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A COLLISION AVOIDANCE PATH PLANNING METHOD OF AGV BASED ON IMPROVED ANT COLONY ALGORITHM

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Abstract. *A collision avoidance path planning method of AGV based on improved ant colony algorithm is proposed. First the two-dimensional warehouse environment is modeled using grid method. Then according to the actual operation of AGV in storage environment and the actual map environment information, ant colony algorithm is improved in three aspects to overcome its shortcomings: the selection range of the next grid is limited to four directions, which can reduce search time and improve efficiency; in order to keep ant colony algorithm from falling into local optimal solution, "roulette" combining the state transition probability is used when selecting the next grid; the path cost function is improved, using the shortest time rule instead of the shortest path rule to reduce the turning times of AGVs. Finally, simulation modeling of the methods based on the basic and improved ant colony algorithm is carried out respectively. Results show that the method based on improved ant colony algorithm has better performance and can reduce the turning times of AGVs.*
Keywords: Improved ant colony algorithm, Grid method, Collision avoidance, Path planning

1. **Introduction.** Using automated guided vehicle (AGV) systems in automated warehouse can improve the picking efficiency and reduce errors, so as to achieve the automation of "goods to people". What is more, as a goods transport system, AGV system can meet the requirements of flexible manufacturing and three-dimensional warehouse, so it becomes one of the most important parts of logistics automation.

In AGV systems, the most important problem is how to plan an optimal path for each AGV, meanwhile to avoid collisions between AGVs and other obstacles [1]. Path planning is always a hot and difficult problem in AGV research field. In the paper, we study the collision avoidance path planning in a static environment, which means the location of the obstacles has been known. It is a global path planning problem and many algorithms have been put forward, including traditional algorithms like graph algorithm [2], Dijkstra algorithm [3] and A* algorithm [4], as well as intelligent algorithms, such as genetic algorithm [5], particle swarm algorithm [6], and ant colony algorithm [7-9].

Ant colony algorithm is proposed as a kind of meta heuristic algorithm to solve combinatorial optimization problems. It uses distributed parallel computer system and is easy to combine with other methods. However, when used in AGV path planning in two-dimensional static environment, the basic ant colony algorithm has disadvantages of long search time, low efficiency, and is easy to fall into the local optimum [7]. So the main problem of this method is how to improve its global search ability and convergence speed. To find the global optimal path quickly, the ant colony algorithm must make the search space as large as possible and take advantage of prior knowledge. The essence is to solve contradictions between the algorithm's randomness and the pheromone update intensity. This problem causes many researchers to perform in-depth research on this topic from two directions: search strategy and pheromone update strategy. Wan et al. [7] updated the pheromone by taking evaporation coefficient adaptive approach and joined the inflection point parameter as one evaluation criterion of the path. Pei and Chen [8] proposed an update rule of the generalized pheromone in order to prevent the ant colony algorithm from falling into deadlock when facing concave obstacles. Guo and Li [9] used ant fall back strategy and penalty function to make the ants jump out of the trap and do not choose this path anymore, so as to avoid path deadlock.

In the paper, ant colony algorithm is improved in three aspects to overcome its shortcomings when used in collision avoidance path planning of AGV. Firstly, according to the actual movement direction of AGV, the selection range of next grid is limited. It can reduce search space and improve efficiency. Secondly, in order to keep ant colony algorithm from falling into local optimal solution, "roulette" combining the state transition probability is used when selecting the next grid. Thirdly, the path cost function of each ant from the starting point to the target point is improved, using the shortest time rule instead of the shortest path rule to reduce turning times of AGV.

The rest of the paper is organized as follows. Firstly, warehouse environment is modeled using grid method. Then according to the actual operation of AGV in storage environment and the actual map environment information, ant colony algorithm is improved in three aspects in order to be used more effectively in the collision avoidance path planning. Finally, simulation is carried out and results are analyzed to show the validity of the improved algorithm.

2. **The Modeling of Warehouse Environment Using Grid Method.** There are many kinds of environment modeling methods, such as grid method, vertex image method, link graph method and topology graph method, among which grid method is widely used in AGV systems.

Map modeling by grid method means that the environment map is divided into many grids of the same size [10]. The value of each grid equals "1" or "0". "1" represents there is an obstacle in the grid and "0" means AGV can pass through the grid, which is called a free gird. By this way, irregular obstacles can be well described. In the working environment of AGV, when we consider path planning in static environment, obstacles are shelves, whose location is known. The size of the grid is selected by the standard which can allow the free movement of one AGV in the space, so that AGVs can transport goods easily. The environment map model used in this paper is shown in Figure 1.

