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Path planning for a mobile robot using ant colony optimization and the influence of critical obstacle

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Abstract

Path planning in mobile robots is important since its performance can significantly affect the utilization of robots. Thus we propose a methodology, ACOIC (Ant colony optimization with the influence of critical obstacle), that utilizes the influence values propagated by critical obstacles as the initial pheromones and initial transition probabilities in ACO. Through this approach, we can enhance the traditional ACO by leading ants toward the preferable direction rather than considering all directions in the same weight. Thus the ants are able to reach the goal efficiently without wandering the regions since the optimal path can be obtained proximal to the critical obstacles. In experiment, we implemented the ACOIC and ACO in 3 different maps in terms of the number and shape of the obstacles in order to see if any differences in performance between those two methods exist. As a result, ACOIC was more capable than ACO for generating an optimal path efficiently.

Keywords
Path planning, Influence propagation, Ant colony optimization, Meta-heuristics

1. Introduction

Path planning is considered to be an important task since the performance of mobile robots is dependent on the quality of solution in path planning. When the complexity of the environment increases, it becomes increasingly challenging to plan an optimal path efficiently from a start to goal point while avoiding the obstacles and satisfying certain criteria such as minimizing the path length, cost, time or maximizing the smoothness (Kala, Shukla, and Tiwari 2011, Han et al. 2011, Hussein et al. 2012).

After the publication of Lozano-Pérez and Wesley (1979), several methodologies have been developed to generate a path in robotics. Among the two categories, classical and heuristic method, the classical approaches such as roadmap, cell decomposition and potential fields were the mainstream in the early days of research (Sariff and Buniyamin 2006, Garcia et al. 2009, Masehian and Sedighizadeh 2007). However, as the environments and situations have become complex and various over time, the heuristic approach began to receive attention because the classical methods were not able to deal with the path planning which is categorized as NP-hard problem (Hussein et al. 2012, Zhang, Gong, and Zhang 2013).

The recent heuristic methods mainly include meta-heuristics such as GA (Genetic Algorithm) (Ismail, Sheta, and Al-Weshah 2008, Hu and Yang 2004), PSO (Particle Swarm Optimization) (Saska et al. 2006, Zhang, Gong, and Zhang 2013) or ABC (Artificial Bee Colony optimization) (Bhattacharjee et al. 2011, Contreras-Cruz, Ayala-Ramirez, and Hernandez-Belmonte 2015). In particular, Wang et al. (2006) used PSO in a dynamic environment to control soccer robots. For finding an optimal path of a multi-robot, ABC was applied to avoid any collision with both other robots and obstacles (Bhattacharjee et al. 2011). The time rolling window strategy was incorporated with ABC to deal with dynamic environments (Ma and Lei 2010).

ACO (Ant Colony Optimization) was also applied in lots of path planning studies due to its strength in finding a route. Fan et al. (2003) considered multiple irregular obstacles in the environment and found a path using ACO, and

Hsiao, Chuang, and Chien (2004) used ACO under the presence of traffic. Especially, Chen et al. (2013) utilized the scent pervasion from the goal and ACO with 1 minus search to improve the convergence speed. In contrast with traditional ACO that deposits pheromones on arcs, Deng, Zhang, and Luo (2013) proposed a modified ACO that pheromones are deposited in nodes for a rapid convergence by integrating pheromones on one node.

Moreover, hybrid methods have been developed to enhance the performance. In Shi et al. (2007), PSO was employed to optimize the parameters in ACO, which ultimately increased the quality of solution. GA and PSO were also incorporated to prevent the solution from falling into a local optimum and to achieve better convergence speed in path planning problem (Li and Wang 2010). SA (Simulated Annealing) algorithm was used with fuzzy logic in dynamic environment (Martínez-Alfaro and Gómez-García 1998).

