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Mobile Robot Path Finding using Nature Inspired Algorithms - A Review

Chika Yinka-Banjo[1] & Ukamaka Agwogie [2]

[1,2] Department of Computer Science, Lagos, Nigeria
cyinkabanjo@unilag.edu.ng
amymathematics@gmail.com

Abstract — In today's world, Mobile Robot has been widely used for various purposes across several aspects of life. The environments could be static and dynamic. Path planning for mobile robot is a very important problem in robotics. Path Planning for robot could be referred to the determination of a path; a robot takes in to perform a task given a set of key inputs. To find the best and optimal path from the starting point to the goal point, such that time and distance is reduce, in any given environment avoiding collision with obstacles is an interesting area for research. This research presents a review on the application of nature inspired algorithms in solving the problem of mobile robot path planning such that the robot reaches the target station from source station without collision with obstacles. The future of these nature-inspired algorithms on mobile robot is also discussed.

Keywords: Index Terms — Nature-Inspired Algorithms, Optimization, Path Planning

1. Introduction

The field robot path planning started in the middle of the 1960's. Path planning is an important part in the design of mobile robots. The objective is to find the best and collision free path from a start position to a target position in a given environment. Path planning would aid robot to automatically decide and execute a sequence of steps in order to accomplish a task without colliding with obstacles in a given environment (Parvez & Dhar,2013). In an environment, there are many paths for a robot to reach the goal, but the best path is selected according to some criteria.

These criteria are the shortest distance, the shortest time, the least energy consumed. The most adopted criteria are the shortest distance. Path planning is an optimization problem since its purpose is to find a path with the shortest distance under certain constraints such as the given environment with collision-free motion (Agarwal & Goel, 2013).

In the past several decades, research on optimization techniques has captured the attention of most researchers. Optimization techniques can be classified in many ways; however, the simplest way is to look at the nature of the algorithm. In this light, they can be grouped into two: deterministic and stochastic techniques (Chen et al ,2011). Deterministic techniques depend on the mathematical nature of the problem, while stochastic methods do not depend on the mathematical nature of the problem. Stochastic techniques use randomization in its techniques to arrive at a solution. They are more appropriate for finding the global optimal solutions for any type of objective function. However, the weakness of the deterministic techniques is its dependence on gradient. Local optima and inefficient in large scale search space and cannot solve discrete functions. Stochastic techniques are more user friendly. The complexity of today's real-world optimization problem has made the use of stochastic techniques inevitable. These algorithms have been discovered to perform better than the classical or gradient based methods, especially in optimizing discrete complex, multimodal and non-differentiable functions (Chen et al ,2011). Nature Inspired algorithms are stochastic techniques that mimic the behaviors of human evolution, certain animals or insects. They have been developed since 1980s. Today, these nature inspired algorithms have already been applied to many areas in engineering fields.

Currently, the existing research in the path finding problem in robotics can be classified in two aspects: classical and heuristic. The most famous classic methods of path planning are potential field methods, grid methods and visibility graph methods. The potential field methods have very simple structures and are used in real time hurdle avoidance. However, there are inbuilt limitations in them; these includes trap conditions due to local minima, no passage between closely spaced objects or obstacles, oscillations in the presence of obstacles and oscillations in narrow paths. In the grid methods where grids are used to form the map of the environment, the size of the grids and the environment representation are directly proportional. The main problem of visibility graph methods is that they have very intricate search paths and very less search efficiency (Nizar & Farah,2014).

To overcome the limitations of classic methods to path planning; researchers have over time move towards heuristics methods. There is an increase in the development on heuristics methods over the past two decades. Heuristics methods has helped to deal with the complexities and computational costs associated with classical methods. However, one is not sure to come across a solution while using the heuristics methods, but if there is a solution it will be found much faster than the classical methods. The following heuristics approaches have been applied to the path planning problem in mobile robot. They are Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Bee Colony Optimization (BCO) etc.

