THE IMPROVED ANT COLONY ALGORITHM BASED ON IMMUNITY SYSTEM GENETIC ALGORITHM AND APPLICATION

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Abstract

In this paper, aims at the weakness of ant colony algorithm that leads to converge rashly to the non-overall superior solution and its calculating time is long, when deals with resolving large optimization problem, a improved ant colony algorithm is presented. The algorithm combines the overall hunting ability with expansibility of the genetic algorithm and the character of immunity system in guiding partial hunting for particular problem. It is applied to the process of searching for the optimization in TSP, compares with the result of GA and ACA, the result of the new algorithm closes to superior solution much more, the validity of the algorithm is verified.

Keywords: *Ant Colony Algorithm (ACA); Genetic Algorithm (GA); Immunity System (IS); TSP.*

1. INTRODUCTION

Ant colony algorithm (ACA) is a strengthen type study system, has the distributive calculation characteristic, be easily inosculated with other algorithms. But at resolving large optimization problems, ACA exists contradiction between searching space and time, easily leads to convergent rashly in the non-overall superior solution and calculating solution needs long time At the same time, how to take the values of the four control parameters (α , β , ρ , q_0) that decide the function of ACA lacks theories support, the function is affected.

Aim at the weakness of the ant system (AS)[1], people pointed out much method to improve ACA [2]-[8]. In reference [3], the knowledge of the past backlog is used better by increasing the density of the pheromone in the superior path, so the constringency speed of the algorithm is expedited; In reference [4], the value of the pheromone is limited in [$\tau_{\min}$, $\tau_{\max}$], sinking into the local optimization is avoided in the largest degree; In reference [5], the pheromone needed to increase has amended according to the searching circumstance of algorithm, namely, it makes the algorithm jump out from the local optimization by using the function Q (t) to replace the constant Q; In reference [6], a kind of strategy that changed the evaporation coefficient self-adaptively avoid the algorithm sink into stagnation; In reference [7], the stagnation is avoided by importing the variation operator.

It is not difficulty to see by analyzing, the algorithm above is mainly improved the AS in three aspects: 1) The pheromone is limited in certain zone, in order to avoiding that the pheromone of some sides is zero; 2) Strengthen the exploitation toward the history knowledge; 3) The current hunting ability of ant colony is judged according to the internal estate or the qualitative analysis, thus the stagnation phenomenon is avoided by renewing the pheromone, changing the evaporation coefficient and the releasing pheromone quality Q.

In order to making up the shortage of the ACA, the algorithm named Immunity Genetic and Ant Colony Algorithm (IGACA) that is combined with GA, IS and MMAS is pointed out.

2. THE IGACA INTELLIGENT ALGORITHM

2.1 Basic Thought of the IGACA

Genetic algorithm is a colony iterating process in essence, it starts from a array of random initial colony, according to the competition principle of "excellent win inferior discard", the more excellent future generation is produced by the optimize process, such as choice, crossover and variation, repeat continuously, until the satisfied result is acquired. It has the fast global hunting ability and the latent parallelism. The calculating process is simply, the contradiction between exploiting optimum solution and searching hunt space is solved commendably. It is easily to expend and combine with other algorithm. But it did not make use of the feedback pheromone in system, usually leaded to useless iterate, the solving efficiency is low; although it guaranteed the evolution in colony, it couldn't avoid presenting the degeneracy phenomenon in certain degree. It is not valid in searching local space, multiplicity of the individual induced fast.

ACA converges the optimum solution by accumulating and renovating pheromone. It has the ability of distributing, paralleling and converging in global. But the shortage of the initial pheromone causes the speed slowly.

For overcoming the weakness of the two kinds of algorithm, and making them can take advantage of each others, the IGACA uses the characteristics of the immunity operator in local hunting, combines GA with it to raise the whole function of the algorithm, and repress the appearance of degeneracy phenomenon by using the characteristic pheromone selectively and purposively; at the same time, do some improvement in encoding, choices, crossover and variation. Produce the inceptive pheromone by using the random hunting and global converging in GA. Then, make full use of the parallelism, positive feedback mechanism, and the high efficiency of ACA. Thus, the coalesced algorithm is better than ACA in time efficiency, is better than GA in solving efficiency, becomes a heuristics algorithm that is better in time efficiency and solving efficiency. The flowchart of the algorithm is shown as Fig.1.

