Shortest Path Calculation for Mobile Robot using ACO

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Abstract - Mobile Robot path planning (RPP) is an important research field of robotics. It refers to the use of some optimization criterion by the mobile robot to search for an optimal, safe and obstacle free path from the initial state to the target state in a work environment with obstacles. In this work, mobile robots path planning has been done by using an ant colony optimization algorithm providing minimum time complexity and good stability with the objectives of finding a collision free & shortest path between start and the end point.

Keywords - Ant Colony optimization (ACO), artificial ant colony system (AACS), Mobile robot, Shortest path.

I. INTRODUCTION

The field of robotics has attracted a lot of attention in research and industrial communities. Currently robots are being used in manufacturing, transportation, medicine, exploration and services. However, in future, robotic systems will need to become more intelligent so that they can execute variety of tasks within minimum time with almost no human intervention. One of the main challenges for an intelligent robot is to determine the safest and fastest(shortest) route to its destination, that is also referred to as the problem of path planning. Path planning is an ordering problem, in which, after beginning at the initial location, the problem is to find a sequence of configurations so as to end at the final goal location. The robot tries to search for an optimal path with respect to a number of performance objectives, such as distance, energy, time, smoothness and safety. Obstacle avoidance is also another main design requirement for a mobile robot. Path planning covers a large area of robotics research as it improves robotic navigation systems in static as well as dynamic environments. With a perfect path planning system, mobile robot can navigate automatically so as to reach the final destination. Robot navigation problems can be generalized into four categories [1], i.e., localization, path planning, motion control and cognitive mapping. If the knowledge of environment is known, the planning of global path can be made offline before the robot starts moving. This path can help the robot to traverse within the real environment. However, one more category of path planning was introduced to solve the robotic path planning problem when the robot is faced with obstacles, and that is known as local path planning. Local path is generally constructed online when the robot avoids the obstacles in a real time environment. Table 1 show the main differences between the two mobile robot navigational approaches [2].

Table 1. Differences in Robot Navigation Approaches

Local Path Planning	Global Path Planning
1. Sensor based system.	1. Map based system
2. Reactive system.	2.Deliberative system
3. Fast response.	3. Slow response.
4. Incomplete knowledge of work space area.	4. Complete knowledge of work space area.
5. The problem is to follow path to avoid obstacle or objects while moving towards target.	5. The problem is to obtain a feasible path leading to goal.

The problem of path planning of mobile robot requires searching through a huge space of possibilities for solutions and often requires the system to be adaptive. Biological evolution is an appealing source of inspiration for addressing such difficult computational problems. A number of nature inspired techniques such as genetic algorithm [4-7], fuzzy logic [8], Artificial neural networks [9], evolutionary algorithm [10], bee swarm optimization [11], etc. have been used by the researchers for the task of robot path planning.
Biological ants in the real world utilize swarm intelligence to determine the shortest route to the nutrients. Ant Colony Optimization (ACO) algorithms mimic behavior of the real ants so as to provide heuristic solutions for the optimization problems. Biological ants exhibit complex social behavior while searching for food depending on the hormones (also called pheromones) deposited by them[3]. Pheromones attract the other ants and give a path to the food source that can be followed by other ants. When more ants walk along the path, more content of pheromone is laid, and the chance of taking that path by the more ants will increase. Most pheromone is deposited on the shortest path to the food as more ants can travel it in less amount of time. A number of researchers have used basic ACO as well as its various variants for the problem of robotic path planning [12-19].
In this work, four different models of ACO; namely ant quantity model, ant density model, ant cycle model and ant cycle model with ellistic ants have been used for finding the optimal (shortest) path for mobile robot and a comparison between the performances of various models of ACO has been made. Rest of the paper is organized as follows:
An introduction to the artificial ant colony system & robot path planning problem has been given in sections II and III respectively. Simulation results are presented in section IV followed by conclusion, future scope and list of references.