In this paper, the ACOIC (Ant colony optimization with the influence of critical obstacle) for path planning is proposed. Unlike the traditional ACO that considers the constant or random value for initial pheromone, given the critical obstacles, that are the obstacles in the way of between a start and goal point, ACOIC utilizes the influence values propagated by those obstacles as the amount of initial pheromones in ACO. Since the values of influence are used to calculate the initial pheromones on arcs, and these values decrease as they become distant from the critical obstacle, ants are more likely to select the next node that is close to the critical obstacles during the initial period. This mechanism eventually leads ants to easily reach the goal by reducing unnecessary searches since the optimal path can be obtained proximal to the critical obstacles.

The rest of the paper is organized as follows: Section 2 describes a problem of path planning for a mobile robot, and the methodology is proposed in section 3. Experiment is conducted in section 4. Finally, conclusions and references are represented in section 5 and 6, respectively.

2. Problem definition

In this paper, a collision-free path from a start to goal position is generated as minimizing the total length in a static and known environment, which indicates that the obstacles are fixed on certain locations and the information about the map is given in advance.

As shown in Figure 1, the map is represented in a 2-dimentional grid map where the set of all grid feasible points and width size are N and w, respectively. Start and goal point, S and G, are given as one of the grid points in free space, and the set of all obstacles is denoted as O. Additionally, we separate the elements in O into two subsets, which are a set of critical obstacles CO and of non-critical obstacles NCO, in terms of whether a certain obstacle is directly intersecting with the line between a start and goal point.

The path is obtained by connecting each neighbor point in N and evaluated by summing the lengths of all segments. Finally, the final best solution is selected by minimizing the total path length.

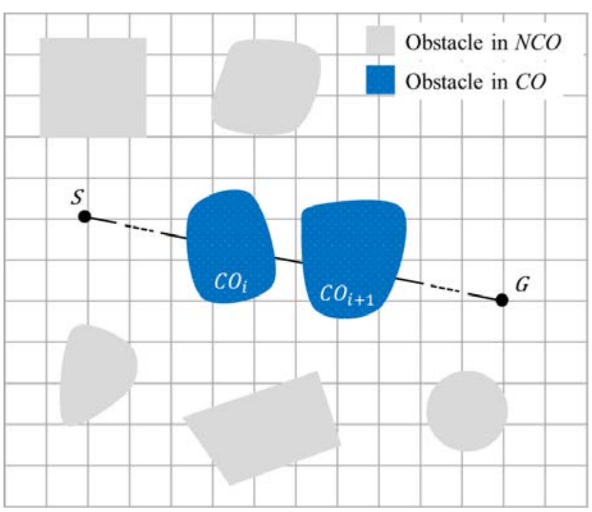


Figure 1. Grid map representation

3. Methodology

This paper proposes a methodology ACOIC to generate a feasible shortest path from a start and goal position by using the ACO and the influence value of all critical obstacles. The procedure of ACOIC is as follows: In the beginning, the influence values of obstacles in *CO* are calculated on every grid feasible points, and then ACO is applied to find a path by utilizing the values calculated previously as initial pheromones and transition probabilities.

3.1. Influence of critical obstacle

The process of propagating the influence of critical obstacles is to assign values gradually on grid points according to their distance from the critical obstacles. Therefore grid points located within close proximity to the critical obstacle have smaller values and indicate the strong influence (line thickness in Figure 2). Through the process, the grid points in the map are no longer identical because they have their own scores. This leads the ants in ACO to choose the next points that are close to the critical obstacles intersecting the line between a start and goal point, which is likely to be the shortest route.

Details of calculating the influence value from a critical obstacle is described in Figure 2. Given a critical obstacle *i*, CO_i, and start and goal point (*S* and *G*) in the map, all neighboring points within width *w* have a value of 1 in the beginning. Then the value of the next neighboring points is increased by 1, and this is repeated until all points have a number. Figure 2 shows that the influence values are assigned on every grid feasible points.

