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Research on Self-adaptive Ant Colony Algorithm Based on Statistical Analysis

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Abstract: Path planning is important in robot field and in this field, many researchers have done a lot of work. This paper proposes an improved ant colony algorithm as traditional ones have a shortage of slowly convergence and easily falling into local optimum. On the basis of traditional ones, the dynamic random statistical analysis and extraction of each generation of Ant Colony are performed the optimal, average and worst ant information constitutes an adaptive operator for adaptive updating of local pheromones. Simulation results demonstrate that it is effective in equilibrium increasing convergence rate and getting into the contradiction of local optimal solution.

1. Introduction

Mobile robot technology is an important part of robot technology. It is widely used in industry, agriculture, medicine treatment and services [1]. Literature [2] proposes that in the next few years, the development of service robots will surpass traditional industrial ones. Path planning technology is one of the core contents of service robot research, so it is necessary to study the path planning of robot [3].

At present, there are a variety of algorithms for robot path planning which are divided into classical algorithms and evolutionary algorithms in literature [4]. Ant colony algorithm is a component of artificial intelligence technology. It was first proposed by Italian scholar Dorigo in the 1990s, which was first successfully applied to solve the TSP problem [5]. Ant colony algorithm is an optimization algorithm with the advantages of self-organization and positive feedback, which has been successfully applied in many fields after a lot of studies by scholars However, ant colony algorithm also faces some challenges. An effective heuristic algorithm must reach a balance between the exploration of unexplored fields and the development of current obtained results. Improving pheromone update mode on the path is the way to achieve this balance.

2. Introduce of classical algorithm

Reference [5] proposed the concept of elite ant, which added the pheromone increment on the optimal path to improve the convergence rate on the basis of basic pheromone update. However, the increase of elite ants leads to a rapid increase of pheromones in the optimal path, which reduces the diversity of the population. On the base of the study of Dorigo.M, many researchers have done a lot of work.

2.1 Aselitist

In each iteration, the path taken by the globally optimal ant obtains additional pheromone updates, which is equivalent to several ants passing through this optimal path and releasing pheromone. This strengthens the influence of the global optimal ant on the subsequent ants, increases the selection probability of the following ants on the global optimal path and the path nearby, further develops the current optimal path, and improves the convergence speed of the algorithm. [5][6]

The pheromone requirements of the elite strategy ant system are calculated as Equation (1).

$$\tau(i,j) \leftarrow (1 - \rho)\tau(i,j)+\Delta\tau(i,j) + \Delta\tau(i,j)^{*} \tag{1}$$

In Equation (1), $\tau(i, j)$ means the number of pheromones in the path,ρ is a fixed parameter, $\Delta\tau(i, j)$ is the same as which in ACO, and $\Delta\tau(i, j)^*$ is the pheromone update increment of elite ants which is computed as Equation (2).

$$\Delta\tau\,(i,j)^{*} = \begin{cases} \sigma * \frac{Q}{L^{*}} \\ 0 \end{cases} \tag{2}$$

if (i, j) is the global optimal path else

In Equation (2), σ is the amount of elitist ants, L^* is the length of global optimal path.

Experimental results show that the ant algorithm based on elite strategy improves the convergence speed of the ant algorithm [5]. However, with the increase of pheromones in the corresponding pathways of elite ants, the diversity of subsequent ant solutions is reduced. Elite algorithm sacrifices the diversity of the algorithm to improve the convergence speed. Its potential defects are similar to the behavior of the optimal individual retained in the genetic algorithm, resulting in the precocity of the algorithm and a ·sharp increase in pheromones on a certain path, which seriously affects the diversity of subsequent ant solutions and makes the algorithm converge to a local optimal solution [7].

As a swarm intelligence evolutionary algorithm, the elite strategy improves the role of the optimal individual in the population, however, it ignores the intelligent behavior of the superior individual in each generation of ants and fails to reflect the characteristics of the population evolution.

2.2 Asrank

Considering the defects of the elite strategy, Bullnheimer Ƀ proposed Asrank the elite ant algorithm based on the ranking, which updates only a certain amount of pheromones in the optimal ant path. The pheromone updating strategy of the improved algorithm follows Equation (3).

$$\tau(i,j) \leftarrow \rho * \tau(i,j)+\Delta\tau(i,j) + \Delta\tau(i,j)^{*} \tag{3}$$

In Equation (3), $\tau(i, j)$ is the original pheromone on the path, ρ is fixed parameters,

$\Delta(i,j)^{\mu}$ is the pheromone increment on the path of the x optimal ant.

$$\Delta\,(i,j)^{\mu} = \begin{cases} (\sigma - \mu) * \frac{Q}{L_{\mu}} \\ 0 \end{cases} \tag{4}$$

if (i,j) is on the path of the μ and else.

In Equation (3), $\Delta\tau(i, j)^*$ is the increment of pheromone update on the global optimal path, is the part that retains the elite strategy, and is also calculated according to Equation (2).

Asrank not only increases the pheromone increment on the optimal path, but also increases the pheromone increment on the suboptimal path. Compared Aselitist, the Asrank improves the diversity of subsequent ant solutions because the guidance for the subsequent ants in the path transfer is not only from the globally optimal ants, but also from the first few superior ants in each iteration. In Asrank , premature convergence can be avoided by selecting some superior individuals [8].

2.3 ACS

In view of the defects of basic ant colony algorithm, ACS is a classical improved algorithm which mainly makes the following changes to state transition rules and pheromone update mode:

In the process of state transition, the pseudo-random probability is used to select the next position, that is, the ant at position "i" selects the next position according to the rules in Equation (5).

$$S=\begin{cases} arg\ max_{u\in j_k(r)}\{[\tau(i,j)]*[\sigma(i,j)]^{\beta}\}\ if\ q\leq q_0 \\ S\ \ else \end{cases} \tag{5}$$

Through the pseudo-random uncertainty, the deterministic relationship between the rules of path selection and pheromones in ACS is changed, and the diversity of solutions in the solution process of ants is increased.

ACS algorithm has two parts: global pheromone update and local pheromone update. The updating of local pheromone makes use of the path information of each generation of ants and improves the diversity of algorithm to some extent. However, the pheromone increment corresponding to the path is the same, and the increment of each generation is also the same. ACS algorithm does not take into account the information of different ants and cannot reflect the characteristics of population evolution.

Global pheromones in ACS follow the rules in Equation (6)

$$\tau(i,j) \leftarrow (1 - \alpha)\tau(i,j) + \alpha \,.\, \Delta\tau(i,j) \tag{6}$$

and

$$\Delta\tau(i,j) = \begin{cases} (L_{gb})^{-1}\ \text{if}(i,j)\ \text{belongs to global} \\ \qquad\qquad \text{optimal path} \\ \qquad\qquad 0 \quad \text{else} \end{cases}$$

What the global pheromone updates is that in the path of the global optimal solution in all current iterations. The enhancement of pheromone on the global optimal path guides the construction process of the following ant solution, so that the adjacent paths on the corresponding path of the current optimal solution are further developed and the convergence rate is increased [9].

3. Self-adaptive ant colony algorithm based on Statistical

In fact, the improved algorithms above all ignores the intelligent behavior of the whole colony of ants, or only use part of the information of ants, or do not consider the evolution of the colony in the iterative process. If ant colony algorithm an evolutionary algorithm use the information of each generation ant colony, the diversity of population can be improved. However, if all the information of all ants is directly used, the effect of the information of the optimal individual will be reduced correspondingly, and then the convergence rate of the algorithm will be reduced. In addition, the complexity of the algorithm will increase as the amount of information exchanged increases. Therefore, a method to utilize the group information without affecting other performance of the algorithm is proposed in this paper.

In statistics, the mean value can represent the relevant characteristic information of a population. In this paper, three characteristic parameters of each generation of ant colony are proposed by using statistical analysis method, that is, except for the optimal value, the mean value and the worst value of each generation of ant information are proposed to represent the information of a generation of ant, and then used in the information exchange of ant colony (pheromone update).

Based on ACS algorithm, elitist strategy and sorting strategy, an adaptive operator is proposed in this paper. Local pheromone updates as Equation (7).

$$\tau(i,j) \leftarrow (1 - \rho)\tau(i,j) + \Delta\tau(i,j) + P \cdot \Delta\tau(i,j) \tag{7}$$

In Equation (7), ρ is variable and Δτ(i, j) is calculated as Equation (8).

$$\Delta\tau(i,j) = \begin{cases} \sigma * (L_k^{-1} - L_{wor}^{-1}) \ if\ (i,j)\ belongs\ to \\ \qquad optimal\ path \\ \sigma * (L^{-1} - L_{ave}^{-1}) \quad else \end{cases} \tag{8}$$

In Equation (8),σ is the amount of the elitist ants, Lk is the shortest path length of optimal ant in every generation. L is the path length of the other optimal ants in each generation.

Lave is the average path length of every generation.

Global pheromone updates as Equation (9).

$$\tau(i,j) \leftarrow (1 - \rho)\tau(i,j) + \alpha \cdot \Delta\tau(i,j)^* \tag{9}$$

In Equation (9), α is variable, Δτ(i, j)* is the pheromone update amount in the path corresponding to the globally optimal ant.

$$(\Delta\tau(i,j)^* = (L_k)^{-1}) \ .$$

4. Experimental results and simulation

In order to verify the effectiveness of the improved algorithm in this paper, this section applies ASelitist, ASrank , ACS and

AS* to the simulation experiment of robot path planning of the grid method respectively.

Firstly, the algorithms above are applied to path planning in different obstacle environments. Parameter Settings in different algorithms are shown in Table 1.

Table 1. Parameter Settings

	Parameter settings in different algorithms			
	No.1	***No.2***	***N0.3***	***No.4***
Global pheromone	0.1a	0.1	0.1	0.08
Local pheromone	0.1	0.1	0.1	0.08
Heuristic factor	2	2	2	2
Pheromone factor	1	1	1	1
Amount of aunts	100	100	100	40
Amount of elitist aunts	5	5	5	5
Pheromone intensity	6	6	6	6
Maximum iterations	200	200	200	250

In Experiment No.1 to No.3, the obstacle is single. In Experiment No.4, the obstacles are multiple.

1) No.1 Experiment

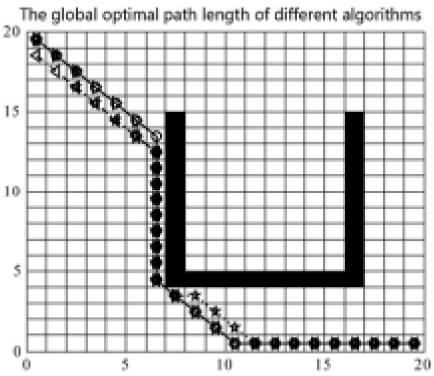

Fig. 1 The path of different algorithms in No.1 experiment

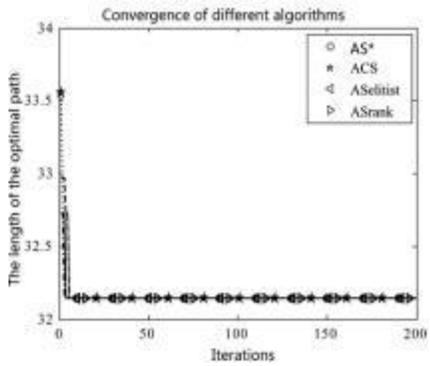

Fig 2 Convergence of different algorithms in No.2 experiment

Figure 1 and Figure 2 respectively show the path planning and iterative curves of the four algorithms with u-shaped obstacle environments. It can be seen that when the u-shaped obstacle is on the right of the map, the four algorithms all can quickly find the optimal path, and the algorithms are not much different.

2) No.2 Experiment

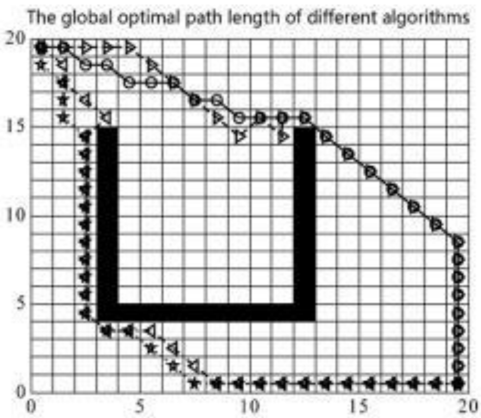

Fig. 3 The path of different algorithms in No.2 experiment

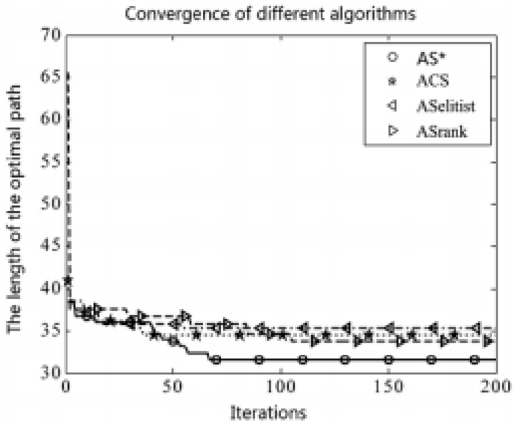

Fig. 4 Convergence of different algorithms in No.2 Experiment

When the ant passes through inside of the u-shaped obstacle which is in the left side of the map, the situation becomes different. ACS has the fastest convergence speed, however, AS * finds the optimal solution, and the corresponding convergence speed is not slow. Except AS *, othe algorithms have failed to find the optimal solution , as shown in Figure 3 and Figure 4.

3) No.3 Experiment

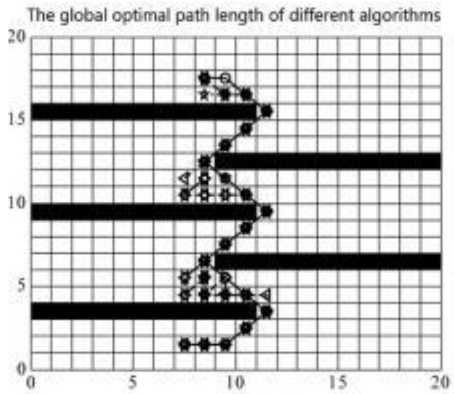

Fig. 5 The path of different algorithms in No.3 experiment

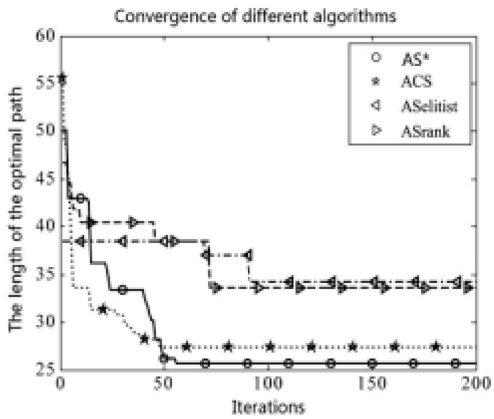

Fig. 6 Convergence of different algorithms in No.3 Experiment

From Figure 5 and Figure 6, ASelitist and ASrank are both failed to find the optimal solution, ACS finds the local optimal solution (nearly finds the global optimal solution) and AS * succeed in finding the global optimal solution. Moreover, the corresponding convergence speed of AS* is fastest.

4) No.4 Experiment

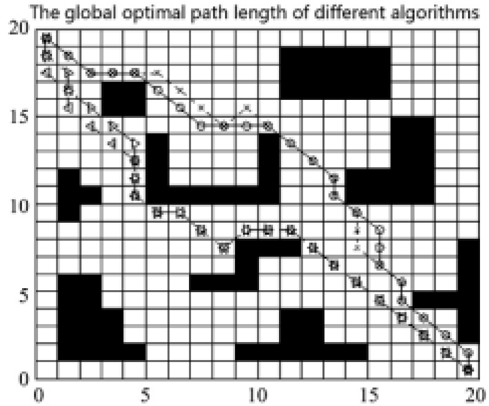

Fig. 7 The path of different algorithms in No.4 experiment

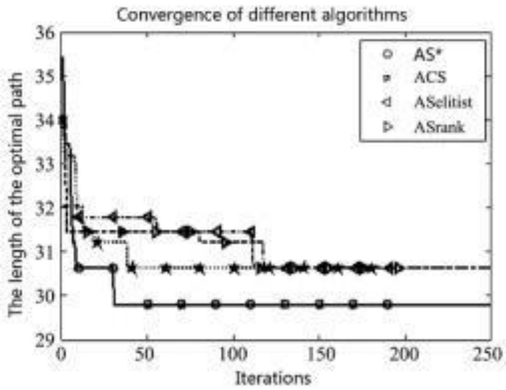

Fig. 8 Convergence of different algorithms in No.4 Experiment

The first three experiments compared the performance of AS *algorithm with that of the classical optimization algorithm under simple conditions, which proved the effectiveness of AS * algorithm. In order to further verify the stability of AS *algorithm, the results of each algorithms are statistically analyzed under complex obstacles. Each algorithm has the same parameters, and the maximum number of iterations turns to 250. The relevant parameters are shown in Table 1, and the statistical analysis results are shown in Table 2.

Table 2. The statistical analysis results

	Performance analysis of different algorithms			
	ACS	ASelitist	ASrank	AS *
Iterations	20	20	20	20
Shortest length in iterations	29.799	29.799	29.799	29.799
Average length of iterations	29.953	30.535	30.330	29.923
Longest length in iterations	31.213	31.213	31.213	31.213
• The number of shortest length occurs in iterations	17	2	7	17
• Mean number of convergence	34.400	125.550	136.600	38.250
• Variancce	0.381	0.295	0.422	0.296

a) The number of optimal solutions obtained by ASelitist and ASrank is relatively small. ASelitist strategy is stable, but it is easy to get into the local optimal solution , as shown in Figure 7.

b) ASrank strategy is better than the diversity of ASelitist, which is consistent with the theoretical analysis in part II. Experimental results of the algorithm also show that most iterations of the two algorithms fall into the local optimal solution as shown in Fig 8.

c) The results of ACS algorithm are also relatively good as the optimal solution can be obtained quickly and stably.

d) The variance of AS * is lower than that of ACS, indicating that AS* algorithm can converge more stably. The results of longest length in AS * is also better than that inACS.

It is known that the algorithm proposed in this paper(AS*) can get the optimal solution quickly and stably.

5. Conclusion

The positive feedback process of ant information in ant colony algorithm are analyzed in this paper. On the basis of the traditional ant colony algorithm only using the optimal or better ant information, an adaptive elite ant colony algorithm (AS*) which is based on statistical analysis proposed in this paper carries out statistical analysis on the overall information of each generation of ants. A S * algorithm extracts the information of not only the elite ants but also the average and worst ones, which make balance between the convergence rate of ant colony algorithm and the local optimal solution.

The algorithm is applied to the global path planning of the robot, and the simulation results prove that AS*algorithm can get the optimal solution with fast convergence speed in both simple and complex environments. In addition, AS * algorithm can adaptively adjust the update process of pheromone according to the overall information of each generation of ant colony, so that it can get a certain range of search solution space, moreover, in complex cases, the effect of this algorithm is more obvious.

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