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Path Planning of the Spherical Robot based on Improved Ant Colony Algorithm

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***Abstract* - With the development and progress of science and technology, the requirement of intelligent algorithm performance in the field of path planning is constantly improved. It is very important to improve the performance of intelligent algorithm and apply it in the field of path planning. In order to overcome the problem that ant colony algorithm tends to fall into local optimal in the early stage and converge slowly in the late stage. This paper proposed an ant colony algorithm based on adaptive pheromone updating strategy and enhanced negative feedback mechanism. The simulation results show that the improved ant colony algorithm is superior to the traditional ant colony algorithm and solves the problem of insufficient convergence in the early stage and low convergence in the late stage. Finally, the algorithm is tested by spherical robot. The experimental results show that the improved ant colony algorithm overcomes the shortcomings of traditional algorithms and verifies the effectiveness and convergence of the algorithm.**

Index Terms - Path planning. Negative feedback mechanism. Pheromone updating strategy. ANT colony Algorithm.

I. Introduction

At present, Amphibious robots has attracted more and more attention [1]. For example, pipeline inspection, resource development and other aspects [2-4]. The difficulty lies in how to find a safe path when the surrounding environment is complex and unknown. The development of path planning also provides a security guarantee for the robot to perform tasks in a practical, safer and more reliable way [5]. Global optimal path planning is an important problem in amphibious mobile robot navigation. There are many solutions to this problem. For example, artificial potential field method, fuzzy control and biological heuristic algorithm [6-10].

Generally speaking, path planning methods include the following two kinds: one is the optimal path planning algorithm composed of exhaustive method, mathematical planning method and dynamic path planning; the other is heuristic algorithm, including ant colony algorithm, genetic algorithm and simulated annealing algorithm [11-14]. Among them, the optimal path planning algorithm is particularly different, because the calculation time will increase sharply with the increase of system scale [15-17]. Up to now, many practical problems, such as travel agent problem, discrete optimization problem, optimal control problem, discrete optimization problem and so on, have been successfully solved by ant colony algorithm, Ant colony algorithm has been widely used in robotics [18-20].

It is easy to fall into the local optimal in the early stage and the convergence is insufficient in the late stage. To solve the above problems, an adaptive pheromone updating strategy and negative feedback mechanism are proposed in this paper. The feasibility is proved by simulation experiments, and the effectiveness of the algorithm is verified by spherical robot.

The rest of this article is organized as follows. In the next section, we will introduce the overall structure of the spherical robot. The third section introduces the method of improved ant colony algorithm, and the fourth section gives the simulation results of the improved algorithm. In the fifth section, the experiment verifies the feasibility of the algorithm. The sixth section gives the conclusion.

II. Structure of the Spherical Amphibious Robot

As shown in Figure 1, the upper half of the robot is made up of a hemispherical waterproof shell made of acrylic material. In order to increase the waterproof performance, the outer part is coated with waterproof glue, and a reasonable space is designed for the placement of sensors. Meanwhile, the structural design is improved to improve the crawling speed and stability of the robot on the land. In order to measure the state of the robot, we install a gyroscope in it, and at the same time. In order to increase the stability of its movement on land, two shaped supports are used to fix the four legs. In order to realize obstacle avoidance of the robot, ultrasonic ranging sensor is added in the robot.

By controlling the voltage, the speed of the water jet motor can be controlled to achieve the force and torque of the robot. By controlling the Angle of the servo motor, the robot can float up and down[21-23].

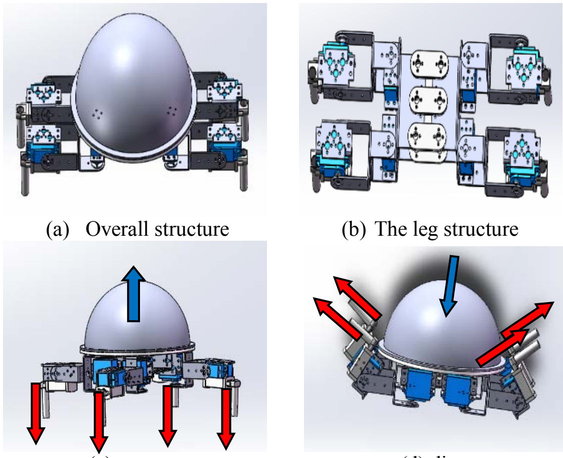


Fig. 1 Structure of the Spherical Amphibious Robot

III. Path Searching Method Based on ACO Algorithm

On the one hand, the height of the obstacle needs to be ignored. On the other hand, irregular obstacles need to be regularized. Figure 2 can be used as the amphibious robot's path planning environment. There are four irregular obstacles in it, and its size is 200*200 square centimeters. S and T represent the starting point and the end point respectively [24-25].