In this research, the application of nature-inspired heuristics algorithms in solving path finding problem in Robotics is reviewed also the expected future of the path finding problem in Robotics using nature-based heuristics algorithms would be discussed. The work is organized as follows: Section 2 deals with path planning optimization techniques, introduced nature-inspired algorithms, and described how some nature inspired algorithms have been applied to the path planning problem, Section 3 gives a summary of the application discussed in section 2, Section 4 gives the expected future trend and Section 5 provides the conclusion.

2.Mobile Robot Path Planning Optimization

Path finding is a fundamental aspect of many applications in the fields of GPS, games, robotics, logistics and crowd simulation (Zeyad et al ,2015). It can be implemented in static, dynamic and real-time environments. Several developments have carried out to improve the accuracy and efficiency of the path finding solutions over the past two decades. However, the problem still attracts a great deal of research. Today, the most important area of concerns is the provision of high performance, realistic paths for users (Zeyad et al ,2015).

In general, there are various kinds of path finding problem, such as single agent, multi-agent, adversarial. Some problems could be in the dynamic environment, heterogeneous terrain, mobile units and incomplete information. Each of these problems has different applications in different fields. Solving path finding problems consists of two main steps: graph generation and a path finding algorithm (Zeyad et al ,2015). Several techniques have been used to solve the graph generation problem; such as cell decomposition and Skeletonization.

The second step in the path finding process is the search algorithm itself. The objective of the algorithm is to return the optimal path to users in an efficient manner. These algorithms can be broadly classified as discrete path planning algorithms and Nature-inspired algorithms. Discrete path planning algorithms, such as potential fields, splines, grid based and tangent finding have been found to have high processing and large memory for computation. However, the nature inspired algorithms have been seen to provide possible solution to the limitations of these discrete techniques. Heuristics algorithms are able to cover a large search space and use a relatively low amount of memory and CPU resources.

2.1 Nature Inspired Algorithms (NIAs)

Nature-inspired algorithms are also referred to as evolutionary algorithms (EAs) (Emad et al ,2005). The limitations associated with using classical optimization techniques on large scale engineering problems have led to the development of alternative solutions. Nature-inspired algorithms are stochastic search methods that mimic the behaviour of natural biological evolution and/or the social behaviour of species. The behaviour of these species is guided by learning, adaptation and evolution. To imitate the efficient behaviour of these species, several researchers have developed computational systems that seek fast and robust solutions to complex optimization problems.

Some of the Nature inspired heuristics algorithms are:

- Genetic Algorithms (Inspired by evolution)
- Memetic algorithms (Inspired by evolution)
- Particle swarm optimization (Inspired by social foraging behaviour of some animals)
- Ant colony systems (Inspired by the foraging behaviour of ants)
- Bee colony system (Inspired by the foraging behaviour of honey bees)
- Fruit fly algorithm (Inspired by the food finding behaviour of fruit flies)
- Firefly algorithm (Inspired by the flashing behaviour of fireflies)
- Bat algorithm (Inspired by the echolocation behaviour of micro bats)
- Simulated annealing (Inspired by the process of annealing in metallurgy)
- Neural Networks (Inspired by the neurons in the human brain) etc.

However, in this study we will look at the application of four of these nature-based heuristics algorithms to the mobile robot path finding problem. They are Genetic Algorithm, Particle swarm optimization, Ant colony systems and Bee colony system.

Genetic Algorithms are search and optimization techniques first proposed by John Holland in the early 1970s (McCall ,2005). It is based on the principles of natural evolution. GA has been recognized as one the most robust search methods for complex and ill-behaved optimization problems. In Genetic Algorithm, a solution to a given problem is given in the form of chromosome, a chromosome consists of a set of elements, called 'genes' that hold a set of values for the optimization variables.

Particle Swarm optimization is a global optimization method proposed by Kennedy and Eberhart in 1995 (Bai, 2010). PSO is a stochastic optimization technique which is also population based like Genetic Algorithm. PSO is inspired by the social foraging of bird flocking together. PSO uses the information sharing mechanism. The population grows from experience learnt from each other.