II. ARTIFICIAL ANT COLONY SYSTEM

An artificial ant colony system is a stochastic population–based heuristic algorithm that simulates the natural behavior of ants. An ACS algorithm performs a loop [20], by mimicking the way the ants construct a solution for the problem in hand & updating the pheromone trail. The probability of adding a new term to the solution under construction is a function of a problem –dependent heuristic and the amount of pheromone previously deposited in the trail. The pheromone trail are updating considering the evaporation rate and the quality of the current solution. The main task of each artificial ant in an ACO algorithm is to get the shortest path between a pair of nodes on the graph (used for problem representation). The decision rules of an ant, 'k' located at node, 'i' use the pheromone trails τ_{ij} , to compute the probability with which it should choose node j as the next node to move to [20] as shown in eqn. 1 (N_i is the set of one step neighbors of node i):

$$p_{ij}^k = \begin{cases} \tau_{ij} / \sum_{j \in N_i} \tau_{ij} & if\ j \in N_i \\ 0 & otherwise \end{cases} \quad (1)$$

Here, the ants are assumed to deposit a constant amount τ_{ij} of the pheromone. An ant moving from node, 'i' to node, 'j' will change the pheromone value τ_{ij} given by eqn. 2.

$$\tau_{ij}(t) \leftarrow \tau_{ij}(t) + \Delta\tau \quad (2)$$

Pheromone trail is updated in the following three ways:

Online step- by- step pheromone update When moving from node i to neighboring node j, the ant can update the pheromone trail τ_{ij} on the arc (i, j).

Online delayed pheromone update once a solution is built; the ant can retrace the same path backward and update the pheromone trail on the traversed path.

Off –line pheromone update Pheromone updates performed using the global information available is called off- line pheromone updates.

After choosing a path with the help of the action choice rule, an ant has to indicate its movement and the quality of the food source obtained so far to its fellow ants. The pheromone updating method is different for different types of ant colony model, as described in the following models:

A. ***Ant –Quantity Model:*** In this model, ants locally update the pheromone trail directly (by using eqn. 3) after moving from one state to the adjacent one.

$$\tau_{ij}(t+1) = \rho\tau_{ij} + \Delta\tau_{ij}(t, t+1) \quad (3)$$

where

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^k$$

$$\Delta\tau_{ij}^k = \begin{cases} Q/d_{ij} & if\ k\ ant\ uses\ edge(i,j) \\ 0 & otherwise \end{cases}$$

Where m= total number of ants

d_{ij}=Euclidean distance calculated for particular stage

Q= constant related to the quantity of the pheromone in trail.

B. ***Ant Density Model:*** In this model, an ant going from i to j leaves a quantity Q of the pheromone on the edge (i, j) every time it goes from i to j. The ant density model is represented by eq. (4)

$$\tau_{ij}\ (t+1) = \rho\tau_{ij}\ (t) + \Delta\tau_{ij}\ (t, t+1) \quad (4)$$

Where

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^k$$

$$\Delta\tau_{ij}^k = \begin{cases} Q & if\ k\ ant\ uses\ \ edge\ (i,j) \\ 0 & otherwise \end{cases}$$

C. ***Ant–cycle Model:*** In this model, the pheromone trails are updated globally by using the eqn. 5. In cycle model, the pheromone trail is updated only after all the ants have constructed their tours and the amount of pheromone deposited by each ant is set to a function of the tour quality.

$$\tau_{ij}(t+n) = \rho\tau_{ij}(t) + \Delta\tau_{ij}(t, t+n) \quad (5)$$

Where

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^k$$

$$\Delta\tau_{ij}^k = \begin{cases} Q/T_k & if\ kth\ ant\ uses\ edge\ (i,j) in\ its\ tour \\ 0 & otherwise \end{cases}$$

Where T_k is the length of the tour taken by the kth ant.

