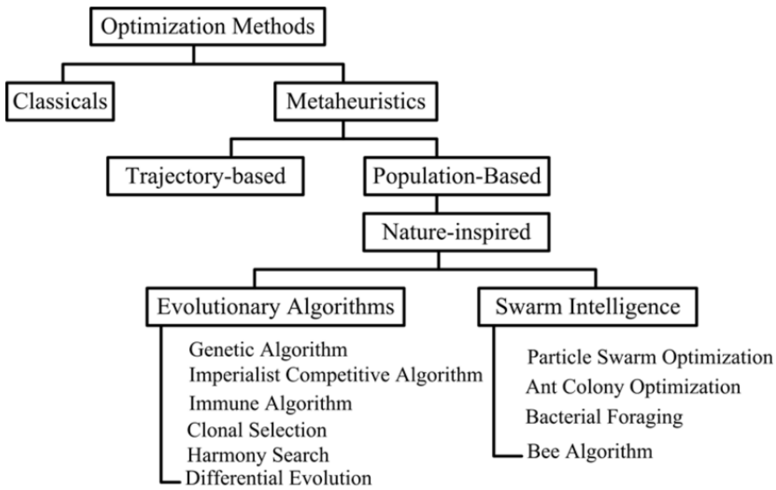

Figure 2. Metaheuristics Optimization Methods Classification [29]

In the last few decades, many metaheuristic algorithms have been developed. GA and PSO have become popular because they have demonstrated two significant benefits over trajectory-based methods: the capacity to tackle complicated problems and parallelism. Furthermore, population-based techniques outperform global optimization and can handle linear or nonlinear, continuous or discontinuous objective functions that are stable or transient [29].

3.1. Bio-inspired methods

3.1.1. Particle swarm optimization

In 1995, Kennedy and Eberhart proposed the PSO technique [34]. This is a swarm intelligence-based meta-heuristic optimization approach. It's a metaheuristic algorithm inspired by nature that simulates the social behavior of animals such as fish schools and flocks of birds. It's also a continually evolving optimization tool for dealing with a wide range of problems. The PSO mimics social animal behavior, but it does not require a group leader to achieve the purpose. When a flock of birds goes in search of food, they do not require leaders; they just follow the individual that is closest to the food. Through excellent communication with the rest of the community, the flock of birds accomplishes its ultimate goal. The PSO method is made up of a collection of particles, each of which represents a potential solution, and each particle moves repeatedly around the problem space in pursuit of the best-fitting answer. The system begins with a population of random solutions, with each particle having a random position and velocity to steer it around its navigation space. Each particle in PSO follows a route in research space, periodically updating its velocity and position vectors. Furthermore, after each iteration, each particle moves toward one of two "best" values: the best fitness (PBest) attained by each particle and the highest fitness (GBest) achieved by the entire swarm. This cycle is repeated until the desired destination is found or the maximum number of iterations is reached [35, 36]. PSO is currently widely employed in the field of mobile robot navigation. Tang X. et al. [37] used a multi-agent particle filter to handle the mapping and localization issues of mobile robot navigation in an unfamiliar environment. PSO use assists in calculation reduction and the maintenance of more constant convergence characteristics. To achieve an accurate trajectory and avoid being stuck in local optima PSO and MADS algorithms were integrated by Xuan et al. [38]. (Mesh Adaptive Direct Search). The PSO MADS algorithm, when combined with the GA and EKF, produces a more efficient output (Extended Kalman Filter) [28]. [39, 40] also employed PSO for mobile robot navigation from the start point to the goal position while avoiding obstacles on the robot's route.

3.1.2. Ant Colony Optimization

Marco Dorigo first proposed the ACO algorithm in his PhD thesis in 1992 [41]. He turned the behavior of ant colonies in terms of how they choose a certain path to seek and collect food into an artificial optimisation method for solving combinatorial issues [42]. The ACO method is a metaheuristic technique for quickly determining an approximate solution to complicated combinatorial optimisation issues [42]. Ant behavior and their ability to locate the shortest path from their nest to a food source inspired the ACO algorithm. Individual ants in a colony initially emerge from the nest and wander in random directions in search of food, according to natural ant traits. They take some of the food they find back home once they've found a food source. They secrete a chemical hormone called Pheromone on their trip back. The amount of Pheromone produced is likely to be influenced by the food's quality and quantity. As the ants follow a specific path, such as one that is shorter than others, more Pheromone is deposited on that path. Other ants will be encouraged to follow the path/trail with more Pheromone, which they will likely prefer over the other paths. In [43-46] used ACO to address path planning issues in complicated settings, and an enhanced version of ACO (IACO) is presented to achieve quicker convergence time and avoid trapping in a local optimum. The IACO gave the best path when compared with other algorithms, nevertheless, it has a low convergence speed. W. Hou et al. [47] proposed an algorithm for an improved ant colony with a communication system. The communication method is inspired by the interaction of ant tentacles in nature, which may combine historical trails to produce a superior composite path, where in mobile robot route planning, the ant colony algorithm faces the issue of not being able to fully exploit the previous pathways traversed by ants.