As shown in Figure 1, the actual working environment of AGV is instead by two-dimensional grids. So an optimal path from the starting grid to the target grid can be

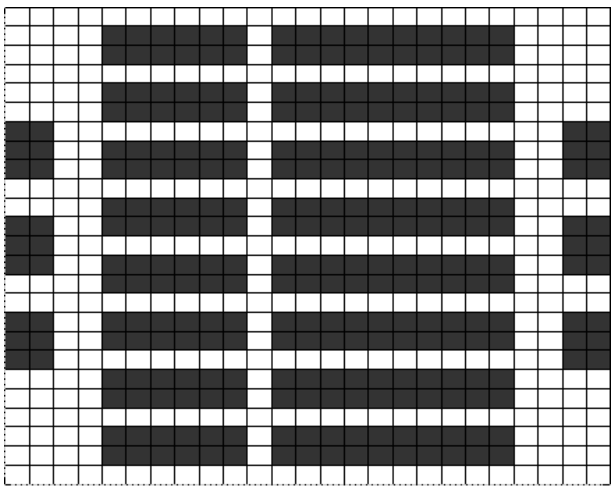


FIGURE 1. Environment map modeled by grid method

searched using related path searching algorithms. In this paper, the passageway between each two shelves is a single channel with two-way traffic, that is, an AGV can run in two directions, but only one AGV can go through each time. Two or more AGVs are not allowed to go through at the same time.

3. **Collision Avoidance Path Planning Based on Improved Ant Colony Algorithm.** Ant colony algorithm is inspired by the observation of real ant colonies. The basic idea of ant colony algorithm [4] to search the optimal path is that ants will release a pheromone on the path traversed, which can be perceived by other ants. Ants guide their search direction based on the intensity of the pheromone. There are two characteristics:

- Ants have a certain memory function and cannot visit the nodes that have been visited. The visited nodes are recorded by tabu list.
- After each iteration, the pheromone will be updated due to its evaporation and reinforcement. Through this continuous pheromone update, finally a solution route can be determined.

3.1. **The improvement of ant colony algorithm in the path planning of AGVs.** In the environment map modeled by grid method, taking AGVs as ants, we can select an optimal path for an AGV from the starting position to the end position using ant colony algorithm. In the process, the selection of path direction and the update of pheromone are two key factors mainly considered. So improvements are made on these two factors to make the algorithm better used in the path planning of AGVs.

3.1.1. *The improvement in the selection of path direction.* Assume that AGV k is in grid i at time t, the state transition probability with which AGV k chooses to go from grid i to grid j is:

$$p_{ij}^k(t) = \begin{cases} \dfrac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum\limits_{k \subset allowed_k} \tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)} & j \in allowed_k \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

$\tau_{ij}(t)$ is the amount of pheromone from grid i to grid j at time t. $\eta_{ij} = 1/d_{ij}$ is the heuristic value of moving from grid i to grid j. d_{ij} is the distance from grid i to grid j. α and β are two parameters that control the relative weight of pheromone and heuristic value. $allowed_k = \{C - tabu_k\}$, where C is the set of all grids and $tabu_k$ is a set of forbidden grids. So $allowed_k$ is the set of grids that can be selected by AGV k for next step.

In the basic ant colony algorithm, the next grids which ants are allowed to select include all the grids that have not been visited and the adjacent grid with the maximum probability will be chosen as the next movement direction of the current AGV. However, according to the actual operation of AGV and the needs of collision avoidance, the basic algorithm should be improved in two aspects. First, the selection range of the adjacent grid is limited to four directions, respectively in the front, back, left and right. It means an AGV has at most 4 grids to select for next direction. Besides, the next grid which ants will choose also needs to meet the following requirements: the grid has not been visited by the ant and the grid is a free grid.

Another improvement is that the method of selecting the next grid combines the state transition probability with "roulette". When selecting the next grid, if you always select the grid with the maximum state transition probability, it will make the algorithm lose its randomness, and thus fall into local optimal solution. Therefore, "roulette" method is introduced to solve the problem. First, the transition probability of candidate grids is accumulated. Then a number between 0 and 1 is randomly generated. The corresponding grid whose cumulative transition probability matches the random number is chosen as the next grid. For example, if there are three candidate grids $[g_1, g_2, g_3]$ and the corresponding state transition probability is $[\varepsilon_1, \varepsilon_2, \varepsilon_3]$ $(0 \le \varepsilon_1, \varepsilon_2, \varepsilon_3 \in (0, 1),\ \varepsilon_1 + \varepsilon_2 + \varepsilon_3 = 1)$. The cumulative transition probability is $[\varepsilon_1, \varepsilon_1 + \varepsilon_2, 1]$. A number x $(x \in (0, 1))$ is randomly generated. If $0 \le x < \varepsilon_1$, then g_1 will be selected. If $\varepsilon_1 \le x < \varepsilon_1 + \varepsilon_2$, then g_2 will be selected. Otherwise, g_3 will be selected.