Ant colony optimization is a meta-heuristic stochastic optimization technique developed by Marco Dorigo in 1992. ACO is inspired from the ants foraging behaviour. The behaviour in particular is how ants can find the shortest paths between their nest and its food sources. Ants deposit pheromone as they move around in search for food. These pheromone serves as a communication information to other ants. It is used to mark the way taken to a destination. Ants can also find the optimum path quickly when an obstacle suddenly appears in their way as they search for food.

The Artificial Bee Colony (ABC) optimization technique is also a population based meta-heuristics algorithms. It is inspired by the intelligent behaviour of real honey bees (Mohd et al ,2015). The algorithm was first proposed by D. Karaboga in 2005 for real parameter optimization problems (Nizar & Farah,2014). The ABC algorithm employs fewer control parameters in its implementation, these characteristics gives it an advantage over other population based algorithms. ABC algorithm has been applied to solve many practical optimization problems because of its flexible, simple and easy to implement.

2.2 Robotic Path Planning Using Nature Inspired Algorithms

2.2.1 Robotic Path Planning using Genetic Algorithm in Dynamic Environment (Arora et al ,2014)

The researchers apply Genetic Algorithm at a point in the problem space unlike the other existing approaches where GA has been applied to the whole problem space. The simulation system was dynamic and it was carried out in a 2-D space. The approach uses 20 randomly generated rectangular obstacles with variable sizes which positions is not known to the root prior to its movement (dynamic system) as shown in Figure 1. The authors allow the robot to begin its movement towards the destination using a diagonal path. On an encounter with an obstacle the robot takes three steps backward and applies Genetic Algorithm to determine the next path as seen in Figure 2. This approach was simulated using MATLAB. CPU utilization was obtained for four iterations as seen in Table 1. However, there was no explicit comparison of this approach to other known results to ascertain the optimality of the approach. The author, however concluded that the approach led to the shortest minimum path or the robot as seen in Figure 4

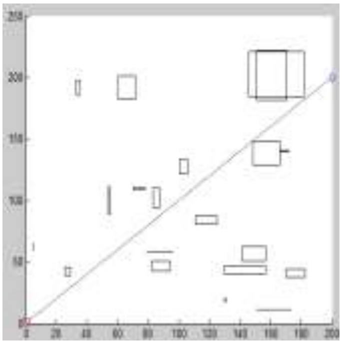


Figure 1: Problem Configuration (Arora et al ,2014)

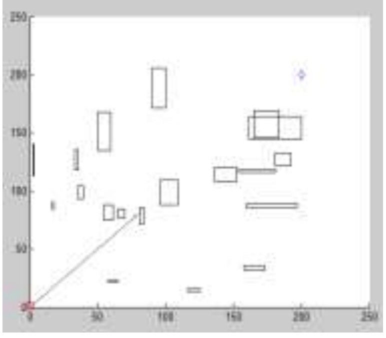


Figure 2: Robot Encounters an Obstacle (Arora et al ,2014)

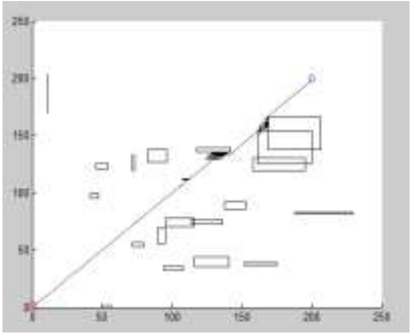


Figure 3: Solution Obtained (Arora et al ,2014)

Table I: Number of Iterations Vs CPU Time in Seconds (Arora et al ,2014).

No. of iterations	CPU Time (sec).
10	26
20	102
30	122
40	139

2.2.2 A Mobile Robot Path Planning Using Genetic Algorithm in Static Environment (AL-Taharwa et al ,2008)

This study shows the implementation of Genetic Algorithm in a static environment, this means the environment has been predefined and the position of obstacles are known to the navigating robot prior to its movement. A simplified fitness function was used; it uses the path length to determine the best individual in a generation. Simulations were done in obstacle free environment and three obstacle full environment. It was discovered that Genetic Algorithm converges irrespective of the population size used. However, increasing the population size increases the computational cost. Table 2, 3, 4 gives a tabular display of the results obtained.

