QoS Multicast Routing Algorithm Based on Crowding Ant Colony Algorithm

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***Abstract*—The basic ant colony algorithm is easy to fall into local optimum and its convergent speed is slow for solving multiple QoS multicast routing problems. Therefore, a crowding ant colony algorithm is proposed in this paper to solve the problems. Crowded degree in artificial fish swarm algorithm is used to adjust nodes transition strategy dynamically according to the congestion of nodes. Stagnation behavior is judged by the similarity of multicast tree and chaos perturbation is utilized to update the pheromone trail on the multicast tree that may fall into local optimum in order that solutions can range out of local optimum. According to simulations, the global search is enhanced at the initial and convergence rate has improved greatly at the later. The improved algorithm is feasible and effective.**

***Index Terms*—ant colony algorithm; QoS multicast routing; crowding; similarity of multicast tree; chaos**

I. INTRODUCTION

With the rapid development of Internet, the network applications which demand point-to-multipoint such as IPTV[1], Audio and video conference[2], Video-on-demand[3], Multiplayer computer games[4], Computer supported cooperative work[5] etc appear constantly, and multicast is exactly a new and efficient transmission technology to satisfy this need of point-to-multipoint communication[6]. The so-called multicast, which is one of the key technologies in distributed multimedia applications, refers to a technology that sends the copies of source node data stream to a group of receivers through the network in multiplex way. Using multicast technology, source node just need to generate and send a data stream, and after the replication and forwarding by the router in multicast tree, it sends the data stream to a group of destination nodes. Compared with unicast, multicast can not only reduce the consumption of network resources greatly, but also relieve the burden of the source node. Where, as the key and core technology of multicast, the multicast routing has been researched deeply by many domestic and international research institutions and organizations.

In mathematics multicast routing problem with constraints can be considered as the Steiner tree problem. Some literatures have proved that it is a NP-complete problem[7-8], and it usually adopts heuristic algorithm, such as ant colony algorithm and genetic algorithm, etc. Literature [9] introduces the knowledge of fuzzy mathematics and microeconomics, a QoS multicast routing scheme supported by ABC is proposed, in which the users' flexible QoS requirements and the inaccuracy of link conditions are described by the intervals and member ship function of edge adaptability. With the edge bandwidth pricing, edge evaluation and multicast tree evaluation introduced and incorporates this idea into the ant algorithm, the scheme proposed seeks a all-win QoS multicast tree. Thus, it achieves good routing optimization effect. Literature [10] puts forward a parallel genetic algorithm based on cluster routers, which can make each slave router initialize population independently. So, this algorithm can reduce the frequency of communication between master and slave router, shorten the convergence time of the algorithm, and improve the optimization efficiency of the algorithm. In literature [11], the author improves the searching capability of the algorithm by imitating the effect which organism through competition to achieve of survival of the fittest in natural world, takes the QoS multicast routing nodes as plant joint, takes the cost of multicast tree routing as the stem that broke though the soil, and creates multicast trees through each joint of the growth mechanism of competition gradually. In literature [12], the author proposes a algorithm that based on ant colony genetic mixed algorithm for QoS multicast routing, which takes the ant colony algorithm and genetic algorithm as one part of each other, takes the process of travel path that acquired by ant colony algorithm as coding and selecting operation of genetic algorithm, takes genetic algorithm as moving path's adjustment or perturbation for ant colony algorithm after acquiring the ants' moving path and before renewing the pheromone, and the genetic algorithm crossover and mutation with a certain probability to obtain a better overall search results. In literature [13], the author improves the ant colony algorithm, he adopts quantum rotation to renew the pheromone, puts forward a kind of strategy of dynamic adjusting rotation angle, and has proved it in theory. The simulation results showed that the algorithm improved the solving precision and efficiency and the performance

Project numbers:Natural Science Foundation of Guangxi Province of China (No.2010GXNSFA013127) and Foundation of Guangxi Educational Department of China (No. 201010LX076) and Youth Foundation of Guagnxi University for Nationalities of China (No. 2011MDQN040).

doi:10.4304/jcp.8.10.2711-2718

was better than that based on ant colony algorithm and quantum evolutionary algorithm. The literature [14] proposes a algorithm based on multi-population genetic algorithm for QoS multicast routing, it adopts multigroup initialization algorithm during the initialization process, and designs a variety of groups of crossover and mutation, which ensures the independence among different population's evolution and the diversity of algorithm, and it also increases the coordinative mechanism among the different population as well as improves algorithm's global convergence.

