

Hybrid metaheuristic approach for robot path planning in dynamic environment

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ABSTRACT

Recently robots have gained great attention due to their ability to operate in dynamic and complex environments with moving obstacles. The path planning of a moving robot in a dynamic environment is to find the shortest and safe possible path from the starting point towards the desired target point. A dynamic environment is a robot's environment that consists of some static and moving obstacles. Therefore, this problem can be considered as an optimization problem and thus it is solved via optimization algorithms. In this paper, three approaches for determining the optimal pathway of a robot in a dynamic environment were proposed. These approaches are; the particle swarming optimization (PSO), ant colony optimization (ACO), and hybrid PSO and ACO. These used to carry out the path planning tasks effectively. A set of certain constraints must be met simultaneously to achieve the goals; the shortest path, the least time, and free from collisions. The results are calculated for the two algorithms separately and then that of the hybrid algorithm is calculated. The effectiveness and superiority of the hybrid algorithm were verified on both PSO and ACO algorithms.

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1. INTRODUCTION

Navigation or path planning is the basic need for movement of robots. It consists of two foremost concerns, the target tracking and the hindrance avoidance [1]. One of the major research domains is the robot's autonomous navigation because of its many applications [2]. The goal of the autonomous robot movement is to reach the destination without collision [3]. So, the movement of the robots must be more efficient [4]. Path planning (PP) can be classified into dynamic and static path planning based on the environment [5]. The environment that includes moving obstacles is the dynamic environment, while the static environment objects does not change with time [6]. Safe and efficient path planning in complex and dynamic environments is crucial for safe navigation of autonomous mobile [7]. Local PP and global PP are the two methods might be utilized for solving mobile robot PP problem [8]. With regard to mobile robots, the main goal of PP is to find a simple path in certain environments, such path starts at a starting point (S) and end at a target point (T) [9]. The problem of path planning becomes even more critical when both targets and obstacles are moving because they must react immediately and effectively to the movements of the goal and the obstacles. Generally, PP in the dynamic environments encompasses was further complicated compared to that in the static environments because of the environment's uncertainty [10]. This environment's complexity results from the number of the moving obstacles [11]. In terms of many practical applications, a few

performance merits for the mobile robot path have been in inconsistency. For instance, reducing the path length is going to lead to an increase in the collision risk degree. While decreasing the collision risk degree is going to result in increasing the path length. Therefore, the performance merits must be well balanced to achieving excellent overall performance [12]. Obstacles in dynamic environments can move and it forces the map to be renewed continuously when changes occur in real time [13]. Thus robots are generating paths while moving with the changes in obstacle position [8]. Even though the issue of the collision avoidance with the moving obstacles is considerably more complicated, there is a large number of approaches performing efficiently in the dynamic environment types [14]. In past few decades, there are various algorithms that have been developed to optimise the robot navigation systems [15]. Several researchers have presented solutions to problems of the MR path planning with the use of the heuristic and classical approaches [16]. Classical approaches though have been widely used in the early years of research have been largely replaced by the heuristic approaches in the recent times. This is due to the fact that the heuristic approaches are close to the human way of behavior learning [17]. The classic algorithms in path planning consists of two types of the behavior; movement toward the target and movement around the obstacles [18]. The metaheuristic has been characterized as one of the most reliable methods for solving the complicated problems of optimization [19]. The higher flexibility and efficient behavior are the main reported benefits in the case where a clever optimization approaches' combined with that of proper metaheuristics has been made [20]. The algorithms of the hybrid swarm intelligence can be defined as bio-inspired, metaheuristic types and combining two swarm approaches or more with a view for the achievement of a higher optimization in the domain where they have been implemented [21]. As a result, the hybridization concern is enhancing the metaheuristics with additional approaches with the objective of improving results, decreasing runtime, or both [20].

The remnant of the paper is regulated is being as; the related works is explained in section 2. Section 3, discusses the PSO, the ACO, and the hybrid PSO and ACO metaheuristic approaches. In section 4, the design of the environment used with the proposed system is explained. Section 5, presents the simulation results and the discussion. Section 6, presents the conclusions and the future work.

