

Methodology for Path Planning Mobile Robots: A Review

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Abstract:- Since the previous three decades, research in mobile robots has been growing. In the current study of mobile robots, the path planning algorithm and optimization in both static and dynamic situations are the key issues that are being addressed. The merits and drawbacks of each of these strategies / methods have been emphasized in a thorough analysis of the broad field of mobile robotic research with a specific focus on the path planning technique in varied crowded situations. Heuristic Methods and Classical Methods are two categories for the path planning strategy used by mobile robots. Additional divisions include (i) Analytical Methods, (ii) Enumerative Methods, (iii) Evolutionary Methods, and (iv) Meta-Heuristic Methods. Each of the aforementioned techniques has benefits and drawbacks of its own. The fundamental flaw, however, is that enumerative methods are concerned about the size of the search area, whereas analytical approaches are too difficult for intangible applications. On the other hand, several evolutionary approaches have been demonstrated to be useless when the search space in the path planning strategy is too broad. Meta-heuristic approaches have been explored a lot in this large field of research to overcome these shortcomings. The most widely used strategies in path planning for mobile robots have been developed around the globe, but are only briefly discussed here.

1. INTRODUCTION

For the autonomous mobile robot, path planning is a crucial task. To safely navigate from the start configuration to the destination configuration in an environment where obstacles are common, it is desired to identify a collision-free mobility [1]. Mobile robots are being used more and more in both static and dynamic contexts. For a robot to reach its destination from its starting point, there are typically many viable routes. However, in some situations, the optimal feasible route is chosen based on certain criteria, such as the shortest distance with the least amount of time required or the smoothness of the path. Local path planning and global path planning are the two categories into which the path planning may be divided. In the local path planning technique, the robot has a limited understanding of the navigational environment (either known or unknown). In contrast, the robot may take a predetermined path to the objective while using global path planning since it has comprehensive information of the navigational environment. Local route planning techniques, on the other hand, are more flexible in partially known or unknown situations and offer an optimum approach, but global path planning techniques have restricted uses because of their reduced resilience in terrain uncertainty [2]. It may also be divided into two categories: classical approach and heuristic method (Artificial Intelligence Technique). Medical and surgical applications, personal assistance, security, stockroom and circulation applications, as well as robotized guided vehicles for transferring goods in a factory, unmanned bomb delivery robots, and planet study robots, all make use of mobile robot path planning and arranging.

2. DIFFERENT PATH PLANNING METHODS

The design of the navigational control behaviour includes crucial elements such as robot path planning. The robot must go the shortest distance possible while still completing the task in the least amount of time. Less computational complexity and power consumption are the other criteria, and only when the robot moves in the shortest path from the start configuration to the target configuration will these criteria be met. The following is a collection of many methodologies and approaches that have been put out by various researchers. The following sections outline each of these strategies along with their benefits, drawbacks, and restrictions.

Table 1. Different Path Planning Approaches.

Classical Approach	Artificial Intelligence (Heuristic Approach)
Potential Field. (1979)	Neural Network Technique. (1943)
Roadmap 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 Approach

2.1.1. Potential Field Method

The difference between things that fascinate and repulse might be thought of as a potential field [32]. The primary inspiration for a possible field approach is nature. For instance, a charged molecule exploring an attracting field or a tiny ball descending down a slope, depending on the quality of the field or the angle of the slope, the molecule or the ball may land to the source of the field, the valley, or the magnet in this case. In robotics, the attraction of a robot may be recreated with identical effects towards its goal by creating an artificial potential field. We can construct the robot display using the fundamentals of insufficient potential field designing. Assume, for illustration, that there are no obstacles in the surroundings and that a robot must find a route to go there. When using traditional planning methods, one must first determine the robot's relative location to the objective before applying the appropriate forces to move the robot in that direction. Simply create an appealing field that moves toward the objective when using a potential field strategy. The potential field is distinct throughout the entirety of free space, and we compute the potential field at the robot's position in each step time before calculating the force this field induces. Robot should then move in accordance with this produced force. Robotic behaviour can also be programmed to avoid impediments. We just construct each barrier and create an offensive field around it. The machine or robot is pushed away from the impediment as it approaches it by the active repulsion power.