The ant colony algorithm which has many features such as robustness, good parallelism and effectiveness etc[15], is an effective method to solve the NP-complete problems[16]. Many scholars use ant colony algorithm to solve the QoS multicast routing problem, and make some achievements. However, the ant colony algorithm generally has many shortcomings such as much time in searching, prematurity and stagnation in solving this problem, and when the problem's scale increases, this influence is more serious.

In order to solve the problems above, this article analyzes the characters of ant colony algorithm and artificial fish swarm algorithm, then fuses the two kinds of algorithms to propose a new kind of algorithm—QoS multicast routing algorithm based on crowding of ant colony algorithm. The new algorithm introduces crowed degree factor in node selection strategy of ant colony algorithm, and adjusts the node selection strategy dynamically. It increases the node selection randomness to expand global search in early stage of the algorithm, strengthens the positive feedback and embodied the certainty fully and accelerates the speed of the algorithm convergence in later stage. It could advance the search process and make the solution to jump out of local extreme value interval by adding the chaos perturbation in pheromone updating mechanism. Simulation experiments showed that the algorithm was effective for solving QoS multicast routing problem.

This paper organizes as follows. In Section Ⅱ, a formal definition of the muticast routing with multiple QoS constraints is introduced. The basic principle of ant colony algorithm is introduced in Section III. In Section Ⅳ, the principle of artificial fish swarm algorithm is introduced. An QoS multicast routing algorithm based on crowing ant colony algorithm is presented in Section V . Experiments are done in Section VI and some concluding remarks are given in Section VII.

II. QOS MUTICAST ROUTING PROBLEMS DESCRIOTION

When researching multicast routing, a network can be represented as an undirected weighted graph $G(V,E)$ [17-20], where $V=\{v_1,v_2...v_n\}$ is the set of all network nodes (includes switches, routers and hosts etc) in the graph and $E=\{e_1,e_2...e_m\}$ is the set of paths. Supposed that $s\in V$ is the source node, $M\in\{V-\{s\}\}$ is the group of destination nodes, R_+ is the set of positive real number, R^+ denotes the set of nonnegative real number. For each communication link e, it has four attributes: delay function $delay(e):E\rightarrow R_+$, bandwidth function $bandwidth(e):E\rightarrow R_+$, delay jitter function $delay\_jitter(e):E\rightarrow R^+$ and cost function $\cos t(e):E\rightarrow R_+$. For each node in network $n\in V$, it also has four attributes, namely delay function $delay(n):V\rightarrow R_+$, packet loss rate function $packet\_loss(n):V\rightarrow R^+$, delay jitter function $delay\_jitter(n):V\rightarrow R^+$, and cost function $\cos t(n):V\rightarrow R_+$. Then for the given source node $s\in V$, the group of destination nodes M, destination node $t\in M$, the multicast tree T(s, M) which is made up of s and M, there relations as followings:

$$delay(p(s,t)=\sum_{e\in p(s,t)}delay(e)+\sum_{n\in p(s,t)}delay(n) \quad (1)$$

$$bandwidth(p(s,t))=\min(bandwidth(e)) \quad (2)$$

$$delay\_jitter(p(s,t))=\sum_{e\in p(s,t)}delay\_jitter(e)+\sum_{n\in p(s,t)}delay\_jitter(n) \quad (3)$$

$$packet\_loss(p(s,t))=1-\prod_{n\in p(s,t)}(1-packet\_loss(n)) \quad (4)$$

$$\cos t(T(s,M))=\sum_{e\in T(s,M)}\cos t(e)+\sum_{n\in T(s,M)}\cos t(n) \quad (5)$$

Where, p(s, t) is the routing path from the source node s to the destination node t in multicast tree T(s, M).

