# An Optimized Hybrid Ant Colony Algorithm for Robot Path Planning

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## Abstract

This study focuses on existing drawbacks of the potential ant colony algorithm. The algorithm has two drawbacks, one is the low initial search efficiency, the other is being easy to fall into the local optimum. This study develops a new optimized hybrid ant colony algorithm to solve these two shortcomings. Firstly, the algorithm uses the target gravitational force generated by the artificial potential field to construct a heuristic factor. The heuristic factor is combined with the initial heuristic factor of the ant colony algorithm to construct the comprehensive heuristic information to improve the search efficiency. Then, the pheromone in the ant colony algorithm is updated by wolves distribution rules to avoid getting into the local optimal; At Last, the planning path is optimized by path optimization algorithm which makes it more suitable for robot execution. Experiments show that the optimized hybrid ant colony algorithm can quickly and efficiently plan the optimal path.

## Keywords

Path planning; ant colony algorithm; artificial potential field; wolves distribution rules; path optimization algorithm.

## 1. Introduction

Path planning is one of the key technologies to realize mobile robot control. The aim is to find an optimal or suboptimal safe collision-free path from the home position to the target location under certain environmental conditions and performance requirements. Aiming at the robot path planning, many domestic and foreign scholars have proposed many planning methods, including artificial potential field method [1], neural network adaptive programming method [2], genetic algorithm [3], colony algorithm [4], particle swarm Algorithm [5] and so on. In recent years, more and more scholars in the study of path planning issues pay more attention to a variety of intelligent algorithms to improve the performance of the algorithm. Such as ImenChâarietal [6], who combined the genetic algorithm with the ant colony algorithm. The former stage uses the genetic algorithm to generate the initial pheromone distribution, and the latter stage uses the ant colony algorithm to find the optimal solution, which can effectively combine the advantages of the two algorithms to improve the ant colony but may fall into local optimum. XO etal[7] proposed a new path planning method based on Particle Swarm Optimization (PSO) and Ant colony optimization (ACO) algorithm. The algorithm uses the method of particle group environment modeling to generate the path from the starting point to the target point, and then uses the improved optimized ant colony to find the best path based on the previously generated path distribution pheromone. The method can shorten the search Time, but the environmental requirements are higher, poor adaptability. In [8] proposed a hybrid algorithm (ACOG) based on ACO and GA techniques. Darwinian Reproduction, Structure-Preserving Crossover and Structure-Preserving Mutation are the three genetic operation adopted to improve the efficiency of the ACO algorithm and to avoid falling into a local optimum. The authors claimed that their method is a

Multi-objective algorithm as it takes into consideration three different parameters: length, smoothness and security of the path. In the simulation work, they argued that the algorithm is able to generate near optimal path. T Zhu, G Dong [9] proposed an algorithm to combine the ant colony algorithm with the artificial potential field method. The algorithm initializes the overall path with the potential field method, optimizes the path ordering of each generation ant and updates the information according to the sorting of the ant path. At the same time, with the help of the pheromone of the elite ants, the crossover and mutation operation of the module algorithm is used on each generated path. The algorithm improves the convergence speed and stability. But because of the artificial potential field method itself is easy to fall into the local deadlock, so the algorithm to find the path easily fall into the local optimal. In Literature [10], a potential ant colony algorithm (PACA) is proposed. The algorithm uses the local force factor of the artificial potential field to transform the pheromone on the path , So that the algorithm has a better search performance, but the initial moment ants are still "blind search", and easy to fall into the local optimal. In summary, a variety of intelligent algorithms combined with the main problem is the initial time search efficiency is low and easy to fall into the local optimal. Zhao[11] proposed a pheromone updating method in ant colony algorithm and introduced the maximum and minimum ant colony system for dealing with the robot path planning problem, the simulation results show that the algorithm can effectively improve search efficiency for optimal path; In [12], Zhang et al. proposed an improved ACO algorithm. The key differences with the traditional ACO algorithm are the definition of an objective attraction function in the transition rule probability which is based on the attraction of the goal position and the use of a modified pheromone update rule. The authors compared the new algorithm with the conventional one in terms of path length and number of cycles and they proved that their algorithm provides more accurate results. But the use of the defined gravitational function results in deterioration of the strain of the algorithm. The algorithm has some limitations.

In this study, we developed a new mobile robot path planning algorithm - Optimized Hybrid Ant Colony Algorithm (OHACA). The algorithm uses the principle of artificial potential field, so that the target has an attractive effect on the ant colony, the ants have the direction to find the path, which improves the search efficiency. The pheromone is updated by the wandering grouping rule. The pheromone on the local optimal path is increased for each iteration, and the pheromone in the local worst path is reduced, which is to avoid the search into the local optimum. Finally, the path optimization algorithm is used to optimize the path, and some unnecessary inflection points are deleted to get an optimal path.