3.1.2. *The improvement in the update of pheromone.* Ants will leave pheromone in the traversed path, so it is necessary to update the pheromone on the path in time. The amount of pheromone of each path is mainly determined by two factors: volatile pheromones and new added pheromones. At time $t + n$, when all ants complete a single iteration, we can update the amount of pheromone from grid i to grid j by the following rule:

$$\tau_{ij}(t + n) = (1 - \rho) \times \tau_{ij}(t) + \Delta\tau_{ij}(t, t + n) \tag{2}$$

$$\Delta\tau_{ij}(t, t + n) = \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t, t + n) \tag{3}$$

The constant $\rho \in (0, 1)$ is pheromone evaporation coefficient, which represents the degree of pheromone loss on the path. ρ is related to the global search ability and the convergence speed of the algorithm. m is the number of ants at each iteration. n is a period of time when all ants finish an iteration. $\Delta\tau_{ij}^{k}(t, t + n)$ represents the pheromone increment of AGV k left on the path (i, j) in the period $(t, t + n)$. At the beginning of the algorithm, $\Delta\tau_{ij}(0)$ is set to be a small positive constant value c on all paths.

Taking account of the warehousing operation environment, we find that AGV will stop and rotate 90 degrees during the turning. Therefore, in this case if we are still in accordance with the old principle of pheromone updating (only considering path length) to update the pheromone, it will cause an inaccurate result of the optimal path. So in the paper, the shortest time rule is used to select the optimal path. Specific improvements are as follows.

The number of all girds which AGVs go through from the starting position S to the target position E is n, including S and E. Among those grids, the number of turning grids is h. AGVs run with a uniform velocity v_s. In the turning, AGVs maintain the same position and rotate with an angular velocity v_c. The length of one grid is l_n.

The initial path cost function of ant colony algorithm is:

$$PL_k = Length_{SE} = (n - 1) \times l_n \tag{4}$$

The improved path cost function is:

$$PL_k = t_{SE} = \frac{(n - 1) \times l_n}{v_s} + h \times \frac{\pi}{2v_c} \tag{5}$$

By this improvement, we can effectively reduce the turning times of AGVs, and can calculate the actual consumed cost of paths.

So, $\Delta\tau_{ij}^{k}(t, t + n)$ can be expressed as:

$$\Delta\tau_{ij}^{k}(t, t + n) = \begin{cases} \dfrac{Q}{PL_k}, & \text{if } (i, j) \in T^k(t) \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

$T^k(t)$ is the path gone through by ant k at iteration t, and PL_k is the time that AGV k spends from S to E. Q represents pheromone intensity.

3.2. **The steps of the path planning method based on improved ant colony algorithm.** In the static environment, the steps of collision avoidance path planning of AGV based on grid method and improved ant colony algorithm are as follows.

Step 1 Parameter initialization: set the initial value of AGV number m, the relative weight of pheromone and heuristic value α and β, pheromone evaporation coefficient ρ, pheromone intensity Q, initial pheromone c and the maximum number of iterations K. Set the starting grid S and the target grid E, place m ants in the starting grid S, and add S to the tabu list.

Step 2 When ants choose next grid, if the current grid is not the target grid, the adjacent grid will be chosen combining the state transition probability with "roulette". Otherwise, ants will finish the task in this iteration.

Step 3 Update the pheromone of path according to Formulae (3) and (6), and calculate the optimal value of time consumption of the ant's path according to Formula (5).

Step 4 Repeat Step 2 and Step 3 until the ant arrives at the target grid or has no way to go.

Step 5 Repeat Step 2, Step 3 and Step 4 until all the ants have completed their task at one iteration.

Step 6 Update the pheromone matrix according to Formula (2). The ants which did not reach the target grid are not included in the calculation.

Step 7 Repeat Step 2 to Step 6 until the iteration number is K.

4. **Simulation Analyses.** In order to validate the method, a large number of simulation experiments of collision avoidance path planning of AGV based on the basic and improved ant colony algorithm are carried out respectively using MATLAB7.5 on the same computer. In the experiments, the grid environment is $25 * 25$, and we set $m = 400$, $\alpha = 1$, $\beta = 5$, $\rho = 0.3$, $Q = 70$, and $K = 100$.