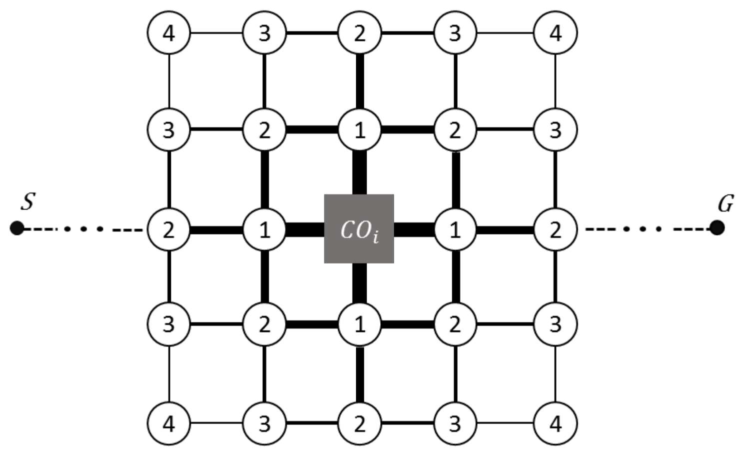


Figure 2. Influence value of the critical obstacle on grid points

3.2. ACOIC (Ant colony optimization with the influence of critical obstacle)

ACOIC is to apply ACO based on the influence values propagated by a certain set of obstacles, which intersect the line between a start and goal point. Unlike the traditional ACO that assigns constant or random amounts of initial pheromones on arcs, ACOIC determines in the initial round how much pheromones are deposited on arcs to lead more ants to move towards the critical obstacles. Through this approach, the ants are able to reach the goal efficiently with less wandering since the critical obstacles are located in the way of the line from start to goal.

After generating the influence values on all feasible nodes, the amount of initial pheromone $\tau_0(i, j)$ is obtained by taking an inverse of the average value between the influence values of critical obstacle assigned on node *i* and *j*, *IC*(*i*) and *IC*(*j*), as in Equation (1). Thus, more pheromones would be deposited on arcs between nodes that are close to the critical obstacles since they have smaller values in *IC*.

$$\tau_0(i, j) = \frac{1}{avg(IC(i), IC(j))} \tag{1}$$

In addition, the initial transition probability can be calculated based on the initial pheromones which gives the information of choosing the next node from node *i*. Where the set of neighbor node *q* from node *i* in 4 directions, up, down, left and right, is denoted as Q, and β controls the relative importance between the visibility $\eta(i,j)^{\beta}$ and the amounts of pheromones, the initial transition probability between node *i* and *j*, $Pr_0(i,j)$, is obtained as in Equation (2).

$$Pr_0(i,j) = \frac{\tau_0(i,j) \cdot \eta(i,j)^{\beta}}{\sum_{q \in Q} \tau_0(i,q) \cdot \eta(i,q)^{\beta}} \tag{2}$$

The strength of this approach is that it induces ants to move closely to the critical obstacles rather than wandering in other regions at the initial stage by putting more pheromones on arcs that are close to the line between the start and goal point. This ultimately lets ants easily reach the goal in that the optimal path can be obtained proximal to the critical obstacles.

After all ants reach the goal, the amount of pheromone and transition probability are updated as each ant goes through the arcs existing in the map. As Equation (3) and (4) show, the pheromone is evaporated at the rate of ρ by iterations and is deposited on every arcs that ants passed by. The amount of pheromone that is deposited on the arc between node *i* and *j* by the ant *k*, $\Delta\tau_t^k(i,j)$, is determined by the path length of ant *k* from the start to the goal. This would be zero if the ant *k* did not go on this arc.

$$\begin{gathered} \tau_{t+1}(i,j) = (1-\rho) \cdot \tau_t(i,j) + \sum_{k=1}^{|M|} \Delta\tau_t^k(i,j) \\ \text{where } 0 < \rho < 1 \; and \; \Delta\tau_t^k(i,j) = \frac{1}{L_k} \end{gathered} \tag{3}$$

Based on the updated pheromone $\tau_{t+1}(i,j)$, the transition probability, $Pr_{t+1}(i,j)$, is updated as follows (Equation (4), and this newly generated probability is utilized for choosing the next node at following iteration *t*+1.

$$Pr_{t+1}(i,j) = \frac{\tau_{t+1}(i,j) \cdot \eta(i,j)^{\beta}}{\sum_{q \in Q} \tau_{t+1}(i,q) \cdot \eta(i,q)^{\beta}} \tag{4}$$

The algorithm of ACOIC is described as follows.