## 2. Environmental Expression and Objective Function

In order to seek an optimal path in an obstacle environment, grid method [13] is used to establish a two-dimensional environment modeling of the robot. The two-dimensional coordinates of the grid represent the position of the robot in the map. A logical variable is used to represent the state of the grid, 1 for the barrier, 0 for the free area. Figure 1 shows the black indicates that the barrier area is represented by a set $f_o$, and the white means that the free area is represented by a set $f_f$ , the entire grid can form a two-dimensional matrix .The Arrows in the grid indicate the direction in which each free area network can move. According to the ant colony algorithm search path principle, ants can move from the starting node, move in the direction of the arrow to the next grid and finally reach the target point. There are many kinds of optional path. The shortest and best path is fond by repeated selection of a path.

In the context of the grid description, the robot starting position is $s(1,1)$ , the target position is $s(M,N)$ . $d(t)$ is the distance of the robot in step t which is from the position $s_t(x,y)$ to the next position $s_{t+1}(x,y)$ .Robot through T step to reach the target location. The objective function of robot path planning [14] is to minimize the total length L of the no-pass path from the starting point to the target point, which is defined as follows:

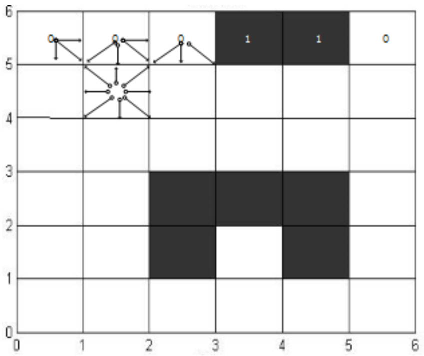


Figure (1) Raster map

$$\min L = \sum_{t=1}^{T} d(t) \tag{1}$$

$$d(t)=\begin{cases} m, & (x(t)=x(t+1)\ or\ (y(t)=y(t+1)) \\ \sqrt{2}m, & (x(t)\neq x(t+1)\ \text{and}\ (y(t)\neq y(t+1)) \end{cases} \tag{2}$$

$$s_t(x,y) \in f_f ands_t(x,y) \notin f_o \tag{3}$$

Where $m$ is the grid side length.

## 3. The basic principle of potential ant colony algorithm (PACA)

In the literature [10], potential ant colony algorithm uses the grid map [15] as the environmental model. In the process of ant colony search, we add the local search and optimization algorithm of the artificial potential field for the specific problem. Force factor is transformed into local diffusion pheromone $\tau_{ij}^{"}$. The pheromone rule $\tau_{ij}^{"}$ and probability $p_{ij}^{k}$ is constructed as follows.

$$\tau_{ij} = \tau_{ij}^{'} + \tau_{ij}^{"} \tag{4}$$

$$p_{ij}{}^{k} = \begin{cases} \dfrac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}(t)\right]^{\beta}}{\sum\limits_{s\in allowed_k}\left[\tau_{is}(t)\right]^{\alpha}\left[\left[\eta_{ij}(t)\right]\right]^{\beta}} & j\in allowed_k \\ 0 & others \end{cases} \tag{5}$$

Where $\eta_{ij} = 1/d_{ij}$ is the heuristic of the transition from raster $i$ to $j$; $d_{ij}$ is the distance from the grid $i$ to $j$ ; $\tau_{ij}(t)$ is the pheromone of the robot moving from the grid $i$ to $j$; $allowed_k = \{0,1,\cdots,n-1\}$ is the position where the ant $k$ is allowed to choose the next step; $\alpha$ , $\beta$ are the weight parameters of $\tau_{ij}(t)$ and $\eta_{ij}(t)$ respectively.

The ant colony algorithm changes the "blind search" of the ant colony into "directional search", strengthens the cooperative ability between the ants individual, reduces the local crossing path, reduces the number of "lost" ants, improves the ant colony algorithm Of the local search ability and the global convergence rate.

But the above algorithm only improves the pheromone update rules. The initial moment pheromone is not obvious. The ants will still fall into the "blind search". After introducing the potential force, the complexity of the obstacle situation will lead to the calculation of the direction of the situation is diverse, which led to increase the complexity of the algorithm. At the same time the algorithm may be affected by the worst path of the ants, into the local optimal. In order to solve these problems, this paper proposes an optimized hybrid ant colony algorithm (OHACA).

# 4. An optimized hybrid ant colony algorithm (OHACA)

## 4.1 Objective attraction function

In order to solve the problem of the "blind search" at the initial moment of the quasi-ant colony algorithm, this paper is based on the principle of gravity field gravity [16]. The introduction of the target attraction factor allows the ants to move towards the target in the initial moment. The concrete realization is as follows:

At the position $P$, the gravitational potential field is usually expressed as follows

$$U_{att}(P) = \frac{1}{2}\xi d^2(P,G) \tag{6}$$

Where $\zeta > 0$ is the gravitational potential ratio factor; $d(P,G)$ represents the distance between the current location of the robot and the target. The target attraction to the robot is the negative gradient of the gravitational field which is expressed as follows:

$$F_{att}(P) = -\nabla U_{att}(P) = \xi d(P,G) n_{PG} \tag{7}$$

Where $n_{PG}$ is the unit vector of the robot pointing to the target.