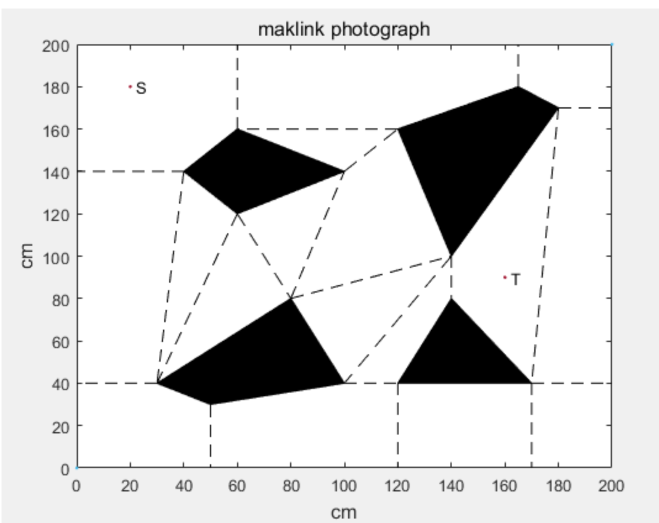


Fig. 2 An environment and its maklink graph.

The free space of amphibious robot in the environment refers to the space where the robot can move freely. Next, maklink line is established in the generated two-dimensional path planning space. V1 and V2 are used to represent the midpoints of free connection line maklink. In order to provide a feasible path for the movement of amphibious robot. The total number of these free connection lines is represented by I on the maklink graph. Taking Fig. 2 as an example, the maklink diagram formed is shown in Fig. 3.

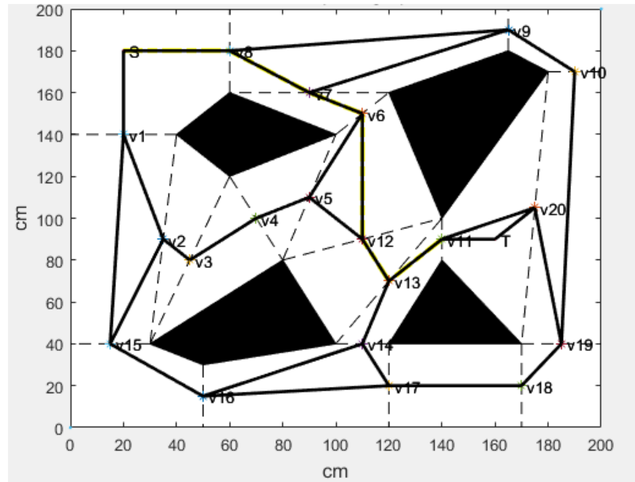


Fig. 3 Network graph for free motion of robot

In this part, the improved ant colony algorithm is used to find the sub-optimal. A key to using Dijkstra is to compute the cost function of the path. In general, the cost function can be represented by the sum of the weights of all the edges on the path, and each edge has a corresponding weight, whose weight is represented by the length of the edge. In order to compute the shortest path, the weight adjacency matrix of the grid graph is defined by Dijkstra algorithm .

$$\mathrm{ad}jlist[a][b] = \begin{cases} length(v_a, v_b), & \text{if edge}(\mathrm{v}_a,\mathrm{v}_b) \in \mathrm{E} \\ \infty, & \text{others} \end{cases} \quad (1)$$

For the example given in Fig. 6, using the Dijkstra algorithm the sub-optimal path is obtained as $S \rightarrow V_8 \rightarrow V_7 \rightarrow V_6 \rightarrow V_{12} \rightarrow V_{13} \rightarrow V_{11} \rightarrow T$ which is shown in Fig. 4.