Algorithm. ACOIC

```
Identify the set of critical obstacles
Calculate the values of the influence of critical obstacles for all grid pints i, i ∈ N
Initialize the parameters of ACO: number of ants, the value of β and evaporation rate
Assign the amount of initial pheromone and initial transition probability for the edge between node i and j by
Equation (1) and (2)
t ← 1
while (termination criteria is met)
    for each ants k ∈ M
        Position ant k at start position
        Put the current position of ant k into the path solution
        while (ant k not reaches goal)
            Choose the neighbor grid point from current position based on the transition probability
            Put the selected point into the path solution
        end
    end
    Update the amount of pheromone for next iteration by Equation (3)
    Update the transition probability for next iteration by Equation (4)
    t ← t + 1
end
```

4. Experiment

4.1. Design of experiment

In experiment, the proposed methodology ACOIC is implemented in several maps in order to see if it is able to find a feasible and shortest path. Additionally, we compared the test results between ACOIC and ACO regarding the quality of solution by also applying ACO only with the constant initial pheromones and transition probabilities.

As Table 1 shows, all 3 maps used are different in terms of the shapes and number of obstacles (http://imr.ciirc.cvut.cz/planning/maps.xml), so that we could test the performance of methodologies in various maps. Each map has 2 to 6 obstacles and was represented as 20x20 grid map with the width size 100 in 2000x2000 (cm).

Table 1. Map information

	Number of obstacles	Map size (cm)
Map 1	6	2000x2000
Map 2	2	2000x2000
Map 3	5	2000x2000

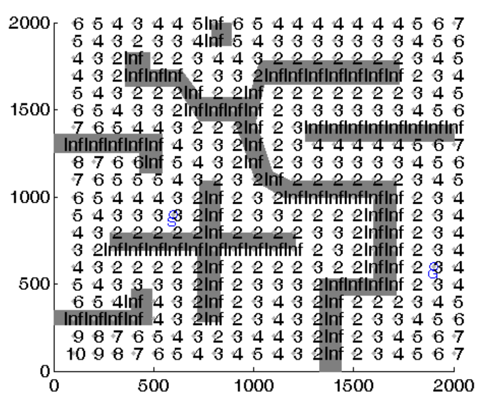
Parameters β and ρ are set as 1 and 0.1, and the number of ants and number of iterations are 15 and 50, respectively. All parameters are equally applied to both ACOIC and ACO. The fitness value of ant k is calculated as the total length of the path from a start to goal point where the path consists of the grid point p as $\{p_1(x,y), p_2(x,y), \ldots, p_l(x,y)\}$ (Equation (5)). Thus, the final best path is the one that has a minimum value in distance.

$$Fitness_t(k) = \sum_{i=1}^{l-1} \|p_i(x,y) - p_{i+1}(x,y)\| \quad (5)$$
$$where\ p \in path\ of\ ant\ k$$

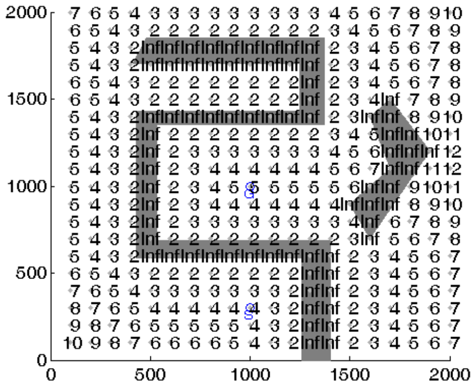
4.2. Experimental results

Experimental results consist of the influence propagated by critical obstacles and the final path generated by ants. Given the start and goal point marked as blue circles, Figure 3 shows the value of influence on all feasible grid points and also indicates that in all 3 maps relatively small and large values were assigned around critical and non-critical obstacles, respectively. Thus, the identification of influence values is able to lead ants to the preferable regions which are close to the shortest path.

