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Autonomous and adaptive resource allocation among multiple nodes and multiple applications in heterogeneous wireless networks

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A B S T R A C T

In the forthcoming future, various means of wireless communication, such as cellular, Wi-Fi, WiMAX, and DSRC, will be available to mobile users and applications. With the development of wireless communication and mobile devices, more and more users and applications will be accommodated in mobile environment. Since mobile users and applications compete for the limited wireless resources whose communication quality dynamically change, we need an adaptive mechanism for mobile users and applications to share the available network resources while satisfying each application's QoS requirements. In this paper, we propose an adaptive resource allocation mechanism where each node autonomously determines wireless network resources to assign to each of networked applications running on it. For this purpose, we adopt an attractor composition model, which is based on an autonomous and adaptive behavior of biological systems. Through numerical analysis, we confirmed that our mechanism could adaptively and stably allocate wireless network resources to applications, while considering their QoS requirements and fairly sharing network resources with other nodes. It also is shown that our mechanism superiors to a mechanism where a node determines resource allocation by solving an optimization problem.

1. Introduction

With the proliferation of wireless network technology, various means of wireless communication will be available to mobile users and applications to support our daily life everywhere in the forthcoming future. Wireless communications, such as cellular, Wi-Fi, WiMAX, and DSRC (Dedicated Short Range Communication) have heterogeneous characteristics in terms of the availability, capacity, delay, connectivity, and cost. Furthermore, most characteristics dynamically change due to instability of wireless communication and competition among users and applications for wireless network resources. The suitable wireless network for each networked application may be different due to different QoS requirement, i.e. low delay in VoIP, low cost in e-mail, and large bandwidth in video streaming. Therefore, it is necessary for a node, that is, equipment where networked applications are running, to choose a wireless network resource dynamically to use for each of applications taking into account the condition of wireless networks and QoS requirements of applications. For example, a VoIP application running on a smartphone requires one-way end-to-end delay of lower than 150 ms for interactive communication [1]. Therefore, it is better to assign a cellular or DSRC network, which provides an application with a connection with small delay and jitter, to a VoIP application. On the other hand, an e-mail application can tolerate delay, while the volume of traffic is large. Therefore, a Wi-Fi or WiMAX network is appropriate for an e-mail application, because those networks can provide an application with high-speed connection for lower cost than a cellular network.

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For effective and efficient use of available wireless networks, in recent years, cognitive networking has been attracting attention of researchers and developers. Cognitive network is, in one definition, the technology that cognizes the condition of wireless networks and selects an appropriate network to efficiently utilize the available network resources [2–6]. In the context of cognitive network, a wireless network resource corresponds to a network, channel, or spectrum distinguished by wireless network technology, MAC protocol, coding algorithm, or frequency. Although existing proposals are useful in adaptive resource allocation in heterogeneous wireless network environment, most of them only deal with either of resource allocation among multiple nodes or resource allocation among multiple applications running on a node. For example, Kassar et al. proposed an automated network selection strategy dealing with resource allocation among multiple nodes in [4]. They proposed a comprehensive decision making mechanism based on multi-attribute decision making algorithms to assist the node in selecting the top candidate network. They consider more than ten network attributes and treat rule-based multi-attribute decision making. However, their approach considers only one network and they did not consider effective and efficient use of multiple networks.

In the environment where a variety of heterogeneous networks are available and there exist multiple nodes having a variety of applications running, we need a mechanism to allocate an appropriate wireless network to each application on each node taking into account characteristics of wireless networks and QoS requirements of the application. Such resource allocation can be formulated as an optimization problem to maximize the degree of satisfaction per node and per application, once information about the current condition of available wireless networks and QoS requirements of all applications is given. However, such optimization requires for a central node, e.g. an access point, to maintain the up-to-date information by frequent and aggressive message exchanges with nodes in the area. Even if the task of derivation of optimal resource allocation is distributed among nodes, nodes need to frequently exchange messages with other nodes to obtain latest information about the current status of applications running on the other nodes. From a viewpoint of dynamic features of wireless networks and cost, e.g. bandwidth and energy, spent in message exchanges, such mechanisms are not feasible at all in the new generation network environment, where various wireless networks are available to a large number of networked applications.

