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Application of Heuristic Integration Ant Colony Optimization in Path Planning

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***Abstract*—**This paper mainly studies the path planning method based on ant colony optimization (ACO), and proposes heuristic integration ant colony optimization (HIACO). This paper not only analyzes and optimizes the principle, but also simulates and analyzes the parameters related to the application of HIACO in path planning. Compared with the original algorithm, the improved algorithm optimizes probability formula, tabu table mechanism and updating mechanism, and introduces more reasonable heuristic factors. The optimized HIACO not only draws on the excellent ideas of the original algorithm, but also solves the problems of premature convergence, convergence to the sub optimal solution and improper exploration to some extent. HIACO can be used to achieve better simulation results and achieve the desired optimization. Combined with the probability formula and update formula, several parameters of HIACO are tested. This paper proves the principle of the HIACO and gives the best parameter range in the research of path planning.

***Keywords*—**Ant colony optimization, heuristic integration, path planning

I. Introduction

ACO is an algorithm inspired by ant colony's foraging behavior. This algorithm was proposed by Dorigo [1], which is mainly used to solve the discrete combination optimization problem [2]. ACO is a kind of evolutionary algorithm, which can be used to solve the traveling salesman problem. It has the characteristics of self-organization, parallel, positive feedback, strong robustness and so on [3]. In addition, ACO, as a bionic algorithm inspired by ants' foraging, to a certain extent conforms to the future research direction of artificial intelligence [4], and provides a good reference for the research of other algorithms.

At present, the main research direction of ACO is robot path planning [2], which has achieved excellent results in some aspects. But there are still many shortcomings in parameter setting, heuristic information adjustment and so on. Most of the research on the path planning method of ACO is aimed at the problem of traveling salesman, but seldom at the problem of finding the shortest path between two nodes. From this point of view, this paper explores the algorithm and parameter design on the shortest path problem, hoping to further improve the current ACO research on the shortest path problem. Aiming at the problems of premature convergence, improper exploration and convergence to sub optimal path, we propose HIACO, which improves probability formula, tabu table mechanism and updating mechanism, and sets more reasonable heuristic information. In addition, we further test the parameters of HIACO, analyze the function of different parameters, and give the optimal range of each parameter.

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II. Related Work

ACO is a simulated evolutionary algorithm, which is derived from foraging model [1]. Different species have different convening mechanisms, which can be either direct information transmission or indirect. Most ant colonies use pheromones to communicate indirectly [2]. When an ant finds food, it drags it back to its nest and leaves pheromones along the way. The foraging ants choose the path by the pheromone concentration in different paths. The higher the concentration of pheromone, the more likely the path will be selected. When more and more ants choose the same specific path, the path is more attractive because more and more pheromones are gathered, so as to attract more ants to take the path. This autocatalytic cooperative behavior forms a positive feedback mechanism, which makes the optimal foraging path more and more ants choose.

Tabu table is a form used to record the nodes that a single ant has passed through in a single iteration [5]. Its survival range is only in the process of single ant's path finding in a single iteration. In each path finding process, a single ant needs to re-initialize the tabu table, and different ants have different exclusive tabu tables. When the tabu table is full but the ant has not reached the destination and the ant has no nodes other than the tabu table to travel, it is necessary to break the tabu table and list the nodes in the tabu table as the nodes to be selected. Tabu table mechanism is proposed in the ant colony system optimization, which is a very important mechanism in the ACO. It can avoid the ant's back and forth between two nodes and the loop's moving condition between multiple nodes, which greatly improves the ant's searching efficiency.

The pheromone updating mechanism is divided into two parts: local updating mechanism and global updating mechanism [6], [7]. The local updating mechanism updates the pheromone concentration in each iteration. In the ant system, every ant will leave pheromones on the path it passes. However, in the ant ranking system, considering that ants with short path should have a higher priority to update pheromone concentration, elite ants can leave more pheromones, while ants with lower rank can update a small amount of pheromones or even not. Global updating does not exist in every iteration, but depends on the global shortest path [8]-[10]. Only when the global shortest path changes, the global updating formula is used to update the pheromone concentration.

There are two main uses of pheromone volatilization mechanism, one is pheromone volatilization, while the other is to limit the upper and lower limits of pheromone concentration [6]. The "two bridge experiment" shows that ant colony converges to a solution quickly, which makes the time of exploring a new path very short. In order to promote the ant colony to explore more new paths and avoid premature convergence, scholars put forward the mechanism of pheromone volatilization, which makes the original pheromone volatilize a certain amount in each iteration.