(a) Map 1



(b) Map 2



(c) Map 3

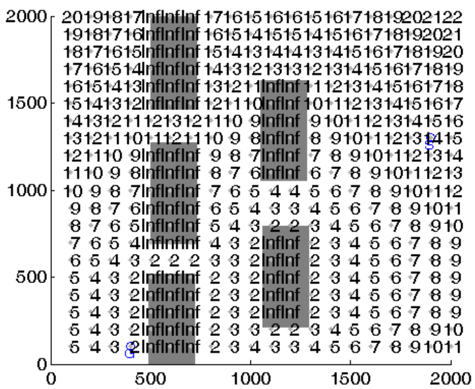
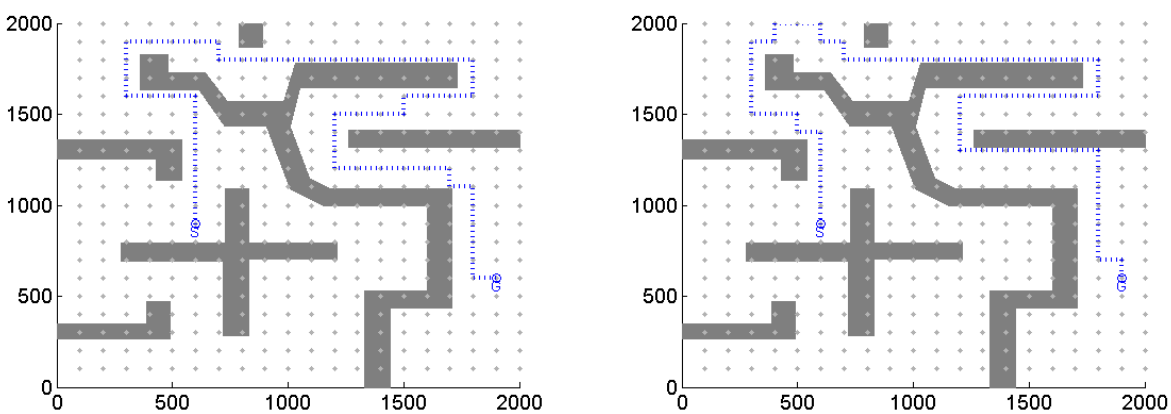


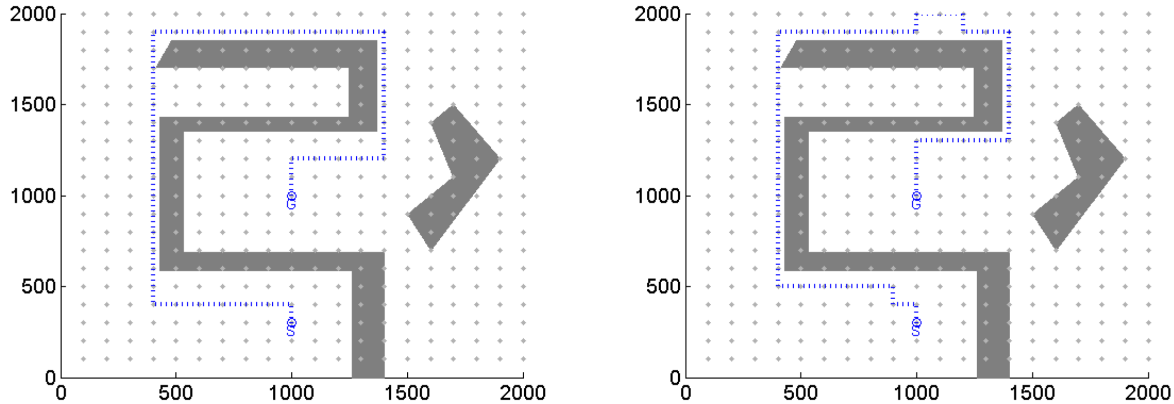
Figure 3. Results of the influence propagation of the critical obstacle