2.2 The Idiographic Design of the Algorithm

2.2.1 The Improved GA

1) Encoding

Binary encoding is fits for all kinds of evolutionary operation, but it isn't provided with regularity. Especially, it sometimes destroys the topology continuity in the space of the feasible solution. Two dots nearby in Ω, but their encoding can stand far away. For an instance, 0111(7) and 1000(8) is nearby, but the binary encoding distance in Hamming is farther most.

In order to overcome the weakness above, the gray encoding is pointed out. Suppose the binary encoding as: $A = a_L a_{L-1},..,a_2 a_1$, the modified code is $G = g_L g_{L-1},..,g_2 g_1$, make it keep the topology continuity in the original space. Consider A,G as L dimensions vectors, and consider to change G=TA or A=$T^T G$ in Hamming space H_L. The conversion formula from binary encoding to gray encoding is as follow:

$$\begin{cases} g_L = a_L \\ g_i = a_{i+1} \oplus a_i, \quad i = L-1, L-2, \cdots, 1 \end{cases}$$

The original binary encoding 0111(7), 1000(8) change into 0100(7), 1100(8). Obviously, gray encoding keeps the topology continuity in original space.

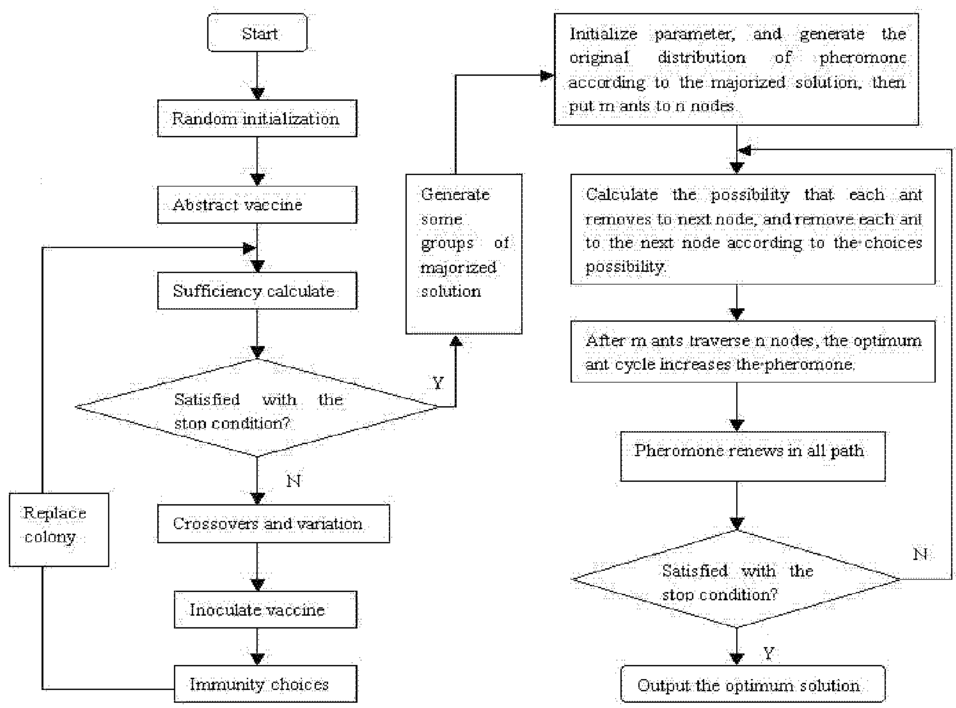

Fig. 1. The Flowchart of the IGACA Intelligent Algorithm

2) Choices

Use the Disruptive choices mode. Toward the given sufficiency measuring J, order

$$U(x_j) = \left| J(x_j) - \bar{J}(x) \right|,$$

Among them, $\bar{J}(x)$ indicates average sufficiency, $U(x_j)$ is the degree of equalizing deviation. Disruptive choices implement choosing based on the degree of deviation in colony, the probability that x_j is chosen is:

$$p\{Y_i = x_j\} = \frac{U(x_j)}{\sum_{k=1}^{N} x_k}, i = 1,2,\cdots N; j = 1,2,\cdots M .$$

From geometric significance, it means: the farther the distance from the individual to average sufficiency is, the higher the chosen opportunity is, show as Fig.2. Consequently, corresponding to the sufficiency of individual, it is not provided with monotony.

