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A Routing Algorithm for Risk-Scanning Agents Using Ant Colony Algorithm in P2P Network

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Abstract: This paper describes a routing algorithm for risk-scanning agents using ant colony algorithm in P2P (peer-to peer) network. Every peer in the P2P network is capable of updating its routing table in a real-time way, which enables agents to dynamically and automatically select, according to current traffic condition of the network, the global optimal traversal path. An adjusting mechanism is given to adjust the routing table when peers join or leave. By means of exchanging pheromone intensity of part of paths, the algorithm provides agents with more choices as to which one to move and avoids prematurely reaching local optimal path. And parameters of the algorithm are determined by lots of simulation testing. And we also compare with other routing algorithms in unstructured P2P network in the end.

Key words: risk; ant colony algorithm; P2P

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0 Introduction

Various risks exist in the P2P network, such as firewall and gateway weaknesses, which challenges P2P applications for the sake of security. In order to avoid disastrous damage caused by the security issues, we need to formulate a mechanism for evaluating the risk in the P2P systems. However, due to the complication and the immensity of the P2P network architecture, many problems exist as follows when performing the risk evaluation:

① Vulnerability and weakness exist at every host on the network, which may be utilized by the intruders. This kind of intrusion may not be detected by the single host risk scanning systems.

② The data needed by the risk scanning system is dispersed around the network, which leads to the difficulties of collecting source data.

All these issues pose new requirements to the risk evaluation system in P2P network. These distributed risk evaluation systems not only collect information about the distributed collaborating intrusion but also have to process big amount of real-time data. In this case, an effective solution is to build up an active P2P network based on the multi-agents.

P2P systems have become an area of active research and development since the popularity of online file-sharing service as Gnutella[1] and Napster[2]. Security and performance[3] are the major issues in P2P systems for trusted and authenticated resource sharing and real-time communication among a large number of peers. P2P system such as Pastry[4] and Chord[5] propose a scalable, distributed object location and routing algorithm for wide-area peer to peer applications and proactively move the data to reduce the distance traveled by messages in the network. Wang Dan *et al*[6] have used parameters such as interests and local knowledge to improve the over all performance of P2P network. However, the systems mentioned above are mainly concerned with developing an infrastructure based on message communication between different peers. The Anthill framework[7] uses agent technology to support the development of the P2P systems. Mobile agents or ants move across the nodes in P2P network to accomplish distributed tasks. Anthill use mobile agent mainly to discover and download resources. Currently, there are several different architectures for P2P networks: Centralized, Decentralized but Structured and Decentralized and Unstructured. For searching and scanning nodes in P2P network, there are several methods, and they are mostly for file searching. However, few people has mentioned the agent routing algorithm, in this paper, we focus on the agent routing algorithm in the unstructured network.

1 Framework of P2P Risk Assessment

Risk scanning for P2P network uses the manger-agent architecture, which divides all the nodes in the network into three categories: risk evaluating servers, weakness scanning consoles and normal peers.

Risk evaluating servers communicate with all the risk evaluating agents residing on different nodes. A risk evaluating agent is capable of managing some weakness scanning devices. Precisely, risk evaluating agents directly manage weakness scanning consoles, which in turn manage one or more scanning devices. After scanning devices finishing its work, weakness scanning consoles directly report to the risk evaluating agents. Then the risk evaluating servers collect all the risk scanning agents' data and create the risk report and take necessary measures to manage the risks. Fig. 1 depicts all the above-mentioned process.

From Fig. 1, we see that as a whole the system have two different agents: risk evaluating agent and weakness scanning agent, whose definitions is as follows:

Risk evaluating agent Risk evaluating agent is static agent, runs at some risk managing node in the P2P network and control one or more weakness scanning consoles in the network. Risk evaluating agent is created by the **weakness scanning console.**