Path selection mechanism is determined by heuristic information and pheromone concentration [2]. In different application areas, ACO has some differences in the construction of this formula, but most of them only have different definitions of pheromone concentration and heuristic information. For example, in the traveling salesman problem, the heuristic information is *1/d*, that is, the reciprocal of the length *d* of the currently available path. The structure and parameter setting of probability calculation formula will directly affect the solution efficiency of ACO. The slight change of some parameters may greatly affect the convergence speed and exploration ability of ACO.

III. HIACO

Aiming at premature convergence, convergence to sub optimal path, improper exploration and other problems, this part proposes HIACO, which makes a series of theoretical analysis and corresponding optimization for the original ACO. Optimization can be divided into two parts. The first part is referential optimization, including some optimizations of tabu table mechanism, local updating mechanism and global updating mechanism. Because some improvement ideas are not compatible with each other, we must have selective reference according to specific problems, and make further improvement on the basis of reference, in order to achieve the best improvement effect. The second part is the original optimization. After referring to the existing optimization algorithm, we reconstruct the probability calculation formula, integrate two heuristic parameters, and enumerate some characteristics of the optimization formula.

A. Referential Optimization

In the original ACO, there is no specific measure to break the tabu table. In some studies [5]-[8], the method of random selection is used to break the tabu table; that is, randomly set a tabu node that the current ant can access as an accessible node, and move to this node. When we use this method for simulation, we find that this situation is not properly handled in some details. When there are fewer alternative routes for ants, it is likely that ants will reciprocate between two nodes. Since no additional processing mechanism is set, the probability of ant selecting the last node is likely to be higher than that of accessing other nodes, and selecting the last node returns to the previous state. This will cause ants to reciprocate between two nodes or increase unnecessary searching time. In order to solve this problem, we add a special processing mechanism, which allows ants to choose the node that is not the previous node first, and return to the previous node only when there is no node that is not the previous node accessible. This mechanism not only improves the ant's exploring ability, but also reduces the ant's searching loop to a certain extent.

$$P^k(t+1)\epsilon \begin{cases} N_i^k(t)-T^k(t), \text{if } N_i^k(t) \nsubseteq T^k(t) \\ N_i^k(t), \text{if } N_i^k(t) \subseteq T^k(t) \text{ and } N_i^k(t)-\{P^k(t-1)\} \neq \emptyset \\ \{P^k(t-1)\}, \text{if } N_i^k(t) \subseteq T^k(t) \text{ and } N_i^k(t)-\{P^k(t-1)\} = \emptyset \end{cases} \quad (1)$$

In (1), $P^k(t)$ is the node where the ant with number k is located at time t, $T^k(t)$ is the tabu table set of ant with number k at time t, and $N_i^k(t)$ is the node set where the ant on node i with number k can access at time t.

In the original local updating mechanism, all ants participate in the updating of pheromone concentration. However, considering the theory of "better solution is close to the best solution" [11], the ants in the lower rank are likely to play a negative role in exploring the shortest path to a large extent. In the early stage, if the ants at the bottom of the ranking can update pheromones, it will undoubtedly slow down the convergence speed of path finding; in the later stage, the ants at the bottom of the ranking are basically similar to the ants at the bottom of the ranking, so the updating of ants at the bottom of the ranking is even more meaningless. We set the number of ants that can update the pheromone concentration to *n;* that is, the ants in the top *n* can update the pheromone.

$$\Delta\tau_{ij}(t) = \sum_{\sigma=1}^{n} \Delta\tau_{ij}^{\sigma}(t) \quad (2)$$

In (2), $\tau_{ij}(t)$ is the pheromone concentration between node i and j at time t, and σ is the ant label. In addition, we also adjusted the increment of pheromone concentration of ants in different rank to make the total updating amount of all ants constant. We assign the pheromone concentration increment to the top n ants in proportion, and the increment formula is shown in (3):

$$\Delta\tau_{ij}^{\sigma}(t) = \begin{cases} \frac{2\sigma\tau_0}{n^2+n}, \text{if } \sigma \in \{1,2,\dots,n\} \\ 0, \text{else} \end{cases} \quad (3)$$

In (3), τ_0 is the preset upper limit of pheromone concentration increment in single updating. If the routes of n ants contain the same road section, the pheromone concentration increment of this road section in this iteration is τ_0.

