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Efficient Routing Algorithm Using Mutually Connected Neural Networks with Waiting Transmitted Information

Tohru Takamizawa†, Takayuki Kimura†, Keisuke Kimura‡ and Kenya Jin'no†

†Department of Electrical and Electronic Engineering, Nippon Institute of Technology
‡Graduate School of Electronics, Information and Media Engineering, Nippon Institute of Technology
4-1-1 Gakuendai, Miyasiro, Minami-Saitama, 345—8501 Japan
Email: e1102304@estu.nit.ac.jp, tkimura@nit.ac.jp, e1092204@estu.nit.ac.jp, jinno@nit.ac.jp

Abstract—Because of the growth of the Internet users, data packets flowing in the computer networks become huge number, and the data packets are congested in the computer networks. If the packet congestion occurs in the computer networks, some packets are trapped into the congested nodes, then, these packets are delayed to be transmitted to the destinations. Further, the packets might be removed from the computer networks in the worst case. To overcome these undesirable problems, an efficient routing method which uses the mutually connected neural networks has been proposed by Horiguchi and Ishioka. This routing method shows good performance for the regular topology of the computer networks. However, the performance is degraded for the irregular topology of the networks. To improve the performance for the irregular networks, we propose a new routing method using mutually connected neural networks which considers the waiting transmitted information on the paths of the transmitted packets in this paper. From the results of the numerical experiments, the proposed method shows better performance than the conventional routing methods if the number of existing packets is small.

1. Introduction

In recent years, the number of users of the packet communication network such as the Internet increases by the spread of mobile devices. The data flowing on the Internet is divided by some pieces of information called the packets. Then, the communication of the information in the communication networks is performed by exchanging these data packets. If the number of flowing packets increases, the packet congestion occurs in the network. Then, if the packets are trapped into the congested node, these packets are delayed to be transmitted to the destinations. Further, the packets might be removed from the computer networks in the worst case.

There are several methods for the routing packet in the real-world, for example, the Dijkstra algorithms[1], Bellman-Ford algorithms[2], Extending Dijkstra algorithm[3] and Warshall-Floyd algorithms[4] and so on. These routing methods show good performance if the number of packets flowing in the computer networks is small. However, if the number of packets flowing the computer networks increases, the performance of these routing methods becomes poor because these methods only consider the shortest path information for routing packets. Then, the packet congestion easily occurs on the node which has many shortest paths.

In general, there are two control methods for the packet routing strategy, the decentralized control and the centralized control. If the size of the networks becomes large, the centralized control is not good strategy for routing packets because the calculation cost becomes large. Then, the decentralized control is suitable for large size computer networks because the one decides the optimal routes for the packets autonomously. As one of the efficient decentralized control routing methods, the routing method using mutually connected neural network is proposed by Horiguchi and Ishioka[5]. This method searches the optimum path of each packet by using the energy minimization principle of mutually connected neural network. Further, the routing method using mutually connected neural networks shows good performance if the method is applied to the regular topological computer networks. However, this method is degraded in case of the irregular topological computer networks. Then, in this paper, to improve the performance for the irregular networks, we propose a routing method with mutually connected neural networks which consider the waiting transmitted information to the destination of the packet. We evaluate this routing method by the irregular topological computer networks[6]. From the results of numerical experiments, the proposed method shows good performance for the irregular network if the number of packets in the network is small.

2. Routing method using mutually connected neural network

A model of the computer network consists of nodes and links. Then, each packet is transmitted between the nodes using FIFO (First-In First-Out) principle. Each node receives multiple packets simultaneously. Each node has a buffer to store the packet. The packets are removed from the computer networks if the packets are transmitted to the nodes which have full of the buffer size. In addition, the packets are also removed when the packets exceed the constraint for the packet movement. The network model has N nodes, and the node i has N_i adjacent nodes. Then, the mutually connected neural network which has N_i neurons is assigned to each node. Figure 1 shows an example of the network model. In the mutually connected neural network, the neuron il corresponds to the connection between the node i and the node l. The routing method using the mutually connected neural network decides transmission node by minimizing energy function defined as follows:

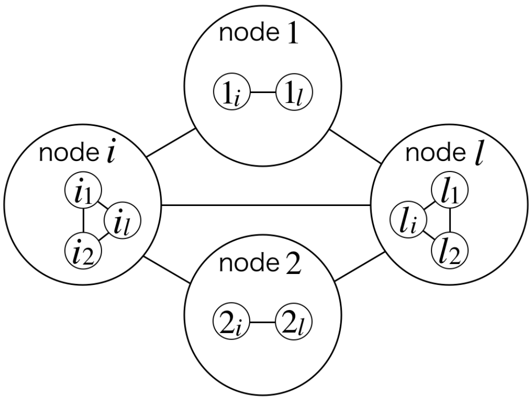

Figure 1: An example of the computer network.

$$E = -\eta \sum_{i=1}^{N} \sum_{l=1}^{N_i} \left\{ 1 - \frac{1}{b_l} \left(q_l + \frac{1}{2} \sum_{j \neq i}^{N_l} v_{jl} \right) \right\} v_{il}$$

$$-(1-\eta) \sum_{i=1}^{N} \sum_{l=1}^{N_i} \left(1 - \frac{d_l}{d_c} \right) v_{il} + \xi \sum_{i=1}^{N} \left(\sum_{l=1}^{N_i} v_{il} - 1 \right)^2, \tag{1}$$

where, b_l is the buffer size of the adjacent nodes l, q_l is the number of stored packet in the buffer of the adjacent nodes l, d_l is the shortest distance from the adjacent node l to the destination node of the packet at the node i, d_c is the longest path length in the network, η is the control parameter that decides the priorities of the first and second terms, and ξ is the control parameter that guarantees the uniqueness of firing neurons.

In Eq. (1), the first term expresses the load distribution of the adjacent nodes, and the second term the distance of the packet from the node i to the destination. The third term guarantees that only one neuron fires in the neural network. Namely, the adjacent node l is easy to be selected as the transmitting node when the distance to the destination of the packet is short from the adjacent node l and the number of packets in the buffer of the adjacent nodes l is small. An internal state of the neural network is updated in the same way as proposed by Hopfield and Tank[7]. Then, the output of the neuron il, v_{il}, is described as follows:

$$v_{il} = \begin{cases} \dfrac{1}{1+\exp(-\beta h_{il})} & \text{(if the node } i \text{ is adjacent to the node } l\text{)}, \\ 0 & \text{(otherwise)}. \end{cases} \tag{2}$$

In Eq. (2), if the neuron il fires, the output v_{il} of the neuron il takes 1 and the node i transmits a packet to the adjacent node l. Then, the internal state of the neuron il, h_{il}, is described as follows:

$$\frac{d}{dt} h_{il}(t) = \eta \left\{ 1 - \frac{1}{b_l} \left(q_l + \sum_{j \neq i}^{N_l} v_{jl}(t) \right) \right\}$$

$$+(1-\eta) \left(1 - \frac{d_l}{d_c} \right) - 2\xi \left(\sum_{k=1}^{N_i} v_{ik}(t) - 1 \right). \tag{3}$$

The Equation. (3) is obtained by differentiating Eq. (1) with respect to t.

3. The routing method with mutually connected neural networks considering the waiting information for transmission

The waiting information for transmission is the accumulated number of waiting packets in the buffer of the packets in each node on the path to the destination in this paper. Then, we realized three different type waiting information, the moving average type waiting information, the weighted average type waiting information and the exponential average type waiting information. Then, we evaluate these three different routing methods and originally proposed routing method using mutually connected routing method for the irregular topological computer networks.

3.1. The routing method with NN using moving average type waiting information

This method decides the transmission node of the packet by minimizing by following energy function.

$$E = -\eta \sum_{i=1}^{N} \sum_{l=1}^{N_i} \left\{ 1 - \left(\frac{1}{\alpha} \right) \sum_{d \in R}^{\alpha} \left(\frac{q_d}{b_d} \right) \right\} v_{il}$$

$$-(1-\eta) \sum_{i=1}^{N} \sum_{l=1}^{N_i} \left(1 - \frac{d_l}{d_c} \right) v_{il} + \xi \sum_{i=1}^{N} \left(\sum_{l=1}^{N_i} v_{il} - 1 \right)^2. \tag{4}$$