Table II: GA Performance with Population Size 10 (Al-Taharwa et al ,2008).

Environment	Population size	Best fitness value	Generation No.
Obstacle-free environment	10	20	60
Indoor Environment	10	38	100
Moderate environment	10	26	90
Complex environment	10	26	80

Table III: GA Performance with Population Size 20 (AL-Taharwa et al ,2008)

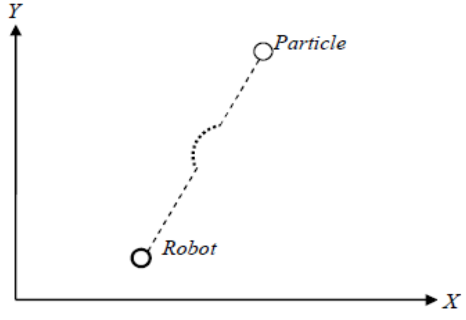
Environment	Population size	Best fitness value	Generation No.
Obstacle-free environment	20	18	60
Indoor Environment	20	32	100
Moderate environment	20	22	90
Complex environment	20	26	30

Table IV: GA Performance with Population size 50 AL Paths by ACO (AL-Taharwa et al ,2008).

Environment	Population size	Best fitness value	Generation No.
Obstacle-free environment	50	18	60
Indoor Environment	50	28	100
Moderate environment	50	20	90
Complex environment	50	24	80

2.2.3 Using Particle Swarm Optimization for Robot Path Planning in Dynamic Environments with Moving Obstacles and Target. (Yarmohamadi et al ,2011)

The study uses the particle swarm optimization techniques in a dynamic environment where the position of the target moves over time. Moving and static obstacles were also present in the system. In order to simulate the proposed approach; assumptions were made. Some of them are that the robot (Vrobot) and target (Vgoal) have maximum footsteps for which they must not exceed and there is also a relocation probability associated to the moving obstacles (Pobs) and the target (Pgoal). Circular shaped obstacles were used and the root moves in a rotational manner, it also investigates its surroundings using a radius from itself in order to find the next position with minimum collisions. A penalty function was introduced to solve the local optimum problem of PSO. This function uses the size and position of the obstacles to determine the next position. Simulations were carried out using MATLAB and it was successful. Figure 4 shows two possible routes the robot could take if an obstacle is encountered; however using the penalty function; the path with the shorter length will be selected. Figure 5 shows the result of the simulations when the relocation probability of the target and moving obstacles are set to 0. Figure 6 shows when the parameters were varied. Again, the performance of the novel approach was not compared to the existing approaches existing in the field.



(a)

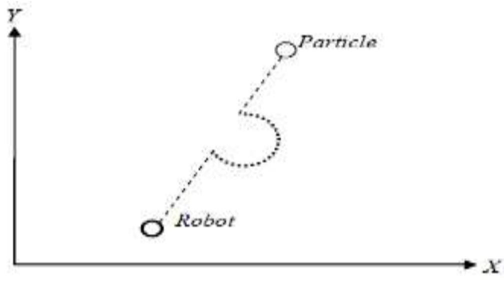
(b)


Figure 4: (a) and (b) are two possible routes the Robot can take. using the Penalty Function the Route (a) Will be Selected (Yarmohamadi et al ,2011).

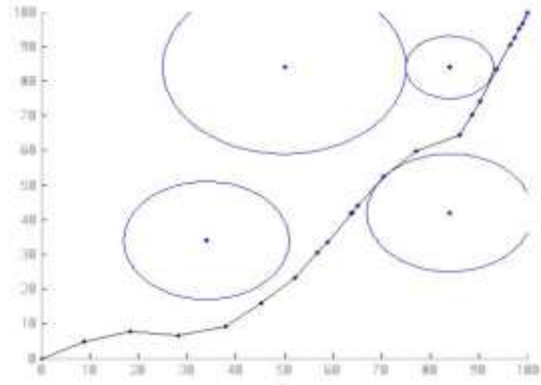


Figure 5. For the Robot, VROBOT =10. For every obstacle, POBS=0. For the goal, PGOAL=0 (Yarmohamadi et al ,2011).