In the path search, the heuristic information which the ants use to find the next location consists of two parts. Part of the heuristic information is formed by the ants being gravitationally gravitational in the environment, which makes the ants tend to walk along the target. The part of the heuristic information is defined as follows:

$$\eta_{F_{att}} = \mathrm{a}^{F_{att}} \tag{8}$$

Where $a(0 < a < 1)$ is a constant. Obviously, under the heuristic information, the ants tend to choose the gravitational direction to travel to the next free area, which helps the robot to choose the path to the target direction.

The other part of the heuristic information is provided by the ant inherent heuristic factor, which is defined as follows

$$\eta_{\mathrm{ij}} = \frac{1}{d_{\mathrm{ij}}} \tag{9}$$

From formula (8) and (9), the heuristic information $\eta_{ij}$ of the whole algorithm is constructed as follows:

$$\eta_{ij} = \eta_{F_{att}} * \eta_d = \frac{a^{F_{att}}}{d_{\mathrm{ij}}} = \frac{\xi d(P,G) n_{PG}}{d_{ij}} \tag{10}$$

It can be seen from the formula (9) that the retrieval efficiency of the algorithm is relatively low because the heuristic information of the ant colony algorithm is not obvious. When the target attraction is introduced, the ants will move toward the target in the initial moment, which improves the search efficiency.

## 4.2 Improvement of pheromone $\tau_{ij}$ by wolves distribution rule

In the potential ant colony algorithm, the pheromone on the worst path can lead to the local optimum. In order to avoid the local optimization and improve the convergence rate, it is proposed to update the pheromone by referring to wolves distribution rules [17]. The study found that in order to survive and expand the number of populations, wolves will give the best food to the strong wolf, and abandon the weak wolf, in this way can they guarantee that the next strong wolf capture more prey. Thus, for each iteration, the pheromone on the local optimal path increases and decreases on the local worst path. Pheromone update rules are as follows:

$$\tau_{ij}(t+1)=(1-\rho)\tau_{ij}(t)+\sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t,t+1)+\Delta\tau_{ij}^{b}-\Delta\tau_{ij}^{w} \tag{11}$$

$$\Delta\tau_{ij}^{b}=\begin{cases} b\left(\dfrac{Q}{L_b}\right), & \text{the local best path from node i to} \\ 0, & \text{other} \end{cases} \tag{12}$$

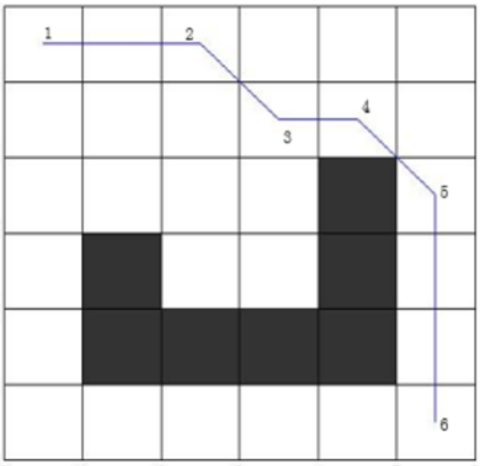
$$\Delta\tau_{ij}^{\mathrm{w}}=\begin{cases} w\left(\dfrac{Q}{L_w}\right), & \text{the local worst path from node i to j} \\ 0, & \text{other} \end{cases} \tag{13}$$

Where $L_b$ , $L_w$ are the length of the local optimal path and the worst path in this iteration respectively; $b$ , $w$ are the number of the local best path and the worst path. The final improved posterior transition probability $P_{ij}^{k}$ is expressed as follows:

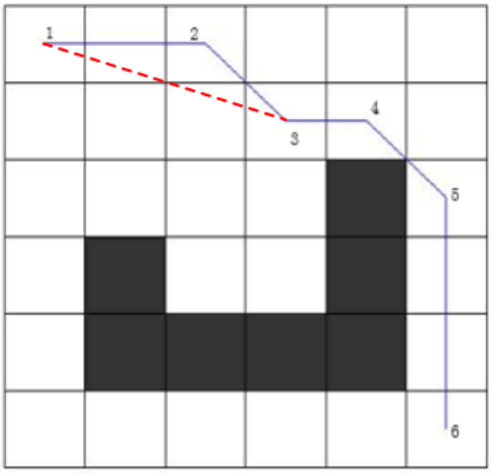
$$p_{ij}{}^{k}=\begin{cases} \dfrac{\left[(1-\rho)\tau_{ij}(t)+\sum\limits_{k=1}^{m}\Delta\tau_{ij}^{k}+\Delta\tau_{ij}^{b}-\Delta\tau_{ij}^{w}\right]^{\alpha}\left[\dfrac{a^{\xi d(P,G)n_{PG}}}{d_{ij}}\right]^{\beta}}{\sum\limits_{s\in allowed_k}\left[(1-\rho)\tau_{is}(t)+\sum\limits_{k=1}^{m}\Delta\tau_{is}^{k}+\Delta\tau_{is}^{b}-\Delta\tau_{is}^{w}\right]^{\alpha}\left[\dfrac{a^{\xi d(P,G)n_{PG}}}{d_{is}}\right]^{\beta}} & j\in allowed_k \\ 0 & other \end{cases} \tag{14}$$

