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Autonomous and Decentralized Optimization for Fair Radio Resource Selection by Higher-Order Neural Networks

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***Abstract*—Various advanced wireless systems have been developed and commercialized in recent years. In order to utilize them efficiently by switching among different wireless networks without interruption of an on-going session, vertical handover technologies have been developed and standardized. Moreover, cognitive radio networking technologies that optimize radio resource usage of a limited frequency band become also an important issue now. In order to optimize radio resource usage, we propose an autonomous and decentralized radio resource selection algorithm based on the optimization dynamics of the mutually-connected neural networks. The proposed neural network maximizes the average throughput per terminal and minimizes the differences of the throughput among the terminals at same time by using the fourth-order energy function. We show that the radio resource usage could be optimized by the proposed method based on decentralized and autonomous computing.**

I. INTRODUCTION

Various wireless systems have been developed and commercialized in recent years. The 2nd and 3rd generation cellular phone systems have been deployed world-wide and the fourth generation system is being developed now. Moreover, high-speed wireless systems for the short distance communications such as wireless LAN and Bluetooth have also been well deployed. WiMAX services are also going to be launched as a large area packet transmission system in a few years. The features of these wireless systems are different in various aspects, such as coverage area, transmission rate, communication cost and so on. In order to always use an appropriate wireless system in such heterogeneous wireless network environment, the vertical handover technologies, which enable switching of communication link without interruptions of the on-going session have been developed and standardized. Recently, available frequency band is getting narrower by deployment of many kinds of wireless systems. Therefore, the technologies to improve efficiency of frequency usage become very important [1].

Up to now, a variety of vertical handover methods have been proposed [2,3]. In order to optimally utilize various kinds of different wireless networks with seamless switching among them, we are developing a new architecture called Cognitive Wireless Clouds (CWC) [4]. Since CWC includes various wireless systems managed by different owners or operators, centralized management methods cannot be applied. Therefore, we apply decentralize radio resource management method.

In this paper, we propose an optimization algorithm of radio resource usage in heterogeneous wireless network environment by autonomous decentralized decision making. In Ref. [5], we have already proposed an algorithm to maximize the average throughput per user, by using decentralized optimization dynamics of the mutually-connected neural networks. However, the difference of the throughput assigned to each terminal becomes large in the previous method. For fair radio resource selection, when we introduce difference of the throughput into the objective function, it becomes fourth-order equation, which cannot be optimized by the conventional Hopfield neural network. In this paper, we introduce the high-order neural network [6], and realize a decentralized optimization algorithm for fair radio resource management.

II. OPTIMIZATION BY MUTUALLY-CONNECTED NEURAL NETWORKS

The mutually-connected neural networks have been applied to various optimization problems. By distributed update of each neuron, the energy function decreases and converges [7]. The update equation of the neuron state is generally given by the following expressions,

$$x_{ij}(t+1) = \begin{cases} 1 & \cdots \quad \sum_{k=1}^{n}\sum_{l=1}^{n} w_{ijkl}\, x_{kl}(t) > \theta_{ij} \\ 0 & \cdots \quad \text{otherwise} \end{cases} \tag{1}$$

,

where $x_{ij}(t)$ is the state of (i, j)th neuron at time t, W_{ijkl} is the connection weights between (i, j)th and (k, l)th neurons, and θ_{ij} is the threshold of the (i, j)th neuron, respectively.

By autonomously updating the state of each neuron by Eq. (1), its energy function in Eq. (2) is minimized in the mutually-connected neural network.

$$E_{2d}(t) = -\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n}\sum_{l=1}^{n} w_{ijkl}\, x_{ij}(t)\, x_{kl}(t) + \sum_{i=1}^{n}\sum_{j=1}^{n}\theta_{ij}\, x_{ij}(t) \quad (2)$$

When a minimum search problem is given and the objective function of the problem can be defined in the form of the energy function in Eq. (2), it can be solved by autonomous neural network update by Eq. (1) with the connection weights and the thresholds obtained by comparing objective function of the minimum search problem and the energy function in Eq. (2).

The optimization problem of radio resource management in Ref. [5] could be solved by this second-order energy function of the neuron state in Ref. [7]. However, in the algorithm which optimizes fairness, the objective function becomes fourth-order function which cannot be optimized by the conventional Hopfield neural networks. In this paper, we introduce the high-order neural network [6] to optimize fairness, by decentralized and autonomous dynamics.