D. ***Ant system with elistic ants:*** in this ant system for the ant cycle model, an elastic ant reinforces the edges belonging to T^+ –the best tour found from the beginning of the trail-by a quantity $Q/_{L^+}$,where $L^+$is the length of T^+ . During each cycle, e elastic ants are added to the usual ants, so that the edges belonging to T^+ get extra reinforcement eQ/L^+.In this method, the globally updated pheromone trail is given by eqn. 6

$$\tau_{ij}(t) = \rho\tau_{ij}\ (t) + \Delta\tau_{ij}\ (t) + e\Delta\tau_{ij}^e(t) \quad (6)$$

where

$$\Delta\tau_{ij}^e(t) = \frac{Q}{L^+}$$

III. ROBOT PATH PLANNING PROBLEM

To represent the path planning problem, a 2-dimension square map overlaid with a uniform pattern of grid points is chosen . The size of a map can be changed arbitrarily; here, the map consists of a 16 x 16 grid. The left bottom corner of the map is the starting point for a path while the right top corner of the map is the destination point for a path. The shape of an obstacle is always a circle, but the size of the obstacle is variable. The goal is to construct a shortest path from the starting point, S, to the destination (goal point,) D, which avoids every obstacle in the map. The robot first ascertains the next position in order to coordinate itself with the destination and constructs a path to that location. The robot will move to the calculated next position if it can align itself towards its goal location without any collision. Experiments have been performed with different number of obstacles. The results are obtained in static as well as dynamic environment.

IV. SIMULATION RESULTS

In this paper, an ant colony optimization algorithms is implemented as a MATLAB script. MATLAB is adopted as a computer language which is used on an i-5 processor running at 2.50 GHZ with a 4GB of RAM. ACO is used to find the optimal path for three different static cases and one dynamic case. Here, four different models of ant colony system i.e. ant density model, ant quantity model, ant cycle model and ant cycle model with elistic ants have been used. For each model of ACO, the optimal path length is determined. The ant population is taken equal to 50. The parameters of ant colony algorithm have a crucial importance. For each specific model, the best combination of main parameters is different. For the problem in this work, the possible ranges of parameters (information inspiration factor (α), hope inspiration factor (β), pheromone intensity Q and rate of pheromone evaporation) is quite vast $(0 \le \alpha \le 10, 0 \le \beta \le 10, 10 \le Q \le 10000, 0 \le \rho \le 1)$. The parameter settings for the path planning problem have been obtained through repeated tests. Corresponding values of the parameters used in this work have been given in Table 2.

Table 2: ACO Parameters values

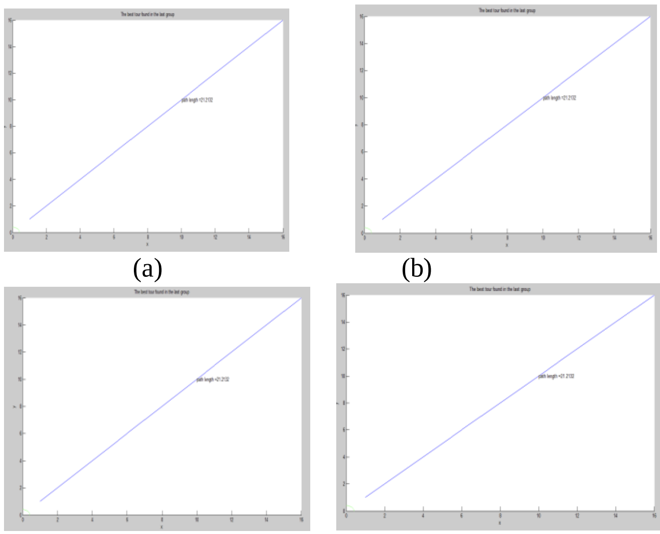
Name of the model	α	β	ρ	Q
Ant density model, Ant quantity model, Ant cycle model, Ant cycle model for elistic ant (Ellistic ants =12)	9.6	6.8	0.8	25.3

A. *ACO Result in Static Environment with Classical Transition Rule*

In this work, ACO is used to determine the optimal (shortest) path for three different static environments taking the ant population equal to 50. The optimal path length obtained in each case by using 4 different models is the same as shown in Figs.1, 3 & 5 respectively. But the time taken by each model to reach the final solution is different which is shown in Table 3. In the same table, a comparison between the models of ACO with classical transition Rule has been given. Figs 2,4 & 6 represent the deposited pheromone in three cases.