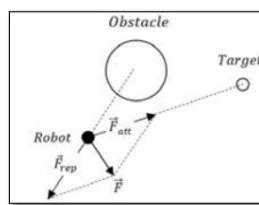


Fig. 1. Attraction and repulsion by target and obstacle

$$\text{Attractive / Repulsive Potential field is given as: } U(q) = U_{att}(q) + U_{rep}(q) \quad (1)$$

where $U_{att}(q)$ is the attractive potential which is responsible to move near to target and $U_{rep}(q)$ is repulsive potential to avoid obstruction.

$$U_{att}(q) = \frac{1}{2} \delta \cdot \rho^m(q, q_{\text{Target}}) \quad (2)$$

$$U_{rep}(q) = \begin{cases} \frac{1}{2} \alpha \left(\frac{1}{\rho(q, q_{obs})} - \frac{1}{\rho_o} \right)^2 \rho^n(q, q_{\text{Target}}) & \text{if } \rho(q, q_{obs}) \leq \rho_o \\ 0 & \text{if } \rho(q, q_{obs}) > \rho_o \end{cases} \quad (3)$$

where δ is a positive scaling factor.

In situations where robots must avoid obstacles, the Potential Field technique and its modified versions are frequently utilised as motion controllers [30–31]. Artificial potential fields have been discussed by Cetin et al. [33], fuzzy logic-based potential fields have been used by Feilit et al. [34], multipoint potential fields have been used in an obstruction prevention problem by Subramanian et al. [35], and decentralised potential field-based controllers have been used by Song [37]. Vinoy and Tanner The potential field for collision avoidance and motion planning in non-holonomic mobile robots is described in [36] by Bence Kovacs et al.[12] According to approach, the contact between humans and robots becomes noticeably more normal and natural by changing the regular movement attributes of animal to robot movement. Additionally, it turns out to be simple to understand the robot's current condition and aspirations for the future. Due to local minima, a lack of separation between widely spaced obstructions, movements inside the line of sight of an obstacle, or in a restricted entry or small passage, the potential field technique is constrained.

2.1.2. Cell Decomposition Method

The cell decomposition method offers a suggestion for distinguishing between geometric areas, or cells, that are empty and areas that are inhabited by items. This is a succinct representation of the fundamental path-planning cell decomposition method.

- First, divide F into fundamental, connected regions known as "cells."
- Second, create a "availability chart" by determining which open cells are adjacent.
- Third, identify the cells in which the underlying and objective configurations are located, then look for a way to connect the underlying and objective cells in the availability chart.

- After finding a grouping of cells using the right search technique, choose a path within each cell, such as by moving through a series of divider following movements or by the midpoints of the cell limits and developments along straight lines.

The assignment of the boundaries between cells in cell breakdown methods is the most crucial factor. The technique is known as precise cell decomposition if the boundaries are determined based on the environment's structure, resulting in a lossless decomposition [41]. The system is known as approximate cell decomposition if it produces a map that is close to the real map [42–43]. Probabilistic cell decomposition [44–45] is similar to approximate cell decomposition, with the exception that cell boundaries do not have any physical significance. Robot motion planning scenarios frequently employ cell decomposition [44,46]. It was suggested by Fujii et al., Yang and Gu et al., and Park et al. [38–40] to divide up big learning environments into a number of smaller ones to facilitate exploration. The two main advantages of this technique are that the robot's workspace will deteriorate naturally and that the state of the cells will be organised in a robust and flexible manner. Both precise and approximative cell breakdown offer benefits and drawbacks. The former are guaranteed to be complete, indicating that if a free path exists, precise cell breakdown will find it; nevertheless, the trade-off for this exactness is a more challenging scientific procedure. Although approximate cell decomposition is less common, it can produce results that are comparable to, if not identical to, those of precise cell decomposition.