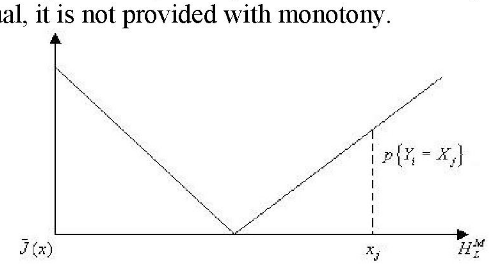

Fig. 2. The Sufficiency Abridged General View

3) Crossovers

If the simple method of one point or several points crossover is applied, non-feasible chromosomes will be produced necessarily with great probability. Therefore, the crossover method [9] that is similar with the partial crossover is adopted in this paper. The method is as follows:

(1) A mating area (between ||) is chosen at random in the array. For example, two father arrays and the mating area is chosen as:

A＝AB|CDEF|GHI

B＝IH|GFED|CBA

(2) Put the mating area of B in front of or behind A, the mating area of A in front of or behind B, the result will be:

A'＝GFED|ABCDEFGHI

B'＝CDEF|IHGFEDCBA

(3) Deleting the encoding of A' and B' in turn behind the self-mating area, which are same as the encodings in the mating area. The final two sub-arrays are:

A" ＝GFEDABCHI

B" ＝CDEFIHGBA

Compared with other methods, on the condition of the same two father categories, the effect of variation will be produced to some extent. It has some effects in maintaining the diversification within the populations. This effect is also indicated by experiment. The crossover ratio is usually 0.7~0.9.

4) Variations

Adopt the inconsistent variation [10], use average random hunting at the beginning stage (t is smaller), but use the local hunting at anaphase (t is near to in T).

5) Sufficiency function

The structure of the sufficiency function can instruct the searching direction of GA to closing to the optimized solutions, it can be expressed as:

$$Q(x) = \frac{1}{f_k(x) + p_k}, k = 1,2\cdots,n$$

Among them, $f_k(x)$ means the objective function that transforms from the multi-objective function.

a_0 is a biggest positive punishment coefficient.

2.2.2 Max-Min Ant System (MMAS)

In the mixture intelligent algorithm, use the MMAS algorithm [11]. It controls the action in searching way by restricting the pheromone on each link. Comparing with the ant algorithm (AA) and ant system (AS), it makes much progress in preventing stagnating early and the aspect of validity. Consider the connection between MMAS and GA, to the pheromone in initialization and renewal, do some disposal as follow.

1) The initialization of the pheromone

The MMAS is to assign the maximum value $\tau_{\max}$ to the initial value of the pheromone in each path, pass GA to get the certain path pheromone, so the initial value of the pheromone establishes for: $\tau_s = \tau_c + \tau_G$.

Among which, τ_G is the pheromone value that changes from the solution in GA; τ_c is a pheromone constant given by the scale of solution, corresponding to $\tau_{\min}$ in MMAS.

2) The model of pheromone renewal

Use the Ant Cycle model to renew pheromone, namely, only the ant on the shortest path can amend and increase pheromone, however, the trace of all the paths renews in the mode as follow:

$$\tau_{ij}(t+1) = \rho\tau_{ij}(t) + \sum \Delta\tau_{ij}^k(t)$$

Among which, $\tau_{ij}(t)$ is the pheromone trace intensity in path (i, j) at the time of t; $\Delta\tau_{ij}^k(t)$ is the quality of unit length trace pheromone left in path (i, j) by ant k; ρ is the perdurability of the trace, $0 \le \rho < 1, 1-\rho$ means the degree of attenuation in the trace.

2.2.3 The Immunity System (IS)

The immunity operator [12] is composes by inoculating vaccine and immunity choices. Vaccine is a kind of basal characteristic information extracted from the prior knowledge. Antibody is a kind of solution according to the characteristic information.

Make $a_{H,k}^{i}$ as the antibody that comes from the vaccine inoculating to the individual a_{k}^{i} of generation k ; P_I is the probability that the individual inoculates the vaccine; P_V is the probability of renewing vaccine; $V(a_k^i, h_j)$ is the operation of inoculating vaccine that amends the gene on individual a_{k}^{i} according to the mode h_j ; m and n are the scales of the colony and the vaccine respectively. So, i to solve some problems, the process that constructs and applies the immunity operator are shown as follows:

(1) Abstract vaccine:

(1.1) Analyze the problem, and collect the characteristic information.