In the original global updating mechanism, whether the global optimal solution is updated in the current iteration or not, the program will call the global update formula [8]. In this way, the current global optimal solution is always strengthened without considering the discovery time of the optimal solution, and the possibility that the global optimal solution may be a local optimal solution is ignored. In this case, if a local optimal solution is found in the early stage of the iteration, but no better solution is found in the subsequent iteration process, the pheromone concentration on the path of the local optimal solution will be continuously strengthened, which will affect the ant colony to further develop the better solution. Therefore, we optimize the call of global updating mechanism. Only when the current iterative optimal solution is smaller than the historical optimal solution, can we call the global updating formula. In addition, we also improve the global updating formula by adding the parameter k, and adjust k according to the actual problem. The global updating formula is as follows:

$$\Delta\tau_{ij}(t) = \begin{cases} \frac{k}{f(d^*(t))}, \text{if } (i,j) \in d^*(t) \\ 0, \text{else} \end{cases} \tag{4}$$

where $d^*(t)$ is the length of the global shortest path. The new global updating mechanism reduces the possibility of continuously strengthening the local optimal solution, and improves the exploration of ant colony to a certain extent.

B. Heuristic Integration

Probability formula is the core formula of ACO. Since it was proposed, no matter the ant colony system, the maximum and minimum system, the fast ant system or the ant ranking system, the probability calculation formula in them has not been greatly improved.

But the calculation formula of probability is not fixed. The earliest probability formula only includes the prior effect (heuristic information) and the posterior effect (pheromone concentration) and balances them. There is no strict mathematical proof for the construction of the formula. To a large extent, the formula is biased to empirical formula, and there is a lot of room for improvement.

In this section, according to the core theory of ACO, we adjust the structure of probability calculation formula. Based on the new formula, we adjust the pheromone concentration and heuristic information to optimize the balance between them. The original probability calculation formula is defined as [2]:

$$p_{ij}^k(t) = \begin{cases} \frac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum_{u \in N_i^k(t)} \tau_{iu}^{\alpha}(t)\eta_{iu}^{\beta}(t)}, \text{if } j \in N_i^k(t) \\ 0, \text{else} \end{cases} \tag{5}$$

where k represents ant sequence number, i and j are node numbers, p is the transfer probability between two nodes, τ is the pheromone concentration between i and j, α is the pheromone enhancement coefficient, η is heuristic information ($1/d$ for path planning problem), β is the heuristic enhancement coefficient.

It is not difficult to see from (5) that the values of α and β determine the influences of pheromone concentration and heuristic information on probability calculation. The value of both does not directly affect the size of single path probability calculation, but on the whole, it will make probability have preference. The higher α is, the greater the effect of pheromone concentration on probability is, and vice versa; β is similar to this.

In the case of determining the effect of a posteriori effect, the calculation of a priori effect can be analyzed. It can be determined that the prior effect of different road sections cannot be exactly the same in this probability formula, because the identical η will cause the prior effect in the probability formula to disappear (the molecule and denominator eliminate η^β at the same time).

In order to find the shortest path, we can further analyze the prior effect. According to the original probability formula, η is the inverse ratio of the length of the road section to be selected, which conforms to the traveling salesman problem. But for finding the shortest path problem, this method is likely to have a negative effect on the problem solving.

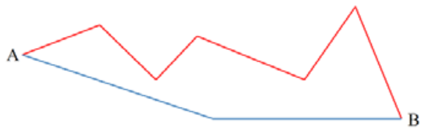

Fig. 1 Two different situations that ant colony may encounter

As shown in Fig. 1, assuming the map is designed according to this, the initial position of ant is A, and the terminal position is B. In the early stage of ACO, ants will randomly select red and blue road sections, and the selection of the two paths is random. If most ants choose the blue path as the initial path, the pheromone concentration will tend to this path. Although random exploration will make the red path possible to be developed, due to the influence of pheromone, the ant colony will eventually converge to the blue path, which will not have a negative impact on the shortest path searching. However, if most ants choose the red path as the initial path, the pheromone concentration and heuristic information will tend to the red path. Although the total length of the red path is far greater than the total length of the blue path, the length of each section in the path is shorter. In this case, pheromone and heuristic information will have the same preference, and ant colony will choose the suboptimal solution which is quite different from the optimal solution. And because of the positive feedback mechanism, the ant colony will continue to strengthen the attraction of red path to the subsequent ants, which makes it difficult for the ant colony to find the optimal solution.