The QoS multicast routing problem is exactly to find a multicast tree T(s, M) from the source node s to the group of destination nodes M in network model $G(V,E)$, which must simultaneously satisfy following conditions:

(1) Delay constraint:

$$delay(p(s,t))\le D \quad (6)$$

(2) Bandwidth constraint:

$$bandwidth(p(s,t))\ge B \quad (7)$$

(3) Delay jitter constraint:

$$delay\_jitter(p(s,t))\le DJ \quad (8)$$

(4) Packet loss constraint:

$$packet\_loss(p(s,t))\le PL \quad (9)$$

(5) Cost constraint: in all multicast trees that meet conditions of (1) - (4), $\cos t(T(s,M))$ is minimum.

Where, p(s, t) is the routing path from the source node s to the destination node t in multicast tree T(s, M),

B is the bandwidth constraint, D, DJ and PL represent delay constraint, delay jitter constraint and packet loss constraint of t respectively. In this model, we assume that the bandwidth constraints of all multicast end node are identical, while delay constraint, delay jitter constraint and packet loss constraint can differ from each other. Figure 1 shows a network structure model of 21 network nodes. In Figure 1 we use a 4-tuple (D, DJ, B, C) to describe the features of edges, where D, DJ, B and C represent delay constraint, delay jitter constraint bandwidth constraint and cost constraint respectively. The property of network nodes is described by the 4-tuple (D, DJ, PL, C), where PL represents packet loss constraint and the rest is like above.

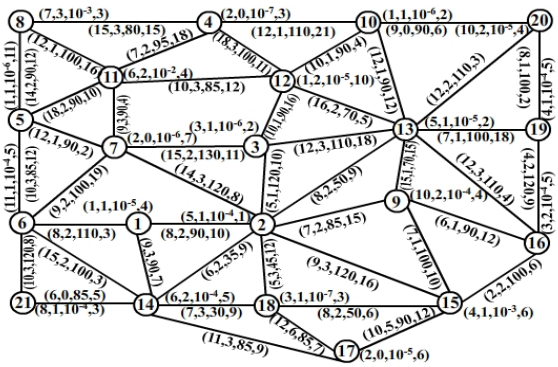


Figure 1. Network Model

III. THE BASIC PRINCIPLE OF ANT COLONY ALGORITHM

Ant colony algorithm[21-26] uses positive feedback of pheromones principle to search the best solution, at the beginning of each path has the same volume of pheromone concentration, as time goes on, the ants gradually leave more pheromones in the optimum path, while more pheromone attracts more ants, ants are more likely to choose this path in the next iteration. With the continuous cycle goes on, more and more ants select this path, eventually all ants choose this path. The core of ant colony algorithm lies in node selecting strategy and pheromone updating mechanism. We will use the following probability calculation formula to select the next node:

$$p_{ij}^{k}(t)=\begin{cases}\dfrac{\tau_{i,j}{}^{\alpha}(t)\eta_{i,j}{}^{\beta}(t)}{\sum\limits_{k\in allowed_k}(\tau_{i,j}{}^{\alpha}(t).\eta_{i,k}{}^{\beta}(t))} & if \quad j\in allowed_k \\ 0 & otherwise\end{cases} \tag{10}$$

See the formula above, $allowed_k=\{C-tabu_k\}$ means the next step which allows ant k to select the collection of cities. The two parameters α and β, which reflect the importance of accumulated information and heuristic information in path selection in ants' moving process respectively. After ants complete a cycle, residual pheromones are updated. At the moment of $t+n$, the paths will be renewed according to the following rules:

$$\tau_{ij}(t+n)=(1-\rho)\tau_{ij}(t)+\Delta\tau_{ij}(t) \tag{11}$$

$$\Delta\tau_{ij}(t)=\sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t) \tag{12}$$