## 4.3 Path optimization algorithm

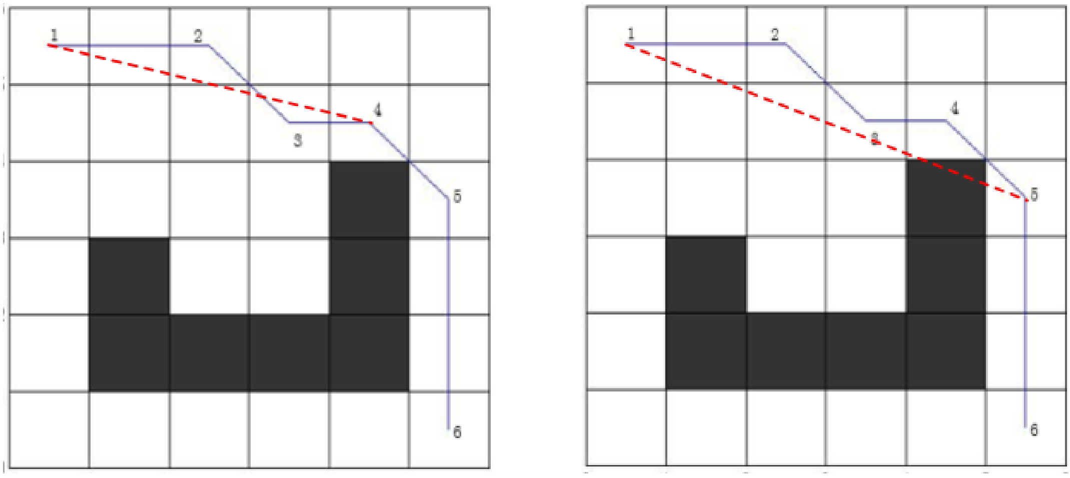
In the ant colony algorithm, the ants can only move in $Q(Q\in(0^{o},45^{o},...,360^{o}))$ eight directions, the limit of freedom makes the path longer, the inflection point increase, the smoothness [13] becomes smaller. But in practice, such a path is not necessarily suitable for robot execution and it is not optimal. Therefore, this paper proposes a new path optimization algorithm to overcome this shortcoming. Using the hybrid ant colony algorithm, the path generated on the raster map is shown in Fig(c).




(a)The original path




(b) The first post-processing path




. (c) The second post-processing path (d) The third post-processing path

Figure 2 Example of path optimization

Assuming that each grid edge is 1, the generated path vertex and inflection point are numbered as` $\{s_1, s_2, s_3, s_4, s_5, s_6\}$ , the path obtained by the ant colony algorithm is $Path_a = \{s_1, s_2, s_3, s_4, s_5, s_6\}$ and the path length is 8.828. And in fact, according to the shortest principle between the two points, the algorithm starts from the starting point, connects with the next node on the path and then performing the obstacle detection process, removing some unnecessary points until the least points of the collision with the obstacle are left getting path $Path_a = \{s_1, s_4, s_5, s_6\}$ as shown in Figure (c). The path length is 8.537, while the path having a smaller deflection angle, which is more suitable for robot to execute.

Specific steps are as follows:

Step 1: First, the first and third points in a path assigned to the $S$ and $N$ ;

Step 2: Determine whether the connection between $S$ and $N$ through the obstacles, if it is to go to Step 4, or go to Step 3;

Step 3: Assign the previous node which located at node $N$ to the $S$ node, then go to Step 2 to continue to judge;

Step 4: Assign the next node to the obstacle detection. To determine whether is the last point, if it is to go to Step 5, or go to Step 2;

Step 5: End the algorithm.

Pseudo-Code 1. Path Optimization Algorithm

```
Begin
Initialize
While(the algorithm termination condition is not satisfied）
{for( j = 0; j < m; j++ )    % m nodes
for( i = j; i < m; i++ )
   {To determine whether through obstacles
         if(the point is not connected)
                {   j = i - 1
        break
         }
   }
         end
end
```

}
return
end

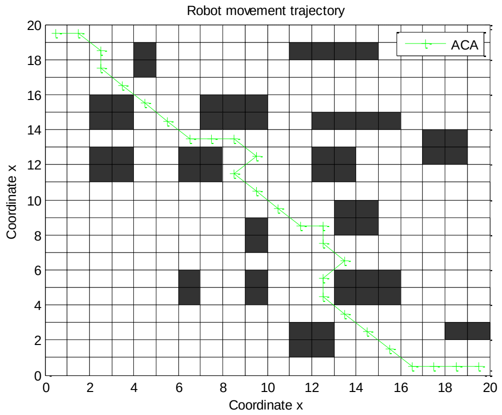
### 4.4 Algorithm Steps

After the brief description of the improved algorithm, The pseudo-code of the algorithm is as follows:
Pseudo-Code 2. An optimized hybrid ant colony algorithm