To solve the above problem, we improve the probability formula and propose HIACO. We change the combination of prior effect and posterior effect in the original formula from multiplication to addition, and integrate the heuristic information.

$$p_{ij}^k(t) = \begin{cases} \frac{\tau_{ij}^{\alpha}(t)+H^*}{\sum_{u \in N_i^k(t)} \tau_{iu}^{\alpha}(t)+H^*}, \text{if } j \in N_i^k(t) \\ 0, \text{else} \end{cases} \tag{6}$$

The probability formula of HIACO has the following characteristics:

1) Disturbance factors and heuristic information are unified. In the research of ACO, the disturbance factor is also a very important parameter. In order to make the ACO more random and exploitable, some scholars proposed to add the disturbance factor to the ACO. On the one hand, this kind of processing is closer to the real ant foraging behavior, which is in line with the development direction of artificial

intelligence. On the other hand, ant colony can avoid premature convergence and lose the ability to develop new paths. In HIACO, new heuristic information plays a role of disturbance.

2) Compared with the original formula, the optimization formula does not break out the balance between pheromone concentration and heuristic information. The original formula is balanced by multiplication combining pheromone and heuristic information. Although the optimization formula breaks the original multiplication, it is rebuilt by addition. However, by adjusting the parameters, the new algorithm does not affect the balance of the two and will not reduce the efficiency of the ACO.
3) The value of new heuristic information is more flexible. The heuristic information of the original formula needs different values in different choices. And it is difficult for the original formula to adapt to some situations where heuristic information is needed and different choices are expected to have equal possibilities. However, because the optimization formula is constructed by addition, it can flexibly adjust the new heuristic information value to variable value or constant according to specific problems.
4) On the premise of not affecting the algorithm function, parameter debugging is more convenient. ACO belongs to artificial intelligence algorithm, with a lot of uncertainties. The core of the algorithm is reflected in the positive feedback mechanism. On the basis of not violating this core theory, combining two heuristic related parameters into one heuristic parameter will undoubtedly reduce the difficulty of parameter debugging.
5) It is convenient to analyze the influence of heuristic information on ACO more scientifically. The original heuristic information is inversely proportional to the length of the road section, and is multiplied by the α power of the pheromone concentration after the calculation of the β power. Multiple operations make the final probability result complex, so it is difficult to analyze the heuristic information directly. Only using simulation results to indirectly analyze, to a great extent, has affected the scholars' further research on ACO.
6) HIACO solves the problem that the original ACO did not deal with the situation described in the previous section properly. This feature is also the starting point for the optimization of the original formula. In the problem described in the previous section, once the ant colony choose the red path in the early stage of the algorithm, the algorithm will hardly find the optimal path. After optimization, because the new heuristic information is not affected by the length of the road, it has the same heuristic effect on different paths, and it will not lead to the pheromone concentration and heuristic information having a common preference for a path. Even if the initial route of the ant colony is wrong, it is still possible for the ant colony to get rid of the wrong path and explore a better solution.

IV. Experiments

In view of the above problems and optimization scheme, this part will verify the performance of HIACO through experiments. Because the parameters of HIACO and ACO are different, the comparison between HIACO and the original algorithm needs to be adjusted separately and then compared. This part will first analyze and adjust the performance and related parameters of HIACO, and give a better parameter configuration according to multiple evaluation indexes. The second part of this chapter will analyze the performance of the original algorithm in the current environment and adjust the appropriate parameters, then compare the performance of ACO and HIACO.

A. Performance in Finding the Shortest Path

We set up a map with 50 nodes and selectively connected some of them. In the set environment, we take the starting node as 10 and the ending node as 26, for example. Fig. 2 (a) shows the location of the start and end nodes in the map. After 100 iterations of HIACO, the global shortest path is shown in the red path in Fig. 2 (b). Fig. 2 (c) shows the concentration map of the final pheromone. The darker the color, the denser the corresponding path pheromone. Fig. 2 (d) shows the average distance of single iteration and the shortest distance of single iteration.

For HIACO, we need to adjust the pheromone influence parameter α and heuristic information parameter H^*. Among them, the selection range of α is {1, 4, 7, 10}, and the selection range of H^* is {0.0001, 0.001, 0.01, 0.1} (too large or too small α or H^* will lead to the ant colony unable to find the shortest path or difficult to converge). When evaluating performance, we will consider average distance, shortest distance, shortest path hit rate, lost rate, distance exploration and node exploration.