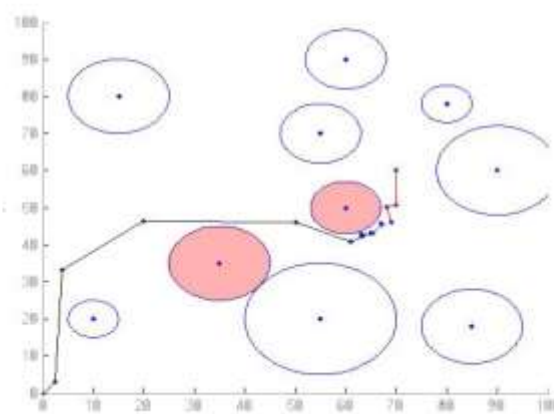


Figure 6. For the robot, VROBOT=30. For the obstacles, VOBS=5; P1obs =0.4 and P2obs=0.7. For the goal, pgoal=0.3 and VGOAL=10 (Yarmohamadi et al ,2011).

2.2.4 Improvement of Robot Path Planning Using Particle warm Optimization in Dynamic Environments with Mobile Obstacles and Target (Nasrollahy & Javadi,2009).

The researchers here improved the penalty function used in (Yarmohamadi et al ,2011). The penalty function was based on the state of the environment. A penalty value is assumed for every obstacle and the influence of the adjacent obstacles are added to the length of the arc for that portion. Simulations were done using MATLAB with four different environmental set up. Table 5 gives the details of the environment. It was concluded that the improved penalty function achieved a better result compared with the results of previous work. Figures 7 and 8 were captured during the simulations with varied parameters.

Table V: Details Of The Four Simulation Environments (Nasrollahy & Javadi,2009).

Figure	No of Obs	No of SObs	No of DObs	Pgoal	Vgoal	Vrobs
7	5	5	0	0	0	10
8	8	8	0	0.3	5	30

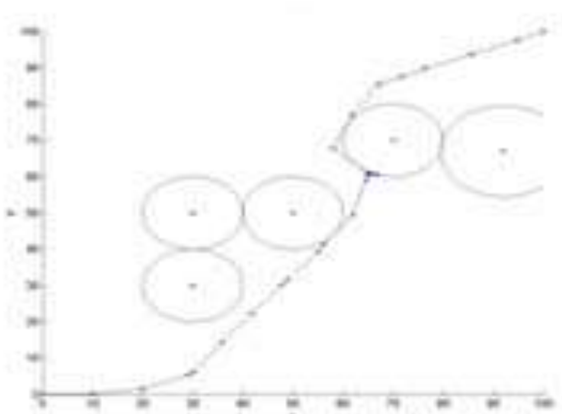


Figure 7 : Path Displayed with Robot Velocity =10 (Nasrollahy & Javadi,2009).

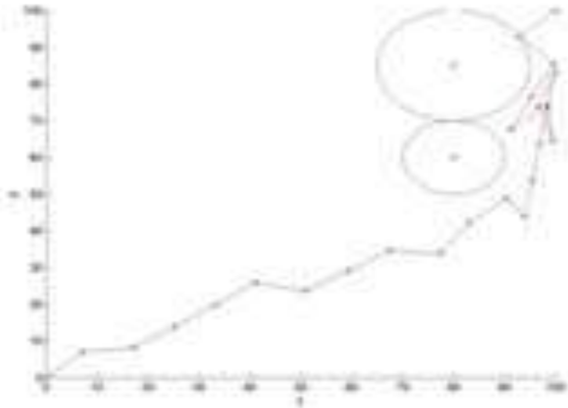


Figure 8: Path Displayed with Robot Velocity = 30 (Nasrollahy & Javadi,2009).

