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Performance Relationship between the Chaotic Routing Strategy and the Complex Networks

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Abstract—
To establish reliable communication between end users, alleviation of the congestion of packets in the communication networks is the most important problem. As one of the effective routing methods for reliable communication, we have proposed a routing method with chaotic neurodynamics, and another routing method with memory information. For recent works on the routing packets, a packet generating rate is used to evaluate the routing method for the communication networks. Thus, we evaluate the effectiveness of the routing method with the memory information using the packet generating rate in this paper. By using memory information effectively, packets are spread into the communication networks, achieving a higher performance than the conventional routing method for the complex network topology.

1. Introduction

To securely communicate between end users in the communication networks, alleviation of packet congestion is strongly desired. It has been shown that the shortest path protocol commonly employed by communication networks is facing serious challenge if the data volume continues to increase[1]. Specifically, the shortest path protocol transmits data using only the distance information of the communication network, and the routers where a large number of shortest paths go through are easily congested. Thus, it is imperative to enhance the transmission strategy to ensure reliable communication through the network. In this connection, an understanding of the data flow dynamics of the packets would be necessary.

To improve the capability of the network in carrying a large volume of data traffic, we need effective routing strategies which can reduce drastically the congestion of the communication network. Recent works in the development of routing strategies have evolved along two basic ideas. The first one is the selection of paths for transmitting packets based on only local information of the communication network such as degree information [2, 3]. The second idea is to utilize global information such as the shortest distance information of the communication network. For example, Horiguchi et al.[4] proposed a routing strategy employing mutual connected neural networks. This method was further improved by incorporation of stochastic effects[5]. To alleviate the packet congestion, one of the possible strategies is to prohibit the transmission of the packets to an adjacent node to which the packets just have been transmitted for a while. From this view point, we have already proposed a routing strategy with chaotic neurodynamics [6, 7, 8, 9, 10].

Incidentally, as for solving the combinatorial optimization problem, chaotic neurodynamics exhibits higher ability to solve the various combinatorial optimization problems, such as the traveling salesman problems (TSP)[11], the quadratic assignment problems (QAP)[12], the motif extraction problems (MEP)[13] and the vehicle routing problems (VRP) [14, 15]. These strategies use the chaotic dynamics of a chaotic neural network[16] to escape from undesirable local minima. Then, the performance of the strategies becomes high. As one of them, the chaotic routing strategy[6]-[10] is an optimization method for the packet routing problems on the communication networks.

In these chaotic routing strategy[6, 7], a refractory effect, which is an important characteristic in nerve membrane[16] and produces the chaotic neurodynamics plays a key role: it memorizes a past routing history. By the refractory effect or the past routing history, the chaotic routing strategy shows high performance for several types of complex network topologies such as the small-world network and the scale-free network. In addition the method[6, 7] is improved by introducing the waiting time information[8, 9, 10]. Then, we also confirmed that the improved chaotic routing strategy has high performance for the various kinds of the complex networks.

If we apply the chaotic routing strategy[6]-[10] to the real communication networks, it is much important to clarify the effectiveness of the routing method for more realistic communication networks. From a view point of realistic application of the chaotic routing strategy, we evaluate the chaotic routing strategy for the scale-free networks with tunable clustering[18] in this paper. From the obtained results, the proposed chaotic routing strategy avoids the packet congestion as compared to the conventional routing strategies.

2. Realization of A Routing Strategy with Chaotic Neural Networks

We explain how to construct the chaotic routing strategy. First of all, let us start with constructing a model communication network. The model communication network has N nodes. The ith node has N_i adjacent nodes $(i = 1, \ldots, N)$. Then, we assign a chaotic neural network to each node. That is, the ith node has its own chaotic neural network which consists of N_i neurons, and these N_i neurons correspond to N_i adjacent nodes. The firing of the ijth neuron $(j = 1, 2, \ldots, N_i)$ encodes the transmission of a packet from the ith node to the jth adjacent node.

The chaotic neural network in each node operates to minimize path distance of the transmitting packet from the ith node to its destination, To realize this routing strategy, the internal state of the ijth neuron in the chaotic neural network is defined as:

$$\xi_{ij}(t+1) = \beta\Biggl\{H\left(1 - \frac{d_{ij} + d_{jg(p_i(t))}}{\sum_{k=1}^{N_i}(d_{ik} + d_{kg(p_i(t))})}\right) + (1-H)\left(1 - \frac{q_j(t)}{\sum_{k=1}^{N_i} q_k(t)}\right)\Biggr\}, \quad (1)$$

where d_{ij} is a static distance from the ith node to its jth adjacent node; $p_i(t)$ is a transmitted packet of the ith node at the tth iteration; $g(p_i(t))$ is a destination of $p_i(t)$; $d_{jg(p_i(t))}$ is a dynamic distance from the jth adjacent node to $g(p_i(t))$, that is, $d_{jg(p_i(t))}$ depends on $g(p_i(t))$; $\beta > 0$ is a control parameter; $q_j(t)$ is the number of accumulated packets at the jth adjacent node at the tth iteration; H decides priority of the first term and the second term.