In Eq. (4), b_d is the buffer size of the node d, q_d is the number of packets in the buffer of the node d, R is set of nodes on the shortest path from the node i to the destination of the packet, and α is the control parameter that decides the acquisition range of the waiting information for transmission. Further, the internal state of the neuron il, h_{il}, is defined as follows:

$$\frac{d}{dt}h_{il}(t) = \eta\left\{1 - \left(\frac{1}{\alpha}\right)\sum_{d\in R}^{\alpha}\left(\frac{q_d}{b_d}\right)\right\}$$

$$+(1-\eta)\left(1 - \frac{d_l}{d_c}\right) - 2\xi\left(\sum_{k=1}^{N_i} v_{ik}(t) - 1\right). \qquad (5)$$

The Equation. (5) is obtained by differentiating Eq. (4) with respect to t.

3.2. The routing method with NN using weighted average type waiting information

This method evaluates the optimal adjacent node for routing the packets by the weighted average type waiting information. The weighted average type waiting information on the path to the destination is linearly decreased. Then, the energy function is defined as follow:

$$E = -\eta\sum_{i=1}^{N}\sum_{l=1}^{N_i}\left(1 - \frac{\sum_{d\in R}^{\alpha}\left(\frac{q_d}{b_d}w_d\right)}{\sum_{d\in R}^{\alpha} w_d}\right)v_{il}$$

$$-(1-\eta)\sum_{i=1}^{N}\sum_{l=1}^{N_i}\left(1 - \frac{d_l}{d_c}\right)v_{il} + \xi\sum_{i=1}^{N}\left(\sum_{l=1}^{N_i} v_{il} - 1\right)^2. \qquad (6)$$

In addition, the weighting parameter w_d is defined by the following equation.

$$w_d = \alpha - (d-1).$$

Further, the internal state of the neuron il, h_{il}, is defined as follows:

$$\frac{d}{dt}h_{il}(t) = \eta\left(1 - \frac{\sum_{d\in R}^{\alpha}\left(\frac{q_d}{b_d}w_d\right)}{\sum_{d\in R}^{\alpha} w_d}\right)$$

$$+(1-\eta)\left(1 - \frac{d_l}{d_c}\right) - 2\xi\left(\sum_{k=1}^{N_i} v_{ik}(t) - 1\right). \qquad (7)$$

The Equation (7) is obtained by differentiating Eq. (6) with respect to t. The parameters in Eqs. (6) and (7) are the same ones in the proposed method described in Section 3.1.

3.3. Routing method with NN using exponential average type waiting information

This method evaluates the optimal adjacent node for routing packets by the exponential average type waiting information. Then, the energy function defined as follow:

$$E = -\eta\sum_{i=1}^{N}\sum_{l=1}^{N_i}\left(1 - \frac{\sum_{d=1}^{\alpha}\left(k_r^{d-1}\frac{q_d}{b_d}\right)}{\sum_{d=1}^{\alpha} k_r^{d-1}}\right)v_{il}$$

$$-(1-\eta)\sum_{i=1}^{N}\sum_{l=1}^{N_i}\left(1 - \frac{d_l}{d_c}\right)v_{il} + \xi\sum_{i=1}^{N}\left(\sum_{l=1}^{N_i} v_{il} - 1\right)^2, \qquad (8)$$

where $k_r (0 < k_r < 1)$ is a decay parameter of the waiting information. In addition, the internal state of the neuron il, h_{il}, is defined as follows:

$$\frac{d}{dt}h_{il}(t) = \eta\left(1 - \frac{\sum_{d=1}^{\alpha}\left(k_r^{d-1}\frac{q_d}{b_d}\right)}{\sum_{d=1}^{\alpha} k_r^{d-1}}\right)$$

$$+(1-\eta)\left(1 - \frac{d_l}{d_c}\right) - 2\xi\left(\sum_{k=1}^{N_i} v_{ik}(t) - 1\right). \qquad (9)$$

The Equation (9) is obtained by differentiating Eq. (8) with respect to t. The parameters in Eqs. (8) and (9) are the same ones in the proposed method described in Section 3.1.