2.2.5 Mobile Robot Path Planning Using Ant Colony Optimization (Mohanraj et al ,2014)

A grid based environment represented in a grid model was used to simulate the path planning of mobile robot. The researcher represents the robot as a point in the grid to reduce computational complexities. A heuristics factor was added to the simple ant colony optimization algorithm. Simulations were done using MATLAB and it was clear that the ACO-MH outperform the SACO. Table 6 shows the parameter specification used for ACO and ACO-MH. Figure 9 and 10 show the map taken by the robot during simulation.

Table VI: Parameter Specification for ACO and ACO-MH Algorithms (Mohanraj et al ,2014).

Parameters	SACO	ACO-MH
No. of Ants (m)	10	10
Weight value (α)	0.25	0.25
Heuristic Factor (β)	0	1
Radius of the obstacles	1	1
pheromone evaporation rate (ρ)	0.1	0.1

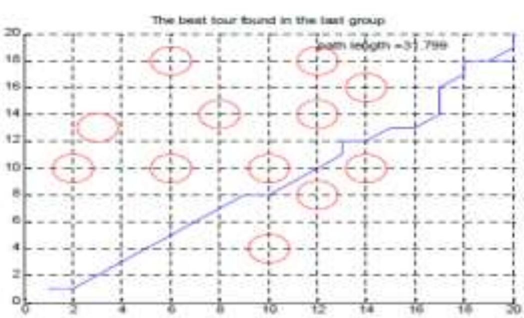


Figure 9: Optimal Path using ACO Algorithm (Mohanraj et al ,2014).

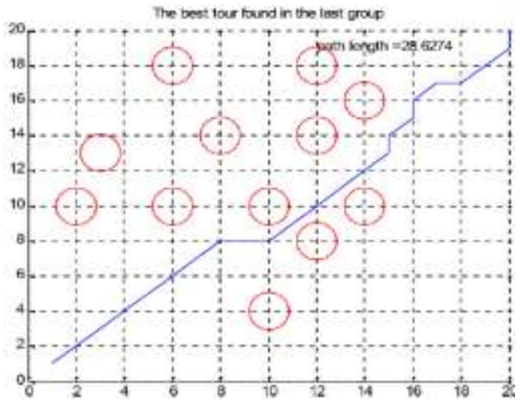


Figure 10: Optimal path found using ACO-MH Algorithm (Mohanraj et al ,2014).

Table VII: Comparison of results for ACO and ACO-MH Algorithms (Mohanraj et al ,2014).

Ex No	SACO (ACS)		ACO -MH	
	Distance (cm)	Time (sec)	Distance (cm)	Time (sec)
1	31.799	3.669818	28.6274	3.26651
2	33.8995	6.5687	32.1421	6.903165
3	32.7279	2.398471	32.1421	2.369687

2.2.6 Path Planning For a Mobile Robot Using Ant Colony Optimization and the Influence of Critical Obstacle (Hyungjune & Seo,2016).

The ant colony optimization was applied to the path finding problem using inference of critical obstacle. The proposed methodology uses the values propagated by the critical obstacles as the initial pheromone and initial transition probabilities. This approach enhances the standard ACO algorithm by directing ants towards the preferable direction rather than allowing them to wander all directions in the same weight. This will enable the ants to reach the target efficiently without considering all regions since the optimal path can be obtained around the critical obstacles. Simulations was carried out in three maps with different configurations. In all the maps, the critical and non-critical obstacles were assigned different values. The performance was compared with the standard ACO algorithm. It was seen that ACOIC out performed ACO.

Table VIII: Result of Path Length (CM) Obtained using Acoic and Aco (Hyungjune & Seo, 2016).

	ACOIC		ACO	
	Length of the best path	Average path length at t=50	Length of the best path	Average path length at t=50
Map 1	5400	6546.7	5600	6706.7
Map 2	4500	5260	4700	5900
Map 3	2700	3446.7	2700	3513.3

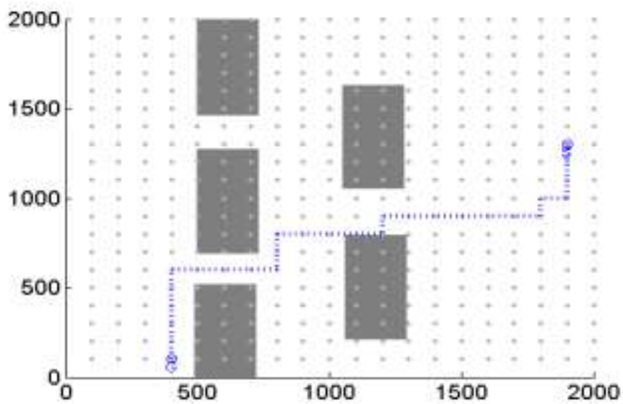


Figure 11: Optimal Paths by Acoic (Hyungjune & Seo, 2016).