In the above, $\rho(0\le\rho<1)$ is pheromone volatilization coefficient, $\Delta\tau_{ij}$ is the pheromone increment of path (i,j) in this cycle, $\Delta\tau_{ij}(t)=0$ is the initial time, and $\Delta\tau_{ij}^{k}(t)$ means the residual pheromone volume in the path (i,j) that the ant k leaves in this cycle, the calculate formula is described as follows (Ant-cycle model):

$$\Delta\tau^{k}{}_{ij}(t)=\begin{cases}Q/L_k & \text{theant k passes}(i,j)\text{ in thiscycle}\\ 0 & \text{otherwise}\end{cases} \tag{13}$$

Q is pheromone strength coefficient, L_k is the total length of the path which the ant k has walked.

IV. ARTIFICIAL FISH SWARM ALGORITHM

Artificial fish-swarm algorithm is a novel optimization algorithm proposed by Scholar Li Xiaolei[27-30] in China, it realizes the optimization goals by imitating the fish feeding, gathering cluster, running after other fish and acting randomly. The algorithm owns distributed parallel searching ability, insensitive to initial value, and it has a faster convergence speed. Meanwhile, the algorithm does not need the rigorous model of solving problems and has a good global search ability.

A. Some Definitions about Artificial Fish Swarm Algorithm model

Artificial fish individual state is $X=(x_1,x_2,...,x_n)$, $x_i(i=1,2,...,n)$ is optimize variables, $Y=f(X)$ indicates the fish food concentration of current location of artificial fish, Y is target function. Artificial fish individual distance among themselves could be defined as $d_{i,j}=\|X_i-X_j\|$, the artificial fish's vision field could be defined as $Visual$, $Step$ is moving step, and δ is crowed degree factor.

B. The Behavior Description of Artificial Fish Swarm Algorithm

(1) Foraging behavior: supposed that artificial fish's current state is X_i, we select a condition X_j randomly in its vision field sight, if the condition is better than the current state, take a step forward in the same direction; otherwise, select X_j randomly again to determine whether they meet forward conditions; after repeating Try_number times, if still not satisfied, then move step randomly.

(2) Swarming behavior: fish cluster naturally when moving to ensure their survival and avoid hazards. Artificial fish X_i searches the number of its partners and the center position X_c in its visual field, if $Y_c / nf > \delta Y_i$, it shows that the center position of partners has more food and less crowded, and then artificial fish X_i takes a step forward to the direction of partner center; otherwise executes foraging behavior.

(3) Following behavior: while the food is found by one or several fish, the neighboring partners will follow them arrive rapidly where foods exist. Artificial fish X_i explores the partner in the current field $d_{i,j} < Visual$, and find out X_j who owns the maximum function value Y_j, if $Y_j / nf > \delta Y_i$, it shows that partner X_j has higher food concentration and less crowded surrounding, then takes a step forward to X_j, otherwise executes foraging behavior.

(4) Random behavior: the current state of artificial fish is X_i, select a state X_j randomly in its horizon.

(5) Moving strategy: by imitating the behavior of artificial fish's cluster and rear-end, we could choose a higher food concentration value to execute, and the default behavior is foraging behavior. We could also perform the rear-end behavior, if no progress, then perform the swarming behavior, and if there is still no progress, execute the random behavior.

(6) Bulletin board: it is used to record the optimal artificial fish individual state. When each artificial fish finished its action, its current state will be compared with bulletin board state, if its state is better than bulletin board's state, we will use its state to renew the bulletin board's state. Otherwise, bulletin board state will not be changed. By this, the bulletin board could record optimal history state.

C. Artificial Fish Swarm Algorithm Behavior Choice

According to the character of problems that we will solve, each artificial fish will do some environmental evaluation, then choose an appropriate action to perform. Such as seeking the maximum value, the simplest way is that, firstly, imitate execution behavior of cluster and rear-end, and then evaluate the acted value, choose one of the maximum value to execute actually, the default behavior is foraging behavior. Finally, a lot of artificial fish gather in several local maxima, and it is helpful to acquire the global optimum extremum region, and the better value in optimum extremum region will be surrounded with artificial fish, which helps to obtain the global extreme value, consequently, we achieve the purpose of searching optima.