3.1.3. Gray Wolf Optimization (GWO) algorithm

Mirjalili's Gray Wolf Optimization (GWO) algorithm, first proposed in 2014, replicates gray wolf hunting strategies and social leadership [48]. This algorithm divides gray wolves into four tiers based on their social hierarchy: alpha, beta, delta, and omega wolves. An alpha wolf, for example, is the leader of the wolf pack, whereas omega wolves are the grey wolves at the bottom of the food chain. This group consists of scouts, guardians, elders, hunters, and caregivers. In addition to the social leadership mechanism, the gray wolf hunting strategy is an intriguing mechanism of the GWO algorithm. To overcome the difficulty of robot route planning, the GWO approach was proposed [49]. To find the shortest path from the starting point to the destination while avoiding obstacles. The zone with three circular obstacles of varied radius was used to assess the GWO algorithm's performance. The GWO method was compared to the Differential Evolution (DE) algorithm, PSO algorithm, Artificial Bee Colony (ABC) algorithm, and Firefly Optimization Algorithm (FOA). The algorithm's performance in addressing path planning issues was evaluated using four well-known metaheuristic algorithms (DE, PSO, ABC, and FOA). The comparative findings indicate that the suggested GWO algorithm may give extremely competitive results.

The gray wolf hunting technique, together with the social leader mechanism, is an intriguing way inside the GWO algorithm. Gray wolves hunt in packs, which is another intriguing social behavior. The gray wolves first find the prey and circle it under the orders of the alpha wolf. The gray wolf hunting strategy's mathematical model proposes that alpha, beta, and delta wolves supply more information about potential forage sites. As a consequence, the top three best solutions (alpha, beta, and delta) are utilized to reposition the wolves in the GWO algorithm. An mathematical model of the gray wolf hunting approach is as follows:

$$\vec{D}_\alpha = \left|\vec{C}_\alpha . \vec{X}_\alpha - \vec{X}_i\right| \tag{1}$$
$$\vec{D}_\beta = \left|\vec{C}_\beta . \vec{X}_\beta - \vec{X}_i\right| \tag{2}$$
$$\vec{D}_\delta = \left|\vec{C}_\delta . \vec{X}_\delta - \vec{X}_i\right| \tag{3}$$
$$\vec{U}_\alpha = \vec{X}_\alpha - \vec{A}_\alpha \vec{D}_\alpha \tag{4}$$
$$\vec{U}_\beta = \vec{X}_\beta - \vec{A}_\beta \vec{D}_\beta \tag{5}$$
$$\vec{U}_\delta = \vec{X}_\delta - \vec{A}_\delta \vec{D}_\delta \tag{6}$$
$$\vec{X}_i = \left(\vec{U}_\alpha + \vec{U}_\beta + \vec{U}_\delta\right) / 3 \tag{7}$$

where $\vec{D}_\alpha$, $\vec{D}_\beta, \vec{D}_\delta$ denotes the distance vector between the prey and the wolf (alpha, beta, delta), $\vec{X}_\alpha, \vec{X}_\beta, \vec{X}_\delta$ denotes the location vector of the prey, $\vec{X}_i$ denotes the position vector of the gray wolf at i_{th} iteration, $\vec{C}_\alpha$, $\vec{C}_\beta, \vec{C}_\delta$ $\vec{A}_\alpha$, $\vec{A}_{\beta,}\vec{A}_\delta$ denotes the coefficient vectors of alpha, beta, and delta wolves, and $\vec{U}_\alpha$, $\vec{U}_\beta, \vec{U}_\delta$ denotes the trial vector for the alpha, beta, and delta wolves. The coefficient vectors for the alpha, beta, and delta wolves are as follows:

$$\vec{A}_\alpha = 2\vec{a}\vec{r}_{\alpha 1} - \vec{a} \tag{8}$$
$$\vec{C}_\alpha = 2\vec{r}_{\alpha 2} \tag{9}$$
$$\vec{A}_\beta = 2\vec{a}\vec{r}_{\beta 1} - \vec{a} \tag{10}$$
$$\vec{C}_\beta = 2\vec{r}_{\beta 2} \tag{11}$$
$$\vec{A}_\delta = 2\vec{a}\vec{r}_{\delta 1} - \vec{a} \tag{12}$$
$$\vec{C}_\delta = 2\vec{r}_{\delta 2} \tag{13}$$

where $\vec{a}$ denotes the vector that was linearly dropped from 2 to 0 throughout the optimization, $\vec{r}_{\alpha 1}$, $\vec{r}_{\beta 1}, \vec{r}_{\delta 1}$denotes the first random vector in [0,1], and $\vec{r}_{\alpha 2}$, $\vec{r}_{\beta 2}, \vec{r}_{\delta 2}$denotes the second random vector in [0,1]. The hunting process of the gray wolf group, is group members adjust their places based on the alpha, beta, and delta wolves and prey. The gray wolves take their victim and end the hunt by attacking it. This condition is described as a decreasing $\vec{a}$ vector in the mathematical model shown below:

$$\vec{a} = 2 - \frac{2 .Iter}{MaxIt} \tag{14}$$

3.1.4. Dragonfly algorithm

The Dragonfly algorithm (DA) was presented by Seyedali Mirjalili in 2015 for tackling multi-objective optimization problems [50]. The DA is based on dragonflies' extraordinary and intelligent swarming behavior, which is a crucial feature of hunting and migratory [50]. The creation of a small group of dragonflies swarming or seeking for food is known as static swarming or hunting. The very large number of dragonflies flying over long distances for migration is referred to as a dynamic swarm or migratory swarm [30, 50]. The exploitation phase of the DA is represented by static swarms, while the exploratory capabilities of DA are represented by dynamic swarms. The DA has been used to guide autonomous mobile robots across an unknown crowded environment with a number of static obstacles [30]. The static and dynamic swarming behaviors of dragonflies in nature inspired this novel meta-heuristic. The distance between the robot, the target, and the obstacles is used to formulate two objective functions: target searching and obstacle avoidance, which are then optimized using the suggested DA to obtain the best path. The robot moves towards the globally best agent in the swarm in a sequence of permutations after each iteration, based on the objective function values, until it reaches the target. The suggested algorithm demonstrates that the robot reaches the objective without colliding with any impediments and creates a smooth ideal trajectory. Despite the fact that the suggested method has proven to be versatile and resilient for local path planning, incorporating reinforcement learning will yield superior outcomes. Furthermore, just the path planning of a single mobile robot with static obstacles is considered in this method, and the program's skills are assessed. Despite its high performance, the swarm intelligence algorithm has flaws such as poor convergence speed.

3.1.5. Bees Colony

The (BA) is a population-based algorithm that solves complicated problems by simulating the behavior of honey bees [51]. In an optimization problem, the BA finds the solution that is closest to the best [52]. Local and global searches are carried out by the BA. Local search speeds up convergence to the best solution by attracting additional worker bees to possibly exploitable areas. Global search, on the other hand, preserves the diversity of solutions while also exploring new promising patches that have yet to be examined [53]. [54] recently presented a real-time path planning solution in an indoor dynamic setting using the bee’s algorithm. There are two steps to the algorithm. Robot route planning is used off-line in the first stage to discover the best path in an area with only static obstacles. The obtained path is then handed to the robot to follow in the second stage. At the same time, the algorithm adjusts the path in real time to avoid colliding with new obstacles and to ensure that sub-paths are optimal. Using a modified type of local search, the path's optimality is preserved. The algorithm's performance was improved by using neighborhood shrinking. The method was evaluated using simulation and experiment with AmigoBot, and it was described as performing well with the optimal path in real time.