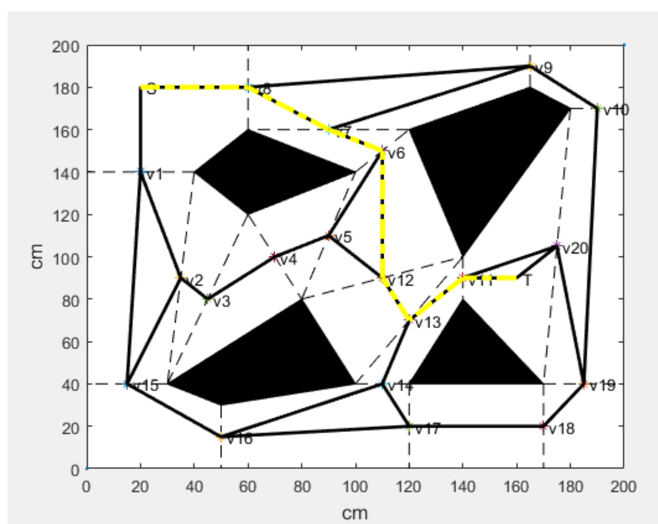


Fig.4 The sub-optimal path generated by Dijkstra algorithm

Firstly, the solution of the path generated by Dijkstra algorithm is saved in the space of sub-optimal solution.

In order to make the generated path shorter, ant colony algorithm is integrated on the basis of the original algorithm.

A. Linear Representation of Solution Space of Sub-optimal Path

The endpoint of the existing Li are $P_i^{(0)}$ and $P_i^{(1)}$.The other points on each maklink free link Li can be expressed as

$$P_i(\Gamma_i) = P_i^{(0)} + \Gamma_i(P_i^{(1)} - P_i^{(0)}),\ \Gamma_i \in [0,1],\ \text{i=1,2,...,d} \quad (2)$$

Γ_i is the parameter. the sequence number of the free connecting line in the solution space. Each parameter corresponds to a feasible node, $S, P_1(\Gamma_1), P_2(\Gamma_2), \ldots P_d(\Gamma_d), T$ forming understanding space E_1 . Since the optimization of the algorithm is based on the path length benchmark, it is also necessary to divide each maklink free connecting line by the fixed distance method. Set length is α ,So the partition number of each maklink free line is

$$\text{n} = \begin{cases} \text{int}(L_i/\alpha), & \text{int}(L_i/\alpha)\ \textit{is even} \\ \text{int}(L_i/\alpha)+1, & \text{int}(L_i/\alpha)\ \textit{is}\ \text{odd} \end{cases} \quad (3)$$

As a result, N + 1 nodes can be selected.

B. Node Selection

A sub-optimal path has been found above, on which the improved ant colony algorithm is used to find an optimal path(Γ_1, Γ_2, Γ_3,..., Γ_d,),Combined with the distance division of formula (3), it is equivalent to divide each parameter into N equal parts, such as formula (4). From formula (3), it is known that there are n + 1 feasible nodes on each free connecting line. The corresponding assumption is that the number of ants is m, the starting point is s, and the ending point is t. the optimization path of the basic ant colony algorithm can be expressed as

$$\Gamma_{ij} = \frac{j \bullet \Gamma_i}{n},\ j = 1, 2, \ldots, n \quad (4)$$

$$\text{S} \rightarrow P_{1j}(\Gamma_{1j}) \rightarrow P_{2j}(\Gamma_{2j}) \rightarrow \ldots P_{dj}(\Gamma_{dj}) \rightarrow T \quad (5)$$

The feasible nodes on each free connecting line are expressed as

$$P_{i,j}(\Gamma_{(i,j)}) = P_i^{(0)} + \Gamma_{(i,j)}(P_i^{(1)} - P_i^{(0)}), \Gamma_{(i,j)} \in [0,1]$$
$$i = 1,2,3,\ldots,d, \quad \text{j=0,1,2,...,n+1} \quad (6)$$

In the formula, $P_d(\Gamma_d)$ is the node corresponding to the parameters of the free connecting line in the suboptimal solution space E1.When each ant selects the node on the next MAKLINK free connection line, it transfers to the next node with probability (7) select the point that can make formula (7) reach the maximum. The probability state transfer formula of ants is:

$$P_{ij}^k = \begin{cases} \dfrac{[\tau_{i,j}(t)]^\alpha [\eta_{i,j}(t)]^\beta}{\sum[\tau_{i,u}(t)]^\alpha [\eta_{i,u}(t)]^\beta}, & \text{u} \in \text{allowed}_N \\ 0 & \text{,otherwise} \end{cases} \quad (7)$$

