Distribution of Mobile Agents in Vulnerable Networks

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Abstract. This paper focuses on behavior analysis on mobile agents used in network routing. We describe a general agent-based routing model and classify it into two cases based on the reaction of mobile agents to a system failure, namely MWRC (mobile agents with weak reaction capability) and MSRC (mobile agents with strong reaction capability). For each case, we analyze the population distribution (the number of mobile agents) of mobile agents which as an important measure for monitoring the computational resource consumption and network performance. Our analysis reveal theoretical insights into the statistical behaviors of mobile agents and provide useful tools for effectively managing mobile agents in large networks.

Keywords: Mobile agents, vulnerable networks, population distribution.

1 Introduction

Mobile agent, a relatively new paradigm for network software development, has become an accessible technology in recent years. The potential benefits of this technology, including the reduction of network bandwidth consumption and latency, have drawn a great deal of attention in both academia and industry [3, 11, 19, 20, 24]. A mobile agent is a program that acts on behalf of a user to perform intelligent decision-making tasks. It is capable of migrating autonomously from node to node in an information network.

In recent years, many intelligent mobile agent-based network management techniques have been proposed and implemented [1, 6, 10, 14]. When a mobile agent is encapsulated with a task, it can be dispatched to a remote node. Once the agent has completed its tasks, the summary report for its trip is sent back to the source node. Since there are very few communications between the agent and the source node during the process of searching, the network traffic generated by mobile agents is very light. So mobile agent is an effective way for improving network performance.

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Network routing is an important issue for network performance. Advanced research in mobile agent has brought in some new methods for network routing [5, 15]. Ant routing algorithm is a recently proposed routing algorithm for use in large dynamic networks [7, 13, 17, 21]. The idea is similar to the shortest path searching process of ants. For an agent-based network, agents can be generated from every node in the network, and each node in the network provides to mobile agents an execution environment. A node which generates mobile agents is called the server of these agents. Once a request for sending a packet is received from a server, the server will generate a number of mobile agents. These agents will then move out from the server to search for the destination. Once a mobile agent finds the destination, the information will be sent back to the server along the same path. When all (or some of) the mobile agents come back, the server will determine the optimal path and send the packet to the destination along the optimal path. At the same time, the server will update its routing table.

Since mobile agents will be generated frequently in the network, there will be many agents running in the network. If there are too many mobile agents running in the network, they will consume too much computational resource, which will affect the network performance due to the limited network resource and ultimately block the entire network. Therefore, analysis on the distribution of mobile agents is necessary and important for network management. Unfortunately, few work has been done on this aspect.

In [18], an ant routing model was proposed . and the number of mobile agents was estimated under the assumption that nodes in the network will not fail. Thus, it can be viewed as a special case of the model in this paper. In [16], a smaller upper bound of the number of mobile agents was provided based on the same model in [18]. In this paper, we describe a general mobile agent-based routing model and classify it into two cases based on the reaction capability of mobile agents to a system failure. For each case, we analyze the population distribution of mobile agents. Our contributions are summarized as follows:

- A general agent-based routing model is described and is classified into two cases based on the reaction of mobile agents to a system failure: MWRC and MSRC.
- Analysis on population distribution of mobile agents is presented for both cases, providing a useful tool to reduce the computational resource consumption by adjusting the number of agents to be generated at individual nodes and the life-span of these mobile agents.

The rest of this paper is organized as follows. Section 2 discusses related work. Section 3 describes our model. Section 4 introduces the notations used in this paper and presents the analytical results for mobile agents. Section 5 concludes the paper.

2 Related Work

A mobile agent is an autonomous object that possesses the ability for migrating autonomously from node to node in a computer network. Usually, the main task of a mobile agent is determined by specified applications of users, which can range from E-shopping and distributed computation to real-time device control. In recent years, a number of research institutions and industrial entities have been engaged in the development of elaborating supporting systems for this technology [11, 23]. In [11], several merits for mobile agents are described, including network load and latency reduction, protocol encapsulation, adaption, heterogeneity, robustness and fault-tolerance. Successful examples using mobile agents can be found in [10, 12].