2. RELATED WORKS

The path planning problem was considered as a topic that most interest the researchers. Providing a mobile robot with a safe is the main goal of the robot PP problem. Moreover, the path is to be optimal. So, different research works related to the PP problem were conducted in the literature, some of their work are; authors Das *et al.* in [22], suggested an approach that combined the PSO with differentially perturbed velocity (DV) algorithms to minimize the arrival time regardless of the path length. The authors have developed the PSO algorithm response by deriving a number of its equations used in it. The results were the convergence of the number of produced paths. The approach has been suggested to simulate an environment with static obstacles. It controlled the robot movement speed by incorporating a vector differential operator inherited from differential evolution (DE) in improved particle swarm optimization (IPSO). The authors also moved some robots within an environment and set a path for each of them. The results indicated that the length of the path was very large, in addition to the slow progress in the event of more than one robot. M. Elhoseny, A. Shehab, and X. Yuan [13], were suggested a genetic algorithm (GA) based path planning method to work in a dynamic environment called GADPP. GADPP method was based on Bezier curve to find the final path according to the identified control points. It uses the performance of robot based applications in terms of the path length, the smoothness of the path, and the required time to get the optimum path. The result ratio of the path length was between 6% and 48%. So, the path smoothness was improved in the range of 8% and 52%. In addition, GADPP reduces the required time to get the optimum path by 6% up to 47%. The D* and the PSO algorithms were presented in [23] for robot path planning in dynamic environments. The approach utilize D* algorithm to analysis the environment from the goal node. While, the PSO algorithm was used to move the robot from the start node by finding and displaying the path. The results were somewhat high and the calculated time was slightly more than the obtained time in the other studies. Dai *et al.* [24] the authors suggested a method based on cuckoo optimization algorithm to plan the robot path in a dynamic environment. The simulation results show that the algorithm performs well in finding a short and collision free path in different environment conditions. Haghghi *et al.* [25] the authors proposed method by the hybridization of the Grey Wolf optimizer-particle swarm optimization algorithm. The method was depended on collision avoidance and detection algorithm. The method added the mutation operators by evolutionary to solve the path safety and smooths it further for a mobile robot. Different simulations have been performed under numerous environments to test the feasibility of the proposed algorithm and it is shown that the algorithm produces more feasible path with a short distance.

In conclusion, from the above, it is clear that, determining the path of the robot is one of the most important problems in the work of the robot. There are wide set of research works that use artificial intelligence algorithms to optimise path planning. Many of the above studies varied the ratios of their results

in terms of accuracy, performance, time taken, and path length. Based on the foregoing, we conclude that the use of hybrid algorithms, as mentioned above, it combined the advantages of the two algorithms to get the shortest path, less time and less cost, to get the optimal solutions.

3. HYBRID METAHEURISTIC APPROACH

The designing and implementing of multi objective optimization for moving a robot to the target is one of the most interesting areas of research. The main purpose of this work is to design the PSO, ACO, and hybrid PSO and ACO approaches with least cost path for a robot path planning.

3.1. Particle swarm optimization

There is a direct data structure mapping from the algorithm domain to the problem domain. In order to produce a mapping of the input of the problem to the input of the algorithm, the cost of each path between the targets is calculated by the initial function. The initial function tries to calculate the cost of each path between targets by making a best first search. This gives more realistic approximation of the cost of the paths among the targets compared to the Euclidean distance. In PSO the swarm population is represented by the particles. These particles search the fitness map by the interaction among them. The interaction is the combination of the recombination, mutation, and selection events. At every generation, the particles that are selected affect the interaction and all the members of the population continue to search by adapting themselves to other particles that have low fitness values. The fitness value is the result of the cost function and it shows the quality of the route built by the particles. Different probabilities in PSO result in different convergence rates. The PSO moves and the particles are affected from each other in the fitness map, as shown in Figure 1.

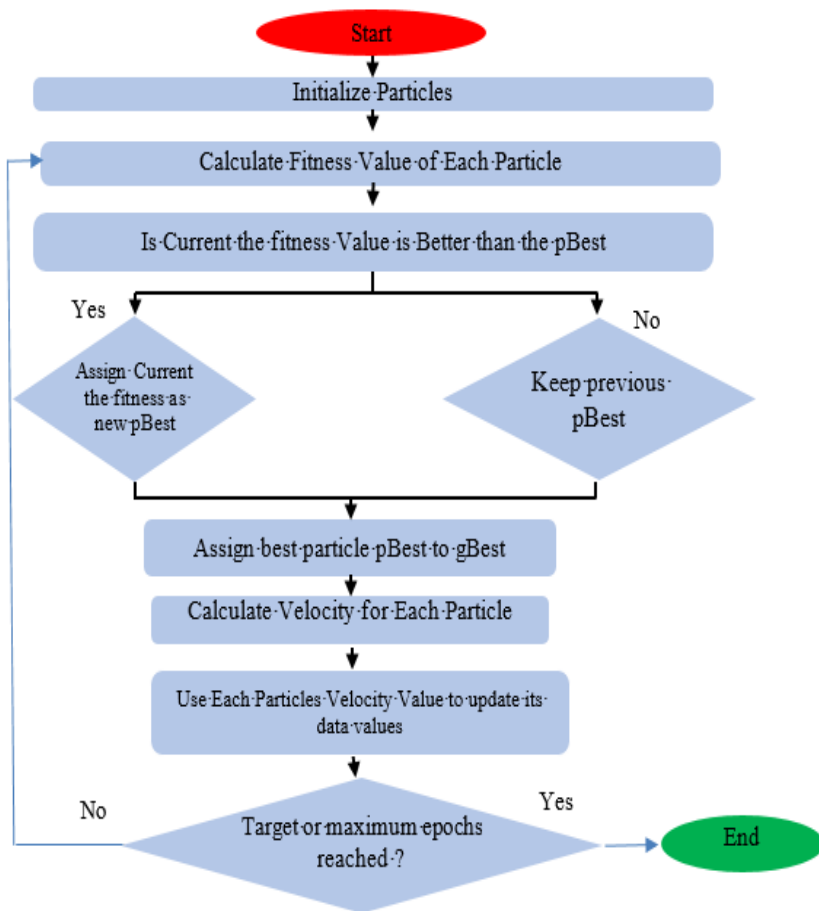


Figure 1. Flowchart of the robot path panning using PSO

3.2. Ant colony optimization

The ACO algorithm is a metaheuristic relies on the behavior related about wandering in search of food or provisions which ants behave. To represent the parameters in the proposed system, the fitness present scaled objective function value. The adaptation of the mutation is the amount of the drop in the pheromone level from the paths taken and the probability. The main flow chart is shown in Figure 2.