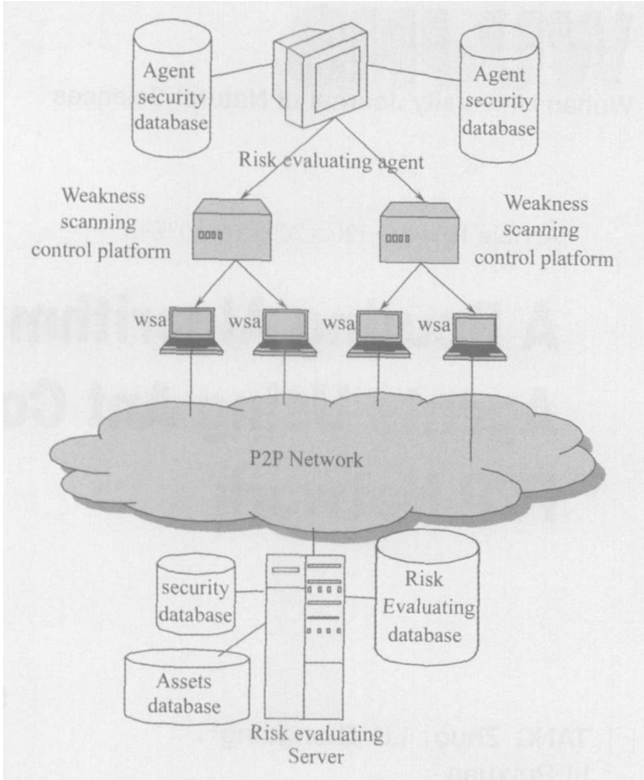

Fig. 1 Framework of P2P Risk Assessment

Weakness scanning agent Weakness scanning agent is intelligent mobile agent (which is called wsa for short), capable of traveling through the autonomous domain and, according to the local agent security information, creating the scanning policy taken back to the weakness scanning console. This paper's main contribution is proposing an agent routing algorithm in P2P network using ant colony algorithm.

2 Ant Colony Algorithm of Risk Scanning Agent

2.1 Basic Principles of Ant Colony Algorithm

Ant colony algorithm is a kind of simulated evolution algorithm based on the research on the ant colony's behaviors in the nature[8,9]. Although single ant's behavior may be too simple, but colony of these simple ants may behave in a complex way and complete intricate tasks. Moreover, ants may responds to the change of environment. For example, when encountering an obstacle in their route, ants can find optimal detour route quickly. People find that ant communicates with each other through so-called pheromone matter to collaborate to cover tasks.

2.2 Ant Colony Algorithm in P2P Network

In this section, we discuss the route algorithm of risk scanning agent in the P2P network using above-mentioned ant colony algorithm. By simulating ants' routing mechanism, at every node in the P2P network, we create a probability-based distributed route table, in which the probabilities of next hop of every possible destination node are recorded. The probability value is equivalent to the pheromone intensity of ants. Every node in the P2P network dispatches an agent (ant) periodically to collect the information of link states and nodes. The target node of detecting ant is selected randomly. When reaching a node, detecting ant will update the pheromone probability of the record whose target node is the source node of the detecting ant in order to increase the probability of selecting the previous node and decrease that of other nodes. Pheromone table is initialized to have an equal probability values for selecting every neighbor nodes, and ants goes ahead by randomly selecting a route according to the pheromone table.

Let m be the amount of the risk scanning agents in the whole system, d_{ij} the distance between node i and j and $b_i(t)$ the amount of risk scanning agents at node i at instant t, then

$$m = \sum_{i=1}^{n} b_i(t) \tag{1}$$

Let $\tau_{ij}(t)$ be amount of pheromone between node i and j at instant t. When initializing, the pheromone values in every route are equal, suppose $\tau_{ij}(0) = C$ (C is constant). Agent $k (1 \le k \le m)$ takes every hop according to the pheromone of every route. Let $p_{ij}^{k}(t)$ be the probability of agent k moving from node i to node j. Based on M. Dorigo's ant colony algorithm[10], we assume that η_{ij} is the route visibility defined as heuristic information of moving from one node to another, α the pheromone intensity of the route, β the weight of heuristic information (initialized according to the circumstances) and V_k the set of nodes that agent k has scanned. Obviously, V_k is dynamically updated.

$$p_{ij}^{k}(t) = \begin{cases} [\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta} / \left[\sum_{j \notin V_k} [\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta} \right] \\ 0, \ j \in V_k \end{cases} \tag{2}$$

When all the agents finish their scanning tasks n instants after the initialization, $V_k (1 \le k \le m)$ is reset and put the current node into V_k preparing for next travel. The path L_k that agent k has gone through can be recorded and the shortest path $L_{\min} = \min\{L_k\}$ $(1 \le k \le m)$.

