AGV path planning combining A* and ant colony algorithm

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Abstract. Aiming at the problems of lack of pheromone, slow convergence, and falling into local optimum when the ant colony algorithm is applied to the AGV path planning of Xinjiang cotton factory, a fusion A* ant colony algorithm path planning is proposed. The algorithm first initializes the ant colony pheromone with the two-way search A* heuristic function to solve the problem of low ant colony efficiency in the early stage. Secondly, according to the different times of selection of different paths, different pheromone weights are set, and the pheromone reaches a certain level. The optimal solution converges. The experimental results show that the improved algorithm effectively solves the problems of slow convergence, long search paths and falling into local optima.

1. Introduction

Path planning is one of the important key technologies for mobile robots to realize positioning and navigation. Path planning is mainly to allow the target object to find a collision-free safe path from the start point to the end point in a specified area [1]. At present, there are many researches on global path planning under the condition of fully known environmental information, such as A* algorithm, genetic algorithm, neural network. The A* algorithm gradually determines the next path grid by comparing the heuristic function values of the neighbors of the current path grid. When there are multiple minimum values, the searched path cannot be guaranteed to be optimal [2]. Although genetic algorithm has strong global search ability, it has a large amount of calculation and slow convergence speed [3]. The neural network has strong learning ability, but when the map changes, the network structure is complex and the threshold value needs to be constantly changed [4].

The ant colony algorithm is an intelligent algorithm that uses a positive feedback mechanism to make the search process converge continuously and each individual can change the surrounding environment by releasing pheromone, and each individual can perceive the real-time changes in the surrounding environment to communicate. This kind of probabilistic search based on heuristics can make the search not easy to fall into the local optimal, and it is easy to find the global optimal solution [5]. It has applications in path planning, vehicle scheduling problems, integrated circuit design, communication networks, etc. However, the ant colony algorithm also has some shortcomings, such as slow convergence, lack of initial pheromone, and limited to local optima.

In order to solve the problem of lack of initial pheromone, slow convergence speed and slow path search speed in traditional ant colony algorithm in path planning, the ant colony algorithm is improved. First, use the improved A* algorithm evaluation function value to construct the heuristic function of the ant colony algorithm. Secondly, improve the pheromone update method of the ant colony algorithm to improve the accuracy of the algorithm. The improved ant colony algorithm can plan the optimal path with fewer iterations, which greatly improves the efficiency and accuracy of path planning.
2. Improved A* ant colony algorithm

2.1. Algorithm principle
The improved ant colony algorithm includes two stages, the combination of the A* algorithm and the ant colony algorithm, and the characteristics and advantages of the two algorithms are used to solve the AGV’s optimal motion path. The ant colony algorithm simulates the behavioral characteristics of ants “exploration”, that is, the ants will use the pheromone left by the former ant during the foraging process. A single ant cannot show information feedback, and it needs to be combined with multiple ants to continuously communicate and communicate. To judge and perceive the concentration of pheromone, and then find the optimal path by judging the concentration of information during the foraging period of ants. Probability of ant algorithm state transition:

\[
P_{ij}^{(t)}(t) = \begin{cases} 
\frac{(\tau_{ij}(t))^\alpha \cdot (\eta_{ij}(t))^\beta}{\sum_{k \in K} (\tau_{ik}(t))^\alpha \cdot (\eta_{ik}(t))^\beta}, & S = K \\
0, & S \notin K 
\end{cases}
\]

K is the set of nodes that the ant is allowed to select in the next step; \(\tau_{ij}\) is the pheromone value of the path \((i, j)\); \(\alpha\) is the pheromone importance factor, which reflects the importance of the pheromone concentration to path selection; \(\beta\) is the expected inspiration Factor, which reflects the importance of heuristic information on the path. \(\eta_{ij}(t)\) is the heuristic function at time \(t\), which represents the degree of expectation that the ant transfers from node \(j\) to the target node \(g\) [7]. Its mathematical expression

\[
\eta_{ij}(t) = \frac{1}{d_{ij}}
\]

2.1.1. Pheromone Update
After all the ants have completed a path search, the pheromone quantity of a single ant's path is updated next. The pheromone volatilization process is set as the value change of the volatilization coefficient \(\rho\) (0<\(\rho<1\)). The pheromone update equation is as follows

\[
\tau_{ij}(t + 1) = (1 - \rho)\tau_{ij}(t) + \Delta\tau_{ij}(t)
\]

\[
\Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau_{ij}^k(t)
\]

\[
\Delta\tau_{ij}^k(t) = \begin{cases} 
\frac{Q}{L^k} & \text{if } k \text{ select } i \text{ to } j \\
0 & \text{else}
\end{cases}
\]

\(\Delta\tau_{ij}(t)\) is the pheromone increment of the distance from node \(i\) to node \(j\); \(\Delta\tau_{ij}^k(t)\) represents the pheromone left by the kth ant on the distance from node \(i\) to node \(j\). Q is the constant refers to the total amount of pheromone left by the ants after the entire path search; it represents the path length of the kth ant in this loop search [8].

2.2. Algorithm improvement
In the first few searches of the ant colony, especially the first search, the pheromone on the path is evenly distributed, so the ant colony can only search blindly, which is extremely inefficient. Therefore, on the basis of the ant colony algorithm, this paper integrates the A* algorithm to initialize the pheromone, improves the heuristic function and the pheromone update formula of the ant colony algorithm, and executes the bidirectional search and planning of the optimal path from the starting point and the target point at the same time, Thereby improving the search efficiency and speed of the algorithm.

