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# On Path Planning and Optimization Strategies: Toward Embedded Road Applications

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**Abstract**—In recent years, the role of robots in science, technology, and research, has become very important. Mobile robots are used in many fields on land, in the air, and underwater, and are integrated into numerous applications such as maintenance, security, detection, exploration of anomalies, decision making, and carrying out operations. These robots have thus taken their place in the terrain where there is an electric field and where they are involved in the maintenance of power lines, even at high voltage. This article deals with one of the principles used to improve the performance of this type of robot, namely path planning. This point is very important to save time and consequently avoid economic losses. Nowadays, many difficulties and challenges have to be overcome in order to navigate autonomously, efficiently, and reliably. This article reviews path planning methods for mobile robots, examines their modeling, algorithms, and optimization criteria, and proposes to open the horizon for embedded road applications (ERA).

**Keywords:** Autonomous navigation; Path planning; Mobile robot; Power distribution grid; Embedded road applications (ERA).

## I. INTRODUCTION

Worldwide, electric utilities are generally responsible for the generation and transmission of electric power to support people's quality of life, the economy, and the industrial sector. The mission of transmission line maintenance is to maintain a safe and continuous transmission system. Continuous maintenance of high voltage transmission systems is one of the most important goals of electric utilities. There is a long history of innovation in the use of robotic technologies for operations and maintenance in the electric utility industry [1]. One of the most important functions that robots perform is their ability to operate in harsh environments that require a high level of safety. An example of this is the power distribution grid, where recent research has been conducted on robots that replace humans in hazardous work on high-voltage power lines. These robots are characterized by their ability to effectively perform "minimally invasive interventions" on the power grid to solve complex and dangerous manual repair problems [2]. This type of robot has optical recognition, motion control, and electromagnetic interference, which gives them the functions of precise positioning and autonomous path planning according to engineering standards [3]. Work is underway to further develop robotic functions to improve the

integration of IoT and robotic technology with smart grid and power grid maintenance services, especially to avoid obstacles and shorten the time for quick repairs with the best path planning strategy. Thus, the main requirements are:

- Safe maintenance: by using robots to maintain high-voltage power grids.
- Fast maintenance: to avoid damage and economic losses caused by delayed maintenance of power transmission networks.
- Reliance on autonomous co-robots: many robotic systems can communicate with each other effectively to detect and fix problems in the high-voltage grid.

The main purpose of this paper is to provide an overview of robotic path planning (Figure 1) and to highlight some strategies that can provide optimization criteria for path planning. Section II presents trajectory planning. Section III discusses optimization criteria for trajectory planning. Section IV presents a comparison of path planning algorithms. Finally, Section V concludes.

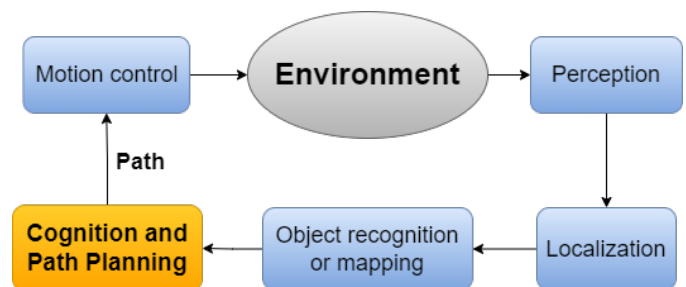


Fig. 1. Classification of mobile robot path planning.

## II. PATH PLANNING

Path planning can be divided into global path planning or classical methods and local path planning or heuristic methods (Figure 2). In global path planning, the robot has complete knowledge of the environment and the start and goal points and is used to maximize the effectiveness and efficiency of the search. In local trajectory planning, the robot has limited domain knowledge, and this method is suitable for real-time navigation due to the short calculation time.

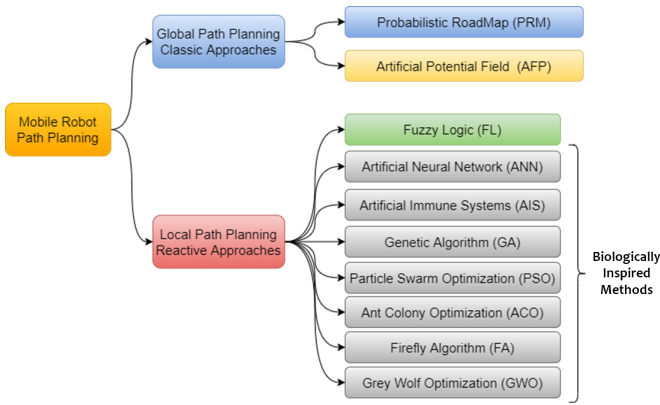


Fig. 2. Classification of mobile robot path planning.