Seen from above-mentioned contents, if the agent doesn't arrive, the pheromone intensity of route will be diluted. Let $1 - \rho$ be the diluteness of pheromone intensity. When agent finishes one run of scanning, pheromone intensity of every route is adjusted conforming to the following formulas[11]:

$$\tau_{ij}(t+n) = \rho \tau_{ij}(t) + \Delta\tau_{ij} \tag{3}$$

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{4}$$

Where $\Delta\tau_{ij}^{k}$ is the additional pheromone intensity of route from node i to j left by agent k, $\Delta\tau_{ij}$ is the total addition of pheromone intensity of the route from node i to j.

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{L_k}, \text{ if agent goes through the node } i \text{ and } j \\ 0, \text{ otherwise} \end{cases} \tag{5}$$

Where Q is a constant representing the total pheromone intensity and L_k is the path the agent has passed through.

2.3 Avoid Local Optimal Solution

For ant colony algorithm, the relative ratio between $\tau_{ij}(t) (j \ne i, \ i = 1, 2, \cdots, n)$ may directly affect the probability p_{ij} of moving from node i to j, thus affecting the quality of the final solution. At the earlier stage of the searching for the solution, pheromone intensity is dispersed around the network. Along with the searching, pheromone intensity will get together at some paths, and accordingly the searching space is determined. The predominance of some paths in terms of pheromone intensity may result in local optimal solution and network congestion[12]. Now, we propose a way to avoiding local optimal solution by exchanging pheromone intensity of parts of the paths.

Let p_i, $i = 1, 2, \cdots, n$ be the exchanging probability among the n nodes and r_i the random variable subject to the (0, 1) distribution. If $r_i \le p_i$, then randomly select some paths from the $n - 1$ paths which start from node i to one of other $n - 1$ nodes. If $r_i > p_i$, nothing is changed.

The exchanging probability p_i is restricted to some value (0.15). By exchanging pheromone intensity of part of the paths, we change the distribution of $\tau_{ij}(t)$, provide a wide choice of nodes for mobile agent and avoid prematurely reaching local optimal solution.

Volatility of pheromone intensity affects to some extend the distribution of pheromone. Note that the value of ρ somewhat determine the effectiveness of the ant colony algorithm. Usually, ρ is supposed to be a constant, and the volatility of every path is equal. Actually, all paths are not necessarily needed to be volatile. For example, during a relative long interval after searching begins, that pheromone intensity of every path doesn't decrease will speed up the searching. The path of higher $\tau_{ij}(t)$ is much more likely to be used to construct the solution. Correspondingly, in order to avoid some paths gathering too much pheromone intensity, such paths is more volatile. And ρ of these paths should be higher to prevent from never being selected due to the inferiority of pheromone intensity. $\rho_{ij}(t)$ is computed according to the following formulae:

$$\rho_{ij}(t) = 1, \ t \le t_e \tag{6}$$

$$\rho_{ij}(t) = \begin{cases} k_1, \ \tau_{ij}(t) \le C, \ t > t_e \\ k_2, \ \tau_{ij}(t) > C, \ t > t_e \end{cases} \tag{7}$$

Where $1 - \rho_{ij}(t)$ is the volatility of pheromone intensity at instant t, t_e the earlier searching time, $k_1, k_2 \in (0, 1)$, $k_1 > k_2$, and C is larger than the average of the $\tau_{ij}(t)$ $(1 \le j \le n, j \ne i)$ and less than their maximum.

When agents finish tour, pheromone intensity of every path is adjusted according to $\rho_{ij}(t)$ and so is part of paths to change the pheromone distribution.

