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Path Planning for Intelligent Parking System Based on Improved Ant Colony Optimization

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ABSTRACT Based on automated guided vehicle (AGV), the intelligent parking system provides a novel solution to the difficulty of parking in large cities. The automation of parking/pick-up in the system hinges on the path planning efficiency of the AGV. Considering the numerous disconnected paths in intelligent parking systems, this paper introduces the fallback strategy to improve ant colony optimization (ACO) for path planning in AGV-based intelligent parking system. Meanwhile, the valuation function was adopted to optimize the calculation process of the heuristic information, and the reward/penalty mechanism was employed to the pheromone update strategy. In this way, the improved ACO could plan the optimal path for the AGV from the starting point to the destination, without sacrificing the search efficiency. Next, the optimal combination of ACO parameters was identified through repeated simulations. Finally, a typical parking lot was abstracted into a topological map, and used to compare the path planning results between the improved ACO and the classic ACO. The comparison confirms the effectiveness of the improved ACO in path planning for AGV-based intelligent parking system.

INDEX TERMS Intelligent parking, automated guided vehicle (AGV), path planning, ant colony optimization (ACO).

I. INTRODUCTION

The rapid growth of car ownership adds to the difficulty of parking in large cities, where parking spaces are already very limited. Based on automated guided vehicle (AGV), the intelligent parking system provides a novel solution to the difficulty. The performance of the system hinges on the path planning for the AGV. Its main purpose is to find an optimal non-collision path for each automatic guide car from the pre-stored parking space to the target parking space, and to orderly complete all the path planning tasks.

Several algorithms have long been applied to plan the optimal path for the AGV, including the Dijkstra's algorithm, the A* algorithm and the genetic algorithm (GA). Based on the Dijkstra's algorithm, Kim and Tanchoco [1] planned AGV path using the free time window (TW) on the TW graph. Yu and Egbelu [2] classified the idle AGV, and minimized the idle time of the AGV through genetic iteration. Mimicking the process of natural evolution, Umar *et al.* [3], [4] applied the GA to search for the optimal path for the AGV.

In recent years, some heuristic algorithms have been introduced to path planning. For example, Occena and Yokota [5] proposed a heuristic search algorithm, in which the best search direction is identified by evaluating every search position, and the optimal path towards the destination is determined by searching along the direction. Meanwhile, some scholars have modified and improved the ant colony optimization (ACO) for path planning [6]–[9]. For instance, Chaari *et al.* [10] combined the ACO with the GA, and improved to crossover operator of the ACO to avoid the local optimum trap. Saidi-Mehrabad *et al.* [11] developed a two-stage ACO for AGV path planning. Some other scholars optimized the ACO with the artificial potential field (APF) method, speeding up the convergence of path planning algorithm [12], [13].

The number of AGVs depends on the number of parking spaces and scale of intelligent parking. The complexity of path planning increases with the number of AGVs. If there is only one AGV [14], the optimal path can be computed

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solely based on the parking environment and node distribution; the path planning is only affected by static factors, rather than the other vehicles. If there are multiple AGVs, the path planning becomes a dynamic problem: the potential conflicts between the target vehicle and other vehicles should be considered, in addition to the shortest length of the path. Smolic-Rocak *et al.* [15] developed a multi-AGV dynamic method to plan the operation paths for multiple vehicles in industrial job-shops. Based on vehicle scheduling model, Nishi *et al.* [16] presented a bi-level decomposition algorithm, which realizes conflict-free path planning for multiple AGVs. Based on the above research results, it can be found that most of the current path planning algorithms for intelligent parking systems are mainly focused on solving collision avoidance conflicts and realizing multi-vehicle scheduling, and rarely involve the improvement of path planning efficiency. In order to improve the operation efficiency of small-scale intelligent parking systems, this research put forward the improved ACO model for single AGV path planning.

