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Application QoS based Optimization of Heterogeneous Wireless Networks by Distributed and Autonomous Neural Network Dynamics

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Abstract—Various radio access network (RAN) services have been developed and commercialized. In order to always use the best connection, vertical handover technologies for adaptively switching among those various different RANs without interruption of an ongoing communication session have been developed, and several protocols to enable such handover have been standardized. In this paper, we propose an optimal RAN selection algorithm, which uses autonomous and distributed neural network dynamics, to optimize radio resources usage and quality of services (QoS) in heterogeneous wireless network environment. We introduce a higher order neural network to optimize satisfaction rate of QoS level required by applications on the user terminals. By computer simulation, we show that the proposal method improves the QoS satisfaction rate by distributed update of neurons, which doesn't require any centralized computation.

1. Introduction

Various wireless communication technologies have been developed and commercialized, and ubiquitous communication services have been realized. As radio access networks (RANs) for short distance wireless communications, wireless LAN, such as IEEE 802.11b, 11g, and 11a, and wireless PAN, such as Bluetooth, have been widely deployed. As RANs with large coverage area, the 2G or the 3G cellular phone systems are available everywhere, and the research and development toward the 4G is now ongoing. Recently, WiMAX services are also gradually expanding. Wireless LAN systems enable high-speed communications, but have the narrow coverage area. On the other hand, cellular phone systems enable seamless mobile communication. The features of those various RANs are different from each other on cell size, transmission speed, communication cost and so on.

In order to always use the best connection, vertical handover technologies for adaptively switching among those various different RANs without interruption of an ongoing communication session have been developed, and several protocols to enable such handover have been standardized, such as the mobile IP [2], IEEE 802.21 [3] and so on. In IEEE 1900.4 [4], the architecture which exchanges various information required in order to optimize radio resource usage has been standardized. By optimally handing over among various different RANs, radio resource efficiency or the quality of services (QoS) level can be optimized across heterogeneous wireless networks.

Different RANs are usually managed by different operator. Therefore, in heterogeneous wireless networks, it may be difficult to perform radio resource usage optimization by centralized algorithm, and autonomous and distributed optimization algorithms may be more suitable. As autonomous and distributed decision making algorithms in heterogeneous wireless networks, the method based on the game theory [5,6] and optimization algorithms by the neural networks [7-9] have been proposed. In the mutually connected neural network, the energy function is minimized by an autonomous and distributed update of each neuron. The algorithm proposed in Ref. [9] using the Hopfield neural network [10] maximizes throughput autonomously and distributively by updates of each neuron. In real situation, there are various mobile applications, such as voice call, video call, email, www, and so on, whose required QoS level is different. Therefore, it is also important to optimize radio resource usage based on the required QoS level, not only mere load balancing optimization.

As a method to satisfy QoS level required by each terminal, we propose an autonomous and distributed optimization method which optimizes satisfaction rate of required QoS level. Since the objective function which optimizes the QoS satisfactory rate becomes the fourth order objective function, we introduce the higher order neural network [11]. We realize such a neural network for optimizing RAN selection by obtaining higher-order connection weights and threshold, and evaluate its performance by computer simulation.

2. Objective Function for Optimal RAN Selection

In this paper, it is assumed that available radio resources are equally shared among the terminals. Under such an assumption, available throughput T_i for the terminal i can be defined by the following equation,

$$T_i = \frac{C_{L(i)}}{N_{L(i)}}, \tag{1}$$

where c_j is the total throughput which the base station j can provide, N_j is the number of terminals which is connecting to the base station j, and $L(i)$ is the base station which the terminal i is connecting, respectively. The optimization problem of the RAN selection which satisfies QoS requirement of each user is defined. Although there are various kinds of QoS parameters, only the throughput is taken into account in this paper to evaluate the performance of our optimization algorithm. At each terminal, a RAN, which provides larger throughput that it requires, should be selected. In order to utilize limited radio resources efficiently, it is important to minimize the difference between the throughput which a terminal requires and that shared to the terminal. Therefore, the objective function for RAN selection which satisfies a QoS requirement is defined as the difference between the throughput which a terminal requires and the shared throughput. It is also necessary to make the shared throughput larger than the throughput which a terminal requires. Therefore, the objective function is defined as follows,

$$F_1 = \sum_{i=1}^{N_m} (T_i - R_i)^2 - \lambda T_i, \tag{2}$$

where N_m is the number of terminals, R_i is the required throughput by the terminal i, and λ is the parameter for the weight on the maximization of the throughput, respectively. The first term means minimization of the difference between the throughput which a terminal requires and the shared throughput. The second term means making a higher throughput than the throughput which a terminal requires.

