Path planning of material handling robot using Ant Colony Optimization (ACO) technique

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ABSTRACT

The present work utilizes Ant Colony Optimization (ACO) technique for the generation of optimal motion planning sequence. The present algorithm is based on ant's behavior, pheromone update & pheromone evaporation and is used to enhance the local search. This procedure is applied for proposed a method for path planning of mobile robot motion in warehouses for materials handling with starting from any location to reach a certain goal. Our technique as based on the well-known environment of the warehouse. To validate the proposed algorithm, the program has been developed in Visual C++.This technique can generated feasible, stable and optimal robotic materials handling sequence and then path sequence can satisfying the materials handling constraints with minimum travel time. The solution is either optimal or near optimal.

Keywords - **ant colony system (ACS), Obstacle avoidance, Ant based Robot Path Planning (ARPP**), **pheromone, visibility graph.**

I. INTRODUCTION

Mobile robot path planning or navigation is an important application for robot control systems and has attracted remarkable attention from many researchers. As a result, many interesting research results have been obtained. A difficult issue in robot navigation or path planning in an unknown environment with static or dynamic obstacles is to find a globally optimal path from the start to the target point and at the same time avoid collisions. [1]

Swarm Intelligence (SI) is an Artificial Intelligence technique involving a new computational and behavioral paradigm for solving distributed problems based on self-organization. Examples of systems like this can be found in natural systems consisting of many individuals, such as ant colonies and flocks of birds, animal herding, honey bees, bacteria, and many more. Swarm-like algorithms, such as Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), have applied successfully for real world Optimization problems in engineering and telecommunication.

Ant Colony Optimization (ACO) is one of the prevailing algorithms in SI at present, which was introduced by Marco Dorigo in 1992 in his PhD thesis [2]. Several ant species are able to select the shortest path, among a set of alternative paths, from their nest to a food source. Ants lay a chemical trail called pheromone when they walk to attract other ants to take the path that has the most pheromone; this mechanism manifests an effect of positive feedback. ACO algorithm is a stochastic, distributed and collective approach that has been used to solve different hard combinatorial optimization problems such as the Traveling Salesman Problem (TSP), Quadratic Assignment, or the Vehicle Routing Problem. The first ACO algorithm was the Ant System (AS), which was designed to solve the TSP

In this paper, we propose a heuristic evolutional algorithm ARPP which is based on ACS framework and applies visibility graph for mobile robot global path planning.

The rest of paper is organized as follows. In section 2 we introduce path planning of warehouse robot. In section 3 we give problem representation including the visibility graph model and ARPP algorithm in section4 its simulation results, then the conclusion of properties of ARPP are given.

II. PATH PLANNING

2.1THE WAREHOUSE ROBOT

The complete system in the warehouse robots consists of a single mobile robot with manipulator with grippers for handling, and picking the materials from the racks or shelves. A few environment sensors, such as wall markers (bar codes, laser reflectors, etc.) that would help to localize the robot with the odometry system existing in the mobile robot platform. The significant features of the warehouse robot are:

1- Obstacle avoidance to move safely in the warehouse.

2- Object and pattern recognition, to identify specified packages and locate them in the right shelves.

3- Path optimization, to minimize time and distance during goods transportation.

2.2 ENVIRONMENT MODEL

Environment model is an important link of the robot path Planning. The essence of environment model is according to the known environmental information, through extracting and analyzing related characteristics, converts them into space that robot can understand. Environment model selection and specific methods to set up the path planning algorithm related and rational selection of model method can reduce the troubles in the process of the path searching. Visibility graph method is used in this paper as a robots roadmap.

III. PROBLEM REPRESENTATION

In this section, we give the assumptions of the GPP problem. When we applied to an optimization problem, the ACO usually involves solution construction on a graph, hence, we present visibility graph model.

3.1. Problem Assumptions

The following assumptions need to be made:

1) We assume the environment is a two-dimensional space; 2) both the environment and obstacles have a polygonal
shape;
3) in order to avoid a moving path too close to the obstacles, the boundaries of every obstacle can be expanded by an amount that is equal to half of the greater size in the length and width of the robot's body plus the minimum measuring distance of the relevant sensors. In this case, the size of the robot can be ignored and we can see the robot as a point robot $\mathfrak{R}$. Fig. 1 illustrates the moving environment of $\mathfrak{R}$,
Which is a 27 by 19 meters including six, obstacles?