The AGV-based intelligent parking systems have several common features: the parking lot usually covers a large area, many paths in the lot are disconnected, and vehicles drive through the same gate upon entry and exit. The characteristics of incomplete path connectivity in AGV-based intelligent parking systems seriously restrict the path search efficiency of classical ant colony algorithm. In the light of these features and the previous studies, this paper introduces the fallback strategy to improve the ACO, and creates a path planning model for intelligent parking system based on the improved ACO. To prevent the ACO from the local optimum trap and poor convergence, the valuation function was adopted to optimize the calculation process of the heuristic information, and the reward/penalty mechanism was employed to the pheromone update strategy, ensuring the search efficiency. Finally, the improved ACO was proved effective for single-AGV path planning, in comparison with the classic ACO. The algorithm proposed in this study can not only improve the efficiency of intelligent guidance vehicle path planning, but also help to improve the theoretical and technical system of the ACO and expand the application field of the ACO.

The remainder of this paper is organized as follows: Section 2 proposes the path planning model for intelligent parking system based on the improved ACO, in the light of the features of intelligent parking system; Section 3 verifies the improved ACO through example analysis, in comparison with the classic ACO; Section 4 puts forward the research conclusions.

II. METHODOLOGY

Intelligent parking system based on AGV has the characteristics of large parking area, many disconnected paths and the same inlet and outlet, etc. According to the abstract topology model of typical underground parking garage, this paper proposes an intelligent parking path planning model based on improved ant colony algorithm by introducing ant regression strategy to enhance the adaptability of the algorithm. The path planning for intelligent parking system was realized in three steps: Firstly, the driving rules of the AGV in intelligent parking system were analyzed, and the constraints of the path planning model were put forward; Next, the environment of parking lot was modelled as a topological map, and the basic requirements were raised for environmental modelling, facilitating the subsequent analysis of data; Finally, the improved ACO based on the fallback strategy was established according to the features of intelligent parking system.

A. CONSTRAINTS

In intelligent parking system, the entry and exit of vehicles are completed by the AGV, eliminating the need for driver operations. It is only necessary to consider the impacts of parking infrastructure and the environment on the AGV. Therefore, there is usually only one gate for both entry and exit in most intelligent parking systems. To increase the number of parking spaces and parking area [17], the internal paths in the parking lot are often bidirectional single-lane roads. In view of the above features, the following constraints were presented to simplify the path planning model for AGV-based intelligent parking system:

(1) Vehicles drive through the same gate to enter or exit the parking lot;

(2) The AGV will start executing the next parking/pick-up task from the end position of the current task;

(3) The internal paths in the parking lot are bidirectional single-lane roads, which are wide enough for the maximum turning radius of the AGV;

(4) In the parking lot, many parking spaces are located at the end of non-connected road sections;

(5) The AGV either starts from or ends up at the gate, i.e. only two kinds of paths need to be planned: the inbound path and the outbound path;

(6) The AGV is regarded as a particle with a safe radius; the AGV drives at a constant speed and makes every turn with the same amount of time.

B. ENVIRONMENTAL MODELLING

This paper models the environment of parking lot as a topological map, with the aim to reflect the features of actual scenario, meet the needs of the parking process, and facilitate the subsequent data analysis. The modelling must satisfy the following requirements: First, the topological map must consider the spatial locations of environmental factors, and demonstrate the relationship between things in the real world; Second, the topological map should be consistent with the actual behavior of path planning for parking, so as to prevent unreasonable planning results; Third, the topological map should be as simple as possible to enhance the planning efficiency and save computing resources, without violating the objective conditions.

C. PATH PLANNING METHOD FOR INTELLIGENT PARKING SYSTEM BASED ON FALLBACK STRATEGY

Considering the model constraints and features of intelligent parking system, the fallback strategy was introduced to the ACO to create a novel path planning method. Moreover, the valuation function was adopted to optimize the calculation process of the heuristic information, and the reward/penalty mechanism was employed to the pheromone update strategy, ensuring the search efficiency.

1) FALLBACK STRATEGY

There are many disconnected paths in the topological map of intelligent parking system. In this scenario, it is difficult for the classic ACO to converge to the optimal path, for the nodes to be updated are selected based on parameters like pheromone weight, heuristic information weight.