3.1.6. Cuckoo optimization algorithm (COA)

Ramin Rajabioun created the Cuckoo optimization algorithm (COA) [55]for tackling nonlinear optimization problems in continuous space, which was inspired by the cuckoo's lifestyle. Cuckoos, unlike other birds, do not build their own nests and instead rely on the nests of other birds to breed. COA begins with a population of mature cuckoos, much like any other population-based algorithm. This population laid eggs in a variety of nests. The COA [56] was developed to solve the challenge of mobile robot path planning in a dynamic environment with several static and moving obstacles in various random polygon shapes. In addition, the feature vector is optimized (i.e., reduced in dimension) by a novel proposed technique to reduce computing complexity. The simulation results demonstrate the proposed algorithm's ability to identify a short, safe, smooth, and collision-free path in a variety of environments.

3.1.7. Improved moth-flame optimization algorithm

Xuefeng Dai and Yang Wei suggested [57] an IMFO algorithm to overcome the limitations of the MFO method, such as slow late convergence and the ease with which It might fall into the local optimum. First, the update formula of the MFO algorithm was improved by including the concept of historical ideal flame mean with reference to the SHO technique, allowing the MFO algorithm to better utilize the information in the flame matrix. The method of getting the best response is abstracted from a moth flying in a spiral around a flame. The position updating mechanism is a critical component of swarm intelligence systems. Individual moths in the MFO algorithm continue to disrupt in a helical flying near the flame as the numeral of algorithm iterations grows until the ideal solution is reached. There are two aspects to the mathematical description: flame-tending behavior and flame-abandoning behavior. The suggested hybrid backward learning technique thus improves population diversity. The IMFO algorithm then demonstrated to be more stable and accurate in terms of convergence than the MFO method. Finally, the IMFO algorithm is used for path planning, and its efficacy is evaluated.

3.1.8. Whale optimization algorithm

Seyedali Mirjalili and Andrew Lewis [58] devised a swarm-based optimization system inspired by humpback whale hunting behavior. The suggested algorithm (WOA) contained three operators to imitate the humpback whales' hunt for prey, surrounding prey, and bubble-net foraging behavior. WOA was inspired by humpback whales' bubble-net hunting method. It is worth noting that bubble-net feeding is a distinct activity found solely in humpback whales. In order to optimize the spiral bubble-net feeding maneuver, it is mathematically modeled. Humpback whales seek at random based on their relative positions.

Dao et al. [10] suggested a multi-objective whale optimization algorithm (MWOA) for mobile robot path planning optimization. In each iteration of robot planning during optimization, the robot workspace's environment comprises of the locations and types of obstacles, and the robot's start and target positions were modeled, as well as search agents mapped to a parsing solution. In the suggested technique, MWOA handles two objectives at the same time: brevity and smoothness. The position of the best whale on the planet is picked and approached by the robot in order in each iteration. Furthermore, when in motion, the robot processor updates its knowledge, and the surroundings are partially unknown to the robot due to the sensor's restricted detection range. The simulation results demonstrate that the suggested strategy successfully gives a compelling performance for the robot route planning job. The robot gets its destination by colliding with free barriers.

3.1.9. Hybrid methods

A double global optimal genetic algorithm-particle swarm optimization (GA-PSO) based on the GA and PSO algorithms is developed [59] to address the welding robot path planning issue, where the shortest collision-free pathways are utilized as the criterion to optimize the welding path. Aside from method effectiveness analysis and verification, simulation results indicated that the algorithm outperforms the fundamental GA and PSO algorithms and may be applied to welding robot route planning.

To tackle the route planning of mobile robots, an improved path planning for mobile robots is proposed based on a hybrid multi-objective bare bones particle swarm optimization (MOBBPSO) [60] coupled with differential evolution. Because the proposed approach includes three optimization indices, namely the path length, smoothness degree, and safety degree of a path, mobile robot path planning is transformed into a multi-objective optimization problem with constraints. A novel Pareto dominance with collision restrictions is created based on the collision degree of a path to evaluate a particle's fitness and pick the personal best position of a particle. Differential evolution is used to stimulate the mutation of infeasible pathways obstructed by obstacles with the difference vector taken from the feasible archive in order to increase the feasibility of an infeasible path.

Faiza et al. [61] suggested a strategy based on a hybridized Grey Wolf optimizer with the PSO method. The approach was based on an obstacle detection and avoidance method. The strategy used evolutionary mutation operation to tackle path integrity and smooth it down even more for an autonomous mobile robot. The methodology is based on the use of meta-heuristics techniques and incorporates three separate algorithms. The suggested approach operates in a sequential manner. To begin, it employs PSO Optimization and the Grey Wolf optimizer to reduce path distance and smooth the path. The generated waypoints from PSO-GWO are then combined with the Local Search technique in the second step to turn all infeasible points into feasible points. Collision avoidance and detection function using a sensing circle to avoid obstacles in the third stage. Hybrid PSO-GWO has been incorporating evolutionary programming. This also reduces the algorithm's duration and computational complexity. A collision-free, smooth, and optimal path is obtained using mutation operators. Several experiments were run in various situations to verify the probability of the suggested approach, and it was discovered that the method provides more viable paths with shorter distances.