4. Numerical experiment

We performed numerical experiments using the irregular network as shown in Fig. 2. Then, we evaluate the conventional method and the proposed method by this irregular network. The numerical experiments are conducted as follow. First, we randomly generate the packets at all nodes in the network, and randomly assign the destination of the packets. Each node simultaneously selects the link to route the packet and the packet transmission to the adjacent node is performed. We set the buffer size of every node to 100, and limitation of the packet movement to 20. The packet is removed when the one violates these limits. In addition, if the packet arrived to the destination or the packet is removed, the same number of the packets that randomly decide source and destination is added in to the network. We set $\beta = 3.0$, $\eta = 0.5$, $\xi = 0.3$, $\alpha = 2.0$, 3.0, and 4.0, and $k_r = 0.9$ in Eqs. (1) ~ (9). We repeat the packet transmission for 1,000 times and average the results. The parameter α was set to 2.0. The results of numerical experiments of irregular network are shown in the Figs. 3 and 4.

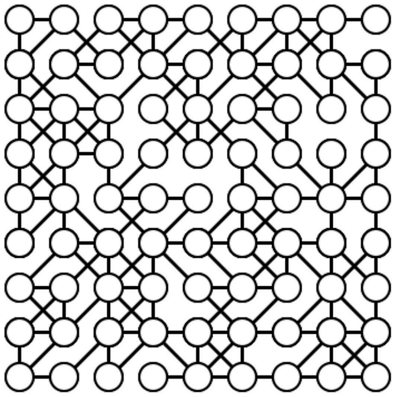

Figure 2: Irregular network

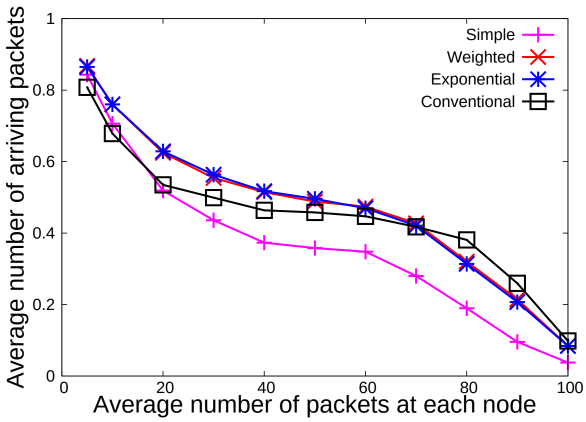

Figure 3: Average number of arriving packets for the irregular network

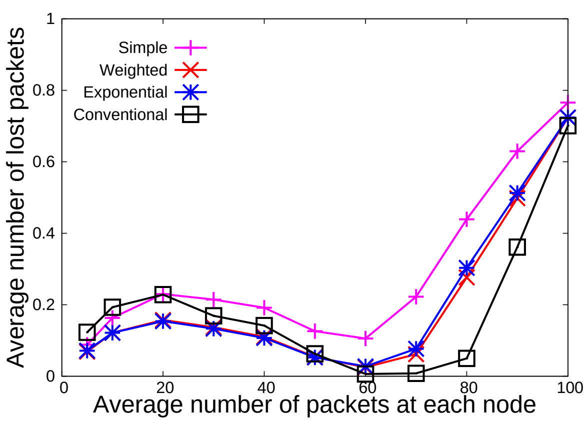

Figure 4: Average number of lost packets for the irregular network

In Fig. 3, the horizontal axis is an average number of packets at each node, and the vartical axis is an average number of arriving packets. From Fig. 3, the weighted method and the exponential method show better arrival rate than the conventional method if the average number of packets at each node is small. In Fig. 4, the horizontal axis is the average number of packets at each node, and the vartical axis is an average number of lost packets. From Fig. 4, the weighted method and the exponential method show lower lost packet rate than the conventional method if the average number of packets at each node is small.

5. Conclusion

In this paper, we propose the routing method with the mutually connected neural network which considers the waiting transmitted information to the destination of the packet. Then, we evaluated the routing method by numerical experiments. We confirmed that the performance of the proposed routing method showed better performance than the originally proposed routing method if the average number of packets at each node is small. On the other hand, the performance of the proposed routing method is degraded if the average number of packets at each node increases. In future works, we propose the routing method that the performance is improved based on the knowledge of complex network theory.

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