α, β represents the important process of pheromone and heuristic information respectively degree J is to select the next node according to roulette. $\tau_{ij}(t)$ represents the pheromone content at the node, $\eta_{ij}(t)$ stands for heuristic value. As an adjustable parameter:

$$\eta_{i,j}(t) = \frac{1}{length\{P_{i-1,j-1}(\Gamma_{i-1,j-1}), P_{i,j}(\Gamma_{i,j})\}} \quad (8)$$

The denominator in the formula represents the Euclidean distance between two nodes. The definition of Euclidean distance is given above.

C. Improved Adaptive Pheromone Update Rules

Node information update mainly refers to the real-time update of pheromone and the global update of path. Each ant must update the pheromone of current node before selecting the next node. The update formula is:

$$\tau_{i,j}(t) = (1-\rho)\tau_{i,j}(t) + \tau_0\rho \quad (9)$$

The volatilization coefficient ρ represents the volatilization degree of pheromone. τ_0 is the initial value of pheromone. After each iteration, when all ants traverse all feasible paths from s to t, the pheromones of all points on the path need to be updated globally. The updating formula is:

$$\tau_{i,j}(t+1) = (1-\rho)\tau_{i,j}(t) + \rho\Delta\tau_{i,j} \quad (10)$$

$$\Delta\tau_{i,j} = \begin{cases} \dfrac{Q}{L_k}, & \text{Path in ant K iteration cycle} \\ 0, & \text{others} \end{cases} \quad (11)$$

L_k is the path length. the value of ρ directly affects the efficiency of the algorithm, and the enhanced positive feedback makes the algorithm converge quickly. so it is very important for the algorithm to adopt the adaptive dynamic adjustment rule of pheromone volatility coefficient in the process from the beginning to the output of the optimal solution. In this paper, the information volatilization coefficient increases with the number of iterations:

$$\bar{\rho} = (1-\rho_0) \times (\frac{N_C}{N_{C\max}}) \quad (12)$$

ρ_0 is the initial definition of pheromone volatilization Coefficient, N_c represents the current number of iterations of statistical algorithm. $N_{c\max}$ represents the maximum number of iterations of the algorithm. Therefore, the improved global update rule of path pheromone is:

$$\tau_{ij}(t+1) = (1-\bar{\rho})\tau_{ij}(t) + \bar{\rho}\Delta\tau_{i,j} \quad (13)$$

D. Increase the Negative Feedback Mechanism

The positive feedback mechanism is a unique feature of ant colony algorithm. On the one hand, the positive feedback mechanism accelerates the convergence speed of ant colony algorithm, and on the other hand, it also leads to the local optimum. Therefore, it is particularly important to balance the positive feedback mechanism. When constructing paths, pheromones are stored in the optimal path as well as the worst path. In order to better balance the problems, in the ant colony algorithm, each ant uses the following formula (14) to select the probability of the next city, and combines with the adaptive pheromone updating rules to update the pheromone. So that the positive feedback pheromones cannot be too much concentrated on one path：

$$P_{ij}^{k}=\begin{cases}\dfrac{[\tau_{i,j}(t)]^{\alpha}[\eta_{i,j}(t)]^{\beta}[\delta-\varphi_{\mathrm{ij}}(t)]^{\gamma}}{\Sigma[\tau_{i,\mathrm{u}}(t)]^{\alpha}[\eta_{i,u}(t)]^{\beta}[\delta-\varphi_{\mathrm{ij}}(t)]^{\gamma}}, & \mathrm{u}\in \mathrm{allowed}_{N}\\ 0 & ,\mathrm{otherwise}\end{cases} \tag{14}$$

δ represent the upper limit of the negative feedback mechanism pheromone for the worst path, γ is the heuristic information factor of the negative feedback mechanism, the formula for $\varphi_{\mathrm{i,j}}(t+1)$ is as follows:

$$\varphi_{i,j}(t+1)=(1-\overline{\rho})\varphi_{i,j}(t)+\overline{\rho}\Delta\varphi_{i,j} \tag{15}$$

$$\Delta\varphi_{i,j}=\begin{cases}\dfrac{Q}{L_{worse}}, & \text{Path in ant K iteration cycle}\\ 0, & \text{others}\end{cases} \tag{16}$$

According to the previous section on the specific improvement of the basic ant colony algorithm in this section, the path for the implementation of the specific steps. The specific steps are as follows:

Step 1. By using Dijkstra, you first find a sub-optimal path(S → P1→ P2→. . . → Pd→ T) without collisions.