### A. Classic Approach: Global Path Planning (GPP)

1) *Probabilistic RoadMap (PRM)*: The probabilistic roadmap approach was proposed by [4] in 1994. This approach can be defined as a graph search algorithm in which the mobile robot's reachable motion space (configuration space) is reduced to a network of one-dimensional lines. In this method, a safe, collision-free network of paths is constructed from the robot's starting position to the target position. The road map must characterize all topologically feasible pathways in the configuration space [5]. The search for the optimal path can be done in different ways, and various methods have been realized and specified by other forms of defining the nodes and the path series. The best-known road maps are the Voronoi diagram [6], the visibility graph [7], and the cell decomposition [8]. The authors of [9] have successfully analyzed the ability of a crewless aerial vehicle to navigate in a 3D environment. The path is generated based on the RoadMap technique with a probabilistic formulation. The authors of [10] present the elastic roadmap framework for a novel feedback motion planning approach that can account for kinematic and dynamic constraints, unpredictable moving obstacles, and global connectivity of the workspace.

2) *Artificial Potential Field (APF)*: The APF approach was first proposed in 1985 by [11] in 1985 to solve the task of obstacle avoidance by a mobile robot. The APF approach is based on the concept of a potential field in physics and defines the target point as attracting fields and the obstacles as repulsive fields. The resulting fields pull the mobile robot toward the target point while avoiding collisions with obstacles, as shown in Figure ?? . The large-scale application of APF has shown promising results for many mobile robot applications, even in a complex and challenging environment, as shown in [12]. The main advantages of APF are the ease of implementation, the low computational cost, and the ability to create a smooth trajectory. However, they also have some disadvantages, in particular, the robot may switch to a local solution or fail to reach the target point if the obstacle is close to the target point. To improve the performance of APF, many combinations

with other optimization methods have been performed. We can mention GA [13], and PSO [14].

### B. Heuristic Approach: Local path planning (LPP)

1) *Fuzzy Logic (FL)*: The concept FL was introduced by [15] in 1965 and has become widely used in almost all areas of research and development. It is used in situations with high uncertainty, complexity, and nonlinearity, such as decision-making, pattern recognition, and automatic control. Linguistic rules characterize fuzzy logic control to manipulate and implement human knowledge into the control system. This approach is commonly used for various robot path planning applications by providing the robot with heuristic knowledge about its environment. FL is commonly used in unstructured static and dynamic environments and avoids navigation problems such as infinite loops, dead ends (U-shaped, maze, snails) [16]. Curved trajectories [17] proposes a data-driven fuzzy approach to solve the dynamic motion problems of a robot. The main result of this research is that the robot can navigate safely in the presence of dynamic obstacles. In [18], a new real-time FLC is developed to enable autonomous parking and parallel parking for a car-like robot. Moreover, a hybrid path planning algorithm for a mobile robot is proposed using a FL and many algorithms such as ACO by [19], PSO by [20]. Many others are proposed to achieve the optimal perception of the environment and enable the robot to overcome a dead-end situation.

2) *Artificial Neural Network (ANN)*: ANN is inspired by the functioning of the human brain, is composed of neurons like the human brain, and is able to learn at high speed based on experience and observation. The performance of ANN depends on how the neuron is defined and how the neurons are interconnected (Figure 3.a). ANN is widely used in robotics for modeling dynamics and kinematics, path planning, and motion control. It provides simple and optimal solutions even in complex situations. [21]. The authors in [22] developed a hybrid approach combining ANN and Q-learning to solve the robot path planning problem. The results show that the hybrid strategy outperforms the other two methods. In [23], a hybrid approach (ANN and FL) was proposed for navigating multiple mobile robots under disordered conditions. It is analyzed in the presence of a static obstacle architecture. In [24], a hybrid approach combining a ANN with a PSO algorithm is proposed, where the PSO performs the trajectory smoothing task.