To overcome the difficulty, this paper introduces the fallback strategy into the ACO to prevent the algorithm from falling into an endless loop and failing to converge to the optimal solution. Under the fallback strategy, a vehicle looking for the optimal path will fall back to the previous node to select another node, if the current node leads to a disconnected path.

On the upside, the fallback strategy makes the ACO adaptable to the path planning for intelligent parking system. On the downside, the ACO with the fallback strategy becomes much less efficient. To ensure the efficiency, both heuristic information and pheromone update strategy were modified.

2) IMPROVE HEURISTIC INFORMATION

The valuation function [18] of the A* algorithm was adopted to improve the heuristic information, making the improved ACO more accurate, efficient and directional in search. The improved heuristic information can be computed by:

$$\eta'_{ij}(t) = \frac{1}{g_{ij}(t) + h_{jn}(t)} \tag{1}$$

where, i and j are node positions; $g_{ij}(t)+h_{ij}(\mathrm{t})$ is the valuation function of candidate node j; $g_{ij}(t)$ is the cost from the current node i to the candidate node j at time t, which equals the weight of edge ij; $h_{ij}(\mathrm{t})$ is the minimum estimated cost from the candidate node j to the destination n, which equals the Manhattan distance between nodes j and n:

$$h_{jn}(t) = |j_t(x) - n_t(x)| + |j_t(y) - n_t(y)| \tag{2}$$

where, $n_t(\mathrm{x})$ and $n_t(\mathrm{y})$ are the x- and y-coordinates of the destination n, respectively; $j_t(\mathrm{x})$ and $j_t(\mathrm{y})$ are the x- and y-coordinates of the candidate node j, respectively.

As shown in (2), the smaller the $h_{jn}(t)$ value, the better the path and the lower the estimated cost from the candidate node to the destination.

3) IMPROVED PHEROMONE UPDATE STRATEGY

In addition to improving the heuristic information, this paper introduces the reward/penalty mechanism to the pheromone update strategy. Under this mechanism, the improved ACO will not fall into the local optimum trap, and become more efficient and effective in iterative updates. The improved pheromone update strategy can be described as:

$$\begin{aligned}\mu_{ij}^{new}(t+1) = \mu_{ij}(t+1) + N_g \times \Delta\mu\left[g_{ij}(t,t+1)\right] \\ -N_b \times \Delta\mu\left[b_{ij}(t,t+1)\right]\end{aligned} \tag{3}$$

$$\Delta\mu\left[g_{ij}(t,t+1)\right] = \begin{cases}\frac{p}{l_g}, & \text{if } (i,j) \in \text{the best path} \\ 0, & \text{otherwise}\end{cases} \tag{4}$$

$$\Delta\mu\left[b_{ij}(t,t+1)\right] = \begin{cases}\frac{p}{l_b}, & \text{if } (i,j) \in \text{the worst path} \\ 0, & \text{otherwise}\end{cases} \tag{5}$$

where, t is the iteration time; p is the pheromone intensity coefficient; $\Delta\mu[g_{ij}(t,t+1)]$ and $\Delta\mu[b_{ij}(t,t+1)]$ are the amounts of pheromone to be rewarded and penalized, respectively; N_g and N_b are the number of ants to be rewarded and penalized, respectively; l_g and l_b are the path lengths to be rewarded and penalized, respectively.

4) WORKFLOW OF THE IMPROVED ACO

Based on the improved heuristic information and pheromone update strategy, the improved ACO can be implemented in the followings steps (Figure 1): initialize the parameters according to the data on the topological map; evaluate the necessity of fallback against the fallback strategy; perform