In this paper, we propose an autonomous, fully distributed, and adaptive mechanism of network resource allocation among multiple nodes and multiple applications. In our mechanism, each node decides wireless networks to use for its applications. A node first recognizes the condition of wireless networks available to the node. Next, it evaluates the degree that applications are satisfied with the allocated networks. Then, it determines a wireless network to allocate to each application. To accomplish stable and adaptive resource allocation in the dynamically changing environment, we adopt a nonlinear mathematical model of dynamical and adaptive behavior of biological systems, which is called an attractor composition model [7]. The attractor composition model is a noise-driven metaheuristic to find a stable solution of an optimization problem in an adaptive manner. Possible solutions are defined as attractors of a dynamical system and the potential of solution space is affected by the goodness of the current solution. When the current solution is appropriate, a basin of attractor corresponding to the solution in the solution space becomes deep and the state of the system statically stays there. Once the current solution becomes inappropriate for the new condition, the basin of attractor becomes shallow and the state begins to change randomly until a new good attractor is found. By defining the degree of satisfaction of node as an indicator of goodness of resource allocation, a node can autonomously find a solution, i.e. resource allocation, which is appropriate for the current condition of wireless networks and QoS requirements of applications. Since the condition of wireless networks is influenced by resource allocation at other nodes, nodes indirectly interact with each other and they eventually share the available network resources in a fair manner.

The rest of the paper is organized as follows. We first introduce the attractor composition model in Section 2. Next in Section 3, we propose a novel resource allocation mechanism for multiple nodes and multiple applications in heterogeneous wireless network environment. Then we show results of numerical evaluation and comparison with a mechanism adopting per-node optimization in Section 4. Finally, we conclude the paper and describe future directions in Section 5.

2. Attractor composition model and its application to resource allocation

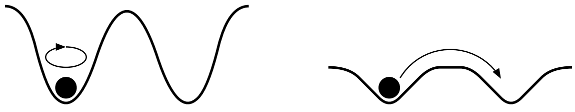
Since the attractor composition model is an extension of the attractor selection model, we first briefly introduce the attractor selection model and then explain the attractor composition model in this section.

2.1. Attractor selection model

The attractor selection model is a metaheuristic of optimization problems that given condition dynamically changes [8]. The model is developed from an adaptive behavior of biological systems leading to symbiotic condition. In biological experiments, mutant *E. coli* cells are manipulated to synthesize two nutrients A and B, which are indispensable for them to grow. Nutrient synthesis is in a mutually inhibiting relation, where synthesis of one nutrient disturbs synthesis of the other nutrient. Nutrient synthesis is governed by the gene expression level of corresponding mRNA.

Temporal differential equations defining the dynamics of mRNA concentrations are given as follows:

$$\frac{dm_1}{dt} = \frac{s(\alpha)}{1+m_2^2} - d(\alpha) \times m_1 + \eta_1, \tag{1}$$



(a) High activity (b) Low activity

Fig. 1. Potential space with two attractors.

$$\frac{dm_2}{dt} = \frac{s(\alpha)}{1+m_1^2} - d(\alpha) \times m_2 + \eta_2, \tag{2}$$

m_1 and m_2 are mRNA concentrations corresponding to nutrient A and B, respectively. A pair of m_1 and m_2, i.e. (m_1, m_2), determines the state of cell. α $(0 \leqslant \alpha \leqslant 1)$ is a parameter called *activity* reflecting the current condition of a cell, e.g. the growth rate, which is a function of the state of cell and the environmental nutrient condition. $s(\alpha)$ and $d(\alpha)$ are functions for synthesis and decomposition of nutrients, respectively. For example, $s(\alpha) = \frac{6\alpha}{2+\alpha}$ and $d(\alpha) = \alpha$ in [8]. η_1 and η_2 correspond to the white Gaussian noise, which implement internal and external noise inherent in biological systems. A dynamical system defined by the above equations has two stable states, called *attractors*, where $m_1 \gg m_2$ or $m_1 \ll m_2$. In other words, the potential space of the dynamical system has two basins of attractors as shown in Fig. 1(a).