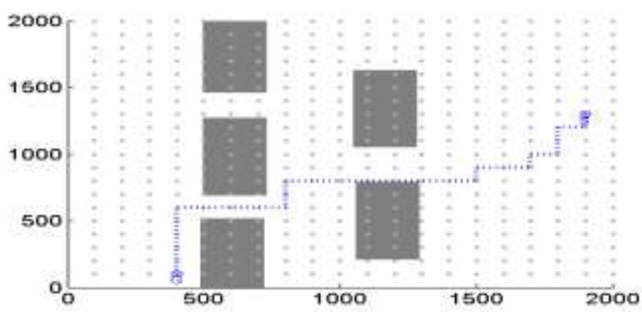


Figure 12: Optimal paths by ACO (Hyungjune & Seo,2016).

2.2.7 Path Planning of Mobile Robots Using Artificial Bee Colony Algorithm (Agarwal & Goel, 2013).

In this work, the researcher applied the artificial bee colony algorithm to find the optimized path for the robot. Two steps were used in the by them; first was to create an initial collision free path from the start point to the goal point and the second was to use the ABC algorithm to find optimal initial path. The proposed algorithm considers that every path consists of straight line segments passing through or from specific points. These points will be selected according to the fitness values to produce a path with shorter lengths. The ABC algorithm5 was used to find this optimal path. The simulation was performed on the grid environment. The population size and number of iterations was kept at 100 and 50 respectively for both environments. The result obtained shows that the ABC algorithm was able to find an optimized path from the start point to the goal point.

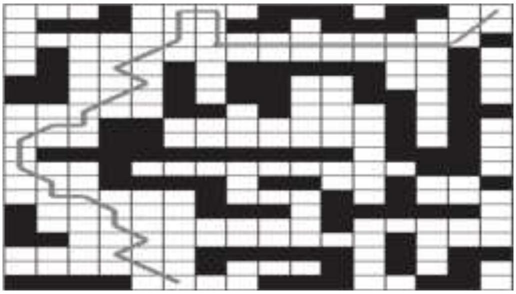


Figure 13: Simulation result in densely occupied environment (Agarwal & Goel, 2013).

3. Application of the Nature Inspired Algorithms to Mobile Robot Path finding Problem.

Nature inspired algorithms have been applied to the mobile robot problem by several researchers. These algorithms have been applied to both the static and dynamic environment. Static environment is when the robot is aware of the obstacles positions in the map and the position of the obstacles do not change with time while in dynamic environment; these obstacles appears unpredictably in course of motion and the position of the obstacles changes with time. In case of robot navigation, a mobile robot reaches the target destination from source station, avoiding collision with obstacles and upon iterations gives an optimal path without any human involvement (Mohanraj et al ,2014).

Genetic Algorithm was applied by (Yarmohamadi et al ,2011) to solve the mobile robot path finding problem in a dynamic environment. They tested the approach using 20 randomly generated obstacles. The location of the obstacles is not known to the robot; hence it is dynamic. Out of the many paths generated; the one with the minimum distance is from start to goal node was selected as the optimal path.

In (AL-Taharwa et al ,2008) Genetic Algorithm was applied in a static environment where the positions of the obstacles were known to the robot prior its movement. A simplified fitness function was used; it uses the path length to determine the best individual in a generation. It was discovered that Genetic Algorithm converges irrespective of the population size used.