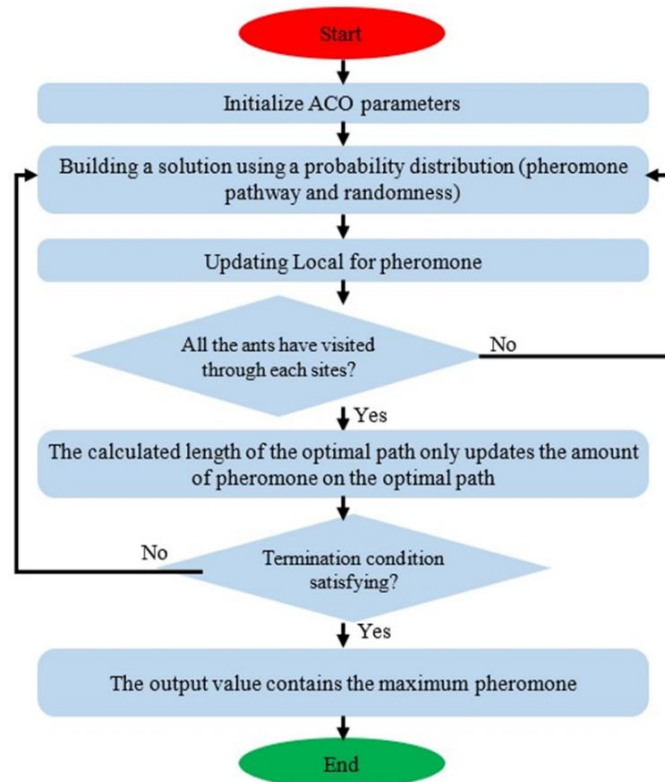


Figure 2. Flowchart of the robot path planning using ACO

3.3. Hybrid PSO_ACO

Hybrid PSO_ACO makes a stochastic search in the fitness landscape, which is the phenotype search space. Phenotype represents the behavioral expression of the genotype in a definite environment. In this paper, the specific environment mentioned corresponds to the MRP search space. Genotype is the sum of inherited characters that are kept within all populations that reproduced. It is often the genetic constitution that underlies one trait or group of traits. The constraints are forming the genotype search space. The particles of the swarm are represented with $X_1 \dots X_m$, where m is the total number of particles searching the fitness landscape for the optimal solution. The PSO_ACO equations take place in the phenotype level. These equations are two equations representing the moves of the particles in the phenotype search space. In (1) calculates a single particle's new velocity.

$$V_{t+1} = C_1 V_t \pm C_2 (P_{i,g,t} - X_t) \pm C_3 (P_{v,g,t} - X_t) \quad (1)$$

And in (2) is used for moving a single particle in a swarm.

$$X_{t+1} = X_t + V_t \quad t = 1 \quad (2)$$

Where V_{t+1} is the particle's new velocity for the next generation, C_1 is the percentage of the number of steps in a velocity to be used. V_t is the current velocity of the particle. C_2 is the percentage of the number of steps in a velocity to be used. $P_{i,g,t}$ is the neighborhood (from i to g) best position. $P_{v,g,t}$ is the global best position. X_t is the present location. C_3 is the percentage of the number of "steps" in a velocity to be used. X_{t+1} is the new "moved" position of the particle.

After applying (1) and (2) to the particle at each generation, the new fitness value of the particle is determined by the cost function. The equations applied to the particles' position (genotype level) produces the fitness values (phenotype level). The particles of the swarm are first scattered randomly in the fitness map. Then, the particles move to their new position in the phenotype search space. In (1) determines each particle's move direction and amount and (2) determines their new position. This process continued till the particles converge at a point or find an acceptable solution. The main flow chart is explained in Figure 3. The improvement using the hybrid technique was done by integrating the PSO and ACO algorithm incorporates the merits of PSO into the ACO algorithm. One of the advantages of applying ACO is that can cluster customers and build routes at the same time. However, laying pheromone (long-term memory) on trails as ant communication medium is time consuming. The merit of PSO is that it can speed convergence through memorizing personal and global best solutions to guide the search direction. Inspired by the merit of PSO, the PSO and ACO algorithm allows artificial ants to memorize their own best solution so far and to share the information of swarm best solution. Hence, PSO and ACO can speed convergence through intensifying pheromone on routes of G best and P best solutions.