2.1.3. Grid Based Method

In a grid-based technique, a grid is superimposed on the configuration space, with the assumption that each configuration is identified by a grid point. Every grid point allows a robot to go to a neighbouring lattice focus as long as the space between them is completely contained inside C_{free} (tested by collision detection). Similar to how A* search algorithms are used to establish a path from the start to the target, this discretizes the arrangement of activities. Finding a grid resolution was necessary for this kind of techniques or approaches. With coarser lattices, pursuit moves more quickly; nevertheless, this algorithm struggles to find paths across small pieces of C_{free} . Furthermore, because of the exponential growth of the number of foci on the matrix in the design space measurement, they are inappropriate for high-dimensional problems. Markus Schutz et al. [11] claim that including free space data into these matrices improves both the performance of the calculation when compared to a point-following calculation and the shape estimation when compared to a box model-based calculation. It is beneficial to lessen the impact of the division and affiliation faults.

2.1.4. Probabilistic Road Map Method

According to the PRM approach, the configuration-free space (prearrangement of practicable motions) is removed, condensed to, or represented by a system of 1-D lines. Movement planning becomes a graph searching challenge as a result of the system-restricted response search. The terms skeleton, retreat, and highway approach are also used to describe this particular strategy. According to this method [26], the robot's locomotion is prepared in three steps: (a) the robot advances from its initial configuration to a point on the probabilistic road map (PRM), using a conventional locomotion strategy; (b) the robot advances from the target configuration through a point on the road map; and (c) finally, the start configuration and target configuration points are combined to obtain the desired path. All topologically discrete viable pathways in configuration space must be characterised by the road map [3]. The robot locomotion algorithm is lacking if not. The Subgoal Network [7], Visibility Graph [76], Cell Decomposition [6], Silhouette [5], and Voronoi Diagram [4] are the preeminent route maps. The main goal of lazy PRM, according to Robert Bohlin et al. [22], is to reduce the amount of crash checks when searching through a roadmap with respect to a PRM organiser in the quickest possible manner, which is done at the expense of standard graph seek.

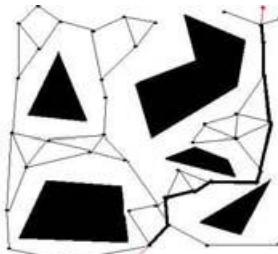


Fig. 2. Probabilistic road map with goal and end points

According to Yan et al. [25], adaptive cross sampling is used in the design phase of multi-robot motion simulation to reduce time and the likelihood of collisions. By employing an intelligent technique in the learning phase that permits deactivation of the least probable configuration, Rantanen and Juhola [27] improve the execution time of the roadmap. Single query roadmaps are used by Nazif et al. [28] to map situations inside uncharted areas using a swarm of robots; benefits include agent failure robustness and efficiency in congested locations with constrained passageways. The configuration space is reduced using Rantanen's [77] modified probabilistic roadmap method by sensing the configuration space for difficult-to-navigate areas

(such as places with tight pathways). With the potential to address a variety of constraints, Yang and Brock [29] used an elastic roadmap framework for motion planning. These constraints included the robot's kinematic and dynamic limitations, challenges brought on by the presence of moving obstacles, limitations resulting from the task, and workspace connectivity.

2.1.5. Rapidly Exploring Random Tree Method

Random trees are a new data structure and method designed for quickly exploring nonconvex high-dimensional areas with resourcefulness. These are built progressively, which quickly reduces the estimated distance between the tree and a randomly chosen location. For planning a path-oriented issue with differentiable restrictions and impediments, they are only partially accepted.