When we introduce the third-order mutual connections for the neuronal update equation as follows,

$$x_{ij}(t+1) = \begin{cases} 1 \cdots \dfrac{1}{6}\displaystyle\sum_{k=1}^{N_m}\sum_{l=1}^{N_{Ap}}\sum_{m=1}^{N_m}\sum_{n=1}^{N_{Ap}}\sum_{o=1}^{N_m}\sum_{p=1}^{N_{Ap}} U_{ijklmnop}\, x_{kl}(t)\, x_{mn}(t)\, x_{op}(t) \\ \quad + \dfrac{1}{2}\displaystyle\sum_{k=1}^{N_m}\sum_{l=1}^{N_{Ap}}\sum_{m=1}^{N_m}\sum_{n=1}^{N_{Ap}} V_{ijklmn}\, x_{kl}(t)\, x_{mn}(t) \\ \quad + \displaystyle\sum_{k=1}^{N_m}\sum_{l=1}^{N_{Ap}} W_{ijkl}\, x_{kl}(t) > \theta_{ij} \\ 0 \cdots \text{otherwise} \end{cases} \quad (3)$$

the energy function becomes a fourth-order function of the neuron state as shown in Eq. (4), which decreases by updating using Eq. (3).

$$E_{4d} = -\frac{1}{24}\sum_{i=1}^{N_m}\sum_{j=1}^{N_{Ap}}\sum_{k=1}^{N_m}\sum_{l=1}^{N_{Ap}}\sum_{m=1}^{N_m}\sum_{n=1}^{N_{Ap}}\sum_{o=1}^{N_m}\sum_{p=1}^{N_{Ap}} U_{ijklmnop}\, x_{ij}x_{kl}x_{mn}x_{op} - \frac{1}{6}\sum_{i=1}^{N_m}\sum_{j=1}^{N_{Ap}}\sum_{k=1}^{N_m}\sum_{l=1}^{N_{Ap}}\sum_{m=1}^{N_m}\sum_{n=1}^{N_{Ap}} V_{ijklmn}\, x_{ij}x_{kl}x_{mn} - \frac{1}{2}\sum_{i=1}^{N_m}\sum_{j=1}^{N_{Ap}}\sum_{k=1}^{N_m}\sum_{l=1}^{N_{Ap}} W_{ijkl}\, x_{ij}x_{kl} - \sum_{i=1}^{N_m}\sum_{j=1}^{N_{Ap}}\theta_{ij}x_{ij} \quad (4)$$

where, $U_{ijklmnop}$ is the third-order connection weights among (i, j)th, (k, l)th, (m, n)th and (o, p)th neurons, and is the second-order connection weights among (i, j)th, (k, l)th and (m, n)th neurons, respectively.

III. AUTONOMOUS AND DECENTRALIZED RADIO RESOURCE SELECTION BY NEURAL NETWORKS

A. *Mapping the problem on the neural network*

In order to apply the optimization dynamics of the mutually-connected neural networks to optimum access point selection, it is necessary to define relation between the output of the neural network and the state of wireless links. In this paper, each wireless link between a terminal and an access point is corresponded to each neuron. When the (i, j)th neuron fires, terminal i establishes a wireless link with the access point j, as shown in Fig. 1.

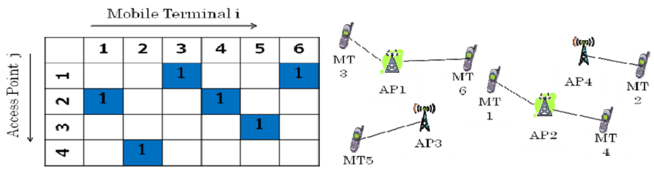

Figure 1. Relation between firing pattern of the neural network and access selection.

B. *Total throughput maximization*

First we show how the average throughput could be maximized by load-balancing based on the mutually-connected neural network dynamics [5]. Here, it is assumed that the terminal can connect with all the access points, and that the terminals connected with the same access point share the throughputs equally among them. One terminal can connect only with one access point. The available throughput for the terminal i at time t, $T_i(t)$, can be defined as follows,

$$T_i(t) = \frac{C_{hL(i)}}{N_{hL(i)}}, \quad (5)$$

where C_j is the capacity(total throughput) of the access point j, N_j is the number of terminals connected with access point j, and $hL(i)$ is the access point which the terminal i is connecting, respectively. From Eq. (5), objective function to optimize the total throughput is given by,

$$F_1 = \sum_{i=1}^{N_m} T_i(t) = \sum_{i=1}^{N_m} \frac{C_{hL(i)}}{N_{hL(i)}} = \sum_{i=1}^{N_m} \frac{C_{hL(i)}}{\sum_{k=1}^{N_m} x_{kL(i)}(t)} \quad (6)$$

In order to apply the Hopfield neural network to optimization of this problem, the state of the neuron $x_{kL(i)}(t)$ has to come to the numerator. Therefore, the problem is replaced to the reciprocal of Eq. (6), and the maximization problem was modified to a minimization problem. Then, the energy function to optimize throughput can be defined as follows,

$$E_1 = \sum_{i=1}^{N_m} \frac{1}{T_i(t)} = \sum_{i=1}^{N_m} \frac{\sum_{k=1}^{N_m} x_{kL(i)}(t)}{C_{hL(i)}} = \sum_{i=1}^{N_m} \sum_{j=1}^{N_{AP}} \sum_{k=1}^{N_m} \frac{1}{C_j} x_{ij} x_{kj} \quad (7)$$

From Eqs. (2) and (7), the connection weights between neurons can be obtained as follows,

$$W_{ijkl} = \begin{cases} -\dfrac{1}{C_j} & for \quad j = l \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

Using this connection weights, the average throughput per terminal can be maximized.