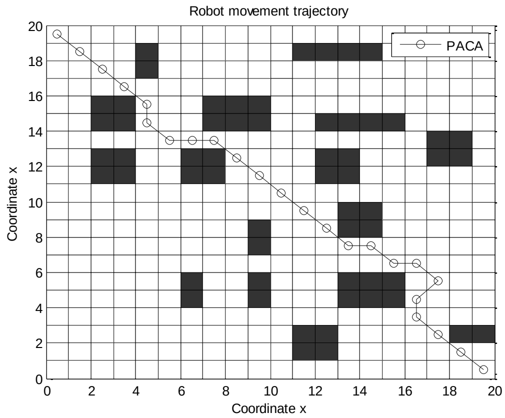
```
Begin
Initialize the parameters
While(Does not satisfy the algorithm termination condition)
 {for( i=0;i<m;i++)                % Place the ants on m grid maps
      for( j=0;j<n;j++)            % Circulate n ants
           {for( i=0;i<m-1;i++)
                Ants i choose the next city with probability p_ij^k
           end
     }
     Find the best result
           Give the best result to the ant i
      end
 {if(The best result is equal to the best results before n cycles)
      According to formula τ_ij = (1-ρ)τ_ij(t) + Σ_{k=1}^{m} Δτ_ij^k + Δτ_ij^b - Δτ_ij^w Update τ_ij
Go through the next cycle
   end
}
end
}
Output the shortest path
Perform route optimization
Output the optimal path
End
```

## 5. Experimental results and analysis

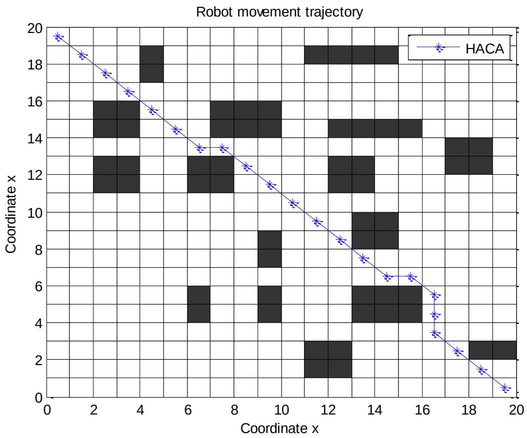
In order to verify the effectiveness of the improved algorithm, the 18 * 18 grid map and the 26 * 26 grid map are used to simulate the basic ant colony algorithm(ACA), the potential field ant colony algorithm(PACA) and the hybrid ant colony algorithm(HACA) in simple map and complex map. Experiment, and analyze their simulation results. Then, the hybrid ant colony algorithm(HACA) and the optimized hybrid ant colony algorithm(OHACA) are simulated and experimented respectively under the same grid map. Finally, the experimental results of the potential field ant colony algorithm and the optimized hybrid ant colony algorithm are further compared on the Pioneer3-DX robot. The parameter settings are: $\alpha=1$, $\beta=2$, $\rho=0.1$, $\zeta=1$, $Q=1$, $\delta=0.01$, $a=0.05$, $N=100$, $M=50$ .The simulation results are as follows:



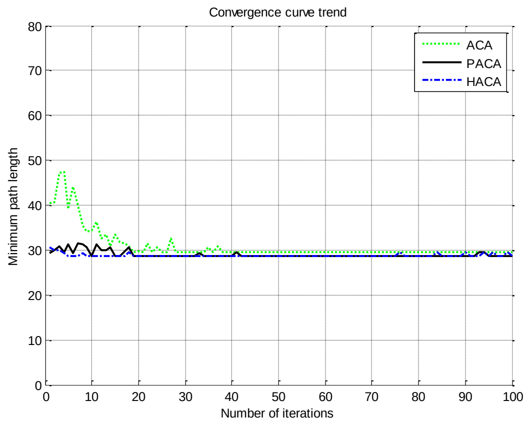

(a)




(b)



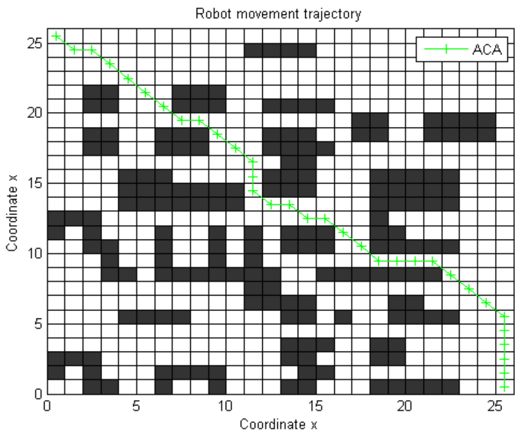

(c)



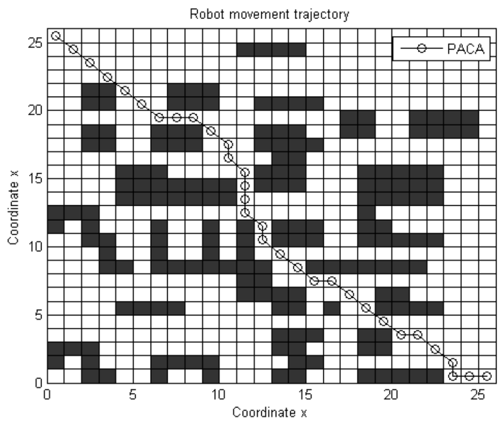

(d)