Network routing is a problem in network management. Ant routing is a recently proposed mobile agent based network routing algorithm for use in these environments [21, 22]. The continuing investigation and research of naturally occurring social systems offer the prospect of creating artificial systems that are controlled by emergent behavior and promise to generate engineering solutions to distributed systems management problems such as those in communication networks [5, 17].

Real ants are able to find the shortest path from a food source to the nest without using visual cues. Also, they can adapt to changes in the environment, for example finding a new shortest path once the old one is no longer feasible due to a new obstacle [2,9]. In the ant routing algorithm described in [7,18], artificial ants are agents which concurrently explore the network from node to node and exchange collected information when they meet each other. They irrespectively choose the node to move by using a probabilistic function which was proposed here to be a function of the connecting situation of each node. Artificial ants probabilistically prefer nodes that are connected immediately. Initially, a number of artificial ants are placed on randomly selected nodes. At each time step they move to new nodes and select useful information. When an ant has completed it's task, it will send a message back to the server.

In [4], Brewington et al formulated a method of mobile agent planning, which is analogous to the travelling salesman problem [8] to decide the sequence of nodes to be visited by minimizing the total execution time until the destination is found. In the preliminary work of this paper [16], the population distribution of mobile agents is analyzed. The model can be seen as a special case of the one in this paper.

3 Mobile Agent-Based Routing Model

Once a request is received by a server, the server generates a number of mobile agents. These agents will then move out from the server searching for the destination. Once an agent finds the destination, it will traverse back to the server following the searched path and leave marks on the nodes along the path. When a certain number of agents have come back (others may have dead, or are still in the searching process), the server will evaluate the costs of those collected paths and pick up the optimal one. The main idea of our algorithm is as follows:

1. In a network with n nodes, agents can be generated from every node in the network. Each node in the network provides mobile agents an execution environment.
2. Initially, there are a pile of requests for sending packets in the network. Then, a number of mobile agents are generated for each request.
3. At any time t, the expected number of requests received from one node is m. Once a request arrives, k agents are created and dispatched into the network.
4. Those agents traverse the network from the server to search for the destination. Once an agent reaches a node, it will check whether the node is its destination or not. If so, the agent will turn back to the server with information of the searched path. Otherwise, it will select a neighboring node to move on.
5. The server will compare all the path collected and pick up the optimal path. Then, the packet is sent out to the destination along the optimal path. At the same time, the server updates its routing table.
6. To avoid the user from waiting for a too long time, an agent will die if it cannot find its destination within a given time bound, which is called the agent's life-span limit in this paper.

4 Mathematical Analysis

Since any component of the network (machine, link, or agent) may fail at any time, we classify mobile agents into two kinds based on their reaction to a failure: weak and strong. A mobile agent with weak reaction capacity (MWRC) will die if it subjects to a failure, while one with strong reaction capacity (MSRC) will go back to the previous node, reselect another node, and go on its trip. In this section, we analyze the population distribution for each case, respectively.

Suppose that the network topology we used in this paper is a connected graph so that there is at least one path (directly or indirectly) between any two nodes. Matrix $\Phi = (\varphi_{ij})_{n\times n}$ is the connectivity matrix which describes the connectivity of the graph, i.e., if there is a direct link between node i and node j, then $\varphi_{ij} = \varphi_{ji} = 1$; otherwise, $\varphi_{ij} = 0$. Specially, $\varphi_{ii} = 0$ for any i. Let φ_j be the j-th column vector of matrix Φ. That is, $\Phi = (\varphi_1, \varphi_2, \cdots, \varphi_n)$. Furthermore, $c_j = \|\varphi_j\|_1 = \sum_{i=1}^{n} |\varphi_{ij}|$, $\sigma_1 = \max\limits_{1\le j\le n} c_j$, and $\sigma_n = \min\limits_{1\le j\le n} c_j$. Obviously, $C =$

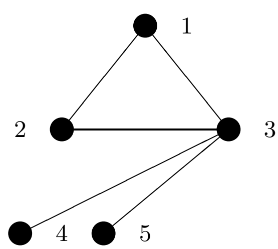

Fig. 1. An example of a small network

$diag(c_1, c_2, \cdots, c_n)$ is a diagonal matrix that indicates the connectivity degree of the network topology. It is easy to see that c_j is the number of neighboring nodes of the j-th node including itself, and $\|\Phi\|_1 = \max_{1\le j\le n} \|\varphi_j\|_1 = \sigma_1$. For example, suppose that the graphical structure of a small network is shown in Figure 1.