2.4 Algorithm for New Node's Joins

Suppose that at instant t, node i neighbors on node n_1, n_2, n_3, …, n_s and that the probabilities of agent k's moving to node i are represented as $p^k_{i,n_1}(t)$, $p^k_{i,n_2}(t)$, $p^k_{i,n_3}(t)$, … $(1 \le k \le m)$. When the new node r join as node it's new neighbor, the probabilities of all the agents moving to all the neighboring nodes are needed to be updated and the probability of agents moving to new joining node is also initialized. The basic idea is that decrease the each probability of moving to each node currently in the table by some part of its current value, and set the probability of moving to new joining node to the sum of these decreased probabilities. The lost part of each probability is proposition to their original value. But there are possible aftereffect is that the new node's current probabilities is higher than the fore highest node, and we don't believe it's the node in the best path for no reason. So, we decrease the divert probabilities of the other nodes, and ensure that the highest node's value is reserved, suppose

$$p^k_{i,n_d}(t) = \max\{p^k_{i,n_1}(t), p^k_{i,n_2}(t), p^k_{i,n_3}(t), \cdots, p^k_{i,n_s}(t)\}$$

The route probabilities are updated in line with the following formula

$$p^k_{i,j}(t) = p^k_{i,j}(t) - p^k_{i,j}(t)(1 - p^k_{i,j}(t)) = [p^k_{i,j}(t)]^2 \quad (n_1 \le j \le n_s, \ j \ne n_d) \tag{8}$$

And the probability of new joining node is computed by:

$$p^k_{i,r}(t) = \sum_{j=n_1, j \ne n_d}^{n_s} [p^k_{i,j}(t)(1 - p^k_{i,j}(t))] \tag{9}$$

$$\sum_{j=n_1}^{n_s} p^k_{i,j}(t) + p^k_{i,r}(t) = 1 \tag{10}$$

For example, suppose that node A has three neighboring nodes represented as B, C, D and the probabilities of moving from node A to its neighboring nodes at some instant t are 0.1, 0.3 and 0.6 respectively. And now, new node E joins, the Fig 2 shows the probabilities before E join, and the Fig 3 shows the probabilities after E join.

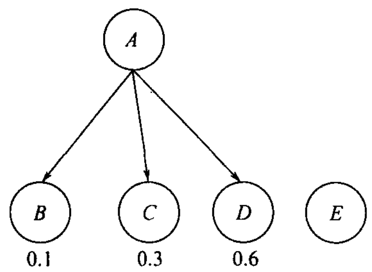

Fig. 2 The probabilities before E join

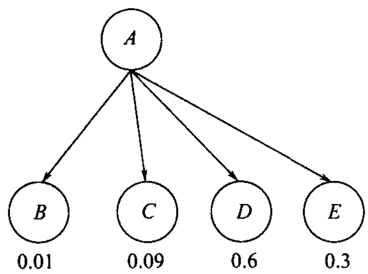

Fig. 3 The probabilities after E join

$p^k_{AD}(t)$ is the node for highest divert possibility, so it's value reserved. According to (8), we can get the probability of agent k after updating nodes B, C and D at some instant t:

$$p^k_{AB}(t) = 0.1^2 = 0.01,$$

$$p^k_{AC}(t) = 0.3^2 = 0.09,$$

And the probability of new join node E is:

$$p^k_{AE}(t) = (0.1 - 0.1^2) + (0.3 - 0.3^2) = 0.3.$$

2.5 Algorithm for Node's Leave

Suppose that node i neighbors on node n_1, n_2, n_3, …, n_s and that the probabilities of agent k are represented as $p^k_{i,n_1}(t)$, $p^k_{i,n_2}(t)$, $p^k_{i,n_3}(t)$, …, $p^k_{i,n_s}(t)$ $(1 \le k \le m)$. If one of the neighboring nodes, say node p, leaves the P2P network, the probability of moving to node p will be set 0 to prevent any agent from moving to node p and consequently probabilities of moving to other nodes will increase by some amount proposition to their current probabilities. Note that the sum of the probabilities should always be 1. The probabilities of nodes neighboring on node i are adjusted according to the following formula:

$$p^k_{i,p}(t) = 0 \tag{11}$$

$$p^k_{i,j}(t) = p^k_{i,j}(t) + p^k_{i,p}(t)\frac{p^k_{i,j}(t)}{\sum_{j\neq p} p^k_{i,j}(t)}$$