3) *Artificial Immune Systems (AIS)*: The immune system has a memory for previous interactions, is capable of constantly learning new encounters, is highly adaptable, and can be represented as shown in Figure 3.b. Recently, computational problems have become increasingly complex, and new approaches are being sought to solve these problems AIS, inspired by the immune system, provides a good way to solve these complex problems. AIS is a computer system that solves problems based on theoretical immunology and

observed immune functions, principles, and patterns [25]. AIS represents a good candidate for solving the mobile robot navigation problem [26], [27]. The most challenging part in applying an artificial immune algorithm is often the definition of the antigen and the antibody. Usually, the antigen can be described as the robot's environment at any given time, and the antibody can be defined as the current environment of the mobile robot, including the distance between the robot and obstacles. To approximate the system to a biological process, [28] developed a method based on the random generation of antibodies. According to [28], the AIS-based algorithm explores unknown environments while learning from previous behavior and searching for the target.

In [29], an artificial immunity algorithm (AIA) is proposed to enable the robot to reach the target object along an optimal path safely. The authors claim that simulation results show that the mobile robot can avoid obstacles and effectively and efficiently achieve the goal using AIA instead of GA.

4) *Genetic Algorithm (GA)*: GA is a non-conventional meta-heuristic technique for generating highly accurate optimized solutions to large search problems. A GA was first introduced by [30] in 1975. GA is inspired by natural selection and uses evolutionary operators such as mutation, crossover, and selection to search for the best answer [31].

The prerequisites for applying GA to a path planning problem include: i- modeling the path by an appropriate "chromosome", ii- developing a strategy for path guidance, iii- developing a method for avoiding obstacles, iv- choosing an appropriate approach for defining constraints to reduce the path [32]. By applying the operators to the parents based on the first generation heuristic knowledge, [33] proposes a knowledge-based GA for path planning. In [34], a dynamic path planning method based on a genetic algorithm is proposed for a mobile robot in an unknown environment. Finally, in [35], a GA-based path planning method with variable length chromosomes is proposed. The flowchart and pseudo code for a robot navigation using the GA, PSO and FA are presented in Figure 3.e.

5) *Particle Swarm Optimization (PSO)*: PSO is a biologically inspired computational search and optimization method introduced by Kennedy and Eberhart in 1995 [36]. It is based on two main methods. First, it is generally associated with collective intelligence, such as the theory of flocks of birds, herds of animals, and schools of fish. Second, it is also associated with evolutionary and genetic theories. PSO is the most commonly used meta-heuristic optimization method. It is suitable for solving optimization problems with multidimensional search spaces [37]. In PSO, an initial swarm population of random solutions is formed. Then, the swarm particles move through the multidimensional search space to find the best solution. Finally, PSO iteratively improves a solution to an optimization problem, collects the extensive data collected from each swarm particle, and shares the information with all swarm members. The motion of the particles is determined

by their velocity. The particle velocity is calculated using the following equations:

$$v_k(t) = \omega v_k(t-1) + c_1 \text{Rand}() (p(t) - x_k(t-1)) + c_2 \text{Rand}() (g(t) - x_k(t-1)) \quad (1)$$

$$x_k(t) = x_k(t-1) + v_k(t) \quad (2)$$

where  $v_k$  is the particle,  $\omega$  is the inertial weight,  $c_1$  and  $c_2$  are constants,  $p(t)$  is the specific best position,  $g(t)$  is the global best position,  $x_k$  is the current particle position, and  $\text{rand}()$  is a random value generation function. Many variations of the PSO algorithm have been introduced to increase the accuracy of the PSO algorithm, solve the time-dependent and dynamic problems of mobile robot planning, and improve obstacle avoidance when multiple mobile robots are navigating. For example, the PSO algorithm using MADS (Mesh Adaptive Direct Search) [38], and Darwinian PSO [39]. In several research studies, PSO performs better than GA [40].

6) *Firefly Algorithm (FA)*: The FA algorithm was presented by Yang in 2008 [43]. It was inspired by the blinking behavior of fireflies. It is based on random states and general identification as a firefly experiment. Through bio-luminescence, fireflies emit flashing lights with varying cadences to communicate and attract other fireflies or scare away predators. In recent years, FA has been used as an optimization tool in many engineering fields, such as mobile robot navigation. The algorithms of FA are used to solve path planning problems of mobile robots in static environments such as in [44] and in dynamic environments [45] where the target and obstacle are moving. It can also be used for all environments such as land, underwater, and airborne (UCAV). The candidate position can be expressed as follows:

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^d (x_i^k - x_j^k)^2} \quad (3)$$

$$B(r) = B_0 e^{-\gamma r_{ij}^m}; m \geq 1 \quad (4)$$

$$x_i^k(t+1) = x_i^k(t) + B(r)(x_j^k - x_i^k) + \alpha(r_{ij} - 1/2) \quad (5)$$

where,  $B$  is the fireflies attractiveness,  $B_0$  is the fireflies attractiveness at ( $r = 0$ ),  $\gamma$  is the light absorption coefficient,  $x_i$  and  $x_j$  are the positions of the first and second fireflies,  $r$  is the distance between  $x_i$  and  $x_j$ ,  $k$  is the dimension,  $t$  is the iteration, and  $\alpha$  is the randomization parameter. Many researchers improve the FA algorithm for robot path planning, such as the FA Q-learning approach [46], the FAABC hybrid approach [47], and others. The results of the FA algorithm show that the three primary navigation goals of a mobile robot - path length, path uniformity, and path safety - can be achieved.

7) *Ant Colony Optimization (ACO)*: The ACO is a swarm intelligence algorithm introduced by Marco Dorigo in 1992 [48]. The ACO algorithm originates in ant foraging, where ants find the shortest path from their nest to a food source while avoiding obstacles. The basic principle of ACO is that

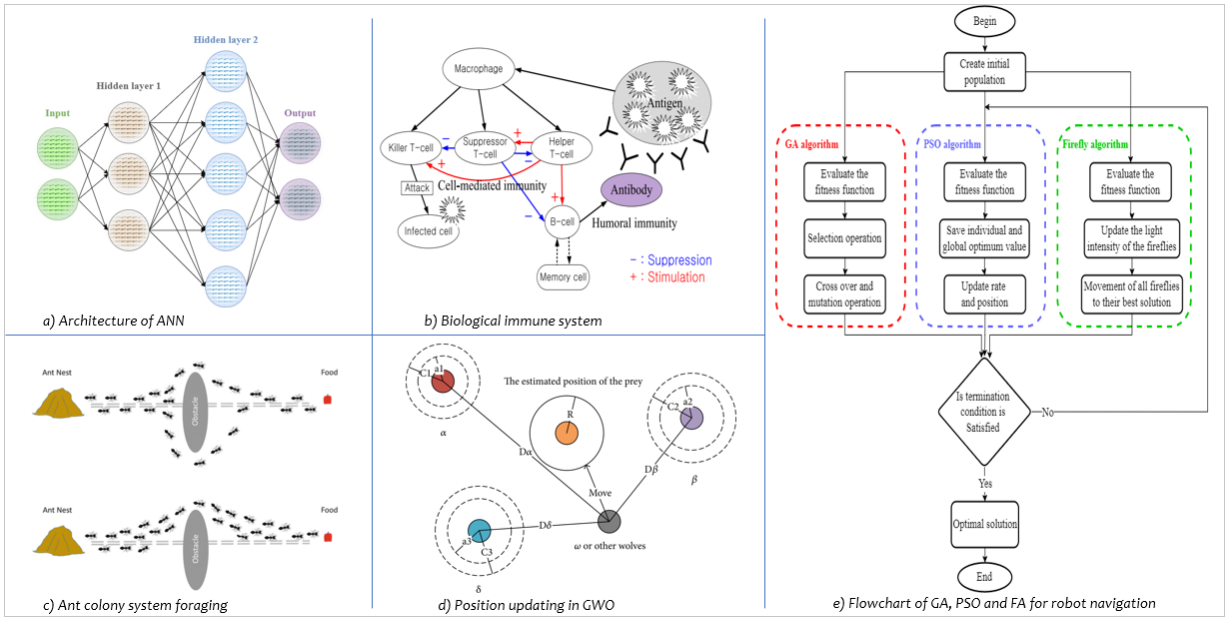


Fig. 3. Local path planning approaches ( b- [27], c- [41] , d- [42] ).

each ant emits a pheromone (a chemical essence) for reference along the path it travels. It also senses the pheromones released by other ants in search of food. Depending on the concentration of pheromones between iterations, the ant colony can communicate with each other and choose the shortest and optimal path, as shown in Figure 3.c. ACO is used by [49] to study global path planning. In addition, [50] discusses various improvements and modifications of ACO to solve path planning of mobile robots. Finally, hybridization of ACO and PSO is also addressed to solve the path planning problem for mobile robots [51]. The simulation results show that the improved algorithms improve the convergence of the algorithm and the global search capabilities even in a complex environment.