V. QOS MULTICAST ROUTING ALGORITHM BASED ON CROWING ANT COLONY ALGORITHM

Both ant colony algorithm and artificial fish swarm algorithm are swarm intelligent optimization algorithm, and the individual of the algorithm does not exist intelligent behavior, but the whole group show strong intelligent behavior. When solving the QoS multicast routing problems, for the reasons of positive feedback mechanism of ant colony algorithm more pheromone will be left on a relatively optimal path. From Eq. (10) and Eq. (11), we know that the more pheromone, the ants will be more possible to select this path in next iteration. Loop continuously, then more and more ants will choose this path, and finally all the ants choose this path. However, once the path selected by the ants is not the global optimal path but only a local optimal path, the whole ant colony will fall into a local optimum, and the algorithm will appear prematurity and stagnation phenomenon. The reason for above-mentioned situation is that the ant colony chooses the path with a higher fitness value by the positive feedback mechanism in the prophase of the exploration, and the pheromone concentration of this path has been strengthened. However, the path which is actually a better path is gradually "forgotten" due to the fewer ants on it in the initial phase. Consequently, the global search ability of ACO is weakened.

A. Crowded Degree Factor δ Approach to Solving the Problem

In the artificial fish swarm algorithm, the existence of crowded degree factor δ can largely avoid falling into the local optimum because of the excessive gather of the fish. This is because of the artificial fish swimming direction depends not only on the current state of optimal value, but also noticing the optimum location of the degree of congestion. If the position is too crowded, even if the area has a superior function value, the artificial fish may also not move to it. Crowded degree factor always plays a role in the whole optimization process of fish swarm algorithm, and the introduction of it effectively avoid the fish centralize excessively in the prophase of the algorithm, prevent premature, stagnation phenomenon, and improve the algorithm's global search ability at the early stage. But on the other hand, in the anaphase of the algorithm for the existence of crowded degree factor δ, artificial fish will repel from each other and the algorithm convergence speed and convergence performance are affected to certain extent, then the fish can't gather around optimal value completely.

Therefore, we can consider that the crowded degree factor δ of the artificial fish algorithm could be introduced in the prophase of ant colony algorithm to improve the global search ability. In the anaphase of algorithm, try to reduce the influence of crowded degree factor and use ant colony historical experience information sufficiently, which can make the search limit in those search interval with high fitness value, and improve the convergence rate of the algorithm.

B. A Node Selection Strategy Embedded With Iterative Operator

Based on the thought above, we can introduce crowded degree factor δ when the ant chooses the next node. The crowded degree of a node can be defined as:

$$\delta = \frac{d}{N_c \cdot m \cdot P} \tag{14}$$

Where, d is the total number of the ants which have passed this node from the first round iteration, N_c is the current iteration times, m is the quantity of the ants, P is the number of the multicast destination node. Easy to see, $0 \le \delta \le 1$, if a node is never passed by the ants, then its crowded degree is 0, and if a node is passed by all the ants, then its crowed degree is 1. Accordingly, this paper has improved node selection formula (1), and the improved node selection formula is:

$$p_{ij}^k(t) = \begin{cases} \dfrac{\tau_{i,j}{}^{\alpha}(t).\eta_{i,j}{}^{\beta}(t).\mu_{i,j}(t)}{\sum_{k \in allowed_k}(\tau_{i,j}{}^{\alpha}(t).\eta_{i,k}{}^{\beta}(t).\mu_{i,j}(t))} & if \ \ j \in allowed_k, \text{且} q > q_0(l); \\ \arg\max\{\tau_{i,j}{}^{\alpha}(t)\eta_{i,j}{}^{\beta}(t)\} & otherwise \end{cases} \tag{15}$$