If the jth adjacent node is the closest to $g(p_i(t))$ and has the small number of the stored packets, $\xi_{ij}(t+1)$ takes a large value. The chaotic routing strategy[6]-[7] calculates the path distance of a packets using only the first term of Eq.(1). The second term of Eq.(1) expresses the accumulated number of packets at the jth adjacent node called the waiting time. By adding the waiting time, each node selects the adjacent node more efficiently and flexibly.

Then, we assign the refractory effect[16] to each neuron. The refractory effect is one of the essential characteristics of a real neuron: a neuron which has just fired hardly fires for a while. In our routing strategy, the refractory effect plays a key role, because it is used as a memory information. Namely, each node can memorize a past routing history using the refractory effect, then, an adjacent node to which many packets have been transmitted is not selected as a transmitted node of the packets for a while. The refractory effect is described as follows:

$$\zeta_{ij}(t+1) = -\alpha \sum_{d=0}^{t} k_r^d x_{ij}(t-d) + \theta, \quad (2)$$

where $\alpha > 0$ is a control parameter of the refractoriness; $0 < k_r < 1$ is a decay parameter of the refractoriness; $x_{ij}(t)$ is the output of the ijth neuron at the tth iteration that will be defined in Eq.(4); θ is a threshold.

Finally, a mutual connection is assigned to each neuron. The mutual connection controls firing rates of the neurons, because too frequent firing often leads to a fatal situation of the packet routing. The mutual connection is defined as follows:

$$\eta_{ij}(t+1) = W - W\sum_{j=1}^{N_i} x_{ij}(t), \quad (3)$$

where $W > 0$ is a control parameter and N_i is the number of adjacent nodes at the ith node.

Then, the output of the ijth neuron is defined as follows:

$$x_{ij}(t+1) = f\{\xi_{ij}(t+1) + \zeta_{ij}(t+1) + \eta_{ij}(t+1)\}, \quad (4)$$

where $f(y) = 1/(1 + e^{-y/\epsilon})$. In our routing strategy, if $x_{ij}(t+1) > 1/2$, the ijth neuron fires; a packet at the ith node is transmitted to the jth adjacent node. If the outputs of multiple neurons exceed $1/2$, we defined that the neuron which has the largest output only fires.

3. Performance Evaluation

To evaluate the performance of the improved chaotic routing strategy, we compared it with two kinds of the conventional routing strategies. The first one is the shortest path routing strategy (SP), which is commonly employed by communication networks. The second one is a gain routing strategy. The gain routing strategy uses only Eq.(1) for determination of the optimum adjacent node. Difference between the routing strategy proposed by P.Echenique et al.[1, 19] and the gain routing strategy is that the Eq.(1) is normalized in the case of the gain routing strategy and the routing strategy[1, 19] uses direct information.

Numerical simulations are conducted as follows. First, packets are created from randomly selected sources and destinations. Then, at every node, an optimal adjacent node was selected using Eqs.(1)–(4), and the packets are simultaneously transmitted to their destinations. We set the parameters in Eqs.(1)–(4) as follows: $\beta = 5.0$, $H = 0.9$, $\alpha = 0.4$, $k_r = 0.8$, $\theta = 0.5$, $W = 0.01$, and $\epsilon = 0.05$. We repeat the node selection and packet transmission, I, for $I = 500$. We generated the packets based on the density of the packet in the communication networks, and evaluated the routing strategies. Further, we conducted 30 simulations to average the results.

To evaluate the performance of the routing strategies, we use the following metrics.

1. Density of the packets (D):

$$D = p \cdot N \cdot Q_{max} \quad (5)$$

where Q_{max} is the maximum sizes of the buffer at each node. We set the Q_{max} to $2,000$ in these simulations. $p (0 < p \leq 1)$ is the ratio of the generated number of packets to the capacity of the communication network. If p increases, a large number of packets are generated at each iteration.

2. Average arrival rate of the packets (A):

$$A = \frac{\sum_{t=1}^{T} N_a(t)}{\sum_{t=1}^{T} D} \quad (6)$$

where $N_a(t)$ is the number of arriving packets at the tth iteration.

We evaluate the performance of the routing strategies for the scale-free networks with tunable clustering[18]. The scale-free networks with tunable clustering are generated as follows. First, we construct a network which has m_0 nodes and no links. Then, we add a node with m links at every step by the preferential attachment or triad formation. In the case of the preferential attachment, m links of the newly added node are connected to the node that already exists in the networks with probability:

$$\Pi(k_i) = k_i / \sum_{j=1}^{N} k_j, \quad (7)$$

where k_i is the degree of the ith node ($i = 1, \dots, N$), and N is the number of the nodes at the current iteration.