Figure 3 Motion trajectory and convergence curve in simple map

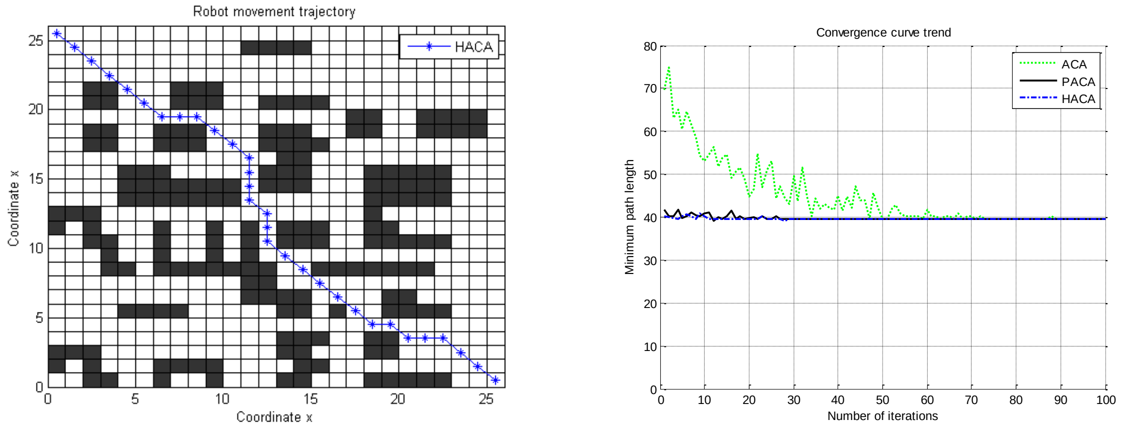
It can be seen from the simulation diagram above: Under the simple map, the number of convergence iterations of the traditional ant colony algorithm, the potential ant colony algorithm and the hybrid ant colony algorithm are 35 times, 16 times and 5 times respectively. The algorithm running time is 24.672s, 21.335s, 17.358s respectively. Path length is 30.654cm, 29.103cm, 28.567cm respectively. The hybrid ant colony algorithm has obvious improvement in convergence speed, search time and the path.




(a)




(b)




(c) (d)

Figure 4 Motion trajectories and convergent curves in complex maps

Under the complex map, the convergence iterations times of the three algorithms are 72 times, 28 times and 15 times respectively. Running time is 59.587s, 51.423s, 47.406s and the path length is 40.758cm, 39.244cm, 38.469cm respectively. It can be seen that the hybrid ant colony algorithm has great advantages in the number of iterations, running time and generating path within simple map environment or complex map environment.

In order to reflect the superiority of the hybrid ant colony algorithm more accurately, this paper conducts 30 experiments in the above simple and complex maps, and the results of the three kinds of path planning algorithms are shown in in Table 1 and Table 2.

Table 1 Experimental results in a simple map environment

| algorithm | Convergence iterations | Average planning time (s) | Path length (cm) | | | | Success rate(%) |
|---|---|---|---|---|---|---|---|
| | | | maximum | average | Minimal | variance | |
| ACA | 27 | 24.750 | 31.162 | 30.566 | 30.358 | 0.263 | 92 |
| PACA | 17 | 21.024 | 29.235 | 29.012 | 28.798 | 0.198 | 95 |
| HACA | 5 | 17.459 | 28.624 | 28.502 | 28.358 | 0.134 | 98 |

Table 2 Experimental results in a complex map environment

| algorithm | Convergence iterations | Average planning time (s) | Path length (cm) | | | | Success rate(%) |
|---|---|---|---|---|---|---|---|
| | | | maximum | average | Minimal | variance | |
| ACA | 64 | 58.750 | 41.041 | 40.604 | 40.455 | 0.326 | 89 |
| PACA | 27 | 51.024 | 39.455 | 39.102 | 38.870 | 0.214 | 93 |
| HACA | 15 | 45.459 | 38.584 | 38.437 | 38.284 | 0.150 | 96 |

Through the statistical data of Table 1 and Table 2, the number of algorithm iterations, the search time, the path length and the success rate are analyzed respectively. In the same map environment, it can be concluded that the average number of iterations of mixed ant colony algorithm is reduced by 75%, the average search time is shortened by 16%, the path length is reduced by 5.3%, and the success rate is increased by 7.8%. And the stability also increased by 54%. The effect of algorithm improvement is obvious.

After the shortest path is obtained by the hybrid ant colony algorithm, a path optimization algorithm is introduced to obtain an optimized hybrid ant colony algorithm. The optimized hybrid ant colony algorithm (OHACA) and hybrid ant colony algorithm are experimented in simple map and complex map respectively, and the simulation is as follows.