Lina Bassem Amar and Wesam M. Jasim [62] suggested a hybrid technique for identifying the best path of a PSO/ACO hybrid robot. These were utilized to successfully carry out path planning operations. To meet the goals, a number of restrictions must be met at the same time, including the shortest path, the shortest time, and the absence of collisions. PSO ACO hybrid conducts a stochastic search in the fitness landscape, which is also the phenotypic search space. The phenotype describes the genotype's behavioral manifestation in a certain context. The suggested hybrid PSO and ACO algorithm was tested in a dynamic setting to determine its efficiency. It is also discovered that the suggested approach outperforms the two existing algorithms, ACO and PSO. Depending on the specified algorithm, the robot recommends a specific path to attain the target at the start of the instruction. The robot then moves from the starting point to the objective, with each step verifying the permeability of movement and the absence of any obstacles in its path. In the case that an obstruction appears in its course, the hybrid PSO and ACO algorithm adjusts the path.

Table 1 compares the discussed methods based on three parameters (cost, time, and path length).

Table 1. Compare Between Methods

Author	Method	Low Cost	High Convergence	Optimal Path
T. F. Abaas and A. H. Shabeeb 2020	PSO [35]	No	Yes	Yes
G. Chen and J. Liu 2019	ACO [45]	Yes	No	Yes
L. Doğan and U. Yüzgeç 2018	GWO [63]	NO	Yes	NO
S. Muthukumaran and R. Sivaramakrishnan 2019	DA [30]	NO	Yes	NO
A. Haj Darwish et al. 2018	BA [54]	NO	NO	Yes
S. Hosseininejad and C. Dadkhah 2019	COA [56]	Yes	NO	Yes

Xuefeng Dai and Yang Wei 2021	IMFO [57]	Yes	No	Yes
Dao et al 2016	MWOA [10]	No	No	Yes
Wang et al. 2016	GA-PSO [59]	Yes	NO	Yes
Zhang et al. 2018	MOBBPSO [60]	NO	NO	Yes
Faiza et al. 2021	PSO-GWO [61]	Yes	Yes	Yes
L. B. Amar and W. M. Jasim 2021	PSO-ACO [62]	Yes	Yes	NO

4. CONCLUSION

Recently, scientists have focused their efforts on the development of robots that use artificial intelligence to achieve mobile robot autonomy. Autonomous mobile robots are becoming more widespread in fields like as space exploration, manufacturing, transportation, and definition, as well as other social domains. As digital electronics and computer technology advanced, so did path planning's compatibility with Artificial Intelligence techniques. Many bio-inspired metaheuristic optimization solutions were provided in this study for overcoming mobile robot navigation difficulties that were challenging for standard path planning approaches based on mathematical models in complex surroundings. Choosing the right path planning algorithm contributes to safe and successful point-to-point navigation. Swarm intelligence is the principal robot route planning approach examined in this review.

REFERENCES

[1] P. Das, S. Pradhan, S. Patro, and B. K. Balabantaray, "Artificial immune system based path planning of mobile robot," in *Soft Computing Techniques in Vision Science*: Springer, 2012, pp. 195-207.

[2] H. S. Dewang, P. K. Mohanty, and S. Kundu, "A robust path planning for mobile robot using smart particle swarm optimization," *Procedia computer science,* vol. 133, pp. 290-297, 2018.

[3] M. A. Hossain and I. Ferdous, "Autonomous robot path planning in dynamic environment using a new optimization technique inspired by bacterial foraging technique," *Robotics and Autonomous Systems,* vol. 64, pp. 137-141, 2015.

[4] G. Wang, L. Guo, H. Duan, L. Liu, and H. Wang, "A bat algorithm with mutation for UCAV path planning," *The Scientific World Journal,* vol. 2012, 2012.

[5] W. Wang, M. Cao, S. Ma, C. Ren, X. Zhu, and H. Lu, "Multi-robot odor source search based on cuckoo search algorithm in ventilated indoor environment," in *2016 12th World Congress on Intelligent Control and Automation (WCICA)*, 2016: IEEE, pp. 1496-1501.