In the above six evaluation indexes, some attributes such as average distance and shortest distance are common evaluation indexes, but the evaluation of exploratory and convergence is not comprehensive enough. After adding other evaluation indexes, the algorithm performance under different parameter settings can be evaluated more comprehensively. Some indexes are related to each other, such as distance exploration and node exploration. And some indexes are antagonistic, such as lost rate and shortest path hit rate. However, there is no linear relationship between them, so they should be evaluated separately.

In Fig. 3, the average distance of different parameter combinations of α and H^* in each iteration is drawn. We can see that the pheromone effect will decrease with the increase of α, and the exploratory ability of ant colony will also increase. The smaller α will make the value of pheromone closer, which will affect the convergence of the average distance.

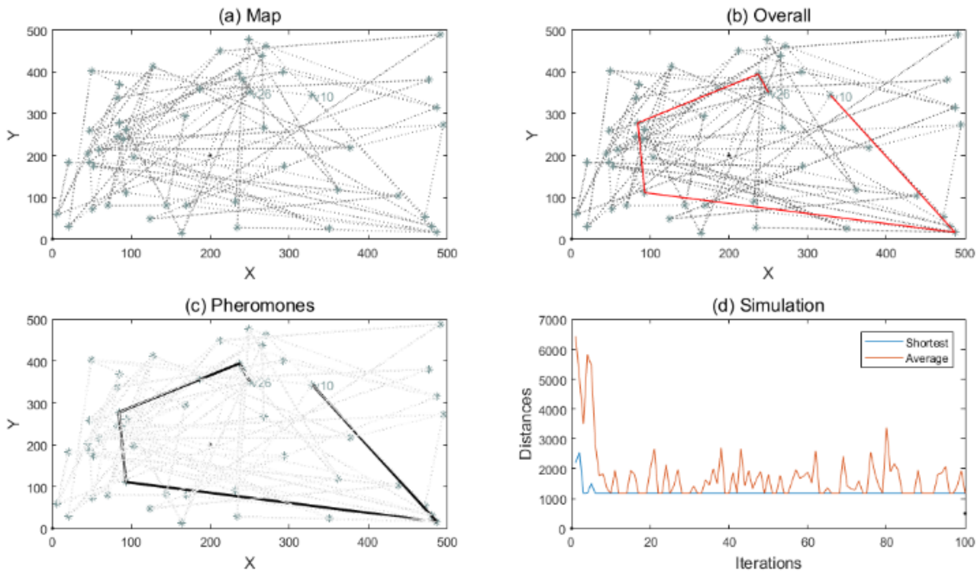

Fig. 2 Some basic images about the environment

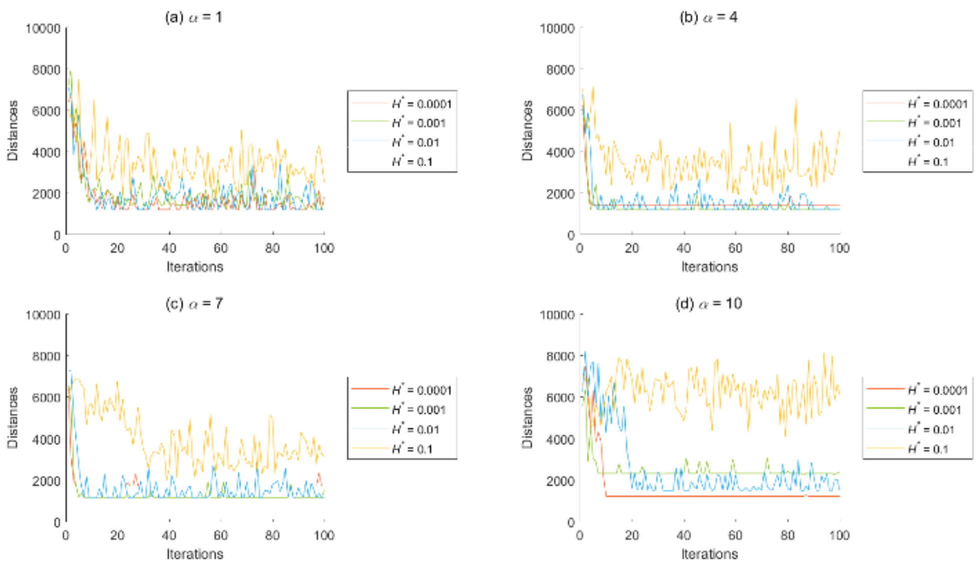

Fig. 3 The average distances of different parameter combinations

Fig. 4 shows the shortest distance image of ant colony under different parameter combinations. We can see that the smaller the values of H^* and α, the stronger the convergence of ant colony. When the H^* and α values increase, the exploratory ability of ant colony will also increase, and the ant colony will have more opportunities to explore a better path. However, the enhancement of exploration will also bring the disadvantages of exploring useless paths. In addition, the shortest path hit rate and the lost rate represent the exploration efficiency of ant colony. Distance exploration and node exploration are based on the shortest distance and average distance, which more intuitively represents the exploration of ant colony.

After giving the above six evaluation values, we can average the evaluation results of 100 iterations of the specified parameters according to the results, and give the overall evaluation value. We also add the global shortest distance and the number of iterations needed to find the global shortest distance, as shown in Table I.

In order to reduce the randomness of the data, we conduct 100 times of each test (fix starting node and end node), and average the results of each index.