C. Fair radio resource optimization

By throughput maximization method in Sec. 3.2, the terminals can select the appropriate access point autonomously. However, since it only optimizes the total throughput, its results sometimes become unfair among the terminals. Then, we propose the method of minimizing the difference of the throughput of each terminal in addition to optimization of the total throughput.

If the reciprocal of Eq. (5) is taken as well as Sec.3.2, the energy function can be defined as follows to minimize the difference of the throughput among terminals,

$$E_2 = \sum_{i=1}^{N_m} \sum_{k=1}^{N_m} \left(\frac{1}{T_i(t)} - \frac{1}{T_k(t)}\right)^2 \quad (9)$$

However, in Eq. (9), the difference of large improvement of the throughput becomes small. It consequently becomes difficult to optimize the throughput maximization and difference minimization at the same time. In order to make it easier for neurons corresponding to big improvement to fire, we introduce $R_i(t)$, as follows by taking inverse of capacity,

$$R_i(t) = \frac{1}{C_{hL(i)}} \frac{1}{N_{hL(i)}} \quad (10)$$

The reciprocal of Eq. (10) can be transformed to a function of the neuron state, $x_{ij}(t)$, as follows,

$$\frac{1}{R_i(t)} = \sum_{m=1}^{N_m} C_{hL(i)} x_{mL(i)}(t) = \sum_{m=1}^{N_m} \sum_{j=1}^{N_{Ap}} C_j x_{mj}(t) x_{ij}(t) \quad (11)$$

Using $1/R_i(t)$, the energy function to optimize fairness of the throughput can be defined as follows,

$$E_2' = \sum_{i=1}^{N_m} \sum_{k=1}^{N_m} \left(\frac{1}{R_i(t)} - \frac{1}{R_k(t)}\right)^2 \quad (12)$$

From Eqs. (11) and (12), the energy function can be obtained as a function of the neuron states, as follows,

$$E_2' = \sum_{i=1}^{N_m} \sum_{k=1}^{N_m} \sum_{m=1}^{N_m} \sum_{j=1}^{N_{Ap}} \sum_{n=1}^{N_m} \sum_{l=1}^{N_{Ap}} C_j C_l (x_{mj} x_{ij} x_{nl} x_{il} - 2 x_{mj} x_{ij} x_{nl} x_{kl} + x_{mj} x_{kj} x_{nl} x_{kl}) \quad (13)$$

By comparing Eqs. (13) and (4) with avoiding the self feedback connections, the connection weights, $U_{ijklmnop}$, V_{ijklmn}, W_{ijkl}, and threshold θ_{ij} can be obtained as follows,

$$\begin{aligned} U_{ijklmnop} = -[&\{2(\delta_{ik}-1)C_j C_l + 2(\delta_{io}-1)C_j C_p \\ &+ 2(\delta_{km}-1)C_l C_n + 2(\delta_{mo}-1)C_n C_p\}\delta_{jn}\delta_{lp} \\ &- \{2(\delta_{im}-1)C_j C_n + 2(\delta_{io}-1)C_j C_p \\ &+ 2(\delta_{km}-1)C_l C_n + 2(\delta_{ko}-1)C_l C_p\}\delta_{jl}\delta_{np} \\ &- \{2(\delta_{ik}-1)C_j C_l + 2(\delta_{im}-1)C_j C_n \\ &+ 2(\delta_{ko}-1)C_l C_p + 2(\delta_{mo}-1)C_n C_p\}\delta_{jp}\delta_{\ln}], \end{aligned} \quad (14)$$

$$\begin{aligned} V_{ijklmn} = -[&C_j C_l \{\delta_{im}\delta_{\ln} + \delta_{km}\delta_{jn} - 5(\delta_{jn} + \delta_{\ln}) \\ &+ 3(\delta_{ik}\delta_{jn} + \delta_{ik}\delta_{\ln}) - 10\delta_{jl}\delta_{jn}\} \\ &+ C_j C_n \{\delta_{ik}\delta_{\ln} + \delta_{km}\delta_{jl} - 5(\delta_{jl} + \delta_{\ln}) \\ &+ 3(\delta_{im}\delta_{jl} + \delta_{im}\delta_{\ln}) - 10\delta_{jl}\delta_{jn}\} \\ &+ C_l C_n \{\delta_{ik}\delta_{jn} + \delta_{im}\delta_{jl} - 5(\delta_{jl} + \delta_{jn}) \\ &+ 3(\delta_{km}\delta_{jl} + \delta_{km}\delta_{jn}) - 10\delta_{jl}\delta_{jn}\}], \end{aligned} \quad (15)$$

$$W_{ijkl} = -2C_j C_l (16\delta_{jl} - 2\delta_{ik} + 2), \quad (16)$$

$$\theta_{ij} = -10 C_j C_l, \quad (17)$$

where, δ_{ij} is the Kronecker delta.