Table 3: Comparison between the models of ACO

S. No	No. of obstacles	Path Length	Computation Time (sec.)			
			Ant quantity model	Ant density model	Ant Cycle model	Ant cycle model with 12 elistic ants
1	0	21.12	21.40	26.4	22.7	14.03
2	10	24.14	29.18	34.5	25.7	19.08
3	18	21.7	22.80	32.5	24.24	15.88



(a) (b) (c) (d)

Fig. 1. Optimal path length in static environment without obstacles a) Ant density model, b) Ant quantity model, c) Ant Cycle model d) Ant Cycle model with elastic ants

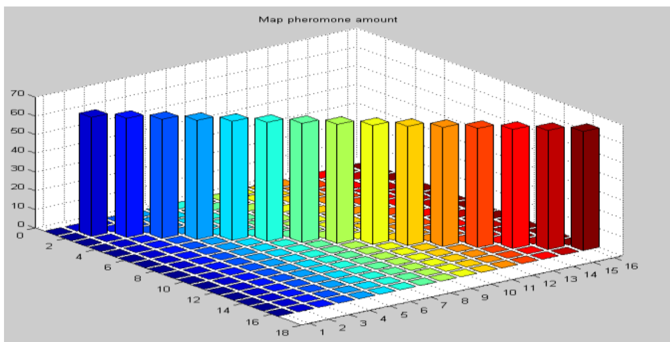
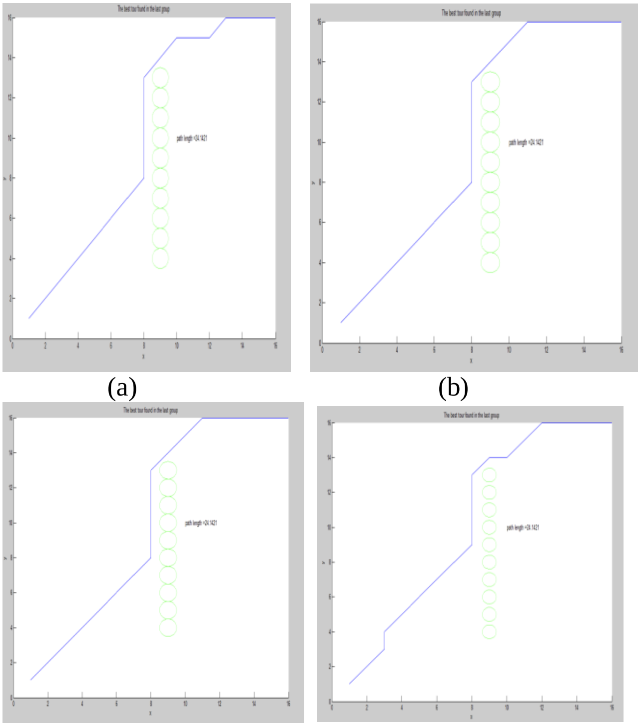
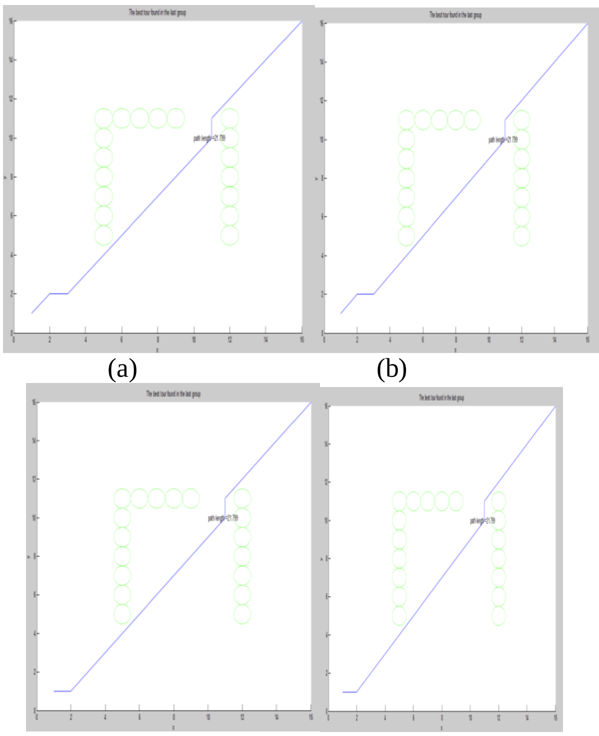