Finally, we choose $\alpha = 4$, $H^* = 0.01$ as the final parameters of HIACO.

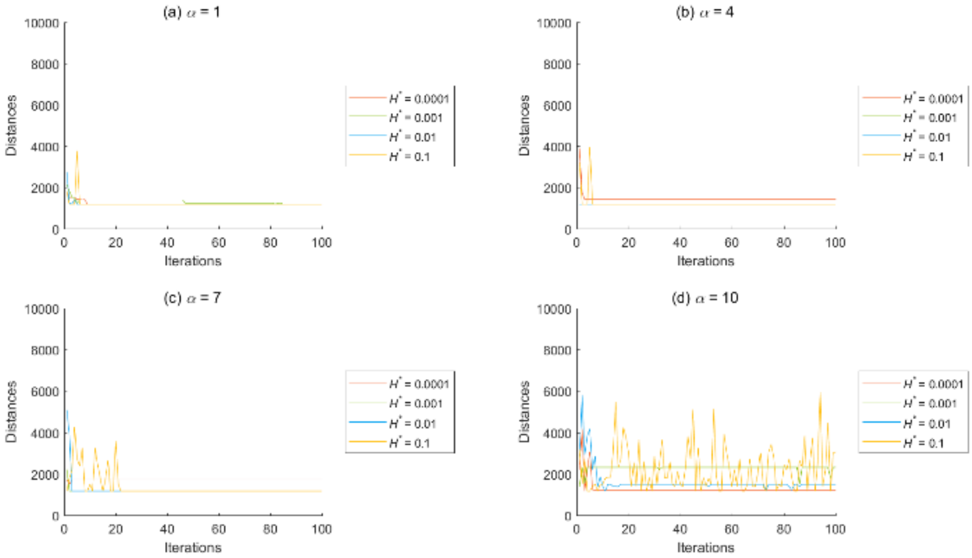

Fig. 4 The shortest distances of different parameter combinations

TABLE I
THE MEANINGS OF DIFFERENT EVALUATION INDEXES

Evaluation index	Meaning
D_{gs}	Global shortest distance found by ant colony
I_s	The number of iterations required by ant colony to find the global shortest path
D_s	The shortest distance found by ant colony
D_{avg}	The average distance of ant colony
P_s	Proportion of ants finding the shortest path
P_l	Proportion of ants unable to reach the destination
E_d	The exploration of ant colony in distance
E_n	The exploration of ant colony in node

B. Performance Comparison between HIACO and Original Algorithm

In this part, we first analyze the parameters of the original algorithm and choose the more appropriate parameters for the original ACO. In the probability formula of the original ACO, both pheromone and heuristic information affect the probability formula in the form of power function. Therefore, to some extent, we can fix one of the pheromones influencing factors and heuristic influencing factors, and adjust the balance between them by changing one of the parameters. As the research focus of this paper is on the influence of exploration factors, we fixed the α of the original algorithm to 1.

After determining the value of α, the next work is to adjust the β according to the actual situation. According to the properties of power function, the influence of heuristic information on probability varies with the change of β. According to Fig. 5, when β is small and heuristic information is close to 0, the β power of heuristic information changes dramatically. This makes ant colony not explore around pheromones, but in the direction of heuristic information preference. When β takes a larger value, the β power of heuristic information will be infinitely close to 0, and the difference of them is very small, which will lose exploration. In addition, the nature of power function also determines that the value of β will also determine that the heuristic information close to 0 is favorable or the heuristic information close to 1 is more favorable, which has a strong bias. Due to the uncertainty of map and nodes, we should consider the possibilities of all heuristic information and put them on the same position. So, we set the β value to 1.