3. Application QoS based Optimization by Distributed and Autonomous Neural Network Dynamics

3.1. Relation between RAN Selection and State of Neural Network

Using the Hopfield neural network [12], we propose the algorithm which solves autonomously and distributively the optimization problem defined in Seq. 2. Relation between firing of the neurons and establishments of the wireless links is shown in Fig. 1. A firing of the neuron (i, j) (x_{ij}=1) is corresponded to that the terminal i connects to the base station j, where x_{ij} is the state of the neuron (i, j).

Based on this definition, Eq. (2) can be expressed as a function of the state of neurons as follows,

$$\begin{aligned} F_1 &= \sum_{i=1}^{N_m} \left\{ \left(T_i - R_i\right)^2 - \lambda T_i \right\} \\ &= \sum_{i=1}^{N_m} \left\{ \left(\frac{C_{L(i)}}{N_{L(i)}} - R_i\right)^2 - \lambda \frac{C_{L(i)}}{N_{L(i)}} \right\} \end{aligned}$$

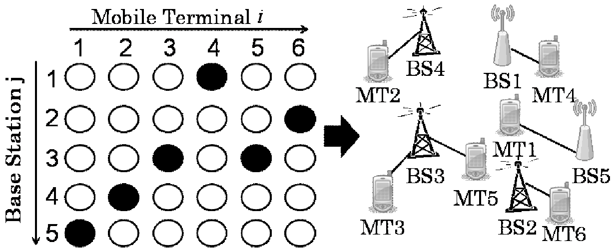

Figure 1: Relation between firings of the neurons and establishments of the wireless links

$$= \sum_{i=1}^{N_m} \left\{ \left(\sum_{j=1}^{N_{BS}} x_{ij} \frac{C_j}{\sum_{k=1}^{N_m} x_{kj}} - R_i \right)^2 - \lambda \sum_{j=1}^{N_{BS}} x_{ij} \frac{C_j}{\sum_{k=1}^{N_m} x_{kj}} \right\}, \tag{3}$$

where N_{BS} is the number of base stations. However, in Eq. (3), since the neuron x_{ij} appears in the denominator, it cannot be transformed into the form of the energy function of the Hopfield neural network. Therefore, we have decided to take the inverse of the throughput and minimize the following equation,

$$F_2 = \sum_{i=1}^{N_m} \left\{ \left(\frac{1}{T_i} - \frac{1}{R_i} \right)^2 + \lambda \frac{1}{T_i} \right\}. \tag{4}$$

Based on this equation, $\frac{1}{T_i}$ can be transformed to the following equation,

$$\frac{1}{T_i} = \sum_{j=1}^{N_{BS}} \sum_{k=1}^{N_m} \frac{1}{C_j} x_{ij} x_{kj}. \tag{5}$$

Therefore, the objective function defined in Eq. (4) can be transformed to the form of the energy function of the Hopfield neural network. In the objective function in Eq. (4), the first term strongly depends on the amount of available throughputs. Therefore, we normalize this term by the capacity of each base station. Then, the final objective function, which we optimize in this paper, is defined as F_3 and is transformed to the function of the neuron state x_{ij} as follows,

$$\begin{aligned} F_3 &= \sum_{i=1}^{N_m} \left\{ \left(\frac{1}{T_i} \cdot \frac{1}{C_{L(i)}} - \frac{1}{R_i} \cdot \frac{1}{C_{L(i)}} \right)^2 + \lambda \frac{1}{T_i} \right\} \\ &= \sum_{i=1}^{N_m} \Bigg[\Big[\sum_{j=1}^{N_{BS}} \Big\{ \sum_{k=1}^{N_m} \Big(\frac{1}{C_j} \Big)^2 x_{ij} x_{kj} - \frac{1}{C_j} \frac{1}{R_i} x_{ij} \Big\} \Big]^2 \\ &\quad + \lambda \sum_{j=1}^{N_{BS}} \sum_{k=1}^{N_m} \frac{1}{C_j} x_{ij} x_{kj} \Bigg]. \end{aligned} \tag{6}$$

Since the objective function of Eq. (6) turns into the forth order function of x_{ij}, the Hopfield neural network which minimizes the second order energy function is inapplicable to this objective function.