In order to maximize throughput and optimize fairness at the same time, the final energy function is defined as follows, from Eqs. (7) and (13).

$$E = AE_1 + BE_2' , \tag{18}$$

where A and B are the parameters which are the weights of each energy function.

IV. Simulation Results

First of all, the average and variance of the throughput are shown in Fig. 2. In this experiment, the number of terminals and access points are four, respectively. The parameter A is fixed at 100, and B is varied. The total capacities of each access point are 2, 10, 10, and 18 Mbps, respectively.

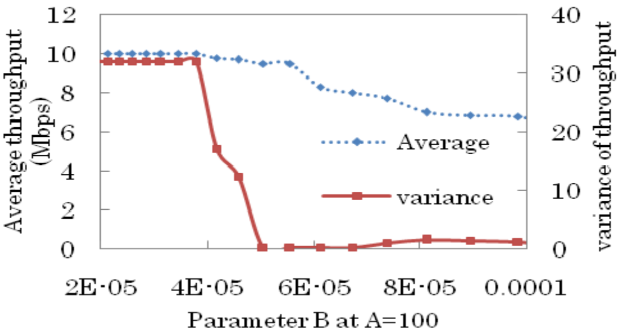

Figure 2. Average and variance of the throughput of the proposal method with $A = 100$.

From Fig. 2, variance is large when B is small. On the other hand, variance becomes smaller as the value of B grows. In this experiment, the average of the throughput and the variance of the throughput become appropriate value by introduced the term of fairness, $E_2{}'$.

Figs. 3 and 4 show the average and variance of the throughput when the number of access points was fixed and the number of terminals was changed. The total capacity of each access point is 2, 2, 10, 10, 10, 10, 18, 18, 24 and 24 Mbps, respectively. Each plot in Figs.3 and 4 is mean value with 500 different initial conditions.

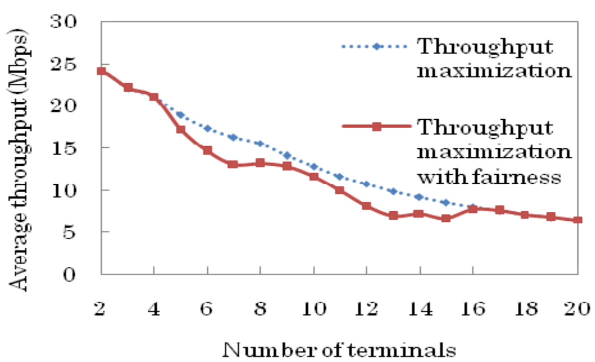

Figure 3. Comparison of average throughput.

From Fig. 4 when the fairness was considered, the variance of the throughput becomes less than a half compared to the result without considering fairness. On the other hand, from Fig. 3, the average of throughput decreases totally about 10%. From these results, the effectiveness of the proposal method was verified.

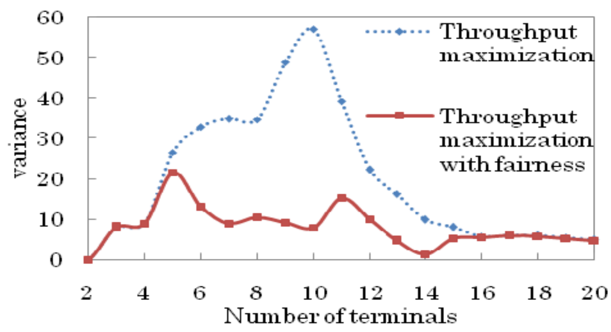

Figure 4. Comparison of variance.

V. Conclusion

In this paper, autonomous and decentralized access point selection that optimizes fairness was proposed by using higher-order neural networks which minimize difference of the available throughputs among the terminals. We confirmed the effectiveness of the proposed approach by computer simulation. Our algorithm can be distributed either into the terminals or into the network side entities. As a future work, we are going to evaluate this approach on a real experimental network with two or more wireless access points based on this simulation result. Although the higher-order neural network requires heavy computational amount, our algorithm runs on a large number of the terminals or the network entities, on each of which computational load is distributed.

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