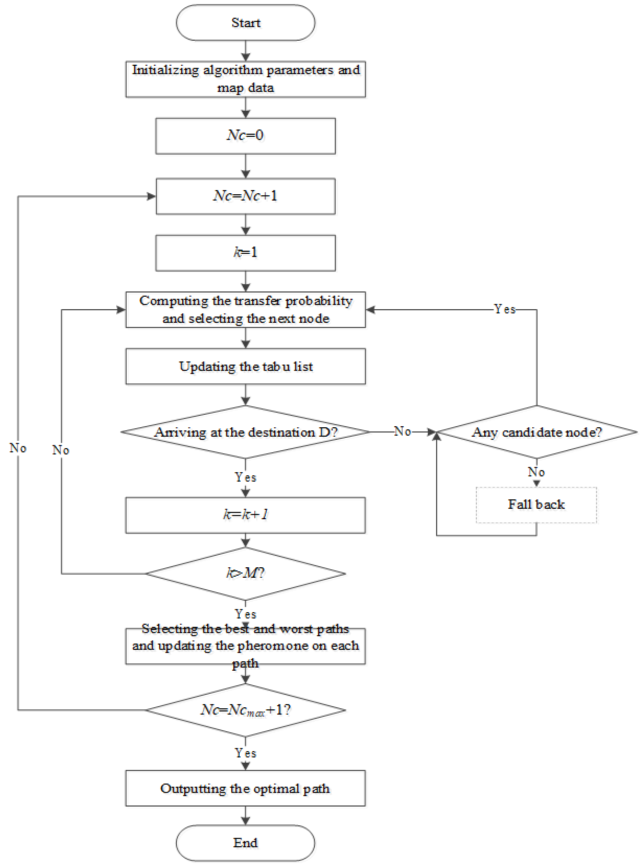
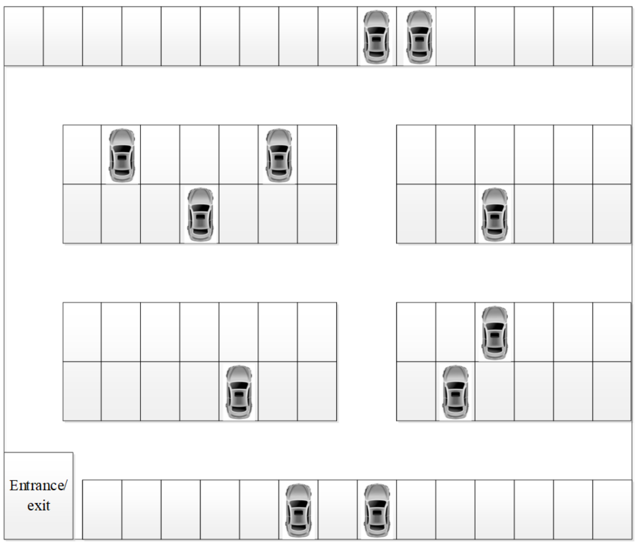


FIGURE 1. Workflow of improved ACO.

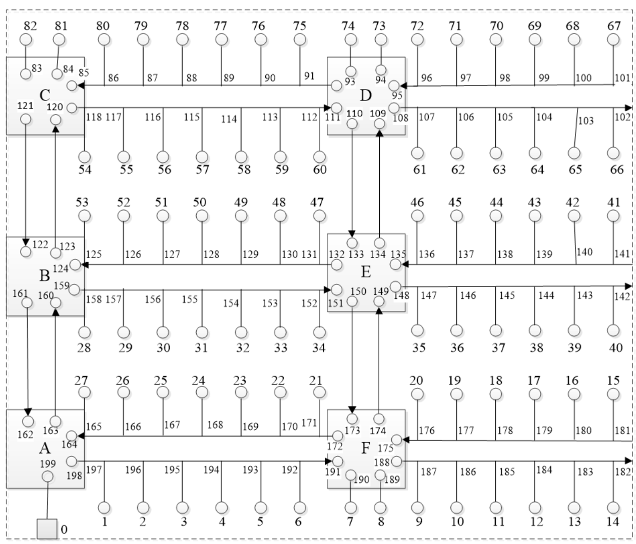
path selection with the improved pheromone update strategy and transfer formula, until all the ants complete path search in the current iteration; calculate the best and worst paths in the current iteration, and update the pheromone on all paths by (3)-(5); execute the previous steps iteratively until reaching the termination condition, and output the optimal path.

III. EXAMPLE ANALYSIS

This section aims to verify the effectiveness of the improved ACO in path planning for AGV-based intelligent parking system. For this purpose, a topological map was plotted for the road network in a typical parking lot, according to the above-mentioned requirements and constraints. The sketch map and topological map of the parking lot are shown in Figures 2(a) and 2(b), respectively. Then, the Matlab program was prepared for the improved ACO, and adopted for path planning on the topological map.