3.2. Higher Order Neural Network [11]

In order to minimize the objective function in Eq. (6), we introduce the higher order neural network [11]. The update equation of the third order neural network used in this paper is the following equation.

$$x_{ij}(t+1) = \begin{cases} 1 \cdots \dfrac{1}{6}\displaystyle\sum_{k=1}^{N_m}\sum_{l=1}^{N_{BS}}\sum_{m=1}^{N_m}\sum_{n=1}^{N_{BS}} \\ \quad \displaystyle\sum_{o=1}^{N_m}\sum_{p=1}^{N_{BS}} U_{ijklmnop}x_{kl}(t)x_{mn}(t)x_{op}(t) \\ \quad +\dfrac{1}{2}\displaystyle\sum_{k=1}^{N_m}\sum_{l=1}^{N_{BS}}\sum_{m=1}^{N_m}\sum_{n=1}^{N_{BS}} V_{ijklmn}x_{kl}(t)x_{mn}(t) \\ \quad +\displaystyle\sum_{k=1}^{N_m}\sum_{l=1}^{N_{BS}} W_{ijkl}x_{kl}(t) + \theta_{ij} > 0 \\ 0 \cdots \quad otherwise, \end{cases} \tag{7}$$

where $U_{ijklmnop}$, V_{ijklmn} ,W_{ijkl} and θ_{ij} are the third, the second and the first order connection weights and the threshold, respectively. By updating each neuron by this equation, the following energy function can be autonomously minimized.

$$\begin{aligned} E_2 \;=\; & -\frac{1}{24}\sum_{i=1}^{N_m}\sum_{j=1}^{N_{BS}}\sum_{k=1}^{N_m}\sum_{l=1}^{N_{BS}}\sum_{m=1}^{N_m}\sum_{n=1}^{N_{BS}}\sum_{o=1}^{N_m}\sum_{p=1}^{N_{BS}} \\ & \quad U_{ijklmnop}x_{kl}(t)x_{mn}(t)x_{op}(t) \\ & -\frac{1}{6}\sum_{i=1}^{N_m}\sum_{j=1}^{N_{BS}}\sum_{k=1}^{N_m}\sum_{l=1}^{N_{BS}}\sum_{m=1}^{N_m}\sum_{n=1}^{N_{BS}} V_{ijklmn}x_{kl}(t)x_{mn}(t) \\ & -\frac{1}{2}\sum_{i=1}^{N_m}\sum_{j=1}^{N_{BS}}\sum_{k=1}^{N_m}\sum_{l=1}^{N_{BS}} W_{ijkl}x_{ij}(t)x_{kl}(t) \\ & -\sum_{i=1}^{N_m}\sum_{j=1}^{N_{BS}} \theta_{ij}x_{ij}. \end{aligned} \tag{8}$$

There are several conditions for autonomous minimization and convergence of the energy function by distributed neuron updates. The first condition is that all the self feedback connections should be 0. The second is that all the symmetric connections should have the same weights. The third is that each neuron is updated asynchronously.

3.3. Application QoS Optimization Algorithm using Higher Order Neural Network

By transforming the Eq. (6) to the form of the Eq. (8) and comparing those coefficients, with satisfying the conditions for minimization described above, $U_{ijklmnop}$, V_{ijklmn}, W_{ijkl} and θ_{ij} for autonomously minimizing the objective function F_3 can be obtained as follows,

$$\begin{aligned} U_{ijklmnop} \;=\; & -(1-\delta_{ik}\delta_{jl})(1-\delta_{im}\delta_{jn})(1-\delta_{io}\delta_{jp}) \\ & \cdot(1-\delta_{km}\delta_{ln})(1-\delta_{ko}\delta_{lp})(1-\delta_{mo}\delta_{np}) \\ & \cdot\Bigg[\Big\{\Big(\frac{1}{C_n}\Big)^2\Big(\frac{1}{C_j}\Big)^2+\Big(\frac{1}{C_p}\Big)\Big(\frac{1}{C_l}\Big)^2\Big\} \\ & \cdot\Big(\delta_{mo}\delta_{jp}\delta_{nl}+\delta_{io}\delta_{np}\delta_{jl}+\delta_{ik}\delta_{nl}\delta_{jp}+\delta_{km}\delta_{pn}\delta_{lj}\Big) \\ & \cdot\Big\{\Big(\frac{1}{C_n}\Big)^2\Big(\frac{1}{C_l}\Big)^2+\Big(\frac{1}{C_p}\Big)\Big(\frac{1}{C_j}\Big)^2\Big\} \\ & \cdot\Big(\delta_{mo}\delta_{lp}\delta_{nj}+\delta_{im}\delta_{np}\delta_{jl}+\delta_{ik}\delta_{pl}\delta_{jn}+\delta_{ko}\delta_{pn}\delta_{lj}\Big) \\ & \cdot\Big\{\Big(\frac{1}{C_l}\Big)^2\Big(\frac{1}{C_j}\Big)^2+\Big(\frac{1}{C_p}\Big)\Big(\frac{1}{C_n}\Big)^2\Big\} \\ & \cdot\Big(\delta_{ko}\delta_{jp}\delta_{nl}+\delta_{km}\delta_{nj}\delta_{lp}+\delta_{io}\delta_{pl}\delta_{jn}+\delta_{im}\delta_{ln}\delta_{jp}\Big)\Bigg], \end{aligned} \tag{9}$$