2.1.6. Virtual Impedance Test

Motion smoothness is improved for a flexible robot using the Virtual Impedance approach. This method improves robot performance under dynamic circumstances with movable and stationary obstacles. Furthermore, it is more effective than earlier methods, as may be seen from the simple structure of the aforementioned algorithm. On a physically movable flexible robot stage in the interior setting, analyses of the process are conducted. By switching the separation flexible robot and impediment to a virtual power dismissing robot from snags, impedance control technique is introduced into crash shirking computation [63]. The main challenge for the adaptable robot headway control is productivity and smoothness change. Teleoperated headway controller connected through self-governing impact shirking is an adequate approach in practical application, especially in light of independent crash evasion's excellent performance in constrained local space. Eun Soo, Seul, and colleagues [63] demonstrated virtual power on a mobile robot by using resistance as a spring and impedance control computation to maintain a desired separation to avoid obstacles. A technique for impact avoidance through its condition is the non-contacting impedance limitation, which is implemented in the controller's conduct control [64]. However, it has also been included into the movement planning of portable robots [65-68]. The non-contacting impedance drive is used by Fumiaki et al. to operate a legged control adaptable robot that can avoid stairs without reaching [65].

2.1.7. Convex Hull and Local Search Method

Convex hulls have shown to be a very useful shape for handling a variety of computational difficulties, such as automated highlight recognition from 2-D and 3-D. The smallest arched polygon that encloses S is the curved frame of an arrangement of foci S in a plane. As it were, the encasing polygon with the smallest region and boundary is the curved structure of an arrangement of foci S in a plane. The framework employs the arched structure limit for the specified arrangement of focuses as its fundamental sub-visit in this instance. A neighbouring inquiry heuristic is gradually connected once all of the offered foci have been incorporated into the method. The relationship between each point inside the curved body limit and the arched edges may be established without a combinatorial search since each point is identified in a family pecking order. Six fundamental processes link the creation of a curved frame limit with the progressive application of a local look heuristic. The first step for a given arrangement of focuses is to create an arched body of these focuses for which a modified Graham scan algorithm is connected, after which comes the system for making locals. If every point is local, local enhancement methodology is used, which typically involves building a raised family tree, after which comes local connecting, and finally a streamlined approach is achieved. If each city is located on the edge of the curved frame, then each euclidean TSP has an optimal configuration, according to Flood [69], who studies these features. To build an inclusion strategy for the focuses that are not on the curved structure limit, the raised frame sub-visit should be combined with a heuristic hunt for a non-specific TSP.

2.1.8. Divide and Conquer Method

Various scholars have provided descriptions of the divide and conquer method's use in mobile robot motion planning. The interaction between the robot and its working environment was covered by Hirota et al. [70]. They have adapted the divide and conquer approach of problem-solving in order to make the search simpler, narrow the search space, make the task of defining fitness functions easier, and acquire a distributed controlling system. Instead of utilising an evolutionary method to create a straight-forward control system, they intended to decompose the overall assignment to meet the behaviour of an architecturally based controller. This would allow them to create discrete behavioural modules and arbitrators. They've also demonstrated their findings through experimentation. A technique based on the quadtree approach has been provided by Nagabhushan et al. [71] for developing the shortest path from a given goal location to any specified destination position. Recursive partition is used in calculation, which defeats plan approach. Their suggested calculations operate in a 2-D stationary state with obstacles of various kinds and virtually unrestricted machine size.