Further, one more link of the newly added node is connected after preferential attachment in the case of the triad formation. For example, if a node v is connected to a node w by the preferential attachment defined by Eq.(7), then, one more link of the node v is connected to the adjacent of the node w. If all adjacent nodes of w were already connected to the node v, the preferential attachment is performed instead. When a node v with m links is added to the existing network, we first perform one preferential attachment. Then, the triad formation is performed using the probability P_t, or the preferential attachment is performed with the probability $1 - P_t$. By tuning the selecting probability, P_t, we can construct the original scale-free networks[20] or the ones with strong clustering property[18].

Figure 1 shows the average arrival rate of the packets (A) by the shortest path routing strategy (SP), the gain routing strategy (Gain), and the chaotic routing strategy (CS) for the scale-free networks with tunable parameter. In these simulations, we set the number of nodes (N) to 100. In Figs. 1 (a), (b) and (C), the proposed chaotic routing strategy (CS) shows higher arrival rate than the other routing strategies for all the cases of the selecting probabilities (P_t). In addition, if the selecting probability increases (Fig. 1 (a)), namely, the scale-free networks have strong clustering, we can see that the performance of all routing strategies are decreased (Figs. 1(a) and (b)).

4. Conclusions

In this paper, we evaluate the performance of the routing strategy with chaotic neurodynamics under realistic communication networks. We evaluated the routing strategies for the scale-free networks with tunable clustering. The numerical simulations tell us that the chaotic routing strategy has higher performance for Obtained results indicate that the chaotic routing strategy has much possibility for application in the real communication networks. To clarify the effectiveness of the proposed routing strategy, we consider to analyze the dynamic property in the networks using the complex network theory in the future works.

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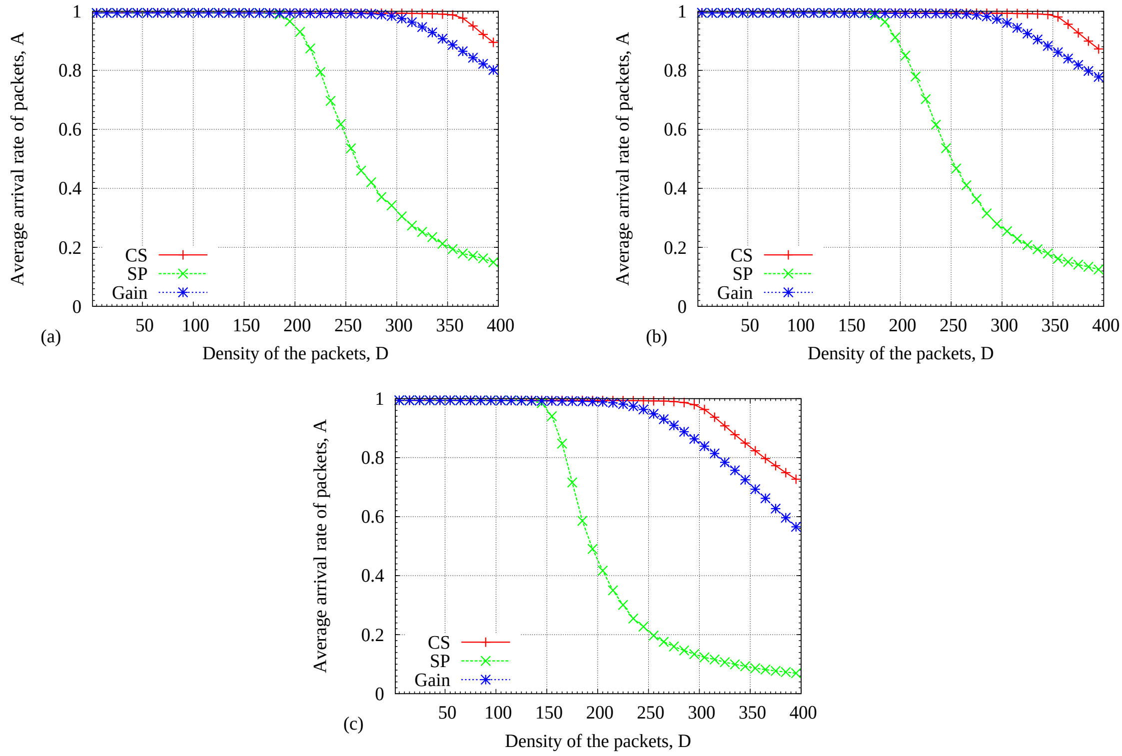

Figure 1: Relationship between the density of the packets (D) and an average arrival rate of the packets (A) for the scale-free networks with tunable clustering, (a) the selection probability (P_t) is 0, (b) P_t is 3, and (c) P_t is 90.

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