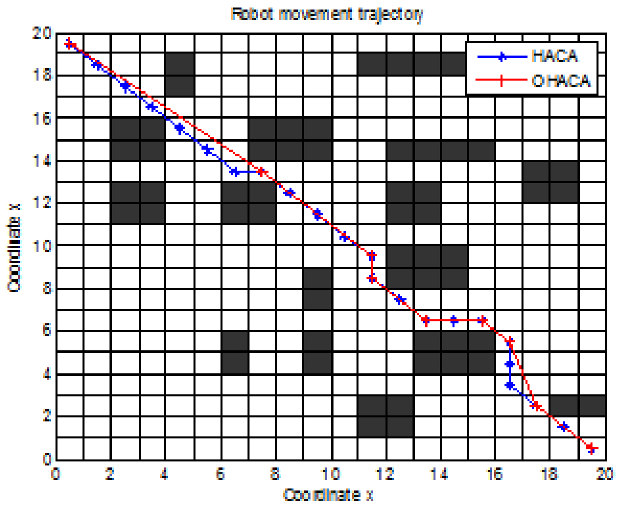



Figure 5 Comparison of motion trajectories in a simple environment

Table 3 Experimental results in a simple environment

| algorithm | Planning time (s) | Path length (cm) | The number of inflection points |
|---|---|---|---|
| HACA | 17.459 | 28.502 | 7 |
| OHACA | 17.563 | 26.657 | 4 |

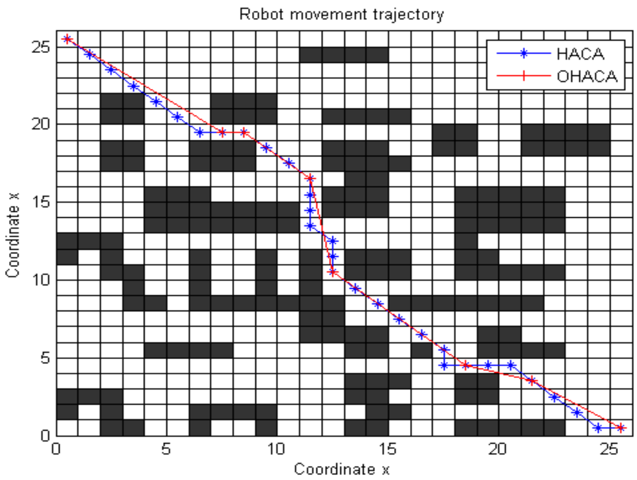



Figure 6 Comparison of motion trajectories in complex environments

Table 4 Experimental results in a complex environment

| algorithm | Planning time (s) | Path length (cm) | The number of inflection points |
|---|---|---|---|
| HACA | 46.859 | 38.454 | 15 |
| OHACA | 47.063 | 36.657 | 7 |

In the above experimental data, it can be concluded that the optimized hybrid ant colony algorithm (OHACA) path length is reduced by an average of 5% and the number of inflection points is reduced by 53%, which is more suitable for robot execution.

Finally, the potential ant colony algorithm and the optimized hybrid ant colony algorithm (OHACA) are verified respectively. The platform is a Pioneer3-DX robot with a URG-hokuyo laser sensor and a notebook with an Intel dual core, CPU 2.19 GHz, and a memory of 4GB. The Linux (Ubuntu14.04) operating system and the indigo version of the ROS (Robot Operating System) system are installed on the notebook. Use the mapping node in ROS to build the environment map, and the resolution of the map is set to 0.05m / pix. The experimental results are as follows:

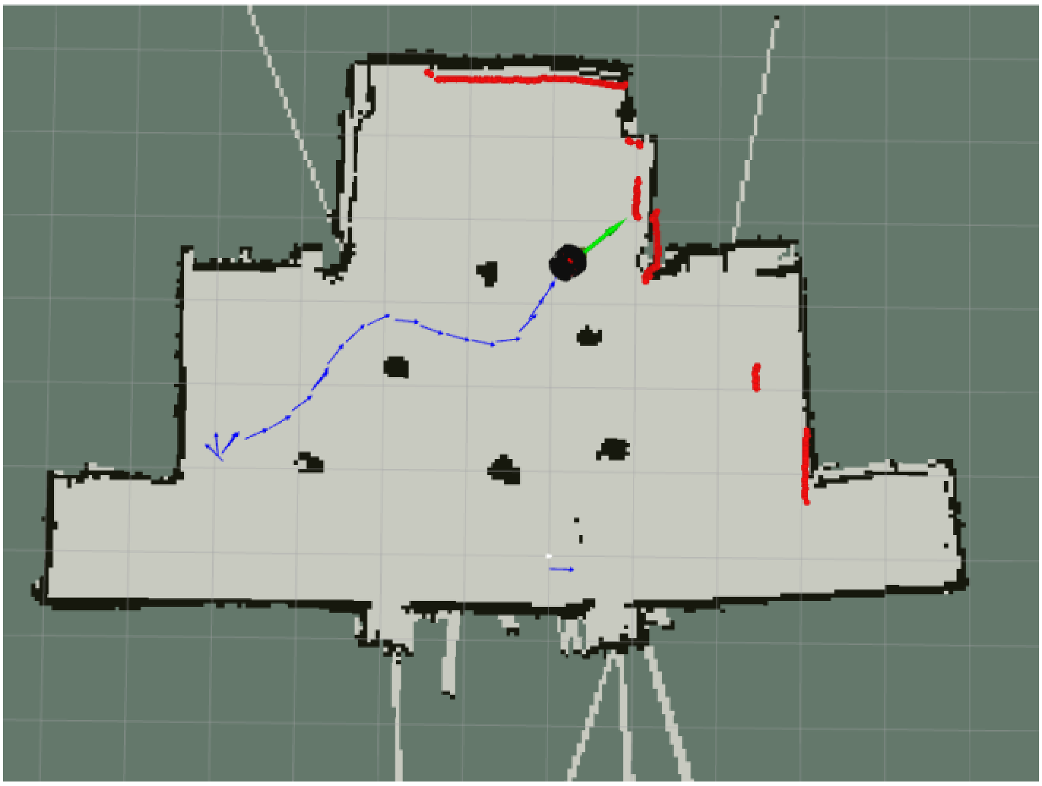


Figure7 Path planning results based on potential ant colony

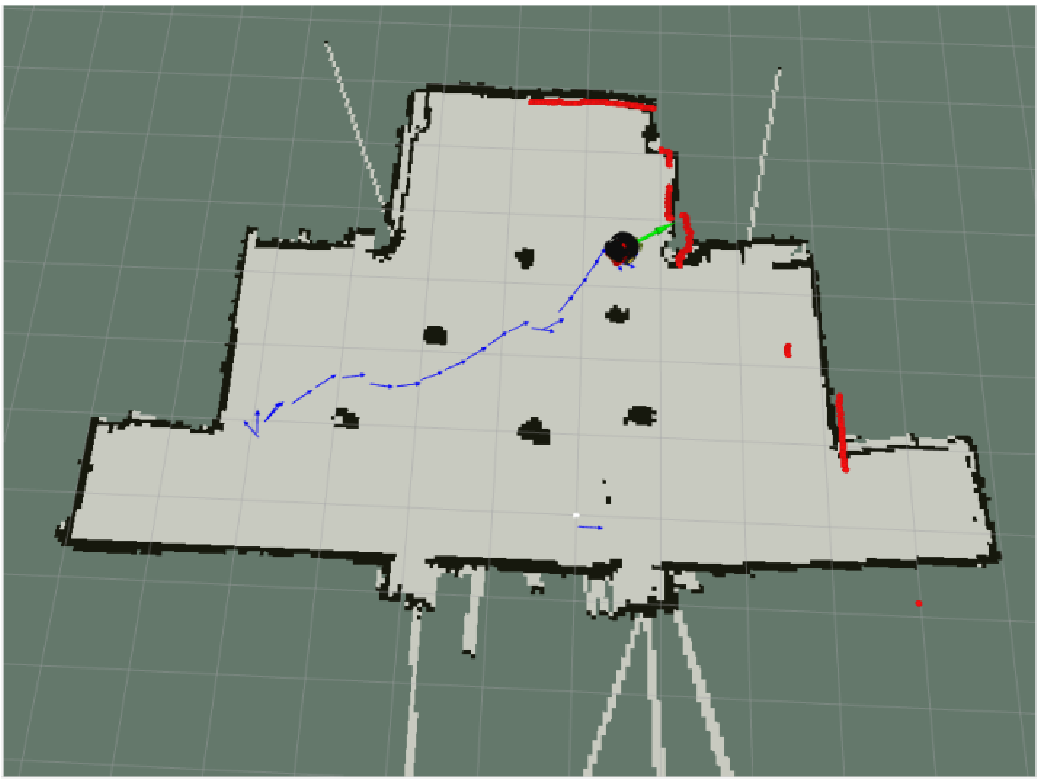


Figure8 Path planning results based on OHACA

In the figure, the dotted line is the movement path of the robot, and the black is the obstacle. It can be seen from experiments that the path length obtained by optimizing the hybrid ant colony algorithm (OHACA) is reduced by 5.6% compared with the potential ant colony and the path is smoother.

In order to verify the stability of the algorithm, 30 experiments were carried out under the same environment map. The results of the potential ant colony and the optimized hybrid ant colony algorithm are shown in Table 3

Table 5 Results of the statistics in the actual environment

| algorithm | Planning time (s) | Path length (cm) | Success rate(%) |
|---|---|---|---|
| PACA | 102 | 562 | 91 |
| OHACA | 86 | 534 | 97 |

The data in Table 3 show that the average time of optimization of the optimized hybrid ant colony algorithm is shortened by 15.7%, the path length is shortened by 6.1% and the success rate also increased by 6.6% than that of potential ant colony, which proves the superiority of algorithm proposed in this paper.

## 6. Conclusion

In this paper, an improved hybrid ant colony algorithm is proposed for global path planning of robots in known environments. The algorithm uses the target as a partial inspiration for the potential gravity of the robot. The heuristic information is effectively combined with the original ant colony heuristic information so that the robot can find the shortest path from the initial position to the target position in the initial direction. The wolves distribution rules are used to improve the pheromone update rules and avoid the local optimum. Finally we get a path with the shortest length and smoothness. Experiments show that this method improves search efficiency by 75% and improves stability by 54%, which is suitable for global path planning of robot in known environment.

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