$$\begin{aligned} V_{ijklmn} \;=\; & -(1-\delta_{ik}\delta_{jl})(1-\delta_{im}\delta_{jn})(1-\delta_{km}\delta_{ln}) \\ & \cdot\Bigg[\delta_{im}\delta_{nl}\Big\{\Big(\frac{1}{C_j}\Big)^2\Big(2\Big(\frac{1}{C_l}\Big)^2+\Big(\frac{1}{C_n}\Big)^2\Big)-2\Big(\frac{1}{C_n}\Big)^2\frac{1}{C_j}\frac{1}{R_m}\Big\} \\ & +\delta_{jl}\delta_{im}\Big\{\Big(\frac{1}{C_n}\Big)^2\Big(2\Big(\frac{1}{C_l}\Big)^2+\Big(\frac{1}{C_j}\Big)^2\Big)-2\Big(\frac{1}{C_j}\Big)^2\frac{1}{C_n}\frac{1}{R_i}\Big\} \\ & +\delta_{ik}\delta_{nl}\Big\{\Big(\frac{1}{C_j}\Big)^2\Big(2\Big(\frac{1}{C_n}\Big)^2+\Big(\frac{1}{C_l}\Big)^2\Big)-2\Big(\frac{1}{C_l}\Big)^2\frac{1}{C_j}\frac{1}{R_k}\Big\} \\ & +\delta_{jn}\delta_{ik}\Big\{\Big(\frac{1}{C_l}\Big)^2\Big(2\Big(\frac{1}{C_n}\Big)^2+\Big(\frac{1}{C_j}\Big)^2\Big)-2\Big(\frac{1}{C_j}\Big)^2\frac{1}{C_l}\frac{1}{R_i}\Big\} \\ & +\delta_{km}\delta_{jn}\Big\{\Big(\frac{1}{C_l}\Big)^2\Big(2\Big(\frac{1}{C_j}\Big)^2+\Big(\frac{1}{C_n}\Big)^2\Big)-2\Big(\frac{1}{C_n}\Big)^2\frac{1}{C_l}\frac{1}{R_m}\Big\} \\ & +\delta_{km}\delta_{lj}\Big\{\Big(\frac{1}{C_n}\Big)^2\Big(2\Big(\frac{1}{C_j}\Big)^2+\Big(\frac{1}{C_l}\Big)^2\Big)-2\Big(\frac{1}{C_l}\Big)^2\frac{1}{C_n}\frac{1}{R_k}\Big\} \\ & +2\delta_{jl}\delta_{jn}\Big(\frac{1}{C_j}\Big)^4+2\delta_{jl}\delta_{nl}\Big(\frac{1}{C_l}\Big)^4+2\delta_{jn}\delta_{nl}\Big(\frac{1}{C_n}\Big)^4\Bigg], \end{aligned} \tag{10}$$

$$\begin{aligned} W_{ijkl} \;=\; & -(1-\delta_{ik}\delta_{jl}) \\ & \cdot\Bigg[\delta_{jl}\Big\{3\Big(\frac{1}{C_j}\Big)^4-2\Big(\frac{1}{C_j}\Big)^3\frac{1}{R_i}+2\lambda\frac{1}{C_j} \\ & \qquad +3\Big(\frac{1}{C_l}\Big)^4-2\Big(\frac{1}{C_l}\Big)^3\frac{1}{R_k}+2\lambda\frac{1}{C_l}\Big\} \\ & \quad +\delta_{ik}\Big\{-2\Big(\frac{1}{C_j}\Big)^2\frac{1}{C_l}\frac{1}{R_i}-2\Big(\frac{1}{C_l}\Big)^2\frac{1}{C_j}\frac{1}{R_k} \\ & \qquad +\frac{1}{C_j}\frac{1}{C_l}\Big(\Big(\frac{1}{R_i}\Big)^2+\Big(\frac{1}{R_k}\Big)^2\Big)\Big\}\Bigg], \end{aligned} \tag{11}$$

$$\theta_{ij} = \Big(\frac{1}{C_j}\Big)^4 - 2\Big(\frac{1}{C_j}\Big)^3\frac{1}{R_i} + \Big(\frac{1}{C_j}\Big)^2\Big(\frac{1}{R_i}\Big)^2 - \lambda\frac{1}{C_j}. \tag{12}$$