2.2. Artificial Intelligence (Heuristic approach)

2.2.1. Neural Network Technique

The organic sensory systems, such as the brain, which process data input are the inspiration for the notion of a neural network used for data management. The brain functions as a highly complex, parallel, nonlinear computer concept. This concept's key component is the framework for processing processed data, which has an inventive structure. Neurons, which are numerous interconnected handling components, are developed to handle certain problems. The robot's restricted 2-D operating environment is completely opaque to obstacles of any kind and does not exhibit any curved suspicion of their presence. Each

neuron and its local has a similar association in the neural system, which uses neural system about a nearby connection to represent the arrangement space of the mechanism work. The neural system has a fairly parallel architecture and uses two paths to transmit data between neurons. Simple, short meetings are the key to the path planning technique. Different preferences are incorporated, such as adaptive learning, self-organization, real-time operation, and fault tolerance through redundant information coding, wherein a system's partial destruction causes the execution of that system to become corrupted. In any event, some system abilities may have the potential for serious system damage. An issue is that the desired quantity will increase as the number of obstructions increases; hence, the ideal path could not be ideal. Lebedev et al. [74] have introduced a new kind of neural system process called the dynamic wave expansion (DWENN) in a neural network. It is used to play out the path generating that didn't require any prior knowledge of the surroundings or a learning process. The DWENN progression causes movement waves to arise in the system field, and a summary of the exchanged action refreshes the corresponding action levels of neurons. Zhu et al. [75] present a system for movement planning that is coordinated with dynamic, many errands task to the group of robots. In light of the neural system, it resolves the problem using the self-organizing map (SOM).

2.2.2. Fuzzy Logic Technique

Lotfi Zadeh introduced the fuzzy logic system for the first time in 1965. Fuzzy logic provides a formal mental process for communicating with and carrying out the heuristic information and observation-based actions of hominid experts. Fuzzy logic is based on the notion that people think about concepts rather than precise numbers while making decisions. A fuzzy logic concept is used in these kinds of circumstances because self-governing mobile robot route planning involves a great deal of environmental sensitivity and is unable to categorise the scenario clearly. Fuzzy logic has the advantages of greater continuous execution, robustness, and the absence of new state changes. This can be explained by the fact that the principles are directly descended from the experience of early hominids and are hence exempt from the problem of local minimization. In a fuzzy based route controller, the problem is broken down into simpler tasks, and each action is composed of a series of fuzzy logic run articulations that are intended to reach a very specific set of destinations. The fuzzy controller divides the routine motion of a mobile robot into three discrete tasks: pursuing a goal, dodging obstacles, and following edges. There has been a thorough examination of fuzzy logic control for movement organising [72]. G. Oriolo [73] presents an algorithmic organisation technique that builds and modifies the environment map using the fuzzy system. Measurement ranges are obtained using the robot's exterior sensors and prepared for use in creating a local map-based depiction of the surrounding area.

2.2.3. Genetic Algorithm Technique

A genetic algorithm (GA) is a novel meta-heuristic advancement technique that relies on the principles of natural selection and genetics. Professor J. Holland of Michigan University first introduced a genetic algorithm in 1975 [47]. The underlying principle behind genetic algorithms is to mimic the concept of "survival of the fittest." These algorithms replicate the processes seen in a typical framework where the strong have a propensity to adapt and survive while the weakest have a propensity to perish [9]. For upgrading and inquiry problems that involve bio-inspired operators like mutation, crossover, and selection, GA provides excellent solutions [48]. Utilizing certain genetic processes like mutation, crossover, and selection, a new population is produced. A series of sentences can be used to address the population (referred as chromosomes). Every generation builds a new chromosome using information derived from the population's fittest chromosomes.

A GA begins its investigation with a random collection of solutions, usually encoded as binary strings. Each agreement has a fitness that is explicitly connected to the pursuit and advancement issue's objective capacity. In this manner, the population for the arrangements is shifted to another population by applying three operators that are similar to natural genetic operators—reproduction, mutation, and crossover. It operates iteratively by gradually applying each of these three operators until a termination requirement is satisfied. Because of their simplicity, global perspective, and inherent parallel handling, GAs have been successfully linked to a wide range of difficulties during the past ten years.

According to Adem Tuncer et al. [23], the enhanced mutation technique simultaneously examines all of the unconnected nodes in the vicinity of the mutation node rather than arbitrarily selecting a node one at a time, and it accepts the node based on the fitness estimation of the overall path rather than the bearing of development through the mutated node. Wang Jianguo et al. [24] demonstrate that the approach prompts join at the worldwide ideal value with high speed, demonstrating the adaptable execution of the advancements of the workplaces.