Let us assume that a cell stays one of attractors and synthesizes nutrient A, i.e. $m_1 \gg m_2$. When the environment, i.e. the culture medium, contains both nutrients sufficiently, the cell can grow well and the activity is high. Therefore, basins of attractors are deep and the force of entrainment of attractors is strong. As a result, although the mRNA concentrations are affected by the noise terms, the cell statically stays at the attractor. Now, assume that the nutrient condition occasionally changes and the environment lacks nutrient B. Since the cell synthesizes nutrient A, it does not have nutrient B sufficient to grow. Consequently, the activity of the cell decreases. Basins of attractors become shallow accordingly. At the same time, the noise terms begin to dominate the state (m_1, m_2). By being driven by the noise, the cell happens to synthesize more nutrient B than nutrient A, i.e. $m_1 < m_2$, and moves toward the attractor as shown in Fig. 1(b). Since such nutrient synthesis is preferable in the current nutrient condition, the cell begins to grow and the activity increases. The increased activity makes basins of attractors deeper and the state is entrained to a new attractor, where $m_1 \ll m_2$. Eventually, the cell begins to synthesize nutrient B statically. In this way, the cell can successfully adapt its nutrient synthesis to dynamic change in the environmental nutrient condition.

In [9], we extended the model to M dimension as,

$$\frac{dm_i}{dt} = \frac{s(\alpha)}{1 + (\max_{1 \leqslant j \leqslant M} m_j)^2 - m_i^2} - d(\alpha) \times m_i + \eta_i \tag{3}$$

where $1 \leqslant i \leqslant M$ and

$$s(\alpha) = \alpha\left(\beta \times \alpha^{\gamma}\right) + \frac{1}{\sqrt{2}}, \tag{4}$$

$$d(\alpha) = \alpha. \tag{5}$$

m_i $(1 \leqslant i \leqslant M)$ are called state values. The model has M attractors where $m_i \gg m_j$ $(1 \leqslant j \leqslant M, j \neq i)$. β and γ are parameters having positive real numbers. With large β, basins of attractors become deep leading to the higher stability of attractors. With large γ, the rate of increase in state value becomes smaller. As a result, the strength of entrainment becomes weaker and the speed of convergence gets slower.

By defining the activity as the goodness of control, e.g. performance, and attractors as alternatives of control, the attractor selection model enables adaptive control to maximize the performance in the dynamically changing environment. For example, the model has been applied to overlay multipath routing [10] and MANET routing [11]. In the case of MANET routing, the activity is determined based on the path length and attractors correspond to selection of neighbor nodes, where M is equal to the number of neighbors. Each node on a path evaluates the attractor selection model and it chooses a neighbor node leading to the shorter path in forwarding a packet. It was shown that the attractor selection-based routing achieves the higher performance than conventional routing in the dynamically changing environment.

2.2. Attractor composition model

Now consider the general model of attractor selection, which is formulated as,

$$\frac{d\vec{m}_i}{dt} = f(\vec{m}_i) \times \alpha_i + \vec{\eta}_i, \quad 1 \leqslant i \leqslant N. \tag{6}$$

$\vec{m}_i$ is a vector of state values of entity i, e.g. a cell and a node, and α_i is the activity of entity i. $f()$ is a function defining attractors. $\vec{\eta}_i$ is a vector of white Gaussian noise to introduce the effect of noise to each of state values. N is the number of entities. As explained in the previous section, the attractor selection model enables each entity i constituting the system to autonomously and adaptively determine its behavior $\vec{m}_i$ leading to the high activity α_i. Although their decision is independent from each other, through mutual interactions among them by sharing the same environment, the system eventually reaches the globally good condition where all entities have high activity and they comfortably coexist. For example, nutrients synthesized by a cell change the concentrations of nutrients in the culture media by membrane permeation. Therefore, adaptive behavior of a cell influences other cells.

In the attractor composition model, interaction among entities is explicitly formulated and the global optimization is accelerated [7]. The attractor composition model is formulated as,

$$\frac{d\vec{m}_i}{dt} = f(\vec{m}_i) \times \alpha + \vec{\eta}_i, \quad 1 \leqslant i \leqslant N. \tag{7}$$

Note here that the activity is now a global parameter reflecting the goodness of the whole system. Therefore, each entity constituting the system autonomously and adaptively determines its behavior to maximize the global activity with this model.