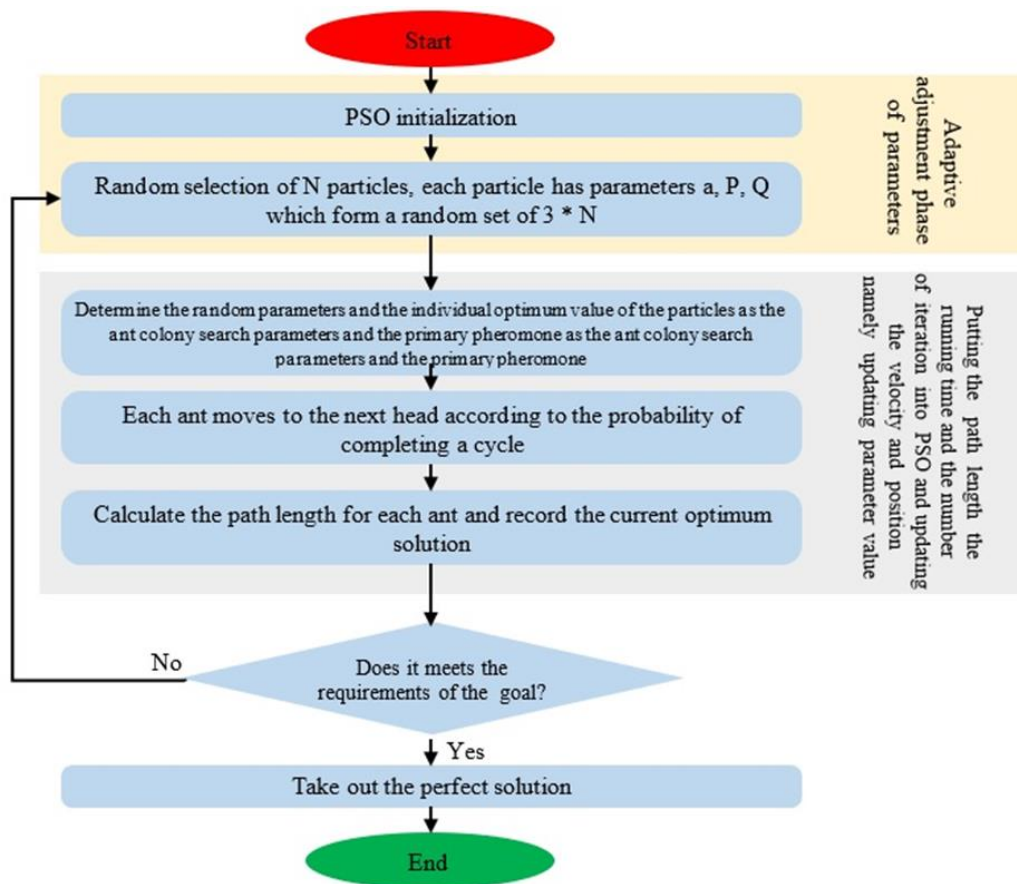


Figure 3. Flowchart of the robot path planning using hybrid PSO and ACO

4. THE ENVIRONMENT DESIGN

The environment is a 2D plane and the target point is a reachable point. In the environment (interested area), there are some obstacles, which is a closed curve with finite length and free boundary. The number of obstacles is also finite. The MR has no prior knowledge of environment parameters such as locations, shapes, and sizes of the obstacles. The robot starts from the starting point heading to the goal point that the environment consists of six shapes. There are two moving shapes and the other shapes are fixed. The robot maybe encounter dynamic obstacle whose moving direction is unknown. So, in each step, the robot must detect the environment information in its detective scope with the sensors. If there are dynamic obstacle, the robot must measure its motion direction and speed, forecast its motion trajectory, then the local dynamic path planning is done based on these actions.

5. SIMULATION RESULTS

The three algorithms were tested using single robot and six fixed and dynamic obstacles. These algorithms were tested with three different starting and targeting points to prove the algorithms validation in MATLAB 2018b. The path length and consumption time to find the best path were the benchmarks used to assess the algorithms performance. In the next paragraphs, the obtained results from applying these three algorithms will discuss.

Using the PSO algorithm, newly generated paths in next iterations of the algorithm are used for robot's observed position as their starting point. The experiments are designed to evaluate the performance of the PSO parameters while a single robot find its path to the target. A number of simulation rounds have been done with one robot of dissimilar initial and targeting points for 500 iterations. The PSO algorithm parameters are illustrated in Table 1.

Table 1. The PSO parameter in proposed work

Description	Value
Number of iterations	500
Swarm size	20
Search velocity factor	10%
Velocity damping factor	0.898
Local fitness significance factor	1.5
Global fitness significance factor	1.5

In this scenario, The PSO algorithm was applied on a dynamic environment as the robot initially proceeds from the starting point to the target with a specific path. In each step the robot moves, it must verify whether it allowed moving to the next step or not. If it is not allowed to move, it rebuilds a new path to reach the target using the algorithm shown in Figure 4. In which, another metric for performance is illustrated, it is the time taken for reaching the optimal solution, i.e. the shortest path for the robot.