[6] T. Y Abdalla and Z. T Allawi, "An ABC-Optimized Reciprocal Velocity Obstacles Algorithm for Navigation of Multiple Mobile Robots," *IRAQI JOURNAL OF COMPUTERS, COMMUNICATIONS, CONTROL AND SYSTEMS ENGINEERING,* vol. 15, no. 2, pp. 47-57, 2015.

[7] T. A. Jaleel and A. K. A. Hassan, "Collision Avoidance Using Cat Swarm Algorithm for Multi Mobile Robot Path Planning in Dynamic Environment," *Iraqi Journal of Science,* pp. 2348-2359, 2016.

[8] A. Shareef and S. Al-Darraji, "Grasshopper optimization algorithm based path planning for autonomous mobile robot," *Bulletin of Electrical Engineering and Informatics,* vol. 11, no. 6, pp. 3551-3561, 2022.

[9] M. K. Muni, D. R. Parhi, and P. B. Kumar, "Improved motion planning of humanoid robots using bacterial foraging optimization," *Robotica,* vol. 39, no. 1, pp. 123-136, 2021.

[10] T.-K. Dao, T.-S. Pan, and J.-S. Pan, "A multi-objective optimal mobile robot path planning based on whale optimization algorithm," in *2016 IEEE 13th International Conference on Signal Processing (ICSP)*, 2016: IEEE, pp. 337-342.

[11] A. Chhillar and A. Choudhary, "Mobile robot path planning based upon updated whale optimization algorithm," in *2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*, 2020: IEEE, pp. 684-691.

[12] X. Dai, S. Long, Z. Zhang, and D. Gong, "Mobile robot path planning based on ant colony algorithm with A* heuristic method," *Frontiers in neurorobotics,* vol. 13, p. 15, 2019.

[13] L. A. Al-Ani, M. S. M. Altaei, and Q. Khamees, "Simulation of Obstacle Avoidance for Auto Guided Land Vehicle," *Iraqi Journal of Science,* pp. 189-203, 2019.

[14] M. Zafar, J. Mohanta, and A. Keshari, "GWO-Potential Field Method for Mobile Robot Path Planning and Navigation Control," *Arabian Journal for Science and Engineering,* vol. 46, no. 8, pp. 8087-8104, 2021.

[15] S. M. LaValle, *Planning algorithms*. Cambridge university press, 2006.

[16] H. Hakim, Z. Alhakeem, and S. Al-Darraji, "Goal location prediction based on deep learning using RGB-D camera," *Bulletin of Electrical Engineering and Informatics,* vol. 10, no. 5, pp. 2811-2820, 2021.