Step 2. m is the number of ants; specify the values of parameters and. Defines a one-dimensional array to hold information in each path node.

Step 3. Initially, the ant needs to be placed at the starting point, where the number of iterations starts at 1 and the maximum number of iterations is set to NC.

Step 4. Set i = 1.

Step 5. Set k = 1.

Step 6. ANT k Selects a node on line L_{i} by using (14), First, ant K is moved to this node, then the node is saved in the path, and finally the pheromone concentration of this node is updated by the local pheromone update rule.

Step 7. Set k=k+1. If k is less than or equal to m, you need to return to the previous step. Otherwise, proceed to the next step.

Step 8. Next, set I = I +1. If I is less than or equal to d, return to the previous step. Otherwise, proceed to the next step.

Step 9. Move the ant from its current position to the goal T.

Step10. Calculate the moving path of each ant, The parameter value of each line is deduced to determine the position of the node on the free connection line. The two connections of the nodes are the moving path of ants, and the European distance accumulation between the two points is the path length.

Step11. Compare the current generated path, find the shortest path, compare the shortest path with the previous shortest path to get the latest shortest path and save $\{\Gamma_1^*,\Gamma_2^*,\Gamma_3^*,\ldots,\Gamma_{\mathrm{d}}^*\}$.

Step12. Global update rules update pheromone content of each node after each iteration.

Step13. If t=t+1, if t<NC and the fitness of each generation is still very active, then step 6 is returned. If t>NC or the fitness of each generation converges to stable, the output shortest path and its corresponding parameters $\{\Gamma_1^*,\Gamma_2^*,\Gamma_3^*,\ldots,\Gamma_{\mathrm{d}}^*\}$.

Ⅳ. SIMULATION ANALYSIS

The simulation Experiment is based on maklink visual graph method to establish two-dimensional path planning space, As shown in Figure 5, it is a traditional ant colony algorithm. It can be seen from the figure that this algorithm has insufficient convergence in the later stage. The parameters were set as β = 2, ρ = 0.1, τ_0 = 0.0005, m = 10, δ =10, γ =2.

Fig. 6 shows the simulation results. Obviously, the improved algorithm, which is also the key to overcome the local optimal problem. Because of the improved ant colony algorithm in this paper the pheromone update rule, using adaptive pheromone update strategy as well as the negative feedback mechanism, makes the pheromone attenuation coefficient with the algorithm gradually increased with the increment of the number of iterations, which makes the iterative initial pheromone legacy path node degree is higher, weakened the ant colony algorithm for the positive feedback effect premature convergence to local optimal path, increase the randomness of the algorithm.

The low degree of pheromone residue in the late iteration makes the algorithm quickly move to the optimal path and improves the convergence rate of the algorithm.

Therefore, from the local perspective of path planning, increases the randomness of the algorithm in the early stage and improves the stability of the convergence in the later stage.