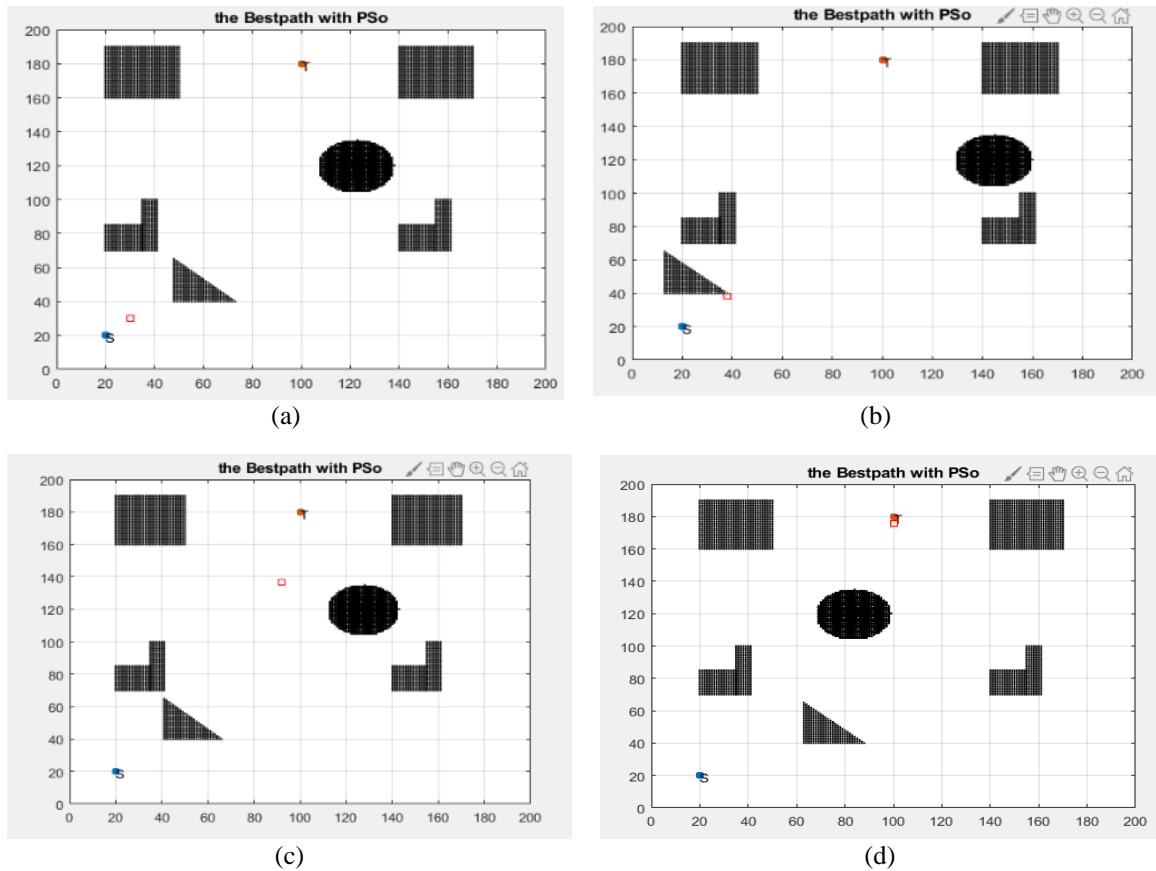


Figure 4. The dynamic map with PSO path planning in four different positions

In simulations of the ACO algorithm, the values of the key parameters of ant colony optimization must be identified first. However, the key parameters includes; number of ants, pheromone concentration stimulating factor, visibility stimulating factor, and pheromone evaporation coefficient given to the method of the parameter analysis. It is possible to obtain the relation among each parameter and the results of simulation were the length of the path and the number of iterations. Through the relation among each parameter and the results of simulation, it is possible to obtain the key parameters' value in the ant colony optimization. The parameter's values in ant colony optimization were shown in Table 2.

Table 2. The ACO parameter in proposed work

Description	Value
ant number	20
coefficient of Pheromone track stimulating factor of visibility	0.5 and 1
Pheromone evaporation coefficient	0.05
Pheromone intensity	100
Number of iterations	500

The ACO algorithm was implemented on the dynamic environment to verify the efficiency of the algorithm. The difference between the static and dynamic environment is that the robot starts with a specific path and does not change it. While, in the dynamic environment, the robot checks the subsequent step whether it is allowed to move or changes the proposed path by relying on the ACO algorithm in each step, as shown in Figure 5. The experiments' results were displayed in Table 3.