$$\mu_{i,j}(t) = 1/(1 + \phi \cdot \delta \cdot e^{N_c / Num}) \tag{16}$$

$$q_0(l) = 1 + \frac{1}{2}(e^{N_c / Num} - e) \tag{17}$$

Where, q is a random number in [0, 1], ϕ is the control parameters of crowded degree, Num is maximum iterations. We can see that, when the number of ants that passed a node grows continuously, its crowded degree factor δ also grows continuously, the value of $\mu_{i,j}(t)$ calculated from Eq. (15) reduces continuously. So, when choose next node, it can inhibit the premature convergence due to excessive proliferation, which helps to expand global search. In order to reflect the regulation function crowded degree factor δ in the prophase of the algorithm, to reduce the influence of crowded degree factor in the anaphase and to improve the convergence rate of the algorithm, this paper introduces Eq. (17). It's easy to see, $q_0(l)$ is an increasing function in (0, 1]. So $q_0(l)$ is smaller in the initial stage of the algorithm, and q is bigger than $q_0(l)$ with greater probability. So, $p_{ij}^k(t)$ is equal to the upper part of Eq. (15) with greater probability as well, which is exactly to calculate the pheromone on the path, weighted value of visibility and crowded influence factor $\mu_{i,j}(t)$. Then we select the path according to the probability, and this mechanism conducive to reflect the randomness sufficiently and expand the algorithm's global search. At the anaphase of the iteration, $q_0(l)$ is bigger, q is smaller than $q_0(l)$ with greater probability, and $p_{ij}^k(t)$ is equal to the lower part of type (15) with greater probability as well. This demonstrates that to select the path that has the maximum pheromone and weighted size of visibility, which reflects the certainty (randomness weaken), and speeds up the convergence rate.

C. Pheromone Update Mechanism Joined With Chaos Disturbance

When solving the QoS multicast routing problem, ants start from the same source node to find more destination nodes. Thus it is easier to fall into local optimum than solving TSP problem. In order to solve this problem, we add the chaos disturbance quantity when adjust pheromone in this paper, so that the solution can jump out of local optimum interval.

Chaos exists widely in the nature[31-34], and it has many features such as "randomness", "ergodicity" and "regularity" etc. It seems chaotic but has a delicate internal structure, and is extremely sensitive to the initial condition. It also can repeatedly traverse all the states in a certain range according to its own rule, so we can use these properties of chaotic motion to optimize the search. Logistic mapping is a typical chaotic system[35-36], and its iterative formula is defined as follows:

$$z_{i+1} = \mu \cdot z_i \cdot (1 - z_i), i = 0,1 \cdots, \mu \in (2,4] \tag{18}$$

Where μ is the control parameter, and when μ =4, $0 \le z_0 \le 1$ Logistic is completely in a chaotic state.

Premature convergence judgment is the basis of prematurity treatment. The experimental results show that when the ant colony algorithm appears premature convergence, local optimum paths it finds are always same or similar[37]. Therefore, the "similar" degree of each path can be used as an important basis for judgment of the premature convergence. Considering that this paper is to solve the QoS multicast routing problem, and its optimal solution is a multicast tree, so the similarity of the n time iterative optimal multicast tree can be calculated as follows:

$$S_n = \frac{1}{p} E(Tree_n, Tree_{n-1}) \tag{19}$$

Where, p is the total number of the nodes in network model, $E(Tree_n, Tree_{n-1})$ is the number of public edges in the optimal multicast tree of n iteration and n-1 iteration. According to the nature of the tree, it is not difficult to see that $0 \le S_n \le 1$, and the higher similarity of the two trees, the bigger S_n is.

If the value of objective function does not change optimal in the given C iteration, and S_n has increasing tendency, we can consider that algorithm has gotten into local optimum, and global pheromone update formula (11) of the algorithm is adjusted as follows:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij} + \xi z_{ij} \tag{20}$$

Where, z_{ij} is the chaotic perturbation variable in [0, 1], by Eq. (18) ξ is disturbance factor.

D. Describing Of Algorithm Step

Step1: Assuming that the source node of requesting multicast routing is s, assemblage of destination nodes is M, we set up the network of each edge weights (d, dj, b, c) and each node weights (d, dj, pl, c), and determine the value of constraint conditions D,DJ,B and PL. Delete the links which are not satisfied with bandwidth constraint, then we will get a new network topology.