2.2.4. Ant Colony Optimization Technique

In order to solve computational difficulties, the widely used ant colony optimization approach, which is probabilistic in nature and may be condensed in order to discover the optimal pathways from the graphs, was introduced by Marco Dorigo [59]. ACO is based on the behaviour of ant colonies. The ants' connected communication, which is the heart of their behaviour, enables them to find the shortest route between their home and their food sources. The best path is found by measuring the amount of pheromones (chemical essence) left behind by ants on their travel routes. These traits/features of actual ants are gathered by the ACO process to address the problem of discrete optimization. The ACO is therefore considerably more suitable for problems where the source and target are clearly established and specific.

The following is the main ACO methodology:

- Produce an ant (or ants) and loop for each ant until the entire assignment is finished.
- pheromone storage on frequented areas and locations that are ant-covered (s).
- Daemon exercises and pheromone dissipation.

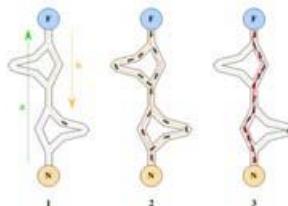


Fig. 3. Ant colony system

The ant colony is combined with a sample-based location-to-location path planning approach to address multi-objective arranging challenges when obstructions are present. Execution is evaluated quantitatively using two preexisting sample-based techniques. The ACO approach provides a trade-off between speed and value of the arrangement. Given the physical constraints of robotics route planning, it is the choice that is made most frequently.

$$p_{ij}^k = \frac{\{\tau_{ij}\}^{\alpha}}{\sum_{j \in N_i^k}^m \{\tau_{ij}\}^{\alpha}} \quad (4)$$

where τ_{ij} is pheromone trail, m is the quantity of ants, α is a constant with positive value termed as weight values, p_{ij}^k is the transition probability in which ant k will move from node i to j .

$$\tau_{ij} = (1 - \rho) * \tau_{ij} \quad (5)$$

where range $(0 < \rho \leq 1)$ is the pheromones dissipation rate and change of pheromone is given as:

$$\tau_{ij} = \tau_{ij} + \sum_{k=1}^m \Delta \tau_{ij} \quad (6)$$

where $\Delta \tau_{ij}$ is the quantity of pheromones ant k deposits on the visited paths, which is given as:

$$\Delta \tau_{ij} = \frac{1}{C^k} \quad (7)$$

where C^k is the length of the path build by the k^{th} .

According to Qi Zhang et al. [61] application of the combination of ant colony, simulated annealing (SA), and framed-quad tree in order to enhance the efficacy of path planning. Shi et al., [62] planned the hybrid of ACO and PSO in a robotics path planning issue.

2.2.5. Partical Swarm Optimization Technique

A populace-based exploring technique is Particle Swarm Optimization (PSO). The most used artificial intelligence optimization technique is PSO. It is based on how fish in a pool or a flock of birds behave when looking for food. In PSO, a population is created by generating a large number of particles at random. In contrast to GA, the particles in PSO are not eliminated. The particles move around the multidimensional space in search of the perfect configuration. A possible resolution is the particle's optimization issue. Within the multidimensional space, every particle moves. The speed of the particle controls how it moves. The following formulae are used to compute the particle velocity:

$$v_{id} = w \times v_{id} + c_1 \times rand() \times (p_{id} - x_{id}) + c_2 \times rand() \times (p_{gd} - x_{id}) \quad (8)$$

$$x_{id} = x_{id} + v_{id} \quad (9)$$

where, v_{id} is particle's velocity, w is the inertial weight, c_1 and c_2 are constant, p_{id} is specific best site, p_{gd} is global best site, x_{id} is current particle site and $rand()$ is function to generate random value.