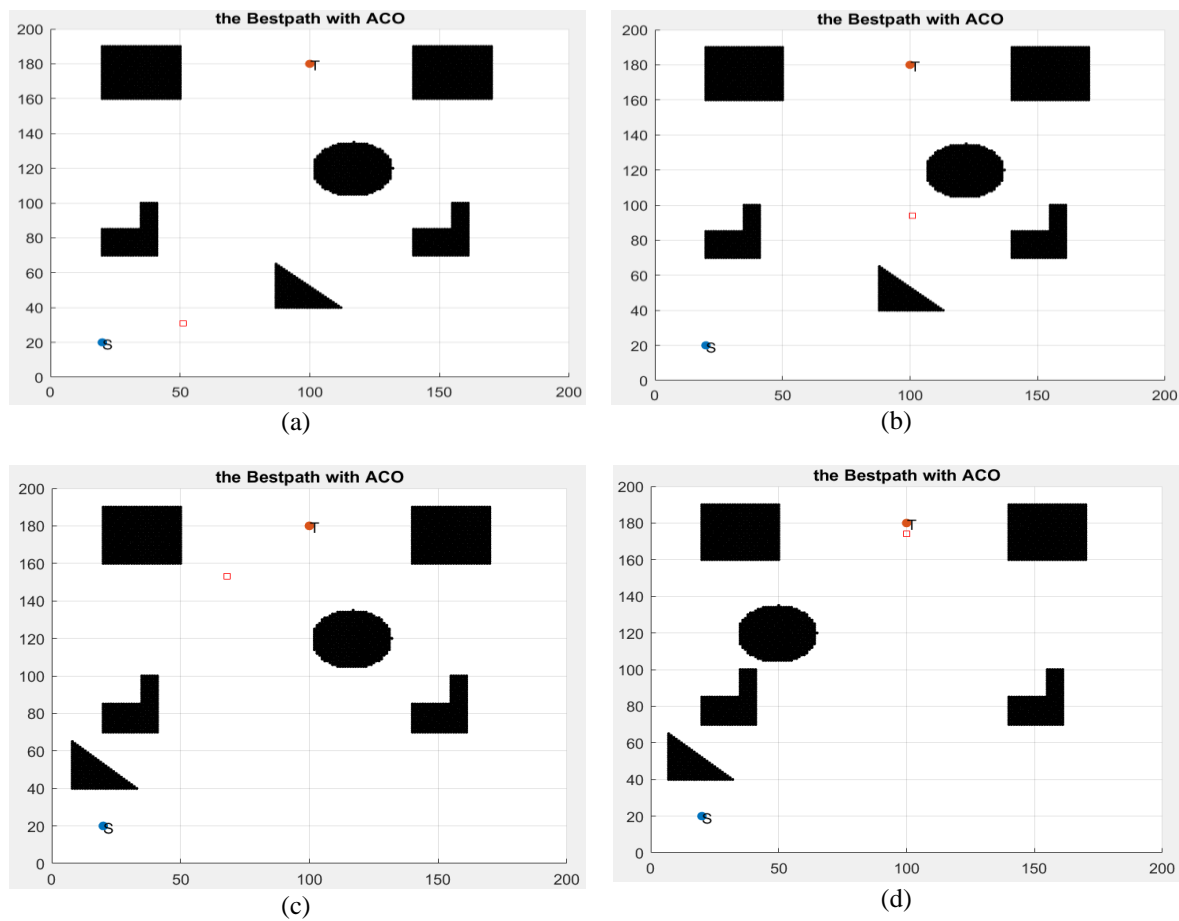


Figure 5. The dynamic map with ACO planning path in four different positions

The hybrid PSO and ACO algorithm was applied in the dynamic environment to measure the efficiency of the proposed algorithm. It is also found that the proposed algorithm is more efficient than the two previously algorithms ACO and PSO. From Figure 6, at the beginning of the command the robot proposes a specific path to reach the goal depending on the proposed algorithm. Then the robot starts from the starting point to the target and at each step it is verified the permeability of movement and the absence of the obstacle in front of it. In the event of appearing an obstacle in it is way, it changes the path depending on the hybrid PSO and ACO algorithm, as shown in the Figure 6.

Table 3. Comparison among the three algorithms with different starting points

Algorithm	Start point		Target point		Number of paths	The time
	X	Y	X	Y		
Hybrid PSO&&ACO	20	20	100	180	162	6419
	100	60	100	180	124	4960
	20	120	100	180	82	3120
ACO	20	20	100	180	266	8841
	100	60	100	180	123	8874
	20	120	100	180	164	8944
PSO	20	20	100	180	166	6579
	100	60	100	180	126	5026
	20	120	100	180	86	3258