8) *Grey Wolf Optimization (GWO)*: The GWO algorithm is inspired by the social-collaborative behavior observed in gray wolves during hunting. To optimize the hunting process, the wolf population divides into subgroups, which are usually guided by  $\alpha$ ,  $\beta$ ,  $\delta$ , and  $\omega$  grades [52]. Each degree of the gray wolf represents a function in the optimization process. The optimization process yields the best solution,  $\alpha$ ,  $\beta$ ,  $\delta$ , and  $\omega$  represent the second, third, and fourth best solutions, respectively (Figure 3.d). The GWO was recently used to solve path planning problems in mobile robot navigation and provides an exciting result even in an uncertain environment [53]. The improvement of such an algorithm has been a subject of intense research. We can cite the modified Gray-Wolf optimization in [54] for path planning of an autonomous robot, and we can note the hybridization of GWO and PSO in [55] to optimize the trajectory of a borehole. In [55], the two criteria of distance and smooth path of robot trajectory planning are transformed into a minimization function for the fitness function. As a result, the robot can achieve the global

best agent position in each iteration in sequence permutation.

### III. OPTIMIZATION CRITERIA FOR PATH PLANNING

The optimization criteria for path planning of mobile robots have been widely studied. The most commonly used in the literature are the multi-objective path planning functions such as path length, smoothness, degree of safety, execution time, and energy consumption.

- 1) Path length: path length is the set of route points for the robot from the starting point to the destination point. The shortest path length (SPL) is the sum of all the distances between the center points generated by the path planning algorithm between the start and destination points.
- 2) Smoothness: the smoothness of the path minimizes the angular difference between the current target position and the proposed current position.
- 3) Degree of safety: the degree of protection (SD) refers to the sum of the degrees of deviation between each path segment and the nearest obstacle.
- 4) Execution time: the execution time refers to the time required for a mobile robot to travel the entire distance from the starting point to the destination point. The shortest execution times are the most productive.
- 5) Energy consumption: Energy consumption refers to the minimum amount of energy consumed or the least effort required by the actuators.

### IV. DISCUSSION

Given the need for good knowledge of the environment, good precision of goals, independence in decision-making, and speed in maintenance, although GPPs are based on good knowledge of the goals, we are looking for a feature that is

TABLE I  
COMPARISON OF PATH PLANNING ALGORITHMS, STRENGTHS AND CHALLENGES  
(S: STATIC, D: DYNAMIC,  $N_S$ : SUBGROUP OF A SWARM NUMBER,  $N_T$ : POPULATION NUMBER).

Algorithms	Ref.	Year	Workspace	Obstacle	Time Complexity	Strengths	Challenges
PRM	[4]	1994	S	S/D	$O(n \log n)$	Complete modeling Probabilistically completeness	Expensive computation Dynamic obstacles are challenging
AFP	[11]	1985	S	S	$O(\log n)$	ease of implementation low computational cost	May fall into local minima
FL	[15]	1965	S	S/D	$O(n^2)$	Dealing with great uncertainty Real-time application	Low accuracy Difficult to create membership functions
ANN	[22]	1996	S/D	S/D	$O(n^2)$	Simple structure High efficiency to avoid S/D obstacles	Increasing Layers Increases Complexity Time-consuming
AIS	[25]	2000	S/D	S	$O(n^2)$	Better convergence than GA Dealing with unknown environments	Complexity of parameters definition
GA	[30]	1975	S/D	S/D	$O(n^2)$	Global search capability Multi-objective optimization	High computation time Poor stability
PSO	[36]	1995	S	S/D	$O(N_T)$	Easy to implement Global and local search	Premature convergence May fall into local minima
FA	[43]	2008	S/D	S/D	$O(2N_S)$	Fast convergence speed Local searchability	Low accuracy May fall into local minima
ACO	[48]	1992	S/D	S/D	$O(N_S)$	Global optimization Avoid premature convergence	Poor in large search space Slow convergence speed
GWO	[52]	2015	S/D	S/D	$O(N_S)$	Optimal search Derivation free	Poor local search Complex scenarios are challenging

better suited for use in a dynamic environment where there are many goals, this is what we can find in LPPs, which require much less time and computation than GPPs and are therefore best suited for real-time navigation. In most applications of LPP, however, one suffers from the complexity of parameter definition and the possibility of falling into local minima. For this reason, we propose to open the horizon toward hybrid embedded road applications (LPP and GPP). Table I provides a detailed analysis of the path planning algorithms used for mobile robots. The performance of each algorithm is evaluated based on parameters such as navigation in static and dynamic environments or obstacles. The strengths and limitations of each algorithm are also presented. Among the classical approaches, it is found that the APF approach has been successfully used to navigate a robot around static and dynamic obstacles. Nowadays, reactive approaches are more popular because they can deal with an uncertain environment quickly and with less computational effort. Table I shows that most reactive approaches have been used to navigate in a dynamic environment with moving obstacles and moving targets. Embedded road applications (ERA) that use hybrid algorithms can be used to solve many problems mentioned previously. These types of algorithms are recently developed for navigation in the presence of moving obstacles and targets. Hybrid algorithms also exhibit good smoothing behavior and can be applied in real-time.