Particles are drawn to migrate toward a place in the search space by the best individual and swarm finds [49]. The PSO termination criterion may be a predetermined number of iterations, particle convergence, or if the global best remains unchanged for a predetermined number of iterations. For PSO to operate at its best, the inertia weights and constants must be chosen properly. In the case of the hill-climbing incapacity solution, it has drawbacks in terms of controlling influences, premature convergence, and a lack of dynamic velocity adjustment react [50]. Numerous adjustments are recommended [50] to address the issue of managing the parameters, and in certain cases, the algorithm would work better if one of the crucial elements of the velocity equation were removed or even if a new element were introduced [51–54]. The two main advantages of PSO in relation to GA, according to Qin et al. [55], are simpler execution and fewer parameters. PSO performance has consistently outperformed GA in research investigations [48,56–58].

According to Kun Su et al. [14], the particle swarm strategy with constant weight exhibits higher performance in quick convergence and dynamic merging and can be a good choice for resolving the robot motion planning issue. According to Md. Rakibul Islam et al. [15], one method to describe the favourable circumstances of the approach is the way that the directions collected are safe and smooth while also being free of local traps due to the incorporation of real-time sensor data in the recalculation of the path. The planned approach is flexible, allowing you to alter any parameters or regulate the importance of avoiding or moving closer to the goal.

2.2.6. Bacterial Foraging Optimization Technique

A new method in the family of optimization techniques inspired by nature is the bacteria foraging optimization algorithm (BFOA). The central concept of the unique approach is the utilisation of a swarm of *E. coli* bacteria's foraging strategy in multi-objective function optimization. An individual bacteria communicates for others by delivering signals. According to Md. Arafat Hossain et al. [18], it selects the particle separation that best fits the objective and the particle's Gaussian cost capability. The choice is then made using a high-level decision making technique, and the conclusion is then dealt with by using a simple robot sensor to deal with the local arena state. According to Xiao-dan Liang et al. [19], that robot mimics bacteria's capacity to control an optimum path free of obstacles between a starting point and a destination point in an environment filled with obstacles.

2.2.7. Bee Colony Optimization Technique

A swarm-based meta-heuristic approach used for improving numerical problems is the artificial bee colony (ABC) algorithm, which was first introduced by D. Karaboga in 2005 [10]. The honey bees' clever foraging techniques brought life to it. Foraging bees that are engaged and not, as well as food sources, are the three main components of the concept. The first two sections look for abundant food sources close to their hive. The two defining characteristics of model behaviour are also enrollment of foragers in rich food sources resulting in positive input and surrender of weak sources by foragers resulting in unfavourable critique, which are essential for self-sorting out and aggregating information. According to Marco Cruz et al. [16], the ABC algorithm is used to carry out local searches that progressively build a path without colliding with the beginning and ending locations of the mobile robot. Evolutionary programming is then used to carry out a refinement of the practical path. Experiments show that the suggested method outperforms the PSO and DE based path planning scheme for two unquestionably well-known metrics: ATPT and AUTD, as stated by Preetha Bhattacharjee et al. [17].

2.2.8. Fire Fly Algorithm Optimization Technique

A firefly produces light through a process called bioluminescence, and the light it emits serves as a signal to attract other fireflies. The rhythm of the ash light is wholly responsible for the appeal with both male and female "reies." It is possible to examine the rate of light extinction and the duration of the process. This may be used as an objective function to describe an unique optimization technique that might be offered to be optimised. Only when the other fly has a higher light intensity is it possible for one fly to become fascinated by the other, and this essential concept served as the foundation for FA's operation.

$$B(r) = B_0 * e^{-\gamma r^m}; m \geq 1 \quad (10)$$

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^d (x_i^k - x_j^k)^2} \quad (11)$$

$$x_i^k(t+1) = x_i^k(t) + B_0 * e^{-\gamma r_{ij}^2} (x_j^k(t) - x_i^k(t)) + \alpha * (r - \frac{r}{2}) \quad (12)$$