In [7], the attractor composition model is applied to the cross-layer optimization in a wireless sensor network where an overlay network for periodic data gathering is organized over a physical sensor network. Based on Eq. (7), each of sensor nodes adaptively changes the operational frequency, while an overlay network adaptively changes the overlay topology. By sharing the same activity, which is defined as the data gathering delay, between layers, autonomous and adaptive control in different layers accomplishes the global goal to minimize the data gathering delay.

2.3. Application of attractor composition model to resource allocation

In applying the attractor composition model to resource allocation among nodes and among applications, there are two alternatives different in interpretation of the global activity shared among entities. When we define the activity α as the goodness of resource allocation in a certain region where multiple nodes exist, entity i corresponds to a node. Such a mechanism requires all nodes or a central node to know the degree of satisfaction of all nodes to derive the activity. It apparently is bandwidth and energy expensive and not feasible.

On the other hand, to define the activity α per node is more practical and feasible. In this case, entities competing for resources correspond to applications. Application i running on a node autonomously decides a wireless network to use by using Eq. (7), where N is the number of applications and M is the number of available network resources. Since the activity α shared among applications is derived from the degree of satisfaction of all applications running on a node, applications behave in a cooperative manner to maximize the degree of satisfaction of the node. Nodes further behave in a cooperative manner through indirect interaction among nodes by sharing network resources. In the next section, we provide details of our proposal based on this interpretation.

3. Autonomous and adaptive resource allocation mechanism

As explained in the previous section, we adopt the attractor composition model to achieve autonomous and adaptive resource allocation among multiple nodes and multiple applications in the environment where heterogeneous wireless networks are available to nodes. In this section, we first explain a scenario considered in the paper and then describe our resource allocation mechanism.

3.1. Target network and application

In this paper, we assume that various wireless networks are available to nodes. In numerical experiments, we consider that cellular, Wi-Fi, WiMAX, and DSRC networks are available and a node allocates one of those networks to each of applications. However, our proposal does not limit target networks to them. Furthermore, resource allocation can be in the arbitrary granularity, from a network distinguished by their technologies, channel, spectrum, and waveform, as far as their characteristics are obtained at that granularity. Those networks have different characteristics in terms of the size of access area, the wireless capacity, the delay in communication and connection establishment, the reliability of connection, the stability of communication, and the cost to use. For example, a cellular network is mostly available except for underground in the urban area. However, the capacity is only about 7.2 or 14.4 Mbps and the effective bandwidth is much smaller than the capacity. Furthermore, there is restriction on the number of simultaneous connections in a cell and communication costs much. On the other hand, a Wi-Fi network provides nodes with the high-speed connection with the capacity of up to 54 Mbps and it is less expensive than a cellular network. However, a Wi-Fi network has the very limited accessibility, whose access area is as long as tens meters in radius from an access point.

A node corresponds to a mobile device such as a smartphone, laptop, and vehicle. On each node, multiple applications are running and they require access to wireless networks. In the case of a car, a variety of applications such as road navigation, automobile condition reporting, video streaming, VoIP, e-mail, and web browsing are operating and each of which has different QoS requirements [12,13]. For example, a video streaming application requires the large bandwidth while a VoIP application requires a connection with low delay jitter. We further assume that there exists a module or a program, which is responsible for allocation of resources to applications. In the case of a car, an OBU (On Board Unit) is equipped with multiple wireless network interfaces to provide applications with access to wireless networks. A node in this case corresponds to a car or more specifically an OBU of a car.

3.2. Overview of our mechanism

At regular control intervals, each application running on a node declares its QoS requirements in terms of the required bandwidth, tolerable delay jitter, and affordable transmission cost, for example, to the node. At the same time, a node obtains the information about the current status of available wireless networks, e.g. the available bandwidth, delay jitter, and transmission cost by using a cognitive radio technology [14–16]. Next, the node evaluates the degree that QoS requirements of each application are satisfied with an allocated network. Then, from the degree of satisfaction of applications, the degree of satisfaction of node is calculated, from which the activity of node is further derived. Based on the activity, a vector of state value of each application is updated by the attractor composition model. Finally, a wireless network with the largest state value is allocated to each application. If the current allocation can satisfy QoS requirements of applications, the activity is high and resource allocation does not change. Otherwise, the activity becomes small and the noise term drives resource allocation to find better allocation.