Accordingly, we have $n = 5$, $\sigma_1 = 4$, $\sigma_5 = 1$. Matrix Φ and matrix C can be given as follows:

$$\Phi = \begin{pmatrix} 0\,1\,1\,0\,0 \\ 1\,0\,1\,0\,0 \\ 1\,1\,0\,1\,1 \\ 0\,0\,1\,0\,0 \\ 0\,0\,1\,0\,0 \end{pmatrix}, \qquad C = \begin{pmatrix} 2\,0\,0\,0\,0 \\ 0\,2\,0\,0\,0 \\ 0\,0\,4\,0\,0 \\ 0\,0\,0\,1\,0 \\ 0\,0\,0\,0\,1 \end{pmatrix}.$$

4.1 The Population Distribution of Mobile Agents for MWRC

First, we consider the situation that the agents run in the network with infinite life-span. Assume that at time $t-1$, there are $p_i(t-1)$ agents in the i-th node, these agents search for the destination locally, and the expected number of agents that cannot find the destination is equal to $\left(1-\frac{1}{n}\right)p_i(t-1)$, and the expected number of mobile agents that move from the i-th node to the j-th node is equal to $\left(1-\frac{1}{n}\right)\frac{1-p}{c_i}p_i(t-1)$. The total number of agents that move to the j-th node at time t is $\sum_{i\in NB(j)}\left(1-\frac{1}{n}\right)\frac{1-p}{c_i}p_i(t-1)$, where $NB(j)$ denotes the set of the neighboring nodes of the j-th node. Consider the new generated agents in the j-th node at time t, we have the following equation:

$$p_j(t) = km - \Omega_j(t) + \sum_{i\in NB(j)}\left(1-\frac{1}{n}\right)\frac{1-p}{c_i}p_i(t-1),$$

where m is the average number of requests initiated at time t at a node, k is the number of agents generated per request, and $\Omega_j(t)$ indicates the number of mobile agents on the j-th node at time t that are generated at time $t-d$. We eliminate the number of these agents from $p_j(t)$ because these agents will die at time t. Let $A = (1-p)(1-\frac{1}{n})(\Phi - I)C^{-1} = (a_1, a_2, \cdots, a_n)$ be an $n\times n$ matrix, where a_j is the j-th column vector of A. Obviously, we have $\|a_j\|_1 = (1-p)(1-\frac{1}{n})\frac{c_j-1}{c_j}$. Let $\overrightarrow{p}(t) = (p_1(t), p_2(t), \cdots, p_n(t))^T$, and $\overrightarrow{e} = (1, \cdots, 1)^T$. At any time, the distribution of newly generated mobile agents is $km\overrightarrow{e}$ based on the assumption that the average number of requests received by a node is m. After searching d nodes, the distribution of survival agents among these agents is $A^d km\overrightarrow{e}$. Therefore, we have $\overrightarrow{\Omega}(t) = (\Omega_1(t), \cdots, \Omega_n(t))^T = A^d km\overrightarrow{e}$. Thus, the population distribution of mobile agents can be expressed in vector-matrix format as follows:

$$\overrightarrow{p}(t) = A\overrightarrow{p}(t-1) + km\overrightarrow{e} - A^d km\overrightarrow{e} \tag{1}$$

Regarding to the population distribution of mobile agents with limited life-span, we have the following theorem based on the above analysis.