(1.2) According to the characteristic information, estimate the mode on specific gene locus:

$H = \{h_j; j = 1,2,\cdots,m\}$.

(2) Make $k = 0, j = 0$;

(3) While (Condition=True)

(3.1) If $\{P_V\}$ =True, well then $j = j+1$;

(3.2) i =0;

(3.3) For ($i \le n$)

(3.3.1) Inoculate vaccine: $a_{H,k}^{i} = V_{\{P_I\}}\{a_k^i, h_j\}$;

(3.3.2) Immunity examination: If $a_{H,k}^{i} < a_{k-1}^{i}$, well then $a_k^i = a_{k-1}^i$; otherwise $a_k^i = a_{H,k}^i$;

(3.3.3) $i = i+1$;

(3.3.4) Annealing choices: $A_{k+1} = S(A_k)$, $k = k+1$.

Among which, the stop condition can use the maximal iterative times or the maximal times that the best sufficiency of the statistical individual is constant continuously.

3. EXAMPLE ANALYSIS

In Traveling Salesman Problem (TSP), a group of finite cities and the nonstop distance between them are given, searching for a closed itinerary in order to satisfy the condition that passing by each city only one time and the total distance is the shortest one. For an instance, Eil51 is the TSP in 51 cities, and KorA100 is the TSP in 100 cities. The coordinate position of city in each problem is fixed and different. TSP exists the theoretical optimum solution, but the effective method to get it isn't found in fact, only can approach toward the optimum solution gradually, namely, only can get the suboptimum solution that nears to the theoretical optimum solution most. TSP is the typical NP problem, and it becomes the reference problem in studying optimized algorithm, it is used for testing and comparing the performance of the algorithm [13][14]. The paper uses IGACA to solve TSP, and compares it with GA and ACA to test the performance.

In the paper, at first, realize the ACA, and operate it 10 times in the problems of Eil51 and Eil76, and operate it 5 times in KorA100, get the optimum value and the average value. The value of GA comes from literature [15]. The value of optimum path at present comes from literature [16]. The outcome is shown in Table1. In order to compare the value clearly, use the optimum path by now as reference, calculate the error percentage from the three kinds of algorithm, the result is shown in Table.2 and Fig3. In order to show the improvement in the calculation time of ACA, taking the problem of KerA100 as an example, the convergence curve of the optimum solution in each algorithm is compared, and the result is shown in Fig 4.

Table 1. The Contrast of Results

	ACA		GA		IGACA		Optimal
	Best	Avg.	Best	Avg.	Best	Avg.	
Eil51	427	439.3	428	441.2	427	431.6	426
Eil76	543	556.8	545	567.3	540	552.7	538
KroA100	21389	21980.4	21761	22097.8	21317	21735	21282

Table 2. The Contrast of Error Percentage (unit:%)

	ACA		GA		IGACA	
	Best	Avg.	Best	Avg.	Best	Avg.
Eil51	0.23	3.12	0.47	3.57	0.23	1.31
Eil76	0.93	3.49	1.30	5.45	0.37	2.73
KroA100	0.50	3.28	2.25	3.83	0.16	2.13