## V. CONCLUSION

In this paper, in order to improve the performance of autonomous mobile robot working on power line maintenance,

we have provided a detailed overview of the different path planning methods applicable to this type of robot. We also classified the different methods into global and local approaches and discussed the strategy and effectiveness of each method from each class. The local approach is better than the global approach. The approach that uses hybrid algorithms (local and global) is more optimal. In the perspective of this work, embedded road applications based on hybrid algorithms will be adopted.

## REFERENCES

- [1] T. Disyadej, J. Promjan, K. Pochinapan, T. Mouktonglang, S. Grzybowski, and P. Muneesawang, "High voltage power line maintenance & inspection by using smart robotics," *2019 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)*, pp. 1–4, 2019.
- [2] W. Jiang, Y. Yan, A. Zhang, L. Yu, G. Zuo, H. J. Li, and W. Chen, "Live maintenance robot for high-voltage transmission lines," *Ind. Robot*, vol. 46, pp. 711–718, 2019.
- [3] H. Zhao, C. Wang, R. Guo, X. Rong, J. Guo, Q. Yang, L. Yang, Y. Zhao, and Y. Li, "Autonomous live working robot navigation with real-time detection and motion planning system on distribution line," *High Voltage*, 2022.
- [4] L. Kavraki and J.-C. Latombe, "Randomized preprocessing of configuration for fast path planning," in *Proceedings of the 1994 IEEE International Conference on Robotics and Automation*. IEEE, pp. 2138–2145.
- [5] Y. K. Hwang and N. Ahuja, "Gross motion planning—a survey," vol. 24, no. 3, pp. 219–291, publisher: ACM New York, NY, USA.
- [6] W. Chi, Z. Ding, J. Wang, G. Chen, and L. Sun, "A generalized voronoi diagram-based efficient heuristic path planning method for rts in mobile robots," *IEEE Transactions on Industrial Electronics*, vol. 69, no. 5, pp. 4926–4937, 2022.
- [7] Y. You, C. Cai, and Y. Wu, "3d visibility graph based motion planning and control," in *Proceedings of the 2019 5th International Conference on Robotics and Artificial Intelligence*, ser. ICRAI '19. New York,