Step2: Assuming that the population of ants is m, the largest number of iterations is Num, the parameter values of α, β, Q, τ_0, ρ, ρ_0, μ, z_0, ξ, ϕ and C are determined.

Step3: The number of iterations $l = l + 1$, each link of pheromone increment $\Delta\tau_{ij} = 0$, in source node, generate m ants, each ant's tabu list $tabu_k$ is generated, and put the source node into the tabu list, $t = 0$.

Step4: $t = \mathrm{t} + 1$, i=1, set the current destination node M_i. According to Eq. (15), each ant k that doesn't finish searching, should determine the next node, and judge links and nodes whether it satisfied with the constraint from s to N_j, details are as follows:

(1) if $N_j \in \phi$, then the ant die;

(2) if $N_j \notin \phi$ and $N_j = M_i$, then the search is completed;

(3) if $N_j \notin \phi$ and $N_j \neq M_i$, then continue to search.

Step5: Repeat Step4, record qualified path from the source node s to the destination node M_i and join them into the multicast tree T(s, M) until all m ants have completed searching.

Step6: i=i+1, we continue to search on the basis of Step4 and Step5 methods, find out qualified paths from the source node s to other destination nodes, and join them to the multicast tree T(s, M).

Step7: After m ants performed a path search on all destination nodes, generate a multicast tree T(s, M) which meets the constraints.

Step8: Compare the optimal multicast tree that acquired by current iterating with global optimal multicast tree, and take the better one as the global optimal multicast tree.

Step9: Update all qualified multicast tree pheromone according to Eq. (11).

Step10: Make a similarity comparison to optimal multicast tree which acquired by C times iteration according to methods mentioned above. If the iterative optimal multicast tree's similarity has a growing trend, and within C times iteration, the objective function value does not get better, then change the pheromone renew rule into Eq. (20).

Step11: If $l < \mathrm{Num}$, execute Step3 or Step12, otherwise execute Step 12.

Step12: Output optimal multicast tree T_{best}, and the algorithm ends.

