1/F NOISE IN THE MULTI-AGENT COOPERATIVE ROUTING

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Agent based routing is a novel routing algorithm with good scalability and robustness. Because the computation in this algorithm is done in a distributed way through the cooperation among software agents, it is difficult to analyze with analytic methods. A 2-D cellular automata model of the computer network is presented in this paper, by means of which the algorithm is analyzed. It is discovered that the procedure of establishing a stable route is a self-organized procedure towards the achievable attractive criticality state, and the time duration for the routing establishment is power-law distributed.

1 Introduction

The explosion of Internet makes the routing a bottleneck to further development. In 1997, Ruud Schoonderwoerd presented the ant-based algorithm [1]. In it, the routers establish routes by the ant packages and forward data packets according to the Pheromone that ant packages deposit on the nodes. The ant package is a kind of software agents that cooperate to work as the same gang. Therefore, the ant-based routing is attributed to Multi-Agent Cooperative Routing. The algorithm shows good adaptability and robustness.

In this article, the computer network is abstracted as a 2-D cellular automata model, and a revised ant-based routing was implemented. By fine-tuning the parameters, a self-organized criticality phenomenon is observed, and the maximum adaptability is achieved at criticality state. Moreover, the time duration for stable routes establishment is power-law distributed, which is a representative character of self-organized criticality. In such a system, the best performance exists "on the edge of chaos", that is between the "dead-lock" and the "chaos". Finding the critical point and persisting nearby is essential for the algorithm to perform best.

Network simulation is a continuously difficult problem. To simplify the complex architecture of the network to a representative model with an acceptable load of computation is the key point. The cellular automata (CA) model has been utilized for simulating many complex systems, such as hydrodynamics, sand pile models and high-way traffics, because it provides not only global information of the system, but also quantitative results in some cases. In this 2-D CA routing model, each router is symbolized as a node, which borders upon four nodes to its up, down, left and right side. Two nodes A and B are arbitrarily selected from the mesh. Routing simulations are conducted between them. The algorithm in [1] is revised in the model, described as followings:

1. Each node maintains two pheromone parameters $H_i^{A\to B}$ and $H_i^{B\to A}$;
2. *Node A* releases ant routing packages at random intervals with the target *Node B*. The ant packages transfer to neighboring nodes on each click of time with the transfer probability p_{ij} (*i* and *j* are neighboring):

$$p_{ij} = \frac{H_j^{B \to A}}{\sum_{k.borders.upon.i} H_k^{B \to A}}$$

3. On reaching target *B*, the ants change the target to *A* and return. On the way back, the transfer probability is determined by $H_j^{A \to B}$, and the formula is the same as above in form.
4. The ants deposit pheromone on the nodes they pass through. For target *node B*, they increase the volume of $H_i^{A \to B}$; while for *A*, $H_i^{B \to A}$. The increment is

$$\Delta H = L^{Age}$$

where *L* is a constant, and *Age* is the steps the ant has passed since it was released from the source node.
5. At each time click, the pheromone of each node vaporizes by multiplying a proportion parameter *D*, called vaporizing rate.

The CA model and the algorithm is implemented in a simulator with the code of C++. Simulations show that stable routes can be established in a distributed way.

2 The self-organized criticality:

The size of the mesh is 30x30 in the simulation, and the number of routing packages is 200. Let *D=0.6*, and *L=0.2*. After about 50 iterations, a stable route is established, and almost all the packages are attracted into this shortest route between A and B.

Fine-tuning the parameters affects the performance. The vaporizing-rate $D(\le 1)$ reflects the system's remembrance of the history status. When *D*=1, all the history status have same power; when *D*<1, the system maintains an exponential decayed memory; if *D* is too small, the cooperation among routing ant packages is very weak so that the stable routes are hard to establish; if *D*=0, there is no cooperation among packages and no stable route can be established, thus all the packages will be randomly strolling; The more close *D* to 1, the stronger the influence of history status. Hence, *D* is a parameter that describes the global characteristics of the system. The cellular automata is a time-discrete, space-discrete, status-discrete and status-finite dynamic system. The evolution of the system is determined by *D*. A too small *D* makes the system chaotic, and a too big *D* makes the system lack of agility to the system state variation. When *D* is properly set between 0.5 and 0.8, the system shows satisfying robustness and adaptability.