(a) Sketch map



(b) Topological map

FIGURE 2. The road network in a typical parking lot.

In the topological map, node 0 is the entrance/exit, nodes 1-82 are parking spaces, and nodes 83-199 are on paths leading to the parking spaces and intersections; A-F are intersections. Note that every path in the parking lot is bidirectional; the AGV must always keep to the right in the forward direction, but it is allowed to cross over the reverse path to enter a parking space; the AGV can go straight, turn left and turn right at each intersection, but not allowed to make a U-turn.

A. PARAMETER SELECTION

The results of the improved ACO could be affected by the combination of parameters and the number of nodes. Hence, the pheromone weight α, the heuristic information weight β and pheromone intensity coefficient ρ were divided into 5 value intervals, respectively; the number of nodes was set to 30, 50, 100, 150 and 200 in turn.

Then, multiple Matlab simulations were conducted on a laptop (CPU: Intel Core i7; Memory: 32G), under different parameter combinations and number of nodes. In each simulation, only one parameter was adjusted, while the other parameters were fixed. Under each number of nodes, every parameter was simulated 10 times. Finally, the optimal parameters were selected by comparing the mean optimal path lengths of different parameter combinations (Table 1).

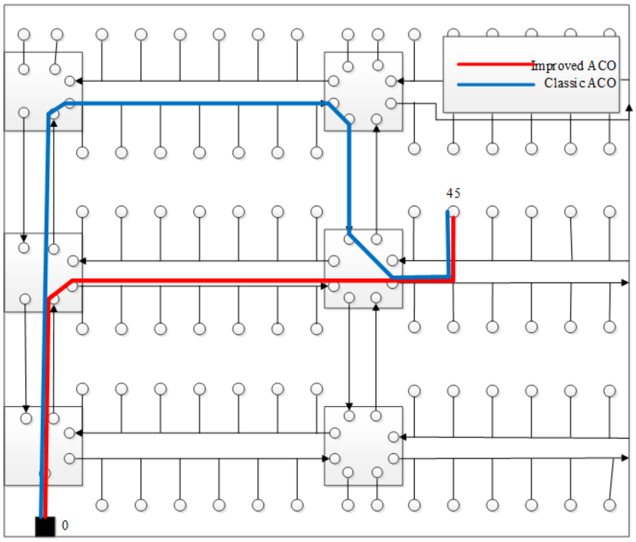
The results in Table 1 show that the parameter combination varies with the number of nodes. The optimal parameter combination under each number of nodes is summarized in Table 2. It can be seen that, when there were fewer than 100 parking spaces, the path length was optimized at $\alpha = 1$,

TABLE 1. The mean optimal path lengths of different parameter combinations.

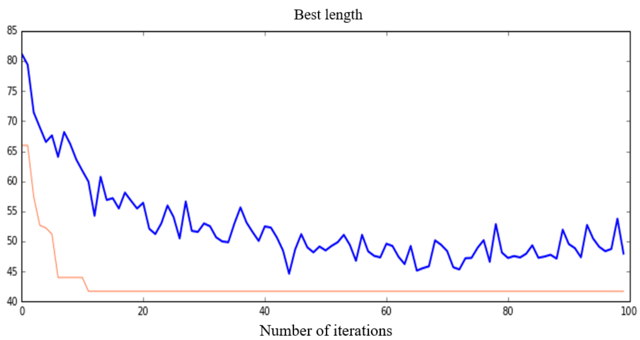
	Number of nodes / Parameter values	30	50	100	150	200
	0	23.51	32.73	97.18	186.68	181.97
	0.5	19.78	27.45	84.26	131.09	149.62
α	1	19.09	28.92	77.26	124.29	108.34
	2	20.51	32.73	87.18	136.69	121.97
	5	24.60	38.63	91.92	157.34	144.70
	0	35.84	38.99	83.60	83.75	142.79
	1	32.51	32.73	85.18	86.68	128.91
β	3	28.31	26.93	82.01	86.20	134.12
	5	34.60	28.63	79.92	67.34	124.70
	8	35.11	41.69	82.11	71.21	94.25
	0.1	30.11	41.69	82.11	121.21	154.25
	0.3	25.04	32.48	75.18	116.68	141.91
ρ	0.5	28.51	32.73	63.73	116.20	134.12
	0.8	31.76	35.82	87.18	136.69	121.97
	1	31.67	41.78	91.92	157.34	144.70

TABLE 2. The optimal parameter combination under each number of nodes.