2.2.9. Gray Wolf Optimization Technique

Grey wolves are at the pinnacle of the natural way of life; they like to live in packs or groups most of the time. They have an incredibly rigid social hierarchy that is quite fascinating. In GWO,, and are frequently used to aid estimation of the hurtling. After these three wolves, it is up to the wolves.

encompassing prey Grey wolves surround their prey during hunting, and it has been projected [13] to statistically illustrate this behaviour in relation to the surrounding circumstances:

$$\bar{D} = |\bar{C}_{\text{coefficient}} \cdot \bar{X}_{\text{prey}}(t) - \bar{X}_{\text{wolf}}(t)| \quad (13)$$

$$\bar{X}(t+1) = \bar{X}_{\text{prey}}(t) - \bar{A}_{\text{coefficient}} \cdot \bar{D} \quad (14)$$

$$\bar{A}_{\text{coefficient}} = 2 \cdot \bar{a} \cdot \bar{r}_1 - \bar{a} \quad (15)$$

$$\bar{C}_{\text{coefficient}} = 2 \cdot \bar{r}_2 \quad (16)$$

Where X_{prey} and X_{wolf} are the position vectors of the prey and wolves, respectively; D is the distance vector between the grey wolf and the prey; C and A are coefficient vectors; t is the current emphasis/current iteration; the vector component of A is directly decreased from 2 to 0 throughout the emphases; and finally, r_1 and r_2 are the irregular vectors as [0,1].

Sen Zhang et al. [20] claim that GWO exhibits an extraordinary aberrant condition of local optima avoidance, increasing the likelihood of locating accurate approximations of the ideal weighted total cost of this approach. Additionally, due to the extensive use of the GWO, the resulting optimal values for weighted sum cost have extremely high accuracy. According to Pei-

Wei Tsai et al. [21], the robot may expand the position of the globally best agent in each iteration using sequence permutation after two standards for distance and smooth path of the robot path arrangement issue are turned into a minimization one for fitness function.

3. SUMMERY AND DISCUSSION

The most widely utilised strategies in path planning for mobile robots are described here for further study, despite the fact that several varied techniques in this regard have been created and are still being worked on globally. Particle swarm, ant colony, bee colony, bacterium forging, and firefly approaches are some of the most recently created ones. The Firefly approach is comparatively new and offers a lot of potential for mobile robot navigation. It comes into contact with every major concert, for instance, FA is able to locate the most practical approach in a comparatively short amount of time, which provides improved efficacy. This technique allows a viable path to avoid any known barrier in the area, ensuring the safety of planning. Additionally, it consistently follows the planned course with accuracy. Additionally, it lowers motion planning problems including computational complexity, local minima, and algorithm tweaking requirements. In terms of time and path attainability, it enhances the excellent arrangement.

4. CONCLUSION

The benefits and drawbacks of various path planning strategies for autonomous mobile robots were briefly presented and evaluated. Each strategy in this vast area of study on mobile robot route planning is thoroughly discussed. A fascinating aspect of this study is that, despite significant advancements over the previous three decades, relatively little work, particularly in multirobotics systems, has been documented. The majority of studies discuss single robotic systems, leaving a large number of topics in coordinated and networked multi-robotics systems available for future research. The motion planning method is divided into two primary folds in this manuscript: a classical approach and a heuristic approach. The traditional strategy is simple to execute, but it frequently needs reliable information about the current navigational environment, necessitating the use of more precise sensors. Heuristic (metaheuristic) techniques are more cerebral and inventive than the traditional approach because they can adapt to both uncertain (unknown) and deficient information in a constantly changing environment. At first, innovative applications such as organise directing, circuit board outline, PC motions, animations, pharmaceutical prescription plans, and computational science further logically more enliven the improvement in path planning. The scientist's team proposes many approaches for dealing with the path planning problem.

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