- NY, USA: Association for Computing Machinery, 2019, p. 48–53. [Online]. Available: <https://doi.org/10.1145/3373724.3373735>
- [8] R. V. Cowlagi and P. Tsiotras, “Multiresolution motion planning for autonomous agents via wavelet-based cell decompositions,” *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 42, no. 5, pp. 1455–1469, 2012.
  - [9] F. Yan, Y.-S. Liu, and J.-Z. Xiao, “Path planning in complex 3d environments using a probabilistic roadmap method,” vol. 10, no. 6, pp. 525–533, publisher: Springer.
  - [10] Y. Yang and O. Brock, “Elastic roadmaps—motion generation for autonomous mobile manipulation,” vol. 28, no. 1, pp. 113–130, publisher: Springer.
  - [11] O. Khatib, “Real-time obstacle avoidance for manipulators and mobile robots,” *The International Journal of Robotics Research*, vol. 5, pp. 90–98, 1985.
  - [12] Z. Daqi, “Path planning for autonomous underwater vehicle based on artificial potential field method,” *Journal of Shanghai, Maritime University*, 2010.
  - [13] R. Raja, A. Dutta, and K. S. Venkatesh, “New potential field method for rough terrain path planning using genetic algorithm for a 6-wheel rover,” *Robotics Auton. Syst.*, vol. 72, pp. 295–306, 2015.
  - [14] P.-H. Kuo, T.-H. S. Li, G.-Y. Chen, Y.-F. Ho, and C.-J. Lin, “A migrant-inspired path planning algorithm for obstacle run using particle swarm optimization, potential field navigation, and fuzzy logic controller,” *The Knowledge Engineering Review*, vol. 32, 2017.
  - [15] L. A. Zadeh, “Fuzzy sets,” in *Fuzzy sets, fuzzy logic, and fuzzy systems: selected papers by Lotfi A Zadeh*. World Scientific, pp. 394–432.
  - [16] S. S. Ge, X.-C. Lai, and A. Al Mamun, “Sensor-based path planning for nonholonomic mobile robots subject to dynamic constraints,” vol. 55, no. 7, pp. 513–526, publisher: Elsevier.
  - [17] H. Lee, J. Jung, K. Choi, J. Park, and H. Myung, “Fuzzy-logic-assisted interacting multiple model (FLAIMM) for mobile robot localization,” vol. 60, no. 12, pp. 1592–1606, publisher: Elsevier.
  - [18] T.-H. Li, S.-J. Chang, and Y.-X. Chen, “Implementation of human-like driving skills by autonomous fuzzy behavior control on an FPGA-based car-like mobile robot,” vol. 50, no. 5, pp. 867–880, publisher: IEEE.
  - [19] C.-T. Yen and M.-F. Cheng, “A study of fuzzy control with ant colony algorithm used in mobile robot for shortest path planning and obstacle avoidance,” vol. 24, no. 1, pp. 125–135, publisher: Springer.
  - [20] D. N. M. Abadi and M. H. Khooban, “Design of optimal mamdani-type fuzzy controller for nonholonomic wheeled mobile robots,” vol. 27, no. 1, pp. 92–100, publisher: Elsevier.
  - [21] A. Atyabi and D. Powers, “Review of classical and heuristic-based navigation and path planning approaches,” vol. 5, no. 14, publisher: Advanced Institute of Convergence Information Technology (AICIT).
  - [22] C. Li, J. Zhang, and Y. Li, “Application of artificial neural network based on q-learning for mobile robot path planning,” in *2006 IEEE International Conference on Information Acquisition*. IEEE, pp. 978–982.
  - [23] J. K. Pothal and D. R. Parhi, “Navigation of multiple mobile robots in a highly clutter terrains using adaptive neuro-fuzzy inference system,” vol. 72, pp. 48–58, publisher: Elsevier.
  - [24] Y. Li and X. Chen, “Mobile robot navigation using particle swarm optimization and adaptive NN,” in *International Conference on Natural Computation*. Springer, pp. 628–631.
  - [25] L. N. De Castro, L. N. Castro, and J. Timmis, *Artificial immune systems: a new computational intelligence approach*. Springer Science & Business Media.
  - [26] P. K. Mohanty, A. A. Kodapurath, and R. K. Singh, “A hybrid artificial immune system for mobile robot navigation in unknown environments,” vol. 44, no. 4, pp. 1619–1631, publisher: Springer.
  - [27] S. Cho, B. Shrestha, W. Jang, and C. Seo, “Trajectory tracking optimization of mobile robot using artificial immune system,” vol. 78, no. 3, pp. 3203–3220, publisher: Springer.
  - [28] R. Challoor, P. Rao, S. Ozcelik, L. Challoor, and S. Li, “Navigation control and path mapping of a mobile robot using artificial immune systems,” vol. 1, no. 1, pp. 1–25, publisher: Citeseer.
  - [29] P. K. Das, S. K. Pradhan, S. N. Patro, and B. K. Balabantaray, “Artificial immune system based path planning of mobile robot,” in *Soft Computing Techniques in Vision Science*. Springer, pp. 195–207.
  - [30] J. R. Sampson, “Adaptation in natural and artificial systems (john h. holland).”