Theorem 1. *The distribution of mobile agents can be expressed as follows:*

$$\overrightarrow{p}(t) = \begin{cases} 0 & t = 0; \\ \sum_{i=0}^{t-1} A^{i-1} km\overrightarrow{e} & 0 < t \leq d; \\ \sum_{i=0}^{d-1} A^{i-1} km\overrightarrow{e} & t > d. \end{cases} \tag{2}$$

Proof. If the distribution of mobile agents generated at time 0 is $\overrightarrow{p}(0)$, then after time t, the distribution of the agents is $A^d\overrightarrow{p}(0)$. Thus, according to the assumption that an agent will die if it cannot find the destination in d steps, we have

(1) When $t \leq d$,

$$\begin{aligned} \overrightarrow{p}(t) &= km\overrightarrow{e} + A\overrightarrow{p}(t-1) \\ &= km\overrightarrow{e} + A\left[km\overrightarrow{e} + A\overrightarrow{p}(t-2)\right] \\ &= (I + A)km\overrightarrow{e} + A^2\overrightarrow{p}(t-2) \\ &= \cdots \\ &= \sum_{i=0}^{t-1} A^i km\overrightarrow{e} + A^t\overrightarrow{p}(0). \end{aligned}$$

Since the initial population of mobile agents $\overrightarrow{p}(0) = 0$, the result for $t \leq d$ is proven.

(2) When $t > d$, then at time t, all the survival agents generated at time $t - d$ will die, so the distribution of agents under this case can be illustrated as

$$\begin{aligned} \overrightarrow{p}(t) &= km\overrightarrow{e} + A\overrightarrow{p}(t-1) - A^d km\overrightarrow{e} \\ &= \sum_{i=0}^{t-d-1} A^i km\overrightarrow{e} + A^{t-d}\overrightarrow{p}(d) - A^d \cdot \sum_{i=0}^{t-d-1} A^i km\overrightarrow{e} \\ &= \sum_{i=0}^{t-d-1} A^i km\overrightarrow{e} + A^{t-d} \cdot \left[\sum_{i=0}^{d-1} km\overrightarrow{e} + A^d\overrightarrow{p}(0)\right] - A^d \cdot \sum_{i=0}^{t-d-1} A^i km\overrightarrow{e} \\ &= \sum_{i=0}^{d-1} A^i km\overrightarrow{e}. \end{aligned}$$

Hence the theorem is proven.

From the theorem above, we can easily see that the distribution of mobile agents will not exceed $(I + A + \cdots + A^{d-1})km\overrightarrow{e}$, that is, the number of mobile agents in our model will not increase infinitely.

Since mobile agents are generated frequently and dispatched to the network, it is important to estimate the maximum number of mobile agents running in the network and in each node. When there are too many agents in the network, they will introduce too much computational overhead to node machines, which will eventually become very busy and indirectly block the network traffic.

Regarding to the number of agents running in the network, we have the following theorem.

Theorem 2. *The number of agents running in the network can be estimated as follows:*

$$\sum_{j=1}^{n} p_j(t) \leq \frac{n^2\sigma_1 km}{n+\sigma_1-1}. \tag{3}$$

Proof. By the definition of matrix 1−norm,we have

$$\begin{aligned}\sum_{j=1}^{n} p_j(t) &= \|\overrightarrow{p}(t)\|_1 \\ &\leq \|km\overrightarrow{e}\|_1 \cdot \|\sum_{i=0}^{d-1} A^i\|_1 \\ &\leq nkm \cdot \sum_{i=0}^{d-1}(\|A\|_1)^i \\ &\leq \frac{nkm}{1-\|A\|_1}.\end{aligned}$$

Due to $\|A\|_1 = (1-p)\left(1-\frac{1}{n}\right)\frac{\sigma_1-1}{\sigma_1}$, it is easy to prove that

$$\begin{aligned}\|\overrightarrow{p}(t)\|_1 &\leq \frac{nkm}{1-(1-p)\left(1-\frac{1}{n}\right)\left(1-\frac{1}{\sigma_1}\right)} \\ &= \frac{n^2\sigma_1 km}{pn\sigma_1+(1-p)(n+\sigma_1-1)}.\end{aligned}$$

Since $n\sigma_1 \geq n+\sigma_1-1$, the theorem is proven.

Regarding to the number of agents running in a node, we have the following theorem.