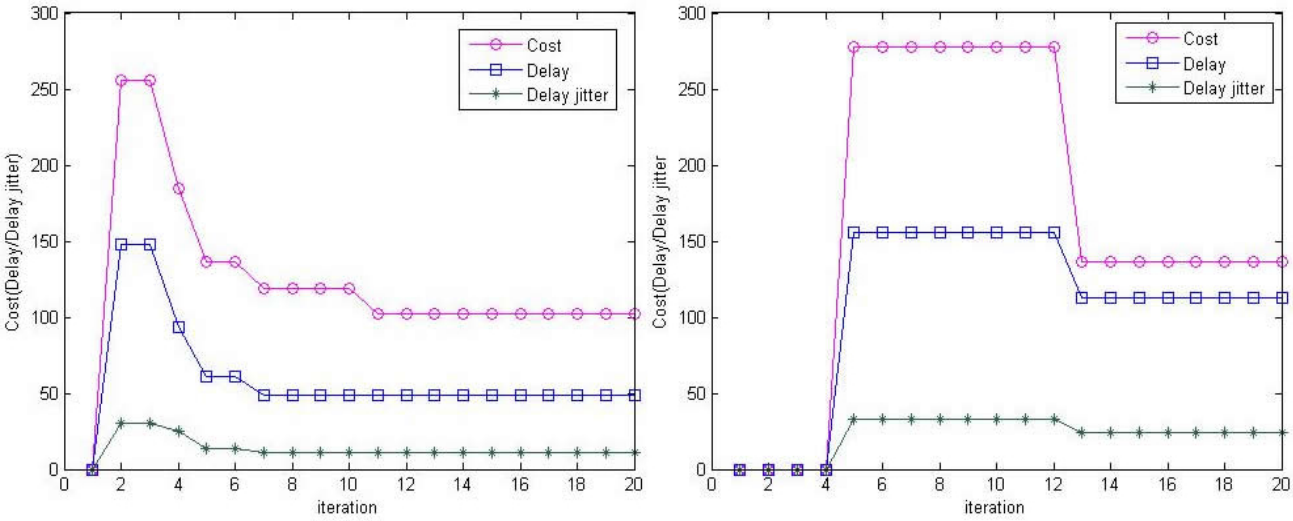
VI. SIMULATION

The network model shown in Figure 1 is simulated by Matlab, the attribute of each node in the network can be described by 4-tuple (delay, delay jitter, packet loss rate and cost), and the attribute of each edge is also described by a 4-tuple (delay, delay jitter, bandwidth and cost).

Supposed that existing business routing request, source node $s = 1$, destination node set M = {5, 9, 17, 20}, delay constraint D=300, delay jitter constraint DJ=80, bandwidth constraint B=20, packet loss rate PL=0.005, parameters selected are: $\alpha = 1$, $\beta = 2$, $Q = 2$, z_0 is a random number in (0, 1), $\mu = 3.8$, initialize pheromone of each edge to 1, initial volatile coefficient $\rho = 0.1$, $\rho_0 = 0.3$, chaos disturbance factor ξ=1.06, the population size of ants at the source node is $m = 10$, maximum iterations is Num=20, convergence judgment algebra is C=Num/5, crowded degree control parameters ϕ=0.6.

Figure 2 is the evolutionary curve of cost, delay and delay jitter for ACO and the improved ACO(IACO) to search the optimal multicast tree in 20 iterations, where (Y-axis is cost, delay and delay jitter, the unit of delay is second, X-axis is iteration, the unit is time). Table 1 is the comparison of experimental results that using IACO and basic ACO to solve the QoS multicast routing problem.

In the multicast tree, delay jitter is the maximum of all the delay jitters of every path of the multicast tree, and so does the delay[38]. From Figure 2 and Table 1, we can see that in IACO there are some fluctuations of the cost, delay and delay jitter in the earlier stage of evolutionary curve, which demonstrates that the global search ability of IACO has been enhanced. Comparing the results of two algorithms, we can see that for the same network model, and the same QoS multicast routing constraints condition is satisfied, the IACO expends no more than 11 iterations to find the optimal solution. However, the basic ACO needs no more than 13 iterations to find the optimal solution and its optimal solution is a local optimum. The simulation results show that IACO have preferable global search ability and can effectively jump out of the local optimum, consequently, the IACO can converge to the global optimal solution quickly. Therefore, the IACO is feasible and effective.



IACO ACO

Figure 2 Convergence curve of two algorithms

TABLE I.

COMPARISON OF EXPERIMENTAL RESULTS

Algorithm	Optimal multicast tree	Delay	Delay jitter	Loss rate	Cost	Iteration
IACO	(1,2), (2,7), (5,7) (2,9),(2,13),(1,14) (14,17) ,(13,20)	49	11	0.0003	102	11
ACO	(1,2),(2,7),(3,7),(5,7) (3,13),(9,13),(9,15) (15,17),(13,20)	113	24	0.0012	136	13

VII. CONCLUSION

This paper analyzes the insufficient of ant colony algorithm in solving QoS multicast routing problem, we blend artificial fish swarm algorithm crowed degree factor in node selection strategy of ant colony algorithm to reduce the positive feedback and increase the node selection randomness, and expand global search in early stage of the algorithm; the positive feedback is strengthened and the speed of the algorithm convergence is accelerated in later stage. We could make premature convergence judgment according to the multicast tree similarity and make the solution to jump out of local extreme value interval by adding the chaos perturbation in pheromone updating mechanism. The simulation results show that this algorithm is feasible and effective.

ACKNOWLEDGMENT

This work is supported by the Application Research Program (Natural Science Foundation) of Guangxi Province of China (No. 2010GXNSFA013127) , and the Research Program (Foundation) of Guagnxi Education Department of China (No. 201010LX076), and the Application Research Program (Youth Foundation) of Guagnxi University for Nationalities of China (No. 2011MDQN040).

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