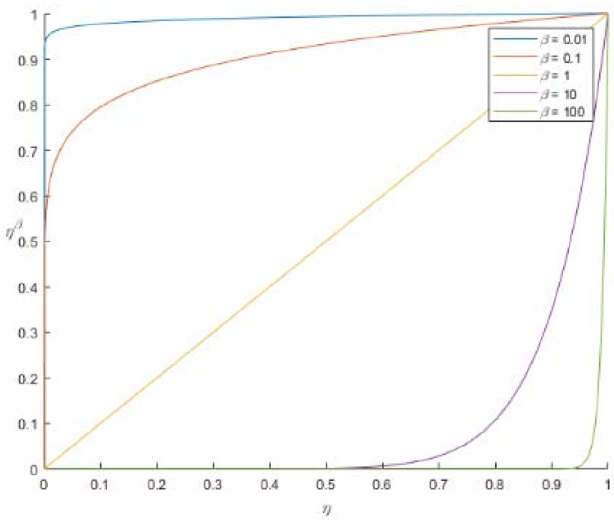

Fig. 5 The image of η^β when β has different values

After determining the corresponding parameters of HIACO and ACO, we can compare the performance of the two algorithms by average distance, shortest distance, lost rate, shortest path hit rate, distance exploration and node exploration.

TABLE II
THE AVERAGE CHANGES OF EACH EVALUATION OF HIACO AND ACO

Start	End	D_{gs}	D_s	D_{avg}	P_s	P_l	E_d	E_n
4	10	-2.06%	6.91%	-1.88%	7.78%	-32.00%	-7.95%	-6.16%
42	5	-15.66%	-4.51%	-14.96%	5.67%	-46.28%	-11.55%	-11.18%
38	24	0.12%	2.70%	-4.29%	8.39%	-42.80%	-6.32%	-6.66%
13	27	-2.98%	8.10%	7.26%	0.61%	-2.72%	-0.48%	-0.61%
10	47	3.36%	18.08%	10.51%	0.81%	-33.10%	-4.82%	-1.61%
22	30	0.00%	24.12%	19.73%	-1.63%	-9.65%	0.98%	0.61%
2	14	1.82%	23.88%	23.20%	-2.80%	9.38%	0.73%	0.16%
1	34	0.00%	0.57%	1.70%	-0.38%	-2.36%	1.03%	0.52%
6	31	0.96%	14.28%	9.63%	2.52%	-4.34%	-2.97%	-0.98%
19	22	5.70%	23.41%	19.96%	-4.11%	-15.53%	-2.00%	-2.35%
9	42	-0.48%	-6.02%	-42.05%	12.82%	-64.70%	-39.15%	-29.17%
11	38	2.08%	15.09%	2.72%	2.77%	-30.13%	-9.52%	-7.63%
7	39	-8.16%	-2.48%	-9.62%	3.29%	-45.63%	-8.28%	-7.42%
12	43	-1.28%	11.18%	3.03%	12.24%	-37.33%	-7.23%	-6.21%
5	47	-8.81%	-48.52%	-52.13%	14.34%	-69.86%	-14.74%	-11.16%
2	5	-17.20%	-3.98%	-4.33%	-0.96%	-20.48%	1.40%	-0.92%
Average		-2.66%	5.18%	-1.97%	3.84%	-27.97%	-6.93%	-5.67%