Some simulation results based on the basic and improved ant colony algorithm are shown in Figure 2 and Figure 3 respectively, in which (a) shows the optimal search result of the corresponding algorithm, (b) shows the convergence curve of minimum path length and (c) shows the convergence curve of average path length.

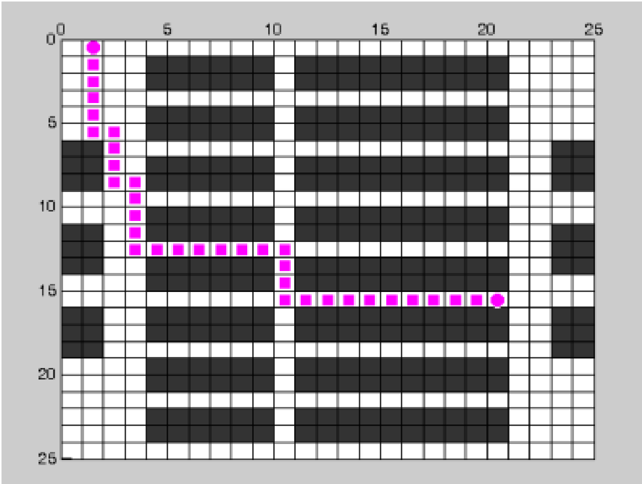
The simulation results of the basic and improved ant colony algorithm are compared, which are shown in Table 1. In the table, ACO is the abbreviation of ant colony optimization algorithm. The calculation methods of the best performance index, the time performance index and the robust performance index were presented in [11]. The best performance index is a measure of the optimization of the search problem. When the value is smaller, the optimization performance is better. The time performance index is a measure of the search speed of ant colony algorithm to solve the problem. When the value is smaller, it represents the convergence rate of ant colony algorithm is faster. The robust performance index is a measure of the dependence degree of ant colony algorithm on random initial value and the operation of the algorithm, so the smaller the value, the better.

Table 1. The comparison of the simulation results of basic and improved ACO

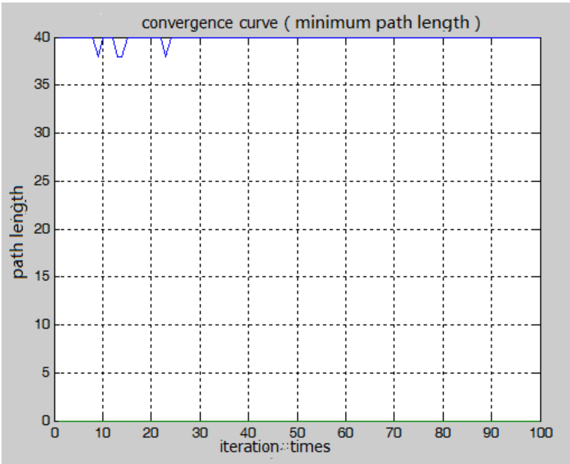
Performance index	Iteration times	The shortest path	Best performance index	Time performance index	Robust performance index
Basic ACO	74	38	2.70%	4.12%	8.11%
Improved ACO	61	37	0.00%	3.32%	0.00%

As shown in the table, in the basic ant colony algorithm, all individuals converge to the optimal path after 74 iterations, while it only needs 61 iterations in the improved ant colony algorithm.

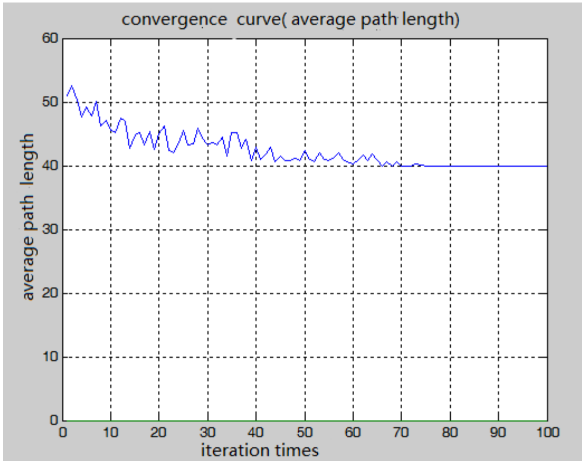
The best performance index of the improved ant colony algorithm is 0.00%, smaller than that of basic ant colony algorithm. That is to say, using the improved ant colony algorithm, the optimal path is gained, while a suboptimal path is got from the basic ant colony algorithm. So compared with the basic ant colony algorithm, the improved algorithm is better and its ability to search the optimal solution is also stronger.