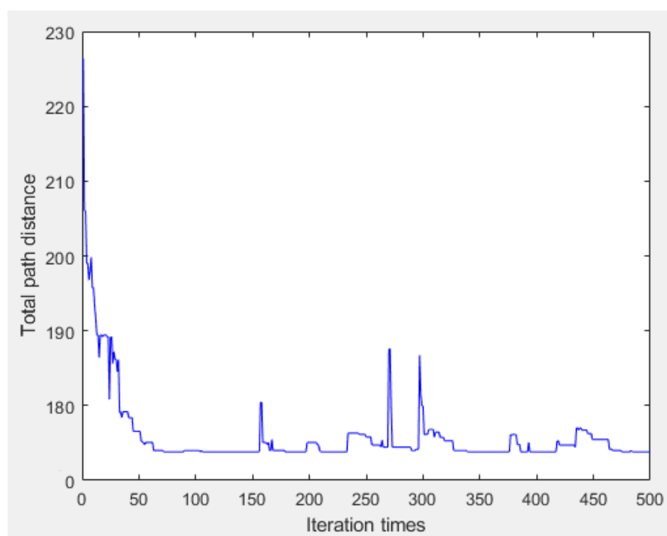


Fig. 5 Convergence results before improvement

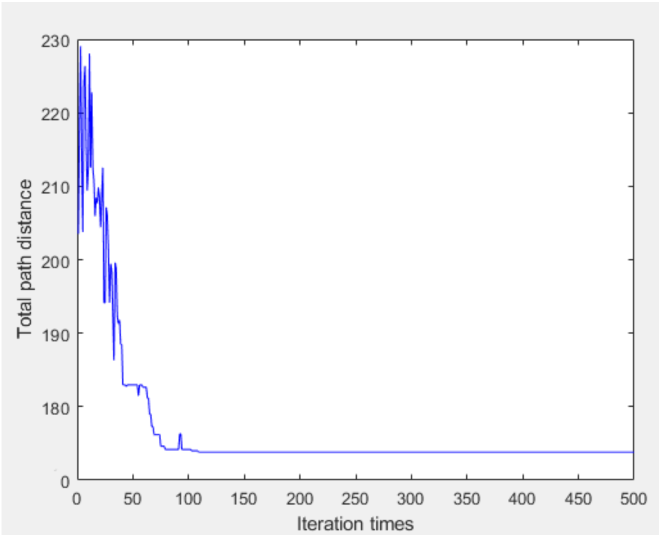


Fig. 6 Convergence results after improvement

V. Experimental Test and Result Analysis

As shown in FIG. 7, obstacles are set up in the experimental site. The environment consists of four obstacles, marked as obstacles 1, 2, 3, and 4. The vertices of each obstacle are denoted by A, B, C, and D. This experiment verifies the proposed path planning algorithm so that the robot can successfully avoid obstacles from the starting point and reach the end point.

A. Data Processing Method for NDI System

In order to accurately describe the spherical underwater robot path, we need the robot's location information collection and feedback, so this article adopted (NDI) optical positioning system to position the spherical robot, NDI is based on the binocular stereo vision tracking and positioning of optical navigation equipment, and recovering the object on the basis of the principle of parallax three-dimensional geometry information, reconstruction of 3d object outline and position. It has USB data communication, wireless Wi-Fi transmission, high-speed Ethernet transmission and other data transmission modes.

NDI dynamically determines the position of any tool in a specific THREE-DIMENSIONAL space by following the passive markers on the passive rigid body, and tracks one or more wireless tools in real time, with a tracking accuracy of 0.15mm. aim-position optical positioning system was used to obtain the position of the spherical under water robot and to feed back the position information to the robot.

The spherical underwater robot is mounted with a passive rigid body fitted with an optical positioning system. The cross center of the passive rigid body is a passive marker, and NDI tracks the position of the passive marker by collecting the location of the passive marker in real time.

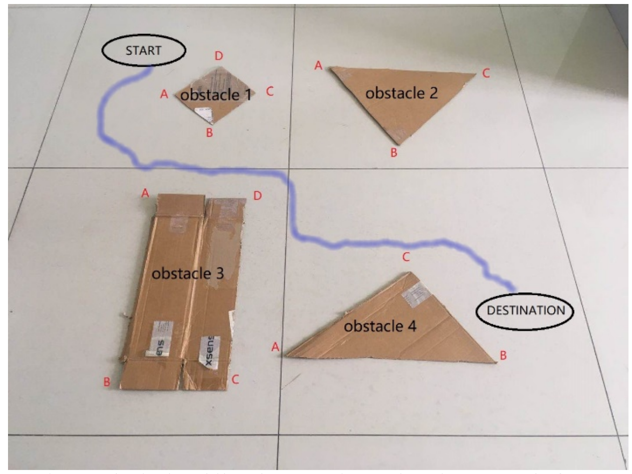


Fig. 7 Spherical mobile robot experimental environment platform.