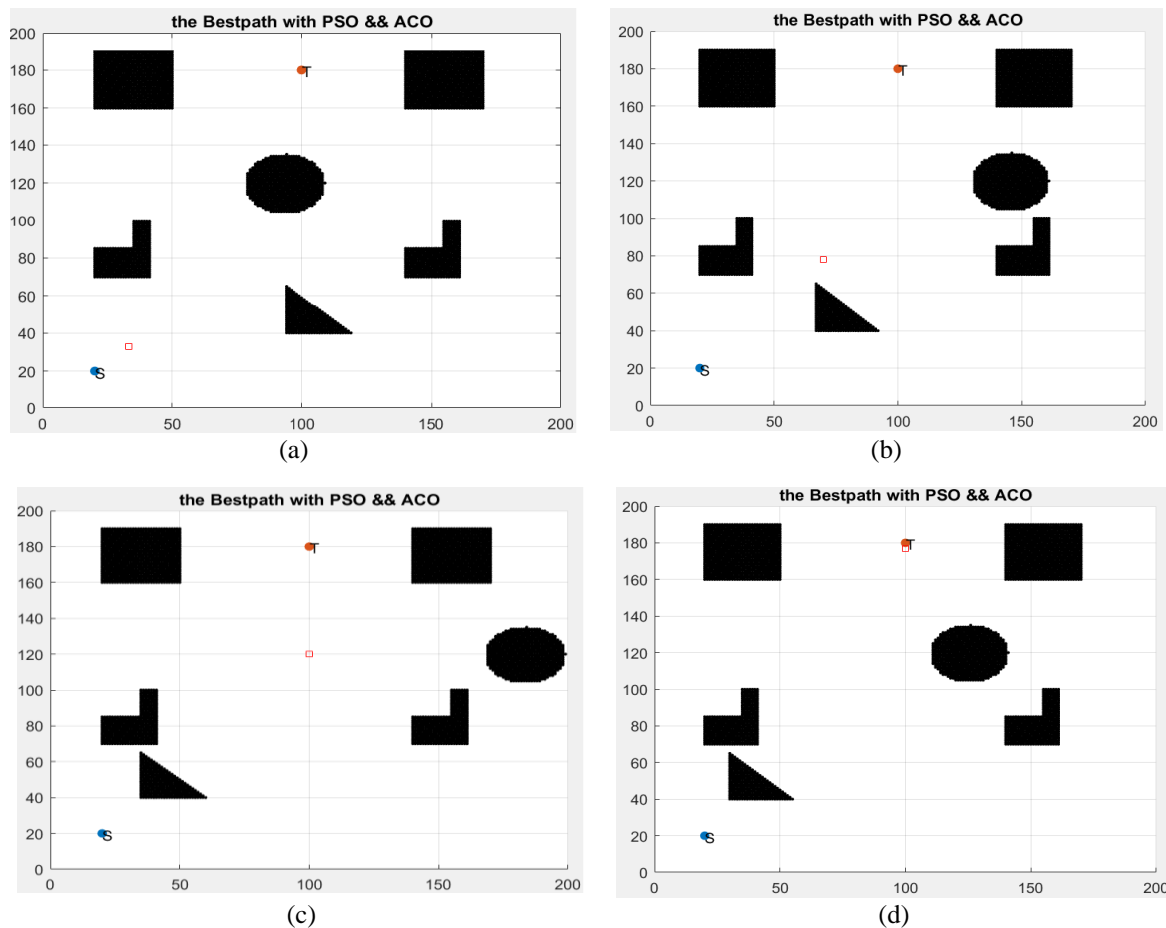


Figure 6. The dynamic map with hybrid PSO and ACO planning path in four different positions

Comparing the three presented methods on the dynamic environment, it can be seen that the hybrid PSO and ACO method was perform better than the ACO and PSO methods. From Figure 7, where the point (20, 20) is the starting point of the robot and the point (180, 100) represent the it is target. In which, the circle and the triangle shapes were moves at the same speed of the robot. All the methods PSO, ACO, PSO and ACO can reach the goal successfully, but the PSO and ACO algorithm reached the goal in shortest time and cost function, it reached the goal in 168 steps, the PSO reached the goal in 172 steps and the ACO algorithm

reached the target in 270 steps. Their values were demonstrated in Table 3. It was also implemented the hybrid PSO & ACO algorithm was applied in the dynamic environment containing obstacles in the form of walls as shown in the Figure 8. To compare our results with previous work, consider Table 4.