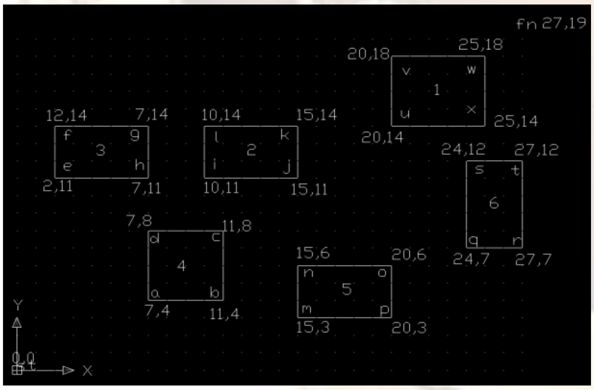


Figure 1. Moving Environment of $\mathfrak{R}$

Fig.1. the (x, y) coordinates of vertices are (0, 0), (07, 04), (11, 04), (11, 08), (07,08), (02, 11), (02, 14), (07, 14), (07,11), (10, 11),(15, 11), (15, 14), (10, 14), (15, 03), (15,06), (20,06), (20,03), (24,07), (27,07), (27,12), (24,12), (20,14), (20,18), (25,18), (25,14), and (27,19) respectively. The (x,y) coordinates of the starting point s (st) and goal point (fn) are (0,0) and (27,19), respectively

3.2. Visibility Graph Model

We consider visibility graph as the roadmap of path planning problem. If we allow visibility graph to be construction graph of the algorithm, the initial search space of the artificial ants can be narrowed dramatically. Hence, in this paper, we use visibility graph as both the roadmap and construction graph to simplify the ARPP problem, Fig.2 illustrates visibility graph

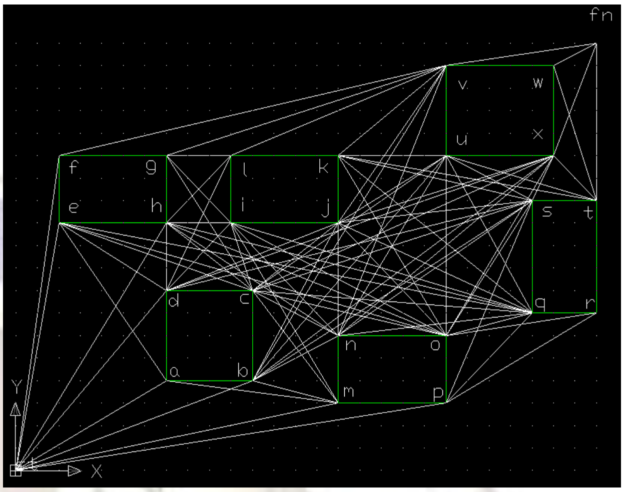


Fig no2.visibility graph

3.3 ARPP Algorithm for path planning (PP)

3.3.1BACKGROUND

Informally, the ACS works as follows: m ants are initially positioned on n cities chosen according to some initialization rule (e.g., randomly). Each ant builds a tour (i.e., a feasible solution) by repeatedly applying a stochastic greedy rule (the state transition rule). While constructing its tour, an ant also modifies the amount of pheromone on the visited edges by applying the local updating rule. Once all ants have terminated their tour, the amount of pheromone on edges is modified again (by applying the global updating rule). As was the case in ant system, ants are guided, in building their tours, by both heuristic information (they prefer to choose short edges) and by pheromone information. An edge with a high amount of pheromone is a very desirable choice. The pheromone updating rules are designed so that they tend to give more pheromone to edges which should be visited by ants.

3.3.2 Active State Transition Rule

In the ACS the state transition rule is as follows: an ant positioned on node (i) chooses the city (j) to move by applying the rule given by (1)

$$P_{ij}^{k}(t) = \begin{cases} \dfrac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum u\epsilon N_i^k(t)\tau_{iu}^{\alpha}(t)\eta_{iu}^{\beta}(t)}, & if j\epsilon N_i^k(t), \\ 0, & if j \notin N_i^k(t), \end{cases} \quad (1)$$