[17] T. T. Mac, C. Copot, D. T. Tran, and R. De Keyser, "Heuristic approaches in robot path planning: A survey," *Robotics and Autonomous Systems,* vol. 86, pp. 13-28, 2016.
[18] L. E. Kavraki, P. Svestka, J.-C. Latombe, and M. H. Overmars, "Probabilistic roadmaps for path planning in high-dimensional configuration spaces," *IEEE transactions on Robotics and Automation,* vol. 12, no. 4, pp. 566-580, 1996.
[19] H. Choset, *Sensor based motion planning: The hierarchical generalized Voronoi graph*. California Institute of Technology, 1996.
[20] S. M. LaValle, "Rapidly-exploring random trees: A new tool for path planning," 1998.
[21] S. M. LaValle and J. J. Kuffner Jr, "Randomized kinodynamic planning," *The international journal of robotics research,* vol. 20, no. 5, pp. 378-400, 2001.
[22] S. Al-Ansarry and S. Al-Darraji, "Hybrid RRT-A*: An Improved Path Planning Method for an Autonomous Mobile Robots," *Iraqi Journal for Electrical & Electronic Engineering,* vol. 17, no. 1, 2021.
[23] S. Al-Ansarry and S. Al-Darraji, "MT Hybrid RRT-A* Regression-based: An Enhanced Path Planning Method for an Autonomous Mobile Robots," *Journal of Basrah Researches ((Sciences)),* vol. 47, no. 1, 2021.
[24] O. Khatib, "Real-time obstacle avoidance for manipulators and mobile robots," in *Proceedings. 1985 IEEE International Conference on Robotics and Automation*, 1985, vol. 2: IEEE, pp. 500-505.
[25] E. W. Dijkstra, "A note on two problems in connexion with graphs:(Numerische Mathematik, 1 (1959), p 269-271)," 1959.
[26] C. Lamini, S. Benhlima, and A. Elbekri, "Genetic algorithm based approach for autonomous mobile robot path planning," *Procedia Computer Science,* vol. 127, pp. 180-189, 2018.
[27] A. Sanyal, N. Zafar, J. Mohanta, and F. Ahmed, "Path Planning Approaches for Mobile Robot Navigation in Various Environments: A Review," *Advances in Interdisciplinary Engineering,* pp. 555-572, 2021.
[28] J. Li, S. X. Yang, and Z. Xu, "A survey on robot path planning using bio-inspired algorithms," in *2019 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, 2019: IEEE, pp. 2111-2116.
[29] S. E. De León-Aldaco, H. Calleja, and J. A. Alquicira, "Metaheuristic optimization methods applied to power converters: A review," *IEEE Transactions on Power Electronics,* vol. 30, no. 12, pp. 6791-6803, 2015.
[30] S. Muthukumaran and R. Sivaramakrishnan, "Optimal path planning for an autonomous mobile robot using dragonfly algorithm," *International Journal of Simulation Modelling,* vol. 18, no. 3, pp. 397-407, 2019.
[31] K. Hussain, M. N. Mohd Salleh, S. Cheng, and Y. Shi, "Metaheuristic research: a comprehensive survey," *Artificial intelligence review,* vol. 52, no. 4, pp. 2191-2233, 2019.
[32] H. Al-Behadili, K. Ku-Mahamud, and R. Sagban, "Genetic-based pruning technique for ant-miner classification algorithm," *International Journal on Advanced Science, Engineering and Information Technology,* vol. 11, no. 1, p. 304, 2021.
[33] H. F. Almazini, S. Mortada, H. F. A. Al-Mazini, H. N. K. Al-Behadili, and J. Alkenani, "Improved discrete plant propagation algorithm for solving the traveling salesman problem," *IAES International Journal of Artificial Intelligence,* vol. 11, no. 1, p. 13, 2022.
[34] D. Wang, D. Tan, and L. Liu, "Particle swarm optimization algorithm: an overview," *Soft Computing,* vol. 22, no. 2, pp. 387-408, 2018.
[35] T. F. Abaas and A. H. Shabeeb, "Autonomous Mobile Robot Navigation Based on PSO Algorithm with Inertia Weight Variants for Optimal Path Planning," in *IOP Conference Series: Materials Science and Engineering*, 2020, vol. 928, no. 2: IOP Publishing, p. 022005.
[36] F. H. Ajeil, I. K. Ibraheem, M. A. Sahib, and A. J. Humaidi, "Multi-objective path planning of an autonomous mobile robot using hybrid PSO-MFB optimization algorithm," *Applied Soft Computing,* vol. 89, p. 106076, 2020.
[37] X.-l. Tang, L.-m. Li, and B.-j. Jiang, "Mobile robot SLAM method based on multi-agent particle swarm optimized particle filter," *The Journal of China Universities of Posts and Telecommunications,* vol. 21, no. 6, pp. 78-86, 2014.
[38] X. V. Ha, C. Ha, and J. Lee, "Novel hybrid optimization algorithm using PSO and MADS for the trajectory estimation of a four track wheel skid-steered mobile robot," *Advanced Robotics,* vol. 27, no. 18, pp. 1421-1437, 2013.
[39] A. J. Mohammed, K. I. Ghathwan, and Y. Yusof, "Optimal robot path planning using enhanced particle swarm optimization algorithm," *Iraqi Journal of Science,* pp. 178-184, 2020.
[40] A. A. Ahmed, T. Y. Abdalla, and A. A. Abed, "Path planning of mobile robot by using modified optimized potential field method," *International Journal of Computer Applications,* vol. 113, no. 4, pp. 6-10, 2015.
[41] M. Dorigo, "Optimization, learning and natural algorithms," *Ph. D. Thesis, Politecnico di Milano,* 1992.
[42] I. Hamad and M. Hasan, "A review: on using aco based hybrid algorithms for path planning of multi-mobile robotics," 2020.
[43] R. Rashid, N. Perumal, I. Elamvazuthi, M. K. Tageldeen, M. A. Khan, and S. Parasuraman, "Mobile robot path planning using Ant Colony Optimization," in *2016 2nd IEEE International Symposium on Robotics and Manufacturing Automation (ROMA)*, 2016: IEEE, pp. 1-6.
[44] I. K. Ibraheem and F. H. Ajeil, "Path planning of an autonomous mobile robot using swarm based optimization techniques," *Al-Khwarizmi Engineering Journal,* vol. 12, no. 4, pp. 12-25, 2016.
[45] G. Chen and J. Liu, "Mobile robot path planning using ant colony algorithm and improved potential field method," *Computational intelligence and neuroscience,* vol. 2019, 2019.
[46] X. Xie, Z. Tang, and J. Cai, "The multi-objective inspection path-planning in radioactive environment based on an improved ant colony optimization algorithm," *Progress in Nuclear Energy,* p. 104076, 2021.