3.3. Resource allocation based on state vector

For attractor composition-based resource allocation, a node maintains a set of N state vectors, where N is the number of applications. State vector $\vec{m}_i$ of application i $(1 \leqslant i \leqslant N)$ is defined as,

$$\vec{m}_i = (m_{i,1}, \ldots, m_{i,j}, \ldots, m_{i,M}), \tag{8}$$

where M is the number of wireless networks available to a node. We assume that wireless networks are indexed, but the order of indexes does not affect resource allocation.

At regular control intervals, the activity α is evaluated and the state vectors are updated accordingly.

$$\frac{dm_{i,j}}{dt} = \frac{s(\alpha)}{1 + (\max_{1 \leqslant k \leqslant M} m_{i,k})^2 - m_{i,j}^2} - d(\alpha) m_{i,j} + \eta_{i,j}, \tag{9}$$

where $\eta_{i,j}$ is the white Gaussian noise with mean zero and standard deviation σ. For $s()$ and $d()$, we use the same functions in Eq. (4) and Eq. (5), respectively. Then, wireless network indexed as j with the largest state value $m_{i,j}$ in vector $\vec{m}_i$ is assigned to application i.

3.4. Activity derivation

Activity α $(0 \leqslant \alpha \leqslant 1)$ indicates the goodness of the current resource allocation. In our proposal, the activity α is derived by the following equation:

$$\alpha = \frac{\sum_{t=0}^{T-1} \alpha_t^*}{T}, \tag{10}$$

where α_0^*, i.e. α_t^* with $t = 0$, is called the current instant activity and α_t^* is the instant activity of t intervals ago. T is a constant defining the window of moving average.

In derivation of the instant activity α_0^*, we use a hysteresis function of the play model [17] to suppress the sensitivity of activity to slight decrease in the degree of satisfaction S of node, which is derived by Eq. (14).

$$\alpha_0^* = \frac{1}{P} \sum_{l=1}^{P} h_l\bigl(p_l(S)\bigr), \tag{11}$$

P is the number of play hysterons. p_l $(l = 1, \ldots, P)$ is a play hysteron, which is defined as,

$$p_l(S) = \max\bigl(\min\bigl(p_l^-, S + \zeta_l\bigr), S - \zeta_l\bigr) \tag{12}$$

where p_l^- is the previous value of p_l and ζ_l is the width of play hysteron p_l. h_l in Eq. (11) is a shape function of p_l, for which we used a sigmoid function as,

$$h_l\bigl(p_l(S)\bigr) = \frac{1}{1 + \exp(-g p_l(S))}, \tag{13}$$

g $(g > 0)$ is a gain of a sigmoid function.

Based on preliminary experiments, we found the threshold of activity of a phase transition exists. When the activity is larger than 0.6, a basin of attractor is deep and resource allocation is stable. When the activity becomes smaller than 0.6,

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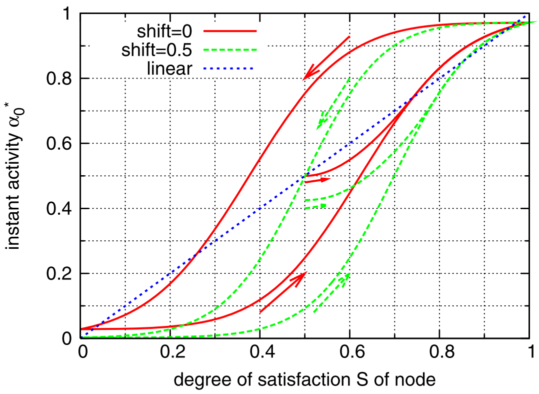

Fig. 2. Hysteresis loop of relationship between the degree of satisfaction of node and the instant activity.

resource allocation begins to be affected by the noise term. If we use the degree of satisfaction S of node as the instant activity depicted as a linear line in Fig. 2, the behavior of node in resource allocation will suffer from instantaneous changes in characteristics of wireless networks and consequently resource allocation becomes unstable.