Number of nodes / Parameters	<100	100-150	>150
Pheromone weight α	1	1	1
Heuristic information weight β	3	5	8
Pheromone intensity coefficient ρ	0.3	0.5	0.8



(a) Optimal paths



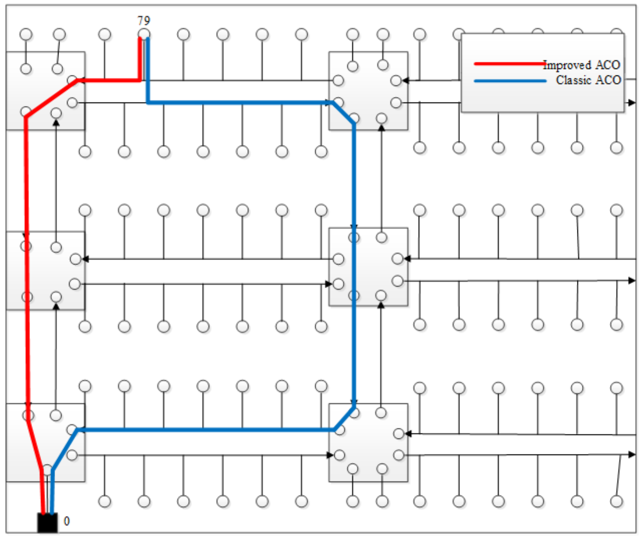
(b) Convergence curves

FIGURE 3. Comparison between improved and classic ACOs in parking task.

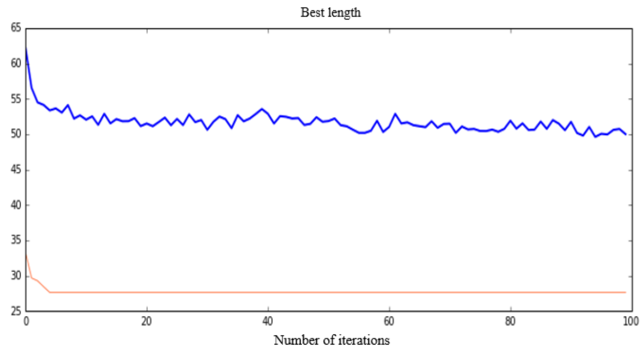
$\beta = 3$ and $\rho = 0.3$; when there were 100 to 150 parking spaces, the path length was optimized at $\alpha = 1$, $\beta = 5$ and $\rho = 0.5$; when there were more than 150 parking spaces, the path length was optimized at $\alpha = 1$, $\beta = 8$ and $\rho = 0.8$.

B. ALGORITHM VERIFICATION

The parking lot selected for simulation contains 82 parking spaces. And there are 199 nodes in the topological map. According to the results in Table 2, the optimal parameter combination was identified as: $\alpha = 1$, $\beta = 8$ and $\rho = 0.8$. In addition, the maximum number of iterations was set to 100 and the number of ants was set to 50. On this basis, the improved ACO and the classic ACO were both applied to plan the optimal path for parking and pick-up tasks. The starting point and destination of the parking task were node 0 and node 70, respectively; the starting point and destination of the pick-up task were node 79 and node 0, respectively.



(a) Optimal paths



(b) Convergence curves

FIGURE 4. Comparison between improved and classic ACOs in pick-up task.