L reflects the system's preference to a shorter route. The bigger *L* is, the stronger the influence of the younger ants relative to the older packages. Hence, the system is liable to establish a shorter route, and the final route that emerges is the shortest route. With the same rule, different pheromone curves can be applied to gain different routes. If ΔH is determined on bandwidth or delay, the maximum bandwidth or minimum delay route will be established. This is helpful to implement the QoS routing.

3 The power-law distribution

The number of routing packages is an important parameter of the system. When it is too small, the agents participating in route searching is not enough so that the establish time will be long. However, if it is too large, the payload will be heavy and the transition efficiency will be low.

In order to analyze the relationship between the establish time of stable routes and the number of ants, we arrange the following simulation. On decreasing the number of ants from 100 to 5, for each number 100 stable routes are established and each duration time of establishment is recorded. The results show that the less the number of ants is, the more dispersively the duration times are distributed, and the higher the statistical average is, and vice versa as shown in Fig I.

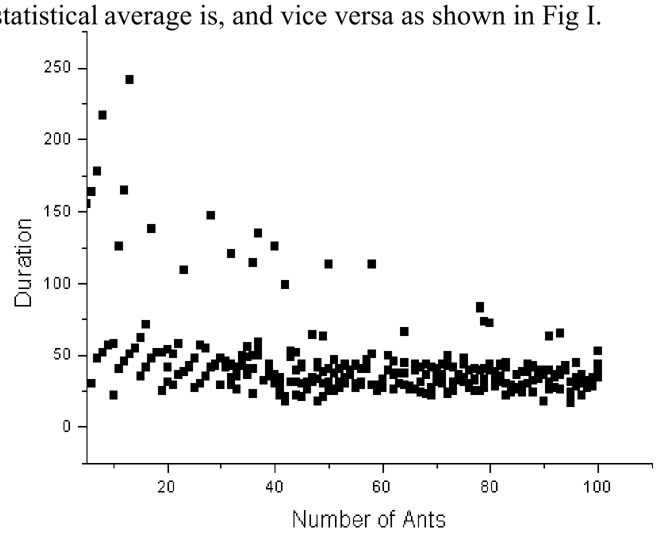

Fig. I The distribution of duration time of establishing a stable route

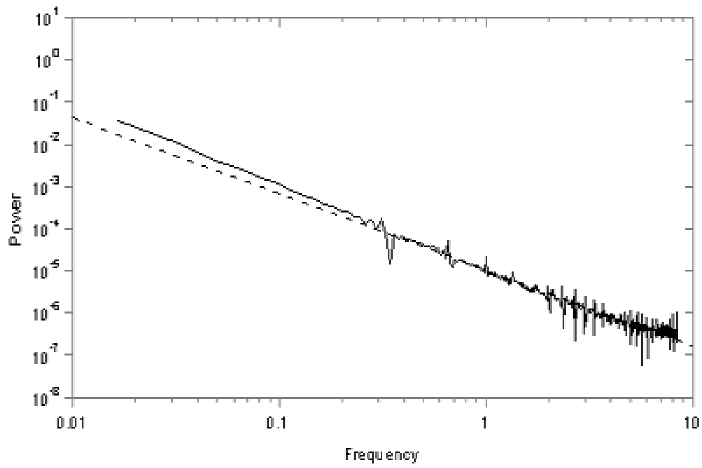

Fig. II The power spectrum of establish time of stable routes.
——— Power spectrum of Number of ant versus Duration time
– – – – Linear fit of the Power spectrum, with a slope of –4.99

Implementing FFT on the number of packages versus establishment time, we get the power spectrum as shown in Fig II. The curve appears the feature of $1/f^{\alpha}$ noise, and has a slope of about ***-4.99***. The system exhibits a self-organized criticality. That is the reason why the stable routes emerge with the cooperation of the agents.

4 Conclusion

According to the results of the simulation, it is concluded that the algorithm works at the criticality state of the network. The agents move to the state spontaneously, in the course of which power-law distribution is shown. It should be mentioned that, in the process of establishing a stable route, no agent obtains the global information of the network. The routes emerge with large amount of agents themselves under non-linear interaction through the local pheromone exchanges. In other words, the computation is done by the network itself with bottom-to-top characteristic, not by a supervisor beyond or above it.

The foundation and thoughtway of the ant-based routing is totally different from the classical routing algorithms. Because of its better robustness, adaptability and scalability, it will serve well in the study of traffic engineering for the Next Generation Internet.

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