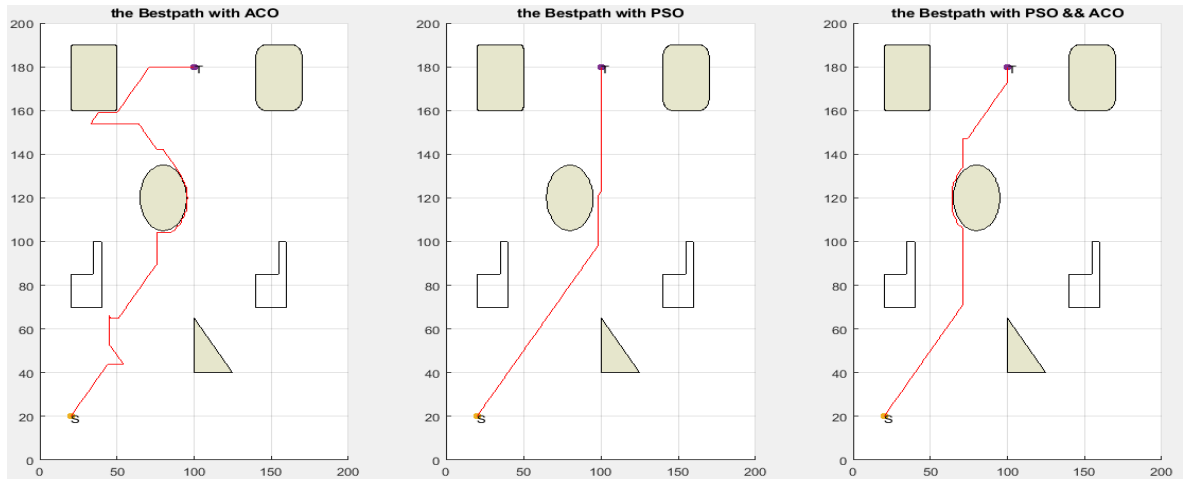


Figure 7. Comparison among the three algorithms

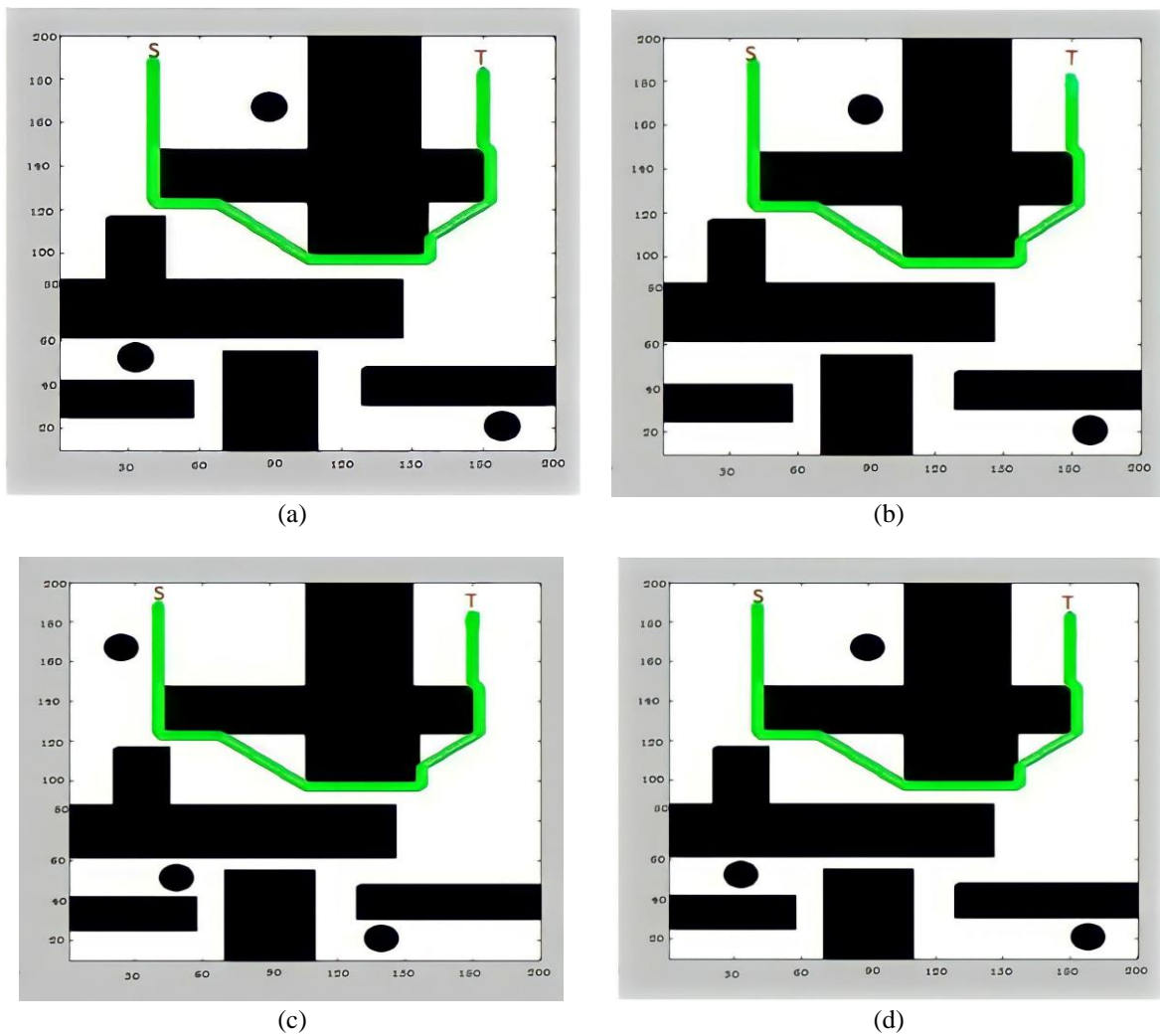


Figure 8. The dynamic map with hybrid PSO & ACO path planning

Table 4. Comparison with some related work

Authors	Step Numbers	Description
Das <i>et al.</i> [22].	24	They present IPSO-DV in a dynamic environment on a 20*20 grid
Cao <i>et al.</i> [23].	31.6586	They present Improve the implementation process of ant colony algorithm on the 20*20 grid
Dai <i>et al.</i> [24].	51.3	They present A* algorithm & MAX-MIN Ant system on 20*20 grid
Haghighi <i>et al.</i> [25].	40	They present A hybrid form of particle swarm optimization (PSO) & genetic algorithm (GA) on a 20*20 grid
The proposed work	168	We present A hybrid PSO&&ACO on 200*200 grid

6. CONCLUSION

This paper describes a proposed methodology for the global path planning problem of a fully autonomous mobile robot works in dynamic environment contains several static and movable obstacles. The proposed algorithm has been proven the ability through a concatenation from simulation experiments. Empirical validation has been performed to validate the suggested navigation algorithm. Some comparative results are presented on the basis of simulation results to illustrate the efficiency and the feasibility of the proposed algorithm. This approach supplies the optimal path with minimum number of iterations. Three different test situations were simulated with obstacles in different positions in each test case. Comparing the obtained results from the PSO, ACO, and hybrid PSO & ACO shows that the best minimum path length and minimum consumption time achieved by applying the hybrid algorithm. While, the PSO algorithm perform better than the ACO algorithm. Our next step is to test these three algorithms in a dynamic environment with moving goal.

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