Where N_i^k is the set of nodes not yet visited by ant k and connected to node i, τ_{ij} represents the pheromone for the link between nodes i and j, and α and β are the positive constant parameters used to amplify the relative importance of the pheromone versus the heuristic function η_{ij} given by (2)

$$\eta_{ij} = \frac{1}{d_{ij}} \quad (2)$$

Where d_{ij} is the distance of the link between node i and j Once all the ants have constructed a path from the source node to the destination node, each ant deposits pheromone in the amount of $\Delta\tau_{ij}^{k}(t)$ at the links of the path using the pheromone updating rule (3).

$$\tau_{ij}\ (t+1)=1(-\rho o).\tau_{ij\,(t)} + \sum_{k=1}^{n_k} \Delta\tau_{ij}^{k}(t),\ (3)$$

Where ρ0 is the evaporation rate parameter distributed in (0, 1), n_k is the number of ants, and $\Delta\tau_{ij}^{k}(t)$ is the amount of pheromone deposited by ant k at link (i, j) at time step t, as given by (4)

$$\Delta\tau_{ij}^{k} = \begin{cases} \frac{Q}{L_{k,}} & if\ ant\ k\ used\ link\ (i,j), \\ 0, & otherwise, \end{cases} \quad (4)$$

Where Q is a constant (normally set to one) and $L_{k,}$ is the total distance of the path constructed by ant k. The main characteristic of the pheromone updating rule in AS is that the pheromone values are updated by all the ants involved in constructing a path from the source node to the destination node.

3.3.3Global Updating Rule

The ARPP has a pheromone trail updating approach that exploits the best solutions found. Both evaporation and new pheromone deposit applied only to the arcs contained in the current best solution. Actually, the deposit of pheromone trail is a kind of positive feedback to reinforce the ant's ability in finding the good solutions. Through the positive feedback, pheromone trails accumulate on good paths, which can guide the whole ant colony in their moving to search good paths directly. Ultimately, pheromone trails steer the ant colony system to evolve towards acquiring the optimal solution. Global Updating Rule is given by (5)

$\tau ij \leftarrow (1-\rho)\tau ij + \rho\ \Delta\tau ijbs,\ \forall lij \in Tbs$ (5)

Where Δτijbs=1/Cbs is additional pheromone, added to the edge lij that belongs to best-so-far solution Tbs .ρ (with $0 < \rho < 1$) is the global evaporation rate , for avoiding the excessive increase in pheromone.

3.3.4Local Updating Rule

The ARPP includes a local pheromone update to reduce emphasis on exploitation of existing solutions, which is applied on only the edges that have been visited by ants. Immediately after an ant adds an arc to its current path the amount of pheromone on the arc is decreased .This is called Local Updating Rule and given by (6)

$\tau\ ij \leftarrow (1-\xi)\tau ij + \xi\tau 0$ (6)

Where ξ is the local evaporation rate and τ0 is the initial amount of pheromone. Actually, Local Updating Rule is a kind of negative feedback which aims to encourage the exploration of new areas of the search space. By evaporating pheromone trails from visited arcs, the exploration of alternative paths is increased. On the contrary, pheromone global updating encourages the exploitation of previously good paths. It is the common efforts of the positive feedback and negative feedback that make the whole process of path optimization evolve.

IV. Performance Analysis of ARPP

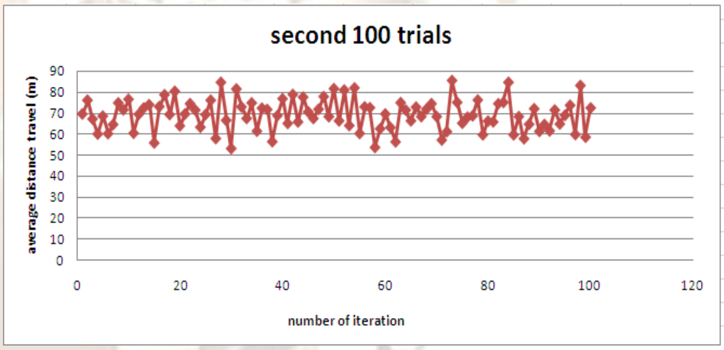
In order to examine the performance of our proposed ARPP algorithm, it constructs an artificial ant colony system Ω by using m ants. Simulation experiments executed up to 100 trials for three times on the visibility graph which have been given in Fig.2. The parameters we set as Table 1 shown:

Parameter	α	β	ξ	ρ	ρ0	*m*
Parameter Value	0.15	2.0	0.15	0.2	0.8	8

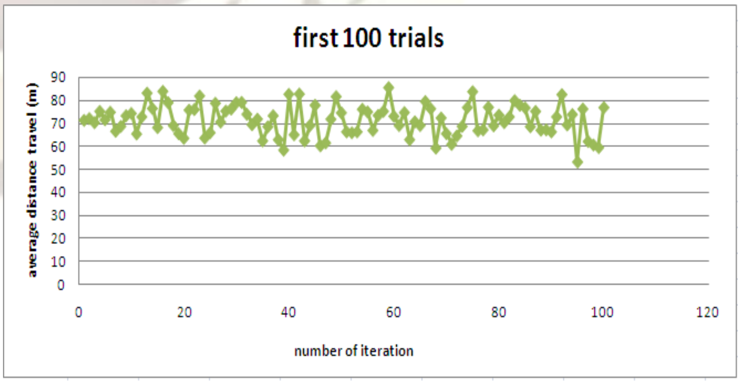
Table no 1: Initial Parameters in ARPP

4.1 Experimental results on environment.

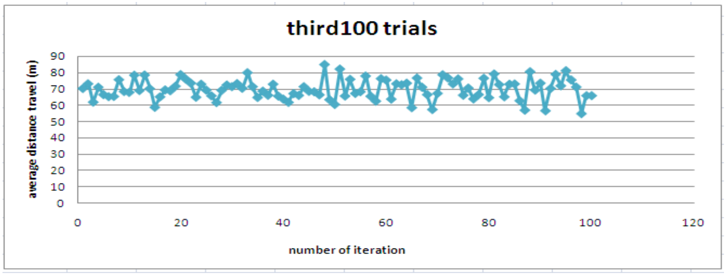
The following graphs show the number of iteration V/S average distance travel by the 8 ants.



Graph no 1: number of iteration V/S average distance travel by the 8 ants for first 100 trials.



Graph no 2: number of iteration V/S average distance travel by the 8 ants for second 100 trials.



Graph no 3: number of iteration V/S average distance travel by the 8 ants for third 100 trials.

By observing the graphs The global-best path of the minimum distance travels by the ants appears in the path shown in Table2 with length of 33 also Statistic results are shown in Table2

	First 100 trials best	Second 100 trials best	third 100 trials best
path	0→2→24→25	0→2→24→25	0→2→24→25
Path value	33	33	33

Table no 2 Statistic Results of Performance of ARPP

From the table no 2 we can say that the optimal path for the robot is 0→2→24→25 which is indicated in the visibility graph by the red line as shown in the fig given below.

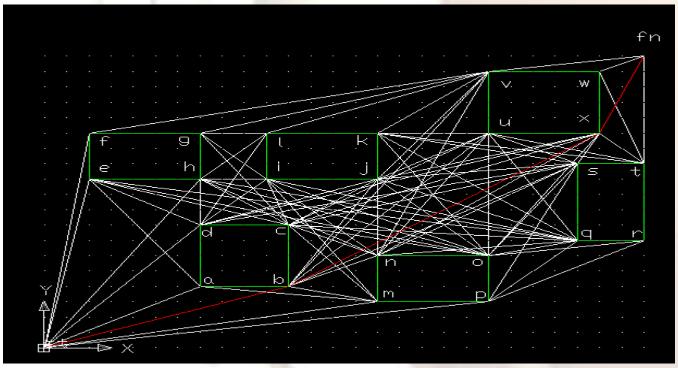


Fig no3.visibility graph of the optimal path

V. CONCLUSION

The proposed algorithm apply visibility graph as the roadmap and construction graph. ARPP algorithm has the advantage of real-time optimization; ACS for ARPP cases within a given map of feasible nodes was proven able to find the optimal path effectively. The optimal path found satisfied the optimization criteria for ARPP purposes which are to reduce the path cost and shorter computation time with smaller number of generations.

Finally we can conclude that to find the navigational path of robots is currently among the most intensively studied and promising area of research which has a significant role in robotics. It has varied application in different field of works, especially where human presence is dangerous, to avoid human error or economically not viable. In this paper, ACS is used to find the shortest navigational path of an autonomous mobile robot avoiding obstacles to reach the target station from the source station. The output is found to be optimal and satisfying for the given problem. In future with increase in complexity of the problem, i.e. with increase in number of obstacles or in dynamic environment, the Ant Colony Optimization Algorithm can be applied effectively giving optimal path in lesser time

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