Theorem 3. *The number of agents running in the j-th node can be estimated as follows:*

$$p_j(t) \leq km + \frac{nc_j km}{(np+1-p)\sigma_n}(1-\alpha^t) \leq km + \frac{nc_j km}{(np+1-p)\sigma_n},$$

where $\alpha = (1-\frac{1}{n})(1-p)$.

Proof. The theorem can be proved by induction. First, for $t=0$, it is easy to see that the theorem is hold. Assume that for any t, the theorem is hold, that is,

$$p_j(t) \le km + \frac{nc_j km}{(np+1-p)\sigma_n}(1-\alpha^t)$$
$$= km + \frac{c_j km}{\sigma_n} km \sum_{l=1}^{t-1} \alpha^l,$$

then for $t+1$, we have

$$\begin{aligned}
p_j(t+1) &= km + \sum_{i \in NB(j)} \left(1 - \frac{1}{n}\right) \frac{1-p}{c_i} p_i(t-1) \\
&= km + \alpha \sum_{i \in NB(j)} \frac{p_i(t-1)}{c_i} \\
&\le km + \alpha \cdot \sum_{i \in NB(j)} \left(\frac{km}{c_i} + \frac{km}{\sigma_n} \sum_{l=1}^{t-1} \alpha^l \right) \\
&\le km + \frac{c_j km}{\sigma_n} \sum_{l=1}^{t} \alpha^l \\
&\le km + \frac{nc_j km}{(np+1-p)\sigma_n}(1-\alpha^{t+1}) \\
&\le km + \frac{nc_j km}{(np+1-p)\sigma_n}.
\end{aligned}$$

Hence, the theorem is proven.

From the above analytical results, we can claim that both the number of mobile agents in the network and the number of mobile agents on each node will not increase infinitely over time t. The upper bound of these two numbers can be controlled by tuning the number of mobile agents generated per request.

4.2 The Population Distribution of Mobile Agents for MSRC

For MSRC, a mobile agent will not die when it moves to a failing node. It will return back to the previous node and reselect another neighboring node to move. Thus, similar to the analysis for MWRC, the population distribution of mobile agents can be expressed as follows.

$$\overrightarrow{p}(t) = \begin{cases} 0 & t = 0; \\ km\overrightarrow{e} & t = 1; \\ A\overrightarrow{p}(t-1) + p \cdot \overrightarrow{p}(t-2) + km\overrightarrow{e} & 2 \le t \le d; \\ A\overrightarrow{p}(t-1) + p \cdot \overrightarrow{p}(t-2) + km\overrightarrow{e} - A^d km\overrightarrow{e} & t \ge d. \end{cases} \quad (4)$$

From Eq. (4), we can estimate the number of mobile agents running in the network as follows:

Theorem 4. *The total number of mobile agents running in the network is no more than* $\frac{n^2\sigma_1 km}{(n+\sigma_1-1)(1-p)}$.

Proof. By the definition of vector norm, the total number of mobile agents running in the network can be expressed as $\sum_{j=1}^{n} p_j(t) = \|\overrightarrow{p}(t)\|_1$. Therefore, from Eq. (4), it is easy to see that

$$\|\overrightarrow{p}(t)\|_1 \leq \|A\|_1 \|\overrightarrow{p}(t-1)\|_1 + p\|\overrightarrow{p}(t-2)\|_1 + \|km\overrightarrow{e}\|_1,$$

since all the parameters a_{ji}, k, m are positive. For $t = 0$ and $t = 1$, we have

$$\|\overrightarrow{p}(0)\|_1 = 0 \leq \frac{n^2\sigma_1 km}{(n+\sigma_1-1)(1-p)}$$

and

$$\|\overrightarrow{p}(1)\|_1 = nkm \leq \frac{n^2\sigma_1 km}{(n+\sigma_1-1)(1-p)}.$$

If the theorem is hold for $t-1$ and $t-2$, then for t, we have

$$\begin{aligned}\|\overrightarrow{p}(t)\|_1 &\leq \left[(1-p)\left(1-\frac{1}{n}\right)\left(1-\frac{1}{\sigma_1}\right)+p\right] \cdot \frac{n^2\sigma_1 km}{(n+\sigma_1-1)(1-p)} + nkm \\ &= \frac{n^2\sigma_1 km}{(n+\sigma_1-1)(1-p)},\end{aligned}$$

where $\|A\|_1 = (1-p)\left(1-\frac{1}{n}\right)\frac{\sigma_1-1}{\sigma_1}$. Hence, the theorem is proven.