Fig. 2. Deposited pheromone in 2-Dimensional space for no obstacle



(a) (b) (c) (d)

Fig. 3. Optimal path length in static environment with ten obstacles a) Ant density model, b) Ant quantity model, c) Ant Cycle model d) Ant Cycle model with elistic ants



(a) (b) (c) (d)

Fig. 5 Optimal path length in static environment with eighteen obstacles a) Ant density model, b) Ant quantity model, c) Ant Cycle model d) Ant Cycle model with elistic ant

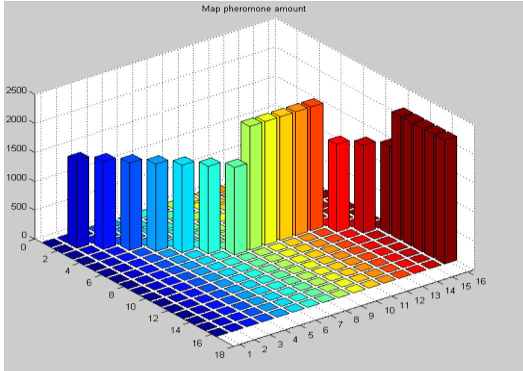
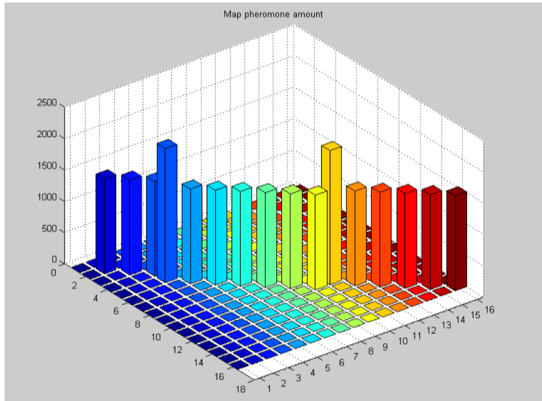


Fig. 4. Deposited pheromone in 2-Dimensional space with ten obstacles

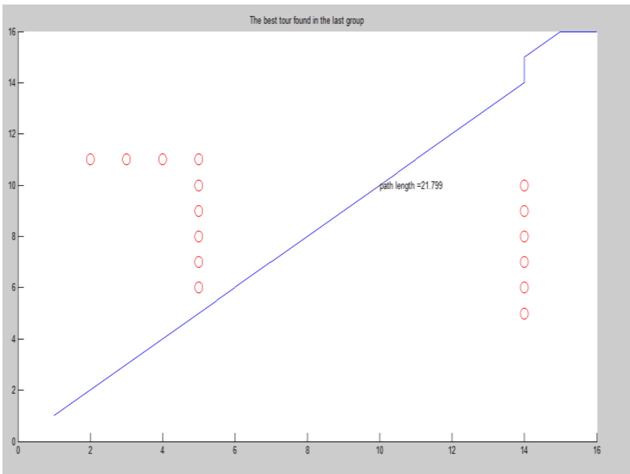


(c)