Fig. 2 shows the relationship between the degree of satisfaction S of node and the instant activity α_0^*. With a hysteresis function, a trajectory draws a loop as shown by a solid curve. When the degree of satisfaction of node increases from zero, the activity remains low at first. However, once the degree of satisfaction of node goes beyond a certain value, the activity begins to increase exponentially. This makes a node keep looking for better resource allocation until the degree of satisfaction of node reaches about 0.67. In addition, resource allocation converges fast once the degree of satisfaction of node becomes sufficiently high. On the contrary, when the degree of satisfaction of node is decreasing, the activity is kept high until a certain point. It contributes to the insensitivity of resource allocation to slight decrease in the degree of satisfaction of node. As a result, a node keeps the current resource allocation even when the degree of satisfaction of node slightly decreases for perturbation. However, by using the hysteresis function, the activity does not drop to 0.6 until the degree of satisfaction of node decreases to about 0.43. It implies that a node does not change the current resource allocation even if the degree of satisfaction of node is as low as 0.5.

Therefore, we shift the loop to the right as shown by a dashed curve in Fig. 2. The degree of satisfaction S of node ranging from 0 to 1 is mapped to -0.5 to 1 by substituting $S \times 1.5 - 0.5$ for S in Eq. (11) and Eq. (12). With the shift, the degree of satisfaction of node at the point that the activity is 0.6 is about 0.74 in the right curve and 0.54 in the left curve, respectively.

3.5. Degree of satisfaction

The degree of satisfaction S of node is derived from the weighted average and the weighted standard deviation of degree of satisfaction of applications to take into account both of the goodness and fairness of resource allocation.

$$S = \frac{\bar{Q}}{1 + b\sigma_Q}, \tag{14}$$

b ($b \geqslant 0$) is a constant. The weighted average $\bar{Q}$ ($0 \leqslant \bar{Q} \leqslant 1$) is derived by the following equation:

$$\bar{Q} = \sum_{i=1}^{N} W_i Q_i, \tag{15}$$

where N is the number of applications. Each application has different level of importance from a viewpoint of a node, which is expressed by the weight W_i ($0 \leqslant W_i \leqslant 1$) of application i and $\sum_{i=1}^{N} W_i = 1$. Q_i is the degree of satisfaction ratio of application i. The weighted standard deviation σ_Q is derived by the following equation:

$$\sigma_Q = \sqrt{\sum_{i=1}^{N} W_i (\bar{Q} - Q_i)^2}. \tag{16}$$

Therefore, the activity becomes high when the degree of satisfaction of application is high and similar among applications.

Each application defines QoS requirements using several QoS criteria, e.g. bandwidth, delay jitter, and cost. The degree of satisfaction of application is derived from the degree that QoS requirements of an application are satisfied with a wireless network allocated to the application. The degree of satisfaction Q_i of application i is derived as follows.

$$Q_i = \bar{q}_i - \sqrt{\sigma_i^2}, \tag{17}$$

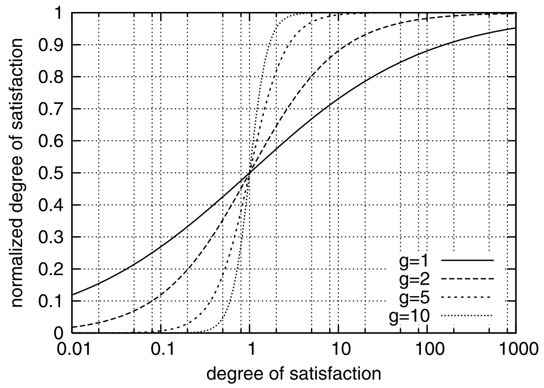

Fig. 3. Slope of sigmoid function used in derivation of degree of satisfaction of QoS on application.

$\bar{q_i}$ and σ_i^2 are the weighted average and weighted variance of degree of satisfaction $q_{i,s}$ of QoS s, respectively:

$$\bar{q_i} = \sum_{s=1}^{K_i} w_{i,s} q_{i,s}, \tag{18}$$

$$\sigma_i^2 = \sum_{s=1}^{K_i} w_{i,s} (\bar{q_i} - q_{i,s})^2. \tag{19}$$

Here, K_i is the number of QoS criteria specified by application i. In the case that application i uses bandwidth, delay jitter, and cost as QoS criteria, $K_i = 3$ and s is either of the three criteria. $w_{i,s}$ ($0 \leqslant w_{i,s} \leqslant 1$, $\sum_{s=1}^{K_i} w_{