Figure 3 compares the optimal paths and convergence curves of the improved ACO and the classic ACO in the parking task. It can be seen that the improved ACO output a 42.34m-long optimal path at the 12th iteration, while the classic ACO output a 50.40m-long optimal path at the 43rd iteration. The optimal paths of the improved and classic ACOs were respectively $0 \rightarrow 199 \rightarrow 163 \rightarrow 160 \rightarrow 159 \rightarrow 158 \rightarrow 157 \rightarrow 156 \rightarrow 155 \rightarrow 154 \rightarrow 153 \rightarrow 152 \rightarrow 151 \rightarrow 148 \rightarrow 147 \rightarrow 146 \rightarrow 137 \rightarrow 45$ and $0 \rightarrow 199 \rightarrow 163 \rightarrow 160 \rightarrow 123 \rightarrow 120 \rightarrow 119 \rightarrow 118 \rightarrow 117 \rightarrow 116 \rightarrow 115 \rightarrow 114 \rightarrow 113 \rightarrow 112 \rightarrow 111 \rightarrow 110 \rightarrow 133 \rightarrow 148 \rightarrow 147 \rightarrow 146 \rightarrow 137 \rightarrow 45$. The improved ACO clearly outshines the classic ACO in AGV-based parking.

Figure 4 compares the optimal paths and convergence curves of the improved ACO and the classic ACO in the pick-up task. It can be seen that the improved ACO output a 27.30m-long optimal path at the 8^{th} iteration, while the classic ACO output a 53.40m-long optimal path at the 23^{rd} iteration. The optimal paths of the improved and classic ACOs were respectively $79 \rightarrow 87 \rightarrow 86 \rightarrow 85 \rightarrow 121 \rightarrow 122 \rightarrow 161 \rightarrow 162 \rightarrow 199 \rightarrow 0$ *and* $79 \rightarrow 87 \rightarrow 116 \rightarrow 115 \rightarrow 114 \rightarrow 113 \rightarrow 112 \rightarrow 111 \rightarrow 110 \rightarrow 133 \rightarrow 150 \rightarrow 173 \rightarrow 172 \rightarrow 171 \rightarrow 170 \rightarrow 169 \rightarrow 168 \rightarrow 167 \rightarrow 166 \rightarrow 165 \rightarrow 164 \rightarrow 199 \rightarrow 0$. The improved ACO still greatly outperforms the classic ACO in AGV-based pick-up. This is because the classic ACO has difficulty in convergence, due to the lack of the fallback strategy. The path selected by the classic algorithm is highly stochastic, and tends to be much longer than that planned by the improved algorithm.

Compared with other similar research results, the search efficiency of the improved ant colony algorithm proposed in this paper can satisfy the intelligent parking path planning of general node size. It should be pointed out that when the node size exceeds 1000, the efficiency of the algorithm is slightly lower than that of the conventional algorithm. In other words, the algorithm in this paper has a more obvious effect on parking path planning for small-scale nodes.

In addition, the above results show that the improved ACO is superior to the classic ACO in both the length of planned path and iterative efficiency, during the execution of parking and pick-up tasks. This fully demonstrates the excellent adaptability of our algorithm to path planning for AGV-based intelligent parking system.

IV. CONCLUSIONS

This paper mainly proposes an improved ACO for the path planning of AGV-based intelligent parking system. Firstly, the constraints of path planning were determined according to the operation features of the intelligent parking system, and the driving rules for the AGV in the parking lot. Next, the topological map of the parking lot was plotted, laying the basis for path planning. Since there are many disconnected paths in the parking lot, the fallback strategy was introduced to the ACO to enhance the search efficiency for effective paths. Considering the significant impact of parameter combinations on ACO results, the optimal combination of parameters was identified through simulations under five different numbers of nodes. Finally, the improved ACO and the classic ACO were separately applied to plan the optimal path for a typical parking lot with the AGV-based intelligent parking system, using the optimal parameter combination. The results show that the improved ACO is more feasible than the classic ACO. Finally, an example is given to show that the improved ACO is more practical than the previous one. Compared with other similar research results, the search efficiency of the improved ACO proposed in this research can meet the requirement of the intelligent parking path planning within general node size. When the node size exceeds 1000, the efficiency of the algorithm is lower than that of the conventional algorithm.

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