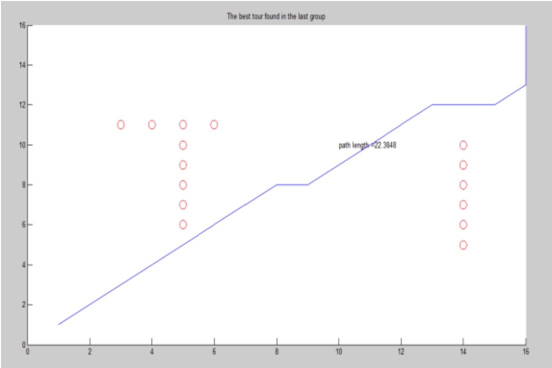
Fig. 6 Deposited pheromone in 2-Dimensional space with eighteen obstacles

B. ACO results in dynamic environment

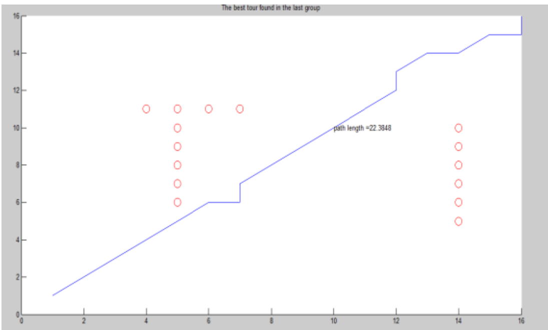
To simulate a dynamic environment, 11 stationery obstacles and 4 moving obstacles are chosen. The speed of the moving obstacle is 1 grid in nine seconds. Using the proposed algorithm the mobile robot is able to find a feasible path from starting to a target with obstacles avoidance as shown in Fig. 7(a-e).



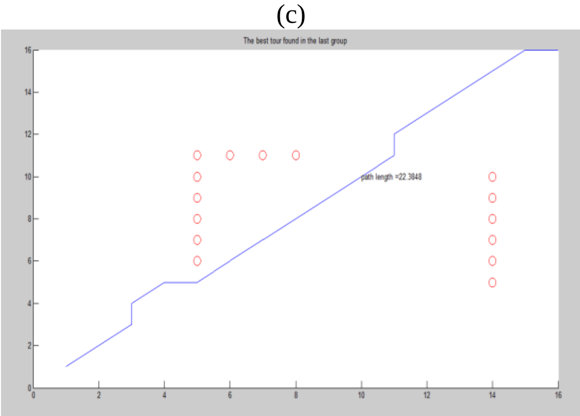
(a)



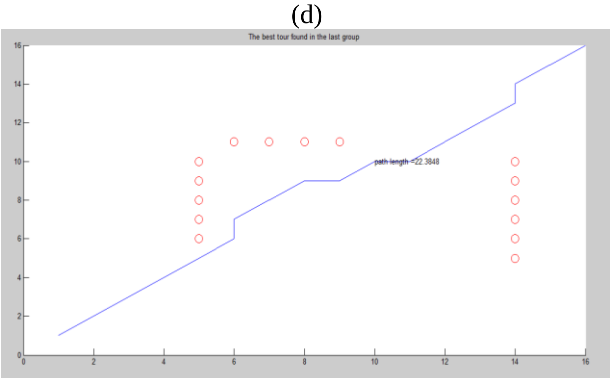
(b)



(c)



(d)



(e)

Fig. 7. Optimal path length in dynamic environment (a) after 9s (b) after 18s (c) after 27s (d) after 36s (e) after 45s

V. CONCLUSION

It has been observed that optimal(shortest) path length can be determined by using any of the four different models of ant colony system i.e. ant density model, ant quantity model, ant cycle model and ant cycle model with elistic ants, but, use of ant cycle model with elistic ants results in minimum computational time. This model has also been successfully tested to give a feasible solution in dynamic environment.

VI. FUTURE SCOPE

In future, this algorithm may be applied to a real robot which has to deal with the nonlinear factors such as noise. Moreover, in this work, a 2- dimensional workspace is considered. Further the work can be extended for a 3-dimensional workspace.

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