B. The Experiments of Motion

First, model the environment. The experimental environment was conducted in a flat area of 200*200cm, and the vertex coordinates of the obstacles were recorded, as shown in table 1. Then input the coordinates of the obstacles into the upper computer, and plan the path in the upper computer. The controller is responsible for encapsulating the calculated data into specific information, such as steering speed, linear speed, and so on, and publishing it to the hardware platform. Control the robot to complete navigation tasks. the collected data to obtain the robot's crawling trajectory, as shown in figure 8. As shown in figure 9, verifying the effectiveness of the improving algorithm.

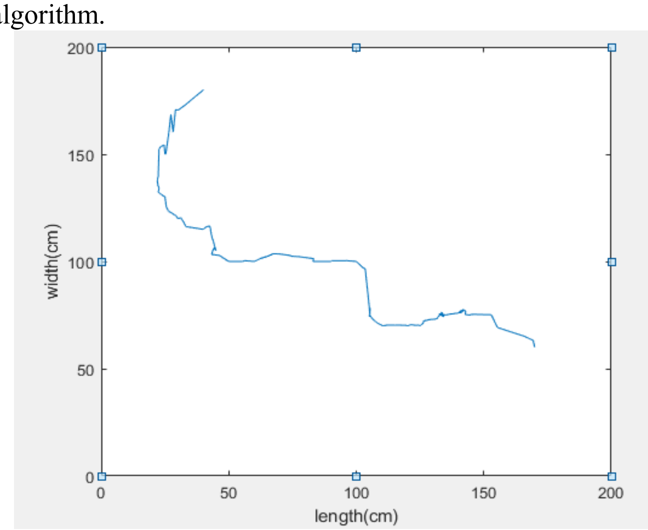
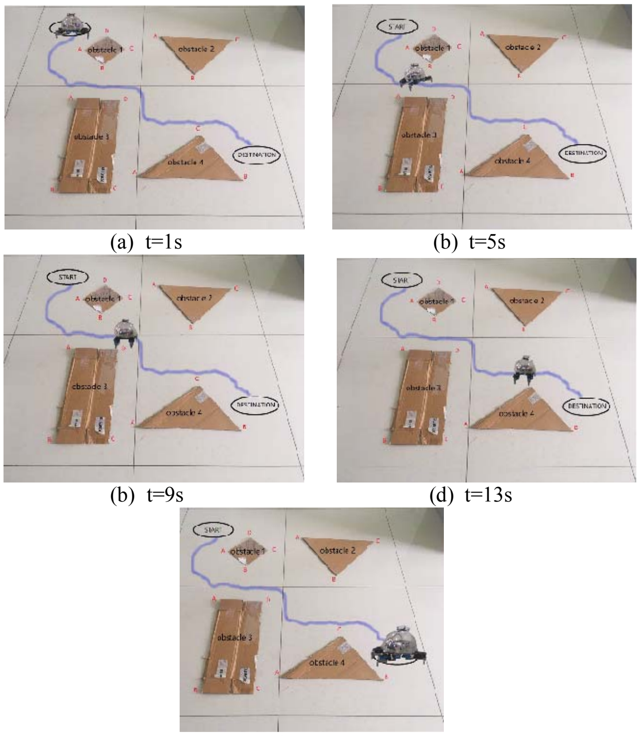


Fig. 8 Experimental trajectory of spherical mobile robot

TABLE I
VERTEX COORDINATES OF OBSTACLES

	A	B	C	D
Obstacle 1	50,160	40,140	60,120	80,140
Obstacle 2	100,160	180,160	140,100	
Obstacle 3	50,80	50,40	80,30	80,80
Obstacle 4	140,60	120,40	170,40	



(a) t=1s (b) t=5s

(b) t=9s (d) t=13s

(e) t=17s

Fig. 9 Spherical robot path planning experimental.

VI. Conclusions and Future Work

In this paper, an improved ant colony algorithm is proposed to solve the problems of Dijkstra and ant colony algorithm in path planning. The adaptive pheromone updating strategy and negative feedback mechanism are added to the traditional ant colony algorithm. The deficiency of ant colony algorithm is solvedSimulation results show that the algorithm is efficient and convergent. Finally, the improved algorithm is applied to the actual environment to make the robot walk safely. In the future, we will study path planning for multiple target points.

Acknowledgments

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