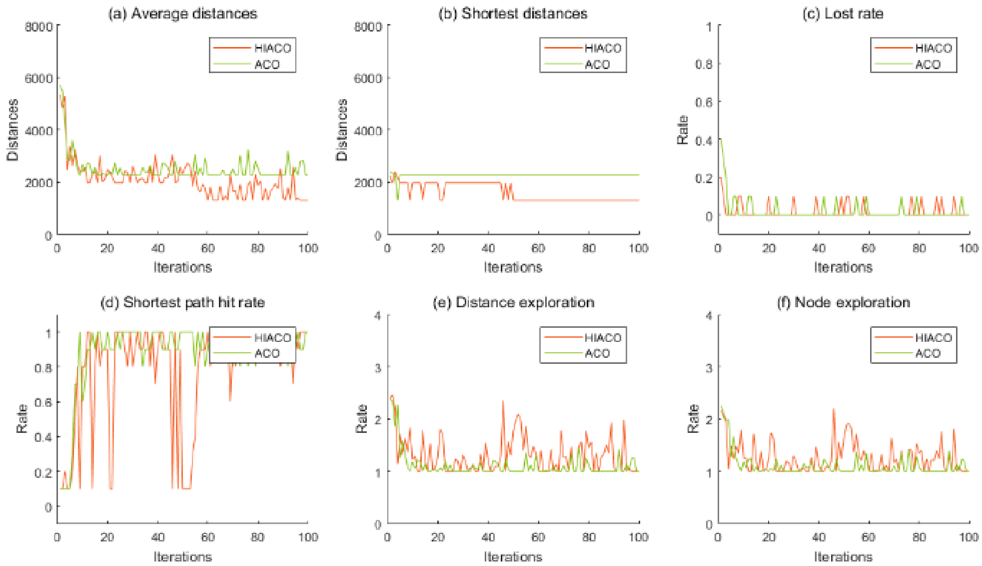

Fig. 6 Performance comparison between HIACO and ACO

Fig. 6 shows the performance of two ACOs starting from starting node 4 and arriving at node 3. Fig. 6 (a) shows the average distance between the two algorithms. We can see that the convergence speed of HIACO is faster than that of the original algorithm in the early stage. In the later stage, the convergence speed is reduced, which ensures the exploration speed and exploration performance. Fig. 6 (b) shows the shortest distance. In the intelligent algorithm, falling into the local optimal solution cannot be completely eliminated. However, we can see that after finding the local optimal solution in the early stage, HIACO still guarantees the exploration of the better shortest path and successfully explores the better shortest distance. Figs. 6 (c) and (d) respectively represent the lost rate and the shortest path hit rate of the algorithm. From the image, we can see that the lost rate of the original algorithm is generally higher than that of HIACO, and the hit rate of the shortest path is lower than that of HIACO (it is necessary to exclude the case of exploring the new shortest path). This means that the exploration of the original algorithm is not around the current solution, but at the expense of the hit rate for random exploration. Figs. 6 (e) and (f) respectively show the exploratory of distance and node. It can be seen that the exploratory difference between the two algorithms is not significant. But combined with other data, we can know that HIACO's exploration is more effective.

In addition to the comparison and analysis of each performance index in a single test, referring to the evaluation method above, we also selected multiple test samples and simulated the two algorithms 100 times. We get more accurate evaluation on the average. Table II shows the changes of each evaluation of HIACO and original ACO.

In finding the shortest path problem, the most critical evaluation index is undoubtedly the global shortest distance. In Table II, we can see that the D_{gs} of HIACO is lower than that of the original ACO. This also verifies the above theoretical analysis, HIACO can find a better shortest path. Taking D_{avg} and P_l as the core indicators, and combining with other evaluation indicators for analysis, we can conclude that HIACO will remain exploratory when it falls into the local optimal solution. Although E_d and E_n are slightly lower than the original ACO, combining with the analysis of P_s and P_l, we can see that the exploration of HIACO is more valuable than the exploration of the original ACO.

V. Discussion and Conclusions

Our main work is to optimize and simulate the ACO for shortest path planning. The original ACO has a good effect in solving the traveling salesman problem, but there are still some shortcomings in the shortest path planning problem.

Firstly, we make a referential optimization to adjust some mechanisms of the original ACO. It includes setting additional restrictions on the tabu table mechanism, adjusting the number of active ants in the local updating mechanism and adjusting the global update formula according to the actual background.

After proposing the referential optimization, we improved the probability formula of ACO. We change the way that heuristic information affects probability and propose HIACO. In HIACO, heuristic information will not have preference, so it is fairer to deal with exploration. In experiments, HIACO can usually find the shortest path better than the original algorithm. In addition, HIACO not only ensures the exploration, but also improves the shortest path hit rate and reduces the lost rate of ant colony, which endows the exploration of ant colony with higher value.

This paper focuses on the balance between pheromone and heuristic information and the efficiency of exploration. In future research, we think that the multi dimension of pheromone and heuristic information will be the next research focus of ACO. More complex pheromones and heuristics may need to be preprocessed before they affect probability. Preprocessing may include encoding, feature extraction, dimension reduction and other operations. If ACO can be combined with the corresponding preprocessing, we believe that it will be further developed in natural language processing, image processing, reinforcement learning and other fields.

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