Next, the final best paths from a start to goal point by ACOIC and ACO were drawn on the left and right side in Figure 4, respectively. The result indicates that ACOIC generated optimal paths in all maps even though ACO found an optimal path only in map 3. In map 1 and 2, ACO included the redundant line segments in the final paths unlike the final paths by ACOIC. Through these final paths from both methodologies, it can be said that 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.

(a) Map 1



(b) Map 2



(c) Map 3

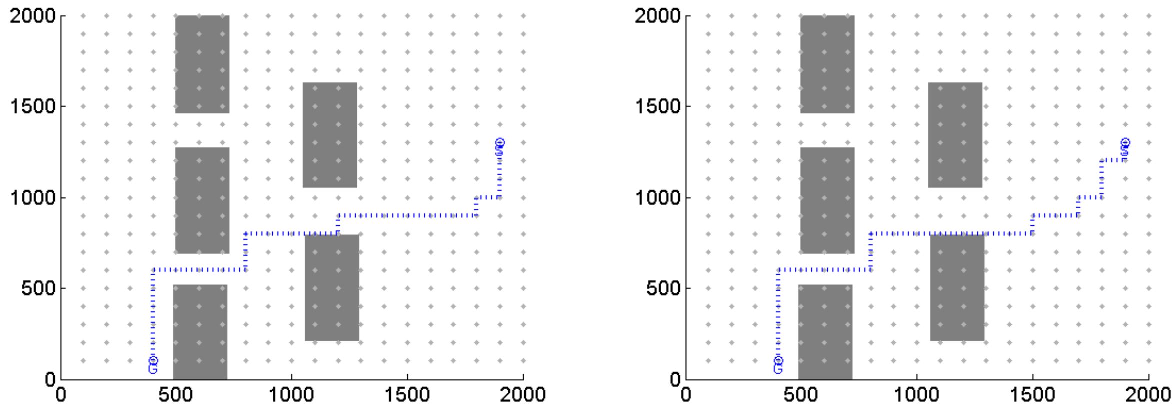


Figure 4. Optimal paths by ACOIC (left) and ACO (right)

These results were also confirmed by the path length in Table 2 since there is a difference in the length of the best path between ACOIC and ACO in map 1 and 2. In particular, the average path lengths at the last iteration were all smaller in ACOIC than in ACO. Thus, we could conclude that the solution of the overall ant colony was better through ACOIC compared to ACO.

Table 2. Results of path lengths (cm)

	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

5. Conclusion

In this paper, we proposed a methodology that combines the ACO with the influence value of critical obstacles as the amount of initial pheromone on each arc in order to induce ants to move in a path closest to a straight line between the start and goal. This approach is effective in finding the optimal path since it is mostly constructed around the critical obstacles. Experiments also proved that the proposed methodology ACOIC is better than ACO in finding the shortest path.

Our method can be utilized in any industry that has to solve a path planning problem efficiently without losing the quality of solution, since it is able to provide the optimal solution even in an environment containing obstacles of complex shapes. Additionally, ACOIC can be applied in dynamic or unknown environments because all we need to know to implement the algorithm is which obstacle is critical, and this information can be obtained by sensors in the mobile robot.

In this paper, we only considered the length for evaluating the path, but generating a smooth path might be important for various reasons. Thus, this research would be further improved by adopting another objective, such as maximizing the total angle between line segments. Moreover, the parameters used in ACO can be optimized to enhance the performance of ACO in future research.

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Biography

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