[47] W. Hou, Z. Xiong, C. Wang, and H. Chen, "Enhanced ant colony algorithm with communication mechanism for mobile robot path planning," *Robotics and Autonomous Systems,* vol. 148, p. 103949, 2022.

[48] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Advances in engineering software,* vol. 69, pp. 46-61, 2014.

[49] U. YÜZGEÇ, "Robot Path Planning using Gray Wolf Optimizer."

[50] S. Mirjalili, "Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems," *Neural computing and applications,* vol. 27, no. 4, pp. 1053-1073, 2016.

[51] D. T. Pham and M. Castellani, "A comparative study of the Bees Algorithm as a tool for function optimisation," *Cogent Engineering,* vol. 2, no. 1, p. 1091540, 2015.

[52] H. Marzi, A. Haj Darwish, and H. Helfawi, "Training ANFIS using the enhanced Bees Algorithm and least squares estimation," *Intelligent Automation & Soft Computing,* vol. 23, no. 2, pp. 227-234, 2017.

[53] W. A. Hussein, S. Sahran, and S. N. H. Sheikh Abdullah, "The variants of the Bees Algorithm (BA): a survey," *Artificial Intelligence Review,* vol. 47, no. 1, pp. 67-121, 2017.

[54] A. Haj Darwish, A. Joukhadar, and M. Kashkash, "Using the Bees Algorithm for wheeled mobile robot path planning in an indoor dynamic environment," *Cogent Engineering,* vol. 5, no. 1, p. 1426539, 2018.

[55] R. Rajabioun, "Cuckoo optimization algorithm," *Applied soft computing,* vol. 11, no. 8, pp. 5508-5518, 2011.

[56] S. Hosseininejad and C. Dadkhah, "Mobile robot path planning in dynamic environment based on cuckoo optimization algorithm," *International Journal of Advanced Robotic Systems,* vol. 16, no. 2, p. 1729881419839575, 2019.

[57] X. Dai and Y. Wei, "Application of Improved Moth-Flame Optimization Algorithm for Robot Path Planning," *IEEE Access,* vol. 9, pp. 105914-105925, 2021.

[58] S. Mirjalili and A. Lewis, "The whale optimization algorithm," *Advances in engineering software,* vol. 95, pp. 51-67, 2016.

[59] X. Wang, Y. Shi, D. Ding, and X. Gu, "Double global optimum genetic algorithm–particle swarm optimization-based welding robot path planning," *Engineering Optimization,* vol. 48, no. 2, pp. 299-316, 2016.

[60] J.-H. Zhang, Y. Zhang, and Y. Zhou, "Path planning of mobile robot based on hybrid multi-objective bare bones particle swarm optimization with differential evolution," *IEEE Access,* vol. 6, pp. 44542-44555, 2018.

[61] F. Gul, W. Rahiman, S. Alhady, A. Ali, I. Mir, and A. Jalil, "Meta-heuristic approach for solving multi-objective path planning for autonomous guided robot using PSO–GWO optimization algorithm with evolutionary programming," *Journal of Ambient Intelligence and Humanized Computing,* vol. 12, no. 7, pp. 7873-7890, 2021.

[62] L. B. Amar and W. M. Jasim, "Hybrid metaheuristic approach for robot path planning in dynamic environment," *Bulletin of Electrical Engineering and Informatics,* vol. 10, no. 4, pp. 2152-2162, 2021.

[63] L. Doğan and U. Yüzgeç, "Robot path planning using gray wolf optimizer," in *Proceedings-International Conference on Advanced Technologies, Computer Engineering and Science (ICATCES'18)*, 2018.