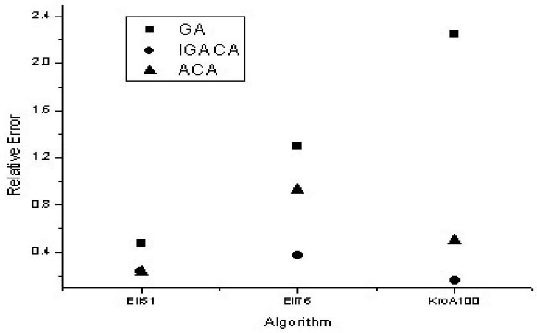

Fig. 3. The Relative Error of the Best Solution in Each Algorithm

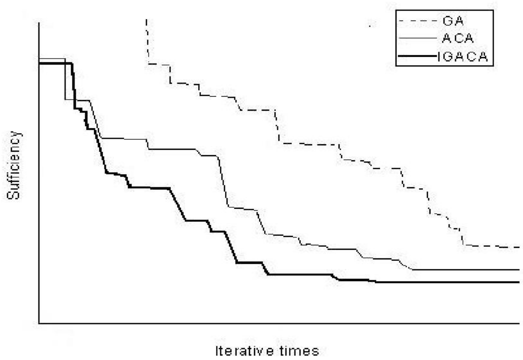

Fig. 4. The Convergence Curve of the Optimum Solution in Each Algorithm

It is not difficult to see from the two tables, the optimum values from ACA and IGACA are same in solving the common NP, but the average error percentage in IGACA is smaller than the other. When adding up the complexity of the problem, the superiority of IGACA is more outstanding. It more fits for solving the complex NP. The instance before verifies the efficiency of the improved algorithm, and equals to the expected result.

4. CONCLUSIONS

In the paper, present an improved ACA, connect it with GA and IS, and use MMAS to limit the pheromone for avoiding the ants traps into a local optimum solution too early. The new algorithm aims to find the balance point between searching the optimum solution and exploring the hunting space. The experiment to TSP indicates that the optimum quality and efficiency of the new algorithm both better than the traditional ACA and GA, near to the theoretical optimum solution more. The new algorithm also can extend to other NP solving process.

References

[1] Ellabib, Issmail; Basir, Otman; Calamai, Paul. "A multiple ant colony system with different communication strategies", WSEAS Transactions on Information Science and Applications, col. 2, no. 6, pp. 663-670, 2005.

[2] De Franca, Fabricio Olivetti; Von Zuben, Fernando J.; De Castro, Leandro Nunes. "MAX MIN Ant System and Capacitated p-Medians: Extensions and improved solutions. Informatica (Ljubljana)", Ant Colonies and Multi-Agent Systems, col. 29, no. 2, pp. 163-171, 2005.

[3] De Franca, Fabricio Olivetti; Von Zuben, Fernando J.; De Castro, Leandro Nunes, "MAX MIN Ant System and Capacitated p-Medians: Extensions and improved solutions. Informatica (Ljubljana)", Ant Colonies and Multi-Agent Systems, col.29, no.2, pp.163-171, 2005.

[4] Stfitzle T,Hoos H H, "Max-min ant system", Future Generation Computer Systems, col.16, no.8, pp.889-914, 2000.

[5] Qin G L,Yang J B, "An improved ant colony algorithm based on adaptively adjusting pheromone", Information and Control, col.31, no.3, pp.198-201, 2002.

[6] Wang Y, Xie J Y, " An adaptive ant colony optimization algorithm and Simulation" , Journal of System Simulation, col.14, no.1, pp.32-33, 2002.

[7] Wu Q H, Zhang J H, Xu X H, "An ant colony algorithm with mutation features" , Journal of Computer Research and Development, col.36, no.10, pp.1240-1245, 1999.

[8] Hu X B, Huang X K, "On hybrid behavior based ant colony algorithm", Control and Decision, col.20, no.1, pp.69-72, 2005.

[9] Yang Y, Xu Y H, Li Q M, Liu F Y, "A multi-object genetic algorithm of QoS routing", Journal of china institute of communication, col.25, no.1, pp.42-51, 2004.

[10] Lai H S, Dong P J, Zhu G R, "A multi-objective genetic algorithm for multi-objective programming problem", Systems engineering, col.21, no.5, pp.24-28, 2003.

[11] Li S Y, Ant colony algorithms with application, The publication of Ha ‘erbin industry university, 2004.

[12] Wang L, Optimization algorithms with application, Beijing: Tsinghua university, 2001.

[13] Hendtlass, Tim, “TSP optimisation using multi tour ants. Lecture Notes in Artificial Intelligence (Subseries of Lecture Notes in Computer Science)”, Innovations in Applied Artificial Intelligence, col.3029, pp.523-532, 2004.

[14] Ellabib, Issmail; Basir, Otman; Calamai, Paul, “A multiple ant colony system with different communication strategies” , WSEAS Transactions on Information Science and Applications, col.2, no.6, pp.663-670, 2005.

[15] Dorigo M, Gambardella L M, “Ant colony system: a cooperative learning approach to the traveling salesman problem”, IEEE Transactions on Evolutionary Computation, col.1, no.1, pp.53-66, 1997.

[16] TSPLIB[EB/OL]. http://www.Iwr.uni-heidelberg. De/groupsdcomopt/software/TSPLIB95/index.html, 2003.