Modified Particle Swarm Optimization was applied to the path finding problem of mobile robot by ((Yarmohamadi et al ,2011). A penalty function was proposed as a constraint optimization to enable the robot finds the shortest path to the destination by observing the size and position of the obstacle which has blocked its trajectory. This approach allows the process not to be trap in local optimum and ensures a path is found always if it exist.

The penalty function introduced in (Arora et al ,2014) was improved upon by (Nasrollahy & Javadi,2009). Every obstacle was given an assume penalty value and the influence of the adjacent obstacles were added to the length of the arc. It was concluded that the improved penalty function achieved a better result compared with the results of previous work.

Ant Colony Optimization algorithm was modified using the inference of critical obstacles to guide the robots in order to find the shortest path to the goal. This approach was proposed by (Hyungjune & Seo,2016). The ACOIC methodology was implemented in several maps in order to find a feasible and shortest path. The results were compared to the standard ACO algorithm. It was seen that ACOIC outperformed the ACO; that is utilizing the initial pheromones to lead ants to the critical obstacles is more effective in quickly finding an optimal path than in applying the constant initial pheromones as done in ACO.

Artificial bee colony was applied by (Agarwal & Goel, 2013) to the problem by using two steps: first was to create an initial collision free path from the start point to the goal point and the second was to use the ABC algorithm to find optimal initial path. The proposed algorithm considers that every path consists of straight line segments passing through or from specific points. These points will be selected according to the fitness values to produce a path with shorter lengths. The ABC algorithm was used to find this optimal path.

Table 9 shows some of the characteristics of the nature inspired algorithms x-rayed. Artificial Bee Colony Optimization algorithm can be concluded due to the few number of parameters that can be tweaked, the implementation is easier compared to Genetic Algorithm whose number of parameters is as high as 5.

Table IX: Some Characteristics of the Nature Inspired Algorithms.

Nature Inspired Algorithms	Genetic Algorithm	Particle Swarm Optimization	Ant Colony Optimization	Artificial Bee Colony
No. of Parameters	5	4	4	2
Large Scale Problems	Yes	Yes	Yes	Yes
Computational time	High	Low	Low	Low
Concept Clarity	Complex	Complex	Complex	Easy
Feedback Mechanism	No	Yes	Yes	Yes
Implementation	Complex	Easy	Complex	Easy

4. Future Trend

The review shows that there is still scope for developing more efficient on-line path planning algorithms (Tang et al ,2015) with moving obstacles that will produce better quality routes by addressing real-time recognition of the moving obstacles and producing the shortest and safe path dynamically.

With the prediction of the future of robotics being the drive for innovation to give company the competitive edge.

Robot should be able to move from point to point without human intervention and smoothly by avoiding collision with obstacles and human in its work space. Introduction of sophisticated sensors and camera in the robot space will aid a smooth path generation by the robot to enable it to achieve the goal with the shortest possible time.

As we know, organisms do not have sensors, but they are able to achieve perfect sense function. In the future nature inspired sensors and cognitive model should be developed in order to improve the precision of the sensors and to reduce the high production cost incurred with the development of high precision sensors. The cognitive model of organisms can also be applied to the mechanism of robots. The performance of these nature inspired algorithms in real applications of mobile robot is also a concern to be addressed in the future. This will lead to the development of robot with high intelligence, self-learning, and self-perception in the mobile robot field. . In the future we hope to see where robots can move in a dynamic environment powered by a more efficient hybridize algorithm, nature inspired sensors and mechanisms.

5. Conclusion

In this work, we have reviewed the application of nature inspired algorithms to the problem of path finding in mobile robot. We can see that several approaches have been used to solve this problem both in static and dynamic environment.

It is clear that nature inspired algorithms is an expandable field with innovative ideas and thoughts. It is also one of the hottest research points in the computation world today and will play an important role in mobile robot control, which will be a good solution to improve the intelligence and autonomy of mobile robot.

Currently, ways of solving the path finding problem in mobile robot based on these algorithms have been explored and the results are exciting to demonstrate the potential of NIAs. However, most of the results available are only conducted by simulation; additional efforts are needed to develop some more efficient NIAs and transit these results to real applications in mobile robot control.

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