Regarding to the maximum number of mobile agents running on a node, we have the following theorem.

Theorem 5. *The number of mobile agents running on a node is no more than* $\frac{nc_j km}{(1-p)\sigma_n}$.

Proof. From Eq. 4, we know that when $t \leq d$,

$$p_j(t) = km + p \cdot p_j(t-2) + \sum_{i \in NB(j)} \left(1-\frac{1}{n}\right)\frac{1-p}{c_i} p_i(t-1).$$

Define $f_j(t) = (1-\frac{1}{n})\frac{1-p}{c_j} p_j(t)$ and substitute it in the above function, we have

$$f_j(t) = \left(1-\frac{1}{n}\right)\frac{1-p}{c_j} km + p \cdot f_j(t-2) + \left(1-\frac{1}{n}\right)\frac{1-p}{c_j} \sum_{i \in NB(j)} f_i(t-1).$$

By induction, we can prove that

$$f_j(t) \leq \frac{n-1}{\sigma_n} km.$$

Therefore, it can be easily prove that for all $0 \leq t \leq d$,

$$p_j \leq \frac{\frac{n-1}{\sigma_n} km}{\left(1-\frac{1}{n}\right)\frac{1-p}{c_j}} = \frac{nc_j km}{\sigma_n(1-p)}.$$

When $t \geq d$, since

$$\overrightarrow{p}(t) = A\overrightarrow{p}(t-1) + p \cdot \overrightarrow{p}(t-2) + km\overrightarrow{e} - A^d km\overrightarrow{e},$$

we have

$$p_j(t) \leq km + p \cdot p_j(t-2) + \sum_{i \in NB(j)} \left(1 - \frac{1}{n}\right) \frac{1-p}{c_i} p_i(t-1).$$

Similar to the analysis for $0 \leq t \leq d$, the upper bound $p_j(t) \leq \frac{nc_j km}{\sigma_n(1-p)}$ is also hold. Hence, the theorem is proven.

It is easy to see that both the total number of mobile agents running in the network and the number of mobile agents running on a node are greater than that for MWRC. The reason is because mobile agents in MWRC case have a higher death rate than in MSRC case. It also can be seen that the number of mobile agents can be justified by tuning the number of mobile agents generated per request.

5 Concluding Remarks

In this paper, we addressed the problem of network routing and management by deploying mobile agents. We analyzed the population growth of mobile agents under our agent-based routing model. For mobile agents with weak reaction capability (MWRC), we obtained the following analytical results: (1) The total number of agents running in the network is less than $\frac{n^2\sigma_1 km}{n+\sigma_1-1}$, where $\sigma_1 = \max_{1\leq j\leq n} c_j$, and m is the average number of requests keyed in one node once. (2) The number of mobile agents running in each node, $p_j(t)$, is less then $km + \frac{nc_j km}{(np+1-p)\sigma_n}$. For mobile agents with strong reaction capability (MSRC), we obtained the following analytical results: (1) $\sum_{j=1}^{n} p_j(t) \leq \frac{n^2\sigma_1 km}{(n+\sigma_1-1)(1-p)}$, where $\sigma_1 = \max_{1\leq j\leq n} c_j$. (2) $p_j(t) \leq \frac{nc_j km}{(1-p)\sigma_n}$, where $\sigma_n = \min_{1\leq j\leq n} c_j$.

We can see that the number of agents is a monotonically increasing function on k, n, d and a monotonically decreasing function on p. We can see that for the same k and p, the number of agents for MWRC are less than those for MSRC. Based on these results, we can dispatch a small number of mobile agents and achieve a good network performance by selecting an optimal number of mobile agents generated per request and giving them an optimal life-span limit.

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