(a) The optimal search result



(b) Convergence curve (1)



(c) Convergence curve (2)

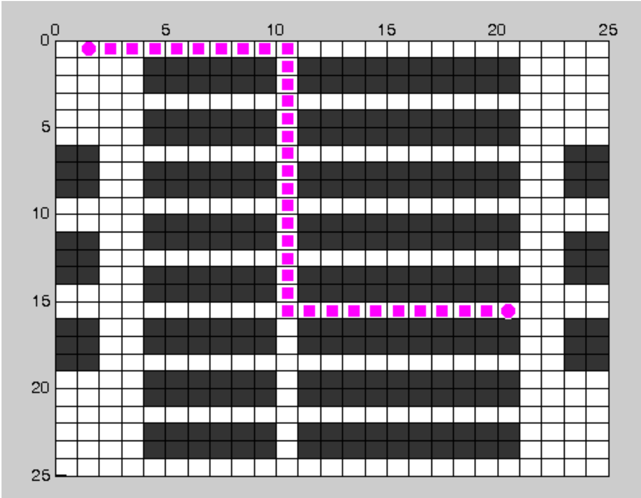
FIGURE 2. Simulation results of the basic ant colony algorithm

According to the time performance index, the improved algorithm is 3.32%, lower than that of the basic algorithm which is 4.12%. It shows that the convergence of the improved algorithm is better.

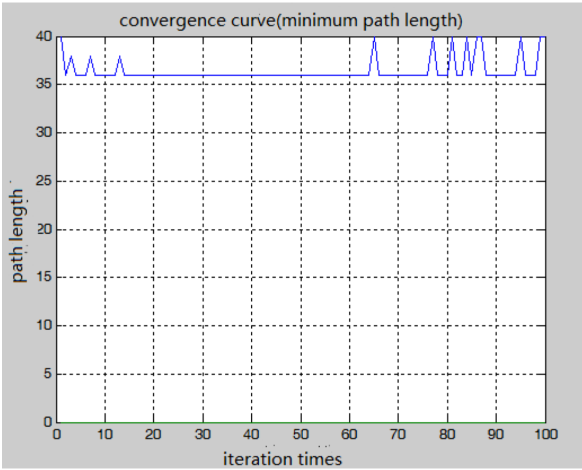
According to the robust performance index, 0.00% of the improved algorithm is far less than 8.11% of the basic ant colony algorithm, which shows that the dependence of the improved algorithm on random initial value and operation is significantly lower than that of the basic algorithm.

To sum up, the improved algorithm has better performance than the basic algorithm and can be more effective to get the optimal path.

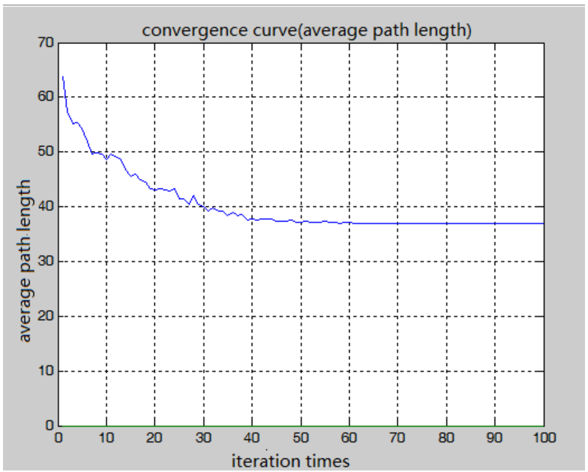
5. **Conclusions.** In the paper, a collision avoidance path planning method of AGV based on improved ant colony algorithm is studied. First, the automated warehousing environment is modeled by grid method. Then according to the actual operation of AGVs in storage environment and the actual map environment information, ant colony algorithm is improved in three aspects: (1) the selection range of the next grid is limited; (2) the method of selecting the next grid combines the state transition probability with "roulette"; (3) the path cost function of each ant from the starting point to the target point is improved. Simulation results show that the method based on the improved ant colony algorithm has stronger ability to search the optimal solution and better performance in convergence and robustness, as well as can reduce turning times of AGV.



(a) The optimal search result



(b) Convergence curve (1)



(c) Convergence curve (2)

Figure 3. Simulation results of the improved ant colony algorithm

Here we mainly study the path planning of AGV in two dimensional static space, in which environmental information is completely known. Although the effectiveness of the improved ant colony algorithm was validated through experiments, the algorithm needs to be further studied considering the path planning of AGVs in dynamic environment.

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