2.2.1. Improvement of heuristic function
The state transition probability function of the classic ant colony algorithm mainly considers the pheromone distribution and the distance between the current point and the adjacent feasible grid point. The heuristic function in the classic ant colony algorithm is constructed by the distance of adjacent grids,
and the obtained numerical difference is very small, and the directionality from the starting point to the
target point is not considered, which leads to the low search efficiency of the algorithm and find The path length increases. In response to this problem, this paper proposes an improvement strategy for the
heuristic function of the ant colony algorithm based on the A* algorithm based on the head-to-tail
bidirectional search. The A* algorithm based on two-way search is an improved method based on the
traditional A* algorithm. The formula of \( h^*(n) \) in the improved A* algorithm is expressed as follows
\[
h^*(n) = \left| x_{sn} - x_{dn} \right| + \left| y_{sn} - y_{dn} \right|
\]
(6)

Among them, represents the coordinates of the node position when walking from the initial position
direction, and represents the node coordinates of the current position searched from the direction of the
end point. The improved A* algorithm is also a two-way ordered heuristic search algorithm, and the
value formula of the evaluation function is as follows
\[
f(n) = g(n) + h^*(n)
\]
(7)

In this formula: \( g(n) \) represents the cost from the initial node \( s \) to the optional node \( n \); \( h^*(n) \) represents
the Manhattan distance between the current optional node \( n \) and the current node \( d \) in another search
direction. Use the improved A* algorithm evaluation function value to construct the heuristic function
of the ant colony algorithm
\[
\eta_q(t) = \frac{1}{D_q + D_{sd}} = \frac{1}{g(n) + h^*(n)}
\]
(8)

Where represents the distance from node \( j \) to target point \( d \). After adding the heuristic function of
bidirectional search, such a new heuristic function Not only the directionality of the source node and the
target node is considered, but also because the search is carried out in parallel from the head to the tail,
it is easier to find the optimal solution than the one-way search. The performance of its running speed
and expanded node size has also been significantly improved, thereby effectively increasing the search
rate.

2.2.2. Elite ant pheromone update and improvement
Pheromone update is mainly used to simulate the accumulation and natural volatilization of natural ant
pheromone over time. After all ants have completed a path search, sort them according to the length of
each ant's walking path, and update the pheromone content left on the path that all ants will walk after
the iteration is completed. The optimal path is selected according to the different weights of pheromone
left by each section of the ant on the walking path. The contribution of each ant to the pheromone update
is weighted according to the order of the ant, and then the importance of the node \( i \) and the node \( j \) on the
path \( k \) is determined. Introduce the path weight \( \varphi \) factor to update the equation.
\[
\Delta r_{ij}^k(t) = \begin{cases} \varphi^*(Q/L^k) & \text{if } k \text{ select } i \text{ to } j \\ 0 & \text{else} \end{cases}
\]
(9)

\[
\varphi = \frac{\bar{L} - L_{p}}{\bar{L} - L^k}
\]
(10)

\( \bar{L} \) is the average length of this cycle, \( L_{p} \) is the path length of the elite ants, and \( L^k \) is the path length
of the Kth ant in this cycle.

3. Simulation experiment and result analysis
In order to verify the effectiveness and versatility of the improved algorithm, a comparative experiment
was carried out with the traditional ant colony algorithm. Use MATLAB software for simulation. The
simulation experiment is carried out under the simulation environment MATLAB2018b. Set the initial
parameters of the algorithm \( m=50, =1, N=100, =7, =0.3, Q=5. \) The environment map is simulated 100
times. The simulation experiment is carried out in a grid map of environment 1 of 20×20. The optimal
path of the algorithm in this paper is shown in Figure 1; the optimal path of the traditional ant colony
algorithm is shown in Figure 2; the minimum path length convergence curve of the traditional algorithm and the improved algorithm is shown in Figure 3. The algorithm lacks the path planning of the target point in the early stage, and is blind, which leads to excessive accumulation of path pheromone in the later stage, and unnecessary inflection points; however, the algorithm in this paper effectively avoids the emergence of the right-angle inflection point of the path and reduces the energy consumption of the AGV. There are no extra tortuous inflection points and it is smoother, and the convergence speed is faster.

![Figure 1 Optimal path of traditional algorithm](image1)

![Figure 2 Improved algorithm optimal path](image2)

![Figure 3 Convergence curve comparison](image3)

| Performance index       | Traditional ant colony algorithm | Improved ant colony algorithm |
|-------------------------|----------------------------------|-------------------------------|
| Minimum path length     | 33.60                            | 29.45                         |
| Number of iterations    | 26                               | 18                            |
| Average time            | 15.56                            | 12.34                         |
| Number of inflection points | 13                          | 8                             |
It can be seen from Table 1 that in a 20×20 grid map environment, using the same number of ant populations and iteration times, the improved algorithm can obtain shorter paths, better convergence speed, fewer inflection points, and paths. Smoother. The improved ant colony algorithm reduces the search time by 20% compared with the traditional ant colony algorithm, and shortens the minimum path length by 4 to 5 meters. For the actual AGV, it effectively reduces the energy and time consumption.

4. Conclusion

Aiming at the slow convergence of the existing ant colony algorithm, which cannot meet the optimal path planning problem of AGV, this paper integrates the A* algorithm into the traditional ant colony algorithm, which greatly reduces the number of points to be extended, and reduces the blindness and calculation of the search cost. On this basis, two groups of ant colonies are set up to perform two-way search from the starting point and target point respectively, and the pheromone method is updated, which greatly improves the global search ability of the ant colony. The convergence speed of the previous algorithm can be improved to avoid the situation that the path is directly output from being trapped in a "concave" obstacle, leading to a local optimal solution. While finding the optimal path, the algorithm in this paper takes less time to calculate the path than traditional algorithms, has faster convergence speed, fewer inflection points, and better path optimization capabilities. The experiment proves the advantages and feasibility of this algorithm in the complex environment of the AGV path planning algorithm.

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