By updating the neuron's states using Eq. (7) with these obtained connection weights and thresholds, the RAN selection problem to optimize the QoS satisfaction rate can be autonomously solved.

4. Simulation and Results

We evaluate the proposed RAN selection method satisfying QoS requirement in the heterogeneous wireless network environment. We prepare 4 base stations, one provides 54Mbps, and other three provides 11Mbps, respectively. We assume all the base stations are available for all users.

We compare the proposed RAN selection method with a simple throughput maximization method. The results are shown in Figs. 2 and 3. In Fig. 2, the throughputs which each terminal requires is set to 0.3, 1.0, 3.0 or 4.0 Mbps. In Fig. 3, those are set to 0.1, 1.0, 3.0 or 5.0 Mbps. Variance of the required throughput in the second experimental setting is relatively larger than the first one.

From the result of Figs. 2 and 3, it is verified that the proposal method using the neural network dynamics improves a QoS satisfaction rate. Comparing Figs. 2 and 3, improvement is larger for the case with larger variance on the QoS requirement in Fig. 3.

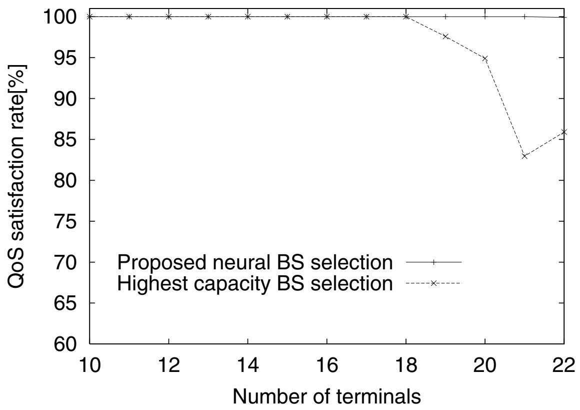

Figure 2: QoS satisfaction rate by the highest capacity base station selection algorithm and the proposed neural base station selection algorithm. The terminals' required throuthputs are 0.3Mbps, 1Mbps, 3Mbps or 4Mbps.

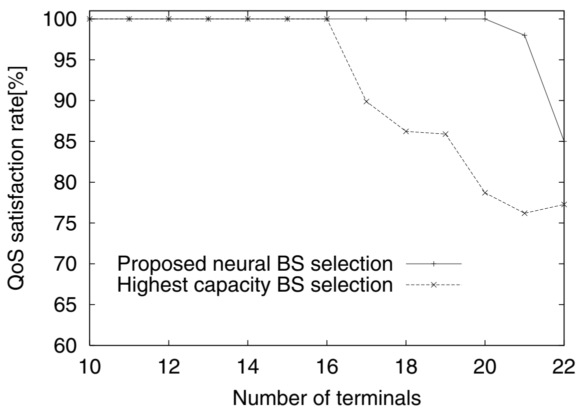

Figure 3: QoS satisfaction rate by the highest capacity base station selection algorithm and the proposed neural base station selection algorithm. The terminals' required throuthputs are 0.1Mbps, 1Mbps, 3Mbps or 5Mbps.

5. Conclusion

In this paper, we have proposed an autonomous and distributed RAN selection satisfying QoS requirement using the higher order neural network. From the simulation results, it is shown that the proposal method improves a QoS satisfactory rate.

Since the proposed algorithm is based on the distributed update of each neuron, it does not need to perform centralized computation. Updating of the neural network can be distributed to the terminals or the base stations, and optimal RAN can be selected based on the neuron state. Therefore, the scalability of the proposed system is very high, and computational load can be distributed. Since the proposal method can select RAN distributively, it is suitable for the heterogeneous wireless networks. In Ref. [12], the optimization method of the load-balancing algorithm which used a neural network dynamics has been designed and implemented in real experimental wireless network [13], and its feasibility has been verified. We are also going to implement the algorithm proposed in this paper on the real experimental wireless network to verify effetiveness of the proposed approach.

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