  - [31] A. S. H. H. V. Injarapu and S. K. Gawre, “A survey of autonomous mobile robot path planning approaches,” in *2017 International conference on recent innovations in signal processing and embedded systems (RISE)*. IEEE, pp. 624–628.
  - [32] E. Masehian and D. Sedighzadeh, “Classic and heuristic approaches in robot motion planning—a chronological review,” vol. 23, no. 5, pp. 101–106.
  - [33] Y. Hu and S. X. Yang, “A knowledge based genetic algorithm for path planning of a mobile robot,” in *IEEE International Conference on Robotics and Automation, 2004. Proceedings. ICRA’04. 2004*, vol. 5. IEEE, pp. 4350–4355.
  - [34] P. Shi and Y. Cui, “Dynamic path planning for mobile robot based on genetic algorithm in unknown environment,” in *2010 Chinese control and decision conference*. IEEE, pp. 4325–4329.
  - [35] J. Tu and S. X. Yang, “Genetic algorithm based path planning for a mobile robot,” in *2003 IEEE International Conference on Robotics and Automation (Cat. No. 03CH37422)*, vol. 1. IEEE, pp. 1221–1226.
  - [36] R. Eberhart and J. Kennedy, “A new optimizer using particle swarm theory,” in *MHS’95. Proceedings of the sixth international symposium on micro machine and human science*. IEEE, pp. 39–43.
  - [37] T. Houda, L. Beji, A. Amouri, and M. Malle, “Handiski simulator performance under PSO-based washout and control parameters optimization,” pp. 1–19, publisher: Springer.
  - [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,” vol. 27, no. 18, pp. 1421–1437, publisher: Taylor & Francis.
  - [39] Q. Tang and P. Eberhard, “Cooperative motion of swarm mobile robots based on particle swarm optimization and multibody system dynamics,” vol. 39, no. 2, pp. 179–193, publisher: Taylor & Francis.
  - [40] J. Pugh and A. Martinoli, “Multi-robot learning with particle swarm optimization,” in *Proceedings of the fifth international joint conference on Autonomous agents and multiagent systems*, pp. 441–448.
  - [41] C. Javad, “Ant Colony Optimization(ACO),” <https://medium.com/@chiragjavad056/ant-colony-optimization-aco-b2716de9252c>, Sep 2, 2019, [Online; accessed 28-August-2022].
  - [42] Q. Gu, X. Li, and S. Jiang, “Hybrid genetic grey wolf algorithm for large-scale global optimization,” vol. 2019, publisher: Hindawi.
  - [43] X.-S. Yang, *Nature-inspired metaheuristic algorithms*. Luniver press.
  - [44] A. Hidalgo-Paniagua, M. A. Vega-Rodríguez, J. Ferruz, and N. Pavón, “Solving the multi-objective path planning problem in mobile robotics with a firefly-based approach,” vol. 21, no. 4, pp. 949–964, publisher: Springer.
  - [45] B. K. Patle, A. Pandey, A. Jagadeesh, and D. R. Parhi, “Path planning in uncertain environment by using firefly algorithm,” vol. 14, no. 6, pp. 691–701, publisher: Elsevier.
  - [46] A. K. Sadhu, A. Konar, T. Bhattacharjee, and S. Das, “Synergism of firefly algorithm and q-learning for robot arm path planning,” vol. 43, pp. 50–68, publisher: Elsevier.
  - [47] N. H. Abbas, “Design of a kinematic neural controller for mobile robots based on enhanced hybrid firefly-artificial bee colony algorithm,” vol. 12, no. 1, pp. 45–60.
  - [48] M. Drigo, “The ant system: Optimization by a colony of cooperating agents,” vol. 26, no. 1, pp. 1–13.
  - [49] H.-j. Wang and W. Xiong, “Research on global path planning based on ant colony optimization for AUV,” vol. 8, no. 1, pp. 58–64, publisher: Springer.
  - [50] X. You, K. Liu, and S. Liu, “A chaotic ant colony system for path planning of mobile robot,” vol. 9, no. 1, pp. 329–338.
  - [51] Q. Zhang, J. Ma, and Q. Liu, “Path planning based quadtree representation for mobile robot using hybrid-simulated annealing and ant colony optimization algorithm,” in *Proceedings of the 10th World Congress on Intelligent Control and Automation*. IEEE, pp. 2537–2542.
  - [52] S. Mirjalili, S. M. Mirjalili, and A. Lewis, “Grey wolf optimizer,” vol. 69, pp. 46–61, publisher: Elsevier.
  - [53] M. Radmanesh, M. Kumar, and M. Sarim, “Grey wolf optimization based sense and avoid algorithm in a bayesian framework for multiple UAV path planning in an uncertain environment,” vol. 77, pp. 168–179, publisher: Elsevier.
  - [54] R. Kumar, L. Singh, and R. Tiwari, “Path planning for the autonomous robots using modified grey wolf optimization approach,” vol. 40, no. 5, pp. 9453–9470, publisher: IOS Press.
  - [55] K. Biswas, P. M. Vasant, J. A. G. Vintaned, and J. Watada, “Cellular automata-based multi-objective hybrid grey wolf optimization and particle swarm optimization algorithm for wellbore trajectory optimization,” vol. 85, p. 103695, publisher: Elsevier.