$$(n_1 \leq j \leq n_s) \tag{12}$$

Obviously,

$$\sum_{j\neq p} p^k_{i,j}(t) = 1,$$

$$n_1 \leq j \leq n_s \tag{13}$$

For example, assume that node A has three neighbors represented as node B, C and D and that the probabilities of agent moving from node A to node B, C, and D are 0.1, 0.3 and 0.6 respectively. And now, node D leaves, then the probability of agent moving from node A to D is set 0 and the probabilities of moving to node B and C are updated as follows:

$$p^k_{AD}(t) = 0$$

$$p^k_{AB}(t) = 0.1 + 0.6 \times \frac{0.1}{0.1 + 0.3} = 0.25$$

$$p^k_{AC}(t) = 0.3 + 0.6 \times \frac{0.3}{0.1 + 0.3} = 0.75$$

The situation is shown as following diagram, the Fig. 4 shows the probabilities before E leave, and the Fig. 5 shows the probabilities after E leave.

2.6 Algorithm for the Whole Processes

Step 1 Initialization

$t = 0$ // t is the time counter

$M = 1$ // M is loop counter

Set maximal loop times $M_{\max}$, p_i, $\rho_{ij}(t)$, $\tau_{ij}(0) = \tau_0 d_{ij}^{-1}$, $\sigma\tau_{ij} = 0$ for every path from i to j.

Step 2 $s = 1$

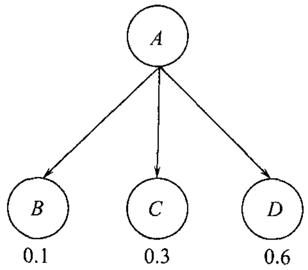

Fig. 4 The probabilities before E leave

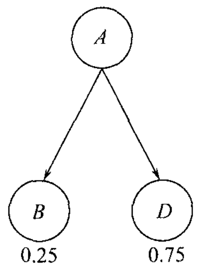

Fig. 5 The probabilities after E leave

For $k = 1$ to m

Put the starting node of agent k to the set V_k

Step 3 Do while V_k is not full

$s = s + 1$

For $i = 0$ to $n - 1$ do

For $k = 1$ to m do

Select next node j according to (2);

Move agent k to node j, insert node j to V_k, and adjust (i, j) locally;

Step 4 For $k = 1$ to m

Dispatch agent k to traverse the P2P network, compute the distance L of agent k, find the shortest path and adjust the globally shortest path accordingly.

Step 5 Based on the exchanging probability p_i, select some node s and randomly select some paths whose starting node is s and then exchange their pheromone intensity

$t = t + n$;

$M = M + 1$;

Set $\Delta\tau_{ij}$ to 0 for every path (i, j);

Step 6 If $(M < M_{\max})$ than

Go to Step 2

Else output the shortest path.

End.

2.7 Complexity Analysis

Let N be the number of the nodes in the P2P network, X the total loop times, m the number of agents. The complexity of algorithm when initialization is $O(X \times m)$, the complexity of agents traversing the network is $O(X \times m \times N^2)$, the complexity of updating $\tau_{ij}(t)$ is $O(X \times m \times N^2)$, the complexity of exchanging pheromone intensity is $O(N^2)$, and the total complexity is $O(X^2 \times m \times N^2)$.

3 Simulation Experiment

Every parameter's value can influence the efficiency of algorithm. At present, the value of parameters only be received through a mass of experiments. This paper set 200 P2P nodes: A_1, A_2, A_3, $\cdots$, A_{200}, the distance matrix of these nodes is generalized through random function. During the experiment, we set that there are K_1 nodes joining and K_2 nodes leave the network, and the $(K_1 + K_2)$ nodes' order is random.

3.1 The Value of the Volatility of Pheromone Intensity: $1 - \rho$

The value of the volatility of pheromone intensity $(1 - \rho)$ influence the algorithm's searching power and its' convergence rate: when the value of $1 - \rho$ is too large, the path which is searched previously may be researched in all probability, the other way round, decreasing volatility of pheromone intensity can heighten the algorithms random and the power of global search, but it will weaken the algorithm's convergence rate. This paper set the value of $1 - \rho$ through mass of experiment.

The value of various parameters:

$\alpha = 1.0$, $\beta = 5.0$, $\rho = 0.1$, $m = 10$, $p_i = 0.1$, $\tau_{ij}(0) = 100$,

$Q = 50$, $M_{\max} = 490$.

The value of ρ is in $\{0.2, 0.4, 0.6, 0.8\}$, the result of the experiment is as Table 1.

Table 1 The result of experiment with value of ρ

$1 - \rho$	Optimization of the scanning ring's length	The circle of the algorithm
0.8	9 446	1 229
0.6	9 663	1 343
0.4	9 531	1 356
0.2	10 028	1 587

Through the above table, the value of ρ is more larger, the positive feedback is more clearer, the random of the route is more better, the algorithm's convergence rate is more slower, reversely, the value of ρ is more smaller, the positive feedback is more clearer, the random of the route is more badly, the algorithm's convergence rate is more rapider, but it is easy result in local optimal solution, the global scan power is weaker. Considering the algorithm's convergence rate and the avoid local optimal solution, this paper set $\rho = 0.4$ finally.

3.2 The Value of the Scanning Agent's Number

The number of the mobile agent which generated by system is an important parameter. If the quantity of the agents is too less, the pheromone intensity which generated by them can't make up the pheromone's volatilization, it can't reflect the route's action. Reversely, if the quantity of the agents is too more, it can't advance the result's availability, and it will aggravate the network's burthen. This algorithm define the agents' number m equal the number of the P2P nodes, when m agents back the source nodes, this searching over.

3.3 The Values of α, β

We assume that η_{ij} is the route visibility defined as heuristic information of moving from one node to another, set $\eta_{ij} = 1/d_{ij}$, α is the pheromone intensity of the route, β is the weight of heuristic information. The value of α which is the expectation's elicitation parameter reflects the intensity of the scanning agents' apriority and confirm. Its value is larger, and that an agent choosing the shortcut in one local network is more possible. It can quicken the pace of the constringency, but the random of searching the best path is weak. the weight of heuristic information β reflect the random of searching the best path, the value is lager, the agents are more possible to choose the iterant path, that weaken the random in their searching, arise the local optimal solution.

We set the parameters follow:

$\rho = 0.4$, $m = 10$, $p_i = 0.1$, $\tau_{ij}(0) = 100$, $Q = 50$

$k_1 = 1$, $k_2 = 0.99$, $M_{\max} = 490$

After testing various combination of α, β, the result of the experiment is as Table 2.

Table 2 The result of experiment with various combination of α, β

α	β	Optimization of the scanning ring's length	The circle of the algorithm
0.1	0.1	11 302	2 054
0.5	2.0	10 653	1 363
1.0	5.0	9 873	1 259
1.5	1.0	10 362	1 464
10.0	10.0	12 347	2 672

By choosing the properly combination of α and β, we can receive the better results, and the circles of the algorithm are less than the others. This paper sets: $\alpha = 1.0$, $\beta = 5.0$.

3.4 The Value of the Total Pheromone Intensity

By the data's analysis above, in the process of agents' routing, the deciding factor is the value of the volatility of pheromone intensity $1 - \rho$, the number of the mobile agent m, the pheromone intensity of the route α, the weight of heuristic information β. The value of the total pheromone intensity depends on the values of the above parameters.

When set

$\alpha = 1.0$, $\beta = 5.0$, $\rho = 0.4$, $m = 10$, $p_i = 0.1$, $\tau_{ij}(0) = 100$,

$k_1 = 1$, $k_2 = 0.99$, $M_{max} = 490$, we can set $Q = 50$.

3.5 The Analysis of the Experiment's Result

We simulate a P2P network which comprises 200 peers, the values of the parameters are:

$\alpha = 1.0$, $\beta = 5.0$, $\rho = 0.1$, $m = 10$, $p_i = 0.1$, $\tau_{ij}(0) = 100$,

$k_1 = 1$, $k_2 = 0.99$, $M_{max} = 490$

Whose value is received by a mass of simulation experiments, and the above value can bring a better result.

By executing the algorithm 25 times, each node will form a routing table, which is comparatively determinate. Every agent moves in the network by this table, and an optimal scanning circle will be shaped finally. The result is: the best length is 9 781, the worst is 12 536, and the average is 10 165.

About routing in unstructured P2P network, there are several methods[13], for example: flooding, heterogeneous search, random worker and so on, the ant colony algorithm can fit the real time and it can suit the dynamic network. We simulate these algorithms in C circumstance, receive the following results:

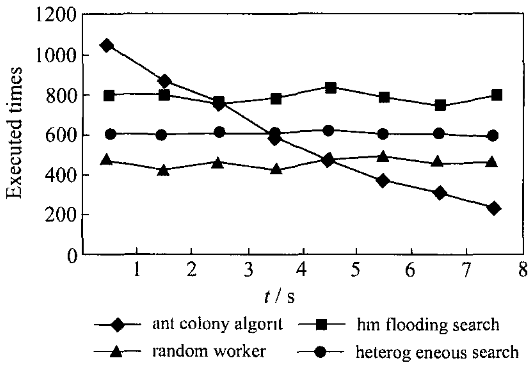

Fig. 6 Several routing algorithms' efficiency in unstructured P2P network

4 Conclusion

The complication and the immensity of P2P network architecture are big challenges to the mobile agent-based risk evaluation systems. This paper proposes a mobile agent route algorithm based on the well known ant colony algorithm. When agents evaluate the risk of the P2P network, risk scanning agents can dynamically and independently choose the optimal traveling route.

At present, the route mechanism based on the ant colony algorithm still needs more attention. In future, we will study the properties of risk evaluation in the P2P network to improve the ant colony based route mechanism.

References

[1] Angelo Sotira. What is Gnutella [EB/OL]. [2006-01-12]. *http://www.gnutella.com.*

[2] Hoover. What is Napster? —A Word Definition from the Webopedia Computer [EB/OL]. [2006-01-12]. *http://www.-webopedia.com/TERM/N/Napster.html.*

[3] Ron C Koren. Stream Theory Completes Merger with Endeavors Technology [EB/OL]. [2005-05-19]. *http://www.endeavors.com.*

[4] Antony I T, Rowstron, Druschel P. Pastry: Scalable, Decentralized Object Location, and Routing for Large-Scale Peer-to-Peer Systems [C]// *Proceedings of the IFIP/ACM International Conference on Distributed Systems Platforms*. Heidelberg, Nov. 2001.

[5] Stoisa I. Chord: A Scalable Peer-to-peer Lookup Protocol for Internet Applications [C]// *Proceedings of the IFIP/ACM International Conference on Distributed Systems Platforms*. Heidelberg, San Diego, CA, 2001:149-160.

[6] Wang Dan. A Resource Discovery Model Based on Multi-Agent Technology in P2P System [C]// *Proceedings of the IEEE/WIC/ACM International Conference on Intelligent Agent Technology*. Beijing, China, September 20-24, 2004.

[7] Pang Xiaolin, Catania Barbara, Tan Kian-Lee. Securing Your Data in Agent-Based P2P Systems [C]// *Proceedings of the Eighth International Conference on Database Systems for Advanced Applications*. Kyoto, Japan, March 26-28, 2003.

[8] Colomi A, Dorigo M, Maniezzo V. Distributed Optimization by Ant Colonies [C]// *Proceeding of The First European Conference Artificial Life*, 1991, **1**(5):134-142.

[9] Dorigo M, Maniezzo V, Colomi A. The Ant System; Optimization by A Colony of Cooperating Agents [J]. *IEEE Transaction on System*, 1996, **26**(1):1-26.

[10] Dorigo M, Gambardella L M. Ant Colony System: A Cooperative Learning Approach to the Traveling Salesman Problem [J]. *IEEE Transaction on Evolutionary Computing* 1997, **1**(1):53-56.

[11] Colomi A, Dorigo M, Maniezzo V. An Investigation of Some Properties of an "Ant Algorithm" [C]// *Proceeding of the Parallel Problem Solving from Nature Conference*. Brussels, Belgium: Elsevier Publishing, 1992:509-520.

[12] Dorigo M, Cargo G D, Gambardella L M. *Ant Algorithm for Distributed Discrete Optimization* [R]. Technical Report 98-10 IRIDIA, University Libre de Brexelles, 1998.

[13] Bao Xiuguo, Fang Binxing, Hu Mingzhen, *et al*. Heterogeneous Search in Unstructured Peer-to-Peer Networks [J]. *IEEE Distributed System Online*, 2005, **6**(2):1541-4922.

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