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A new improved ant colony algorithm with levy mutation[1]

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Abstract. In this paper, an improved ant colony optimization (hereinafter referred to as ACO) with levy mutation is proposed, and levy mutation is introduced into basic ACO to address the shortcoming that basic ACO can easily fall into local optimum and stagnation. After all the ants have completed the primary optimization, all the solutions are conducted with levy mutation, increasing the diversity of the basic ACO population and enhancing the basic ACO's ability of escaping the local optimum, and thus more effectively improving the performance of basic ACO. Simulation of the test function shows the effectiveness of the improved ACO with levy mutation.

Key words. ACO, levy, mutation.

1. Introduction

ACO is a kind of random search method of seeking optimization. As a global optimization algorithm, it has been widely used in various fields [1]–[5] because of its good positive feedback mechanism and parallel computing power. But as scholars continue to study the algorithm in depth, basic ACO's falling into the local optimum, slow convergence and other deficiencies are gradually emerging. In view of these shortcomings, the scholars put forward different improvement strategies, including search strategy improvement [6], pheromone improvement [7] and combination of other intelligent algorithms [8–9].

Levy is in a "thick tail" distribution, therefore,it has a better disturbance ability, and higher possibility of jumping out of the excellent optimum. In this paper, an improved ACO with levy mutation is proposed, and levy mutation is introduced into basic ACO. After all the ants have completed the primary optimization, all

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the solutions are conducted with levy mutation to improve the performance of basic ACO. Simulation of the test function shows the effectiveness of the improved ACO with levy mutation.

2. Basic ACO

Basic ACO is a bionic random search algorithm proposed by M. Dorigo et al. [10] in the 1990s. Based on the analysis of the foraging behavior of ants in nature, with positive feedback, self-organization, parallel search, strong robustness and easy combination with other algorithms, the algorithm was used to find the optimal path [11]. When ants are looking for food, they will release a "pheromone" at any time on the path, and can sense the "pheromone" released by other ants. The more ants passing through a path, the higher concentration of the pheromone secreted by ants on the path. In a certain period of time, more ants going through a shorter path, and ants tend to move to the path with a higher pheromone concentration, and later the probability of the ants to choose the path is greater. Finally, ant colony will find a shortest path. ACO solves the combinational optimization problem by selection mechanism, updating mechanism and coordination mechanism.

2.1. Selection mechanism

Supposing there are n cities, m ants, $\tau_{ij}(t)$ is the pheromone concentration between point i and point j at the time t, the initial pheromone concentrations $\tau_{ij}(0)$ of paths are the same. The ants determine to access the node according to the pheromone concentration, and the probability of ant k moving from node j to node i is

$$P_{ij}^{k}=\begin{cases}\frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}}{\sum_{s\in \mathrm{allow}_k}[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}}, & s\in \mathrm{allow}_k\\ 0, \ \text{other}, & \end{cases} \tag{1}$$

where, α is the importance factor of pheromone reflecting the collaboration ability of ants, β is the importance factor of inspiration function reflecting the ants' degree of attention to the inspiration information. Symbol $\eta_{ij}(t)$ is the inspiration function, reflecting the expectation of ant moving from node i to node j, $\eta_{ij}(t) = 1/d_{ij}$, d_{ij} is the distance between the two nodes, allow_k is the collection of nodes to be accessed by ant k.

2.2. Updating mechanism

Due to the positive feedback effect of ACO, the pheromone concentration on the path needs to be updated in order to prevent the residual pheromone content on the path from being too high when all the ants have completed a cycle, the updating mechanism of the pheromone concentration

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

where

$$\Delta\tau_{ij} = \sum_{k=1}^{n} \Delta\tau_{ij}^{k} \,. \tag{3}$$

Ant cycle system model can be written in the form

$$\Delta\tau_{ij}^{k} = \begin{cases} Q/L_k \,, \\ \\ 0 \,, \end{cases} \tag{4}$$

where, ρ is the pheromone volatilization, $\rho \in (0, 1)$. Symbol $\Delta\tau_{ij}$ is the sum of the ants' pheromone concentrations between node i and node j, $\Delta\tau_{ij}^{k}$ is the pheromone concentration released by the kth ant in the path between node i and node j. Quantity Q is the total amount of pheromone released by the ant after one cycle, where the size of Q has an impact on the convergence rate of the algorithm. Finally, L_k is the length of the path went through by the kth ant.

3. Improved ACO with levy mutation

Basic ACO is characterized by positive feedback mechanism, parallel search, self-organization and strong robustness. Ant colony utilizes positive feedback mechanism to convey information through environment indirectly, and converges to the optimal value under the joint action of ants, but basic ACO prone to have stagnation and slow convergence rate, and easily falling into local optimum [12]. In order to overcome these shortcomings, levy mutation is introduced into the basic ACO and an improved ACO with levy mutation is proposed. The main idea of this improved algorithm is that when all the ants complete the primary optimization, all the solutions are conducted with levy mutation. The role of levy mutation is to increase the diversity of artificial fish and improve the ability of global search.

3.1. Levy mutation

For the traditional evolutionary algorithm, the initial population contains n individuals, each representing a set of real vectors $(\overrightarrow{x_i}, \overrightarrow{\sigma_i})$, $i = 1, 2, 3, \ldots n$. Here

$$\overrightarrow{x_i} = \{x_i(1), x_i(2), \ldots x_i(m) \,, \tag{5}$$

$$\overrightarrow{\sigma_i} = \{\sigma_i(1), \sigma_i(2), \ldots \sigma_i(m) \,. \tag{6}$$

Under the action of the mutation operator, the initial population generates a new individual $(\overrightarrow{x_i}', \overrightarrow{\sigma_i}')$ according to the following formula:

$$x_i'(j) = x_i(j) + \sigma_i^{'}(j)\delta_j(t) \,, \tag{7}$$

$$\sigma_i'(j) = \sigma_i(j) \exp\{(\tau' N(0,1) + \tau N_j(0,1)\}\,, \tag{8}$$

where $j = 1, 2..., m$, $N(0,1)$ is used to generate the Gaussian distribution random number of the individual and $N_j(0,1)$ is used to generate a new Gaussian distribution random number for each component. The parameters τ and τ' are defined as

$$\tau = \frac{1}{\sqrt{2\sqrt{n}}}\,, \tag{9}$$

$$\tau' = \frac{1}{\sqrt{2n}}\,. \tag{10}$$

In the above mutation operations, when different random numbers are selected by $\delta_j(t)$, different mutation operators are generated.

The levy mutation operator with levy distribution random number has a better mutation step length, and the perturbation effect is stronger. The levy mutation is introduced to improve the global optimization ability of the algorithm, and it is better for the algorithm to jump out of the local optimum solution and to maintain the diversity of the population.

When $\delta_j(t)$ is a levy distribution random number, formula (10) evolves into a levy speech operator, namely

$$x_i'(j) = x_i(j) + \sigma_i'(j) L_j(t)\,. \tag{11}$$

Here, $L_j(t)$ is a random number that obeys the levy distribution.

3.2. Improved algorithm flow

Step 1. Parameter initialization, including ACO parameters of α, β, ρ and Q and characteristic parameters of levy mutation.

Step 2. Let $N_c = 0$ (N_c being the number of iterations), m ants are randomly placed in n cities.

Step 3. Calculate the transition probability of ants based on formula (1), select and move to the next city j, and add j to $tabu_k$.

Step 4. If $tabu_k$ is full, go back to step 3, otherwise, continue step 4.

Step 5 Conduct global updates of pheromone by formulae (2)–(4).

Step 6 Conduct levy mutation for all solutions.

Step 7 Determine whether $N_c \leq N_{c\,max}$, if yes, repeat steps 3–6, otherwise, finish iteration and output the optimal solution.

4. Simulation experiment

In order to verify the effectiveness of the algorithm, the algorithm performance test was carried out by using three test sets of Oliver30, BAYA29 and DANTZIG42 in TSPLIB standard library [13]. Set the number of iterations $N_{c\,max} = 800$, pheromone importance factor $\alpha = 1$, inspiration function importance factor $\beta = 5$, pheromone global volatilization factor $\rho = 0.6$, pheromone release total $Q = 100$. Table 1 shows the optimal solution, the worst solution and the mean value obtained by the three test sets after 30 times of repeated experiments. Table 2 shows the success rate, mean convergence algebra and standard deviation obtained by the three test sets.

Table 1. The optimal solution, the worst solution and the mean value

	Best		Worst		Ave	
	ACO	Levy-ACO	ACO	Levy-ACO	ACO	Levy-ACO
Oliver30	429.50	424.60	436.50	425.60	433.96	424.96
BAYA29	9638	9192	9954	9253	9794.4	9205.3
DANTZIG42	692.8	985.2	704.8	690.7	696.72	687.45

Table 2. The success rate, mean convergence algebra and standard deviation

	Success rate		ACA		Standard deviation		Thres-hold
	ACO	Levy-ACO	ACO	Levy-ACO	ACO	Levy-ACO	
Oliver30	30%	100%	413.3	225.2	3.06	0.42	430
BAYA29	20%	100%	558.4	317.7	105.45	24.92	9700
DANTZIG42	50%	100%	413.5	284.2	3.86	2.06	695

Figures 1–3 show a comparison of the convergence curves between the improved algorithm and the basic ACO in the three test sets.

It can be seen from the above test that in terms of ability of seeking optimization, the optimal solution, the worst solution and the mean value of the improved ACO are better than that of the basic ACO. In terms of convergence rate, the average convergence algebra of the improved ACO is less than that of the basic ACO. In terms of stability, the standard deviation of the improved ACO is less than that of the basic ACO. It can be seen that the improved ACO with levy mutation is more effective than basic ACO.

5. Summary

In this paper, an improved ACO with levy mutation is proposed, and levy mutation is introduced into basic ACO to increase population diversity and to address the shortcoming that basic ACO can easily fall into local extremum. Experimental simulation shows that the improved algorithm is more effective than basic ACO in terms of searching ability, convergence rate and stability.

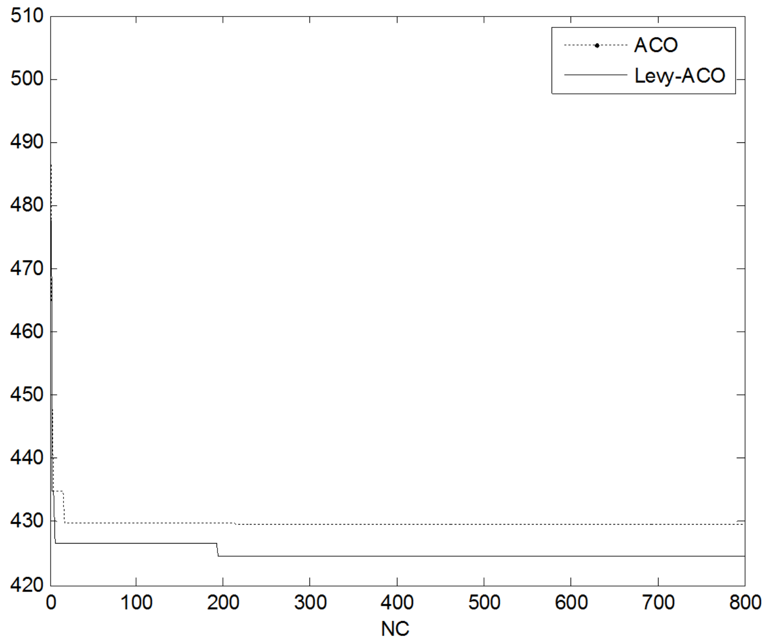

Fig. 1. Comparison of optimization curves (Oliver30)

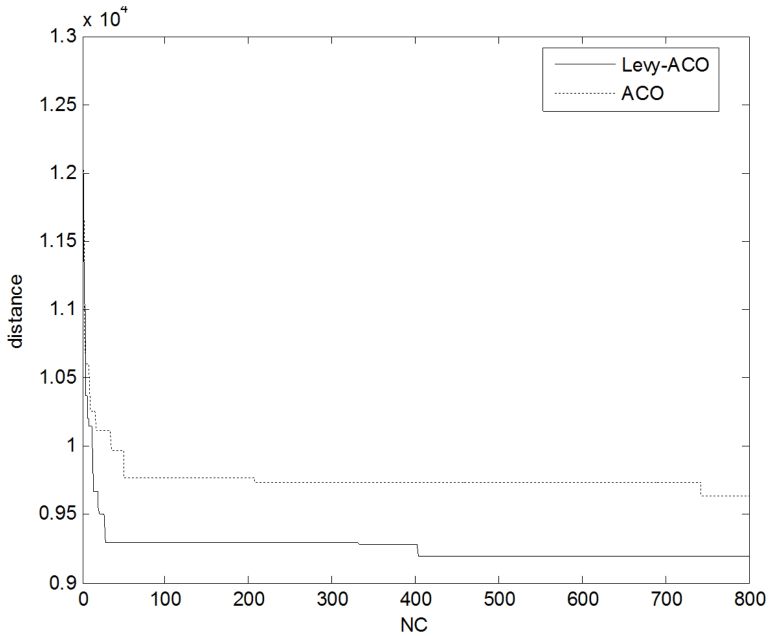

Fig. 2. Comparison of optimization curves (BAYA29)

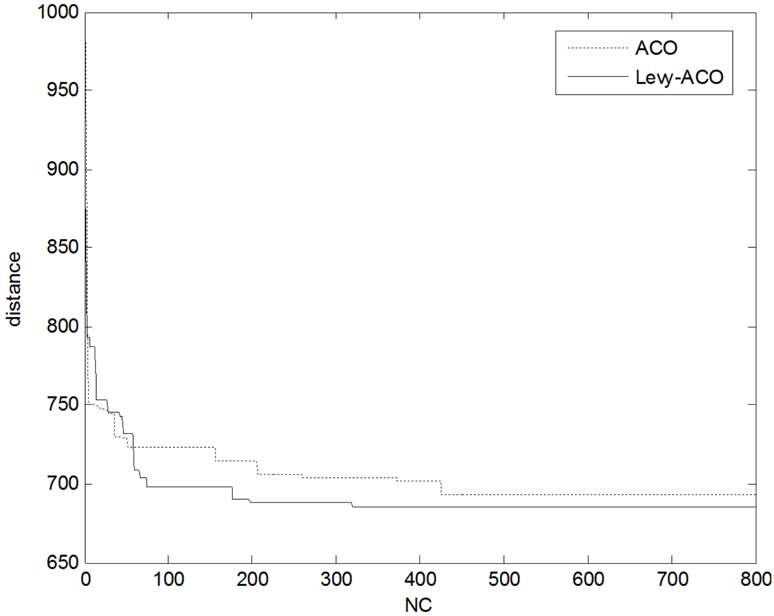

Fig. 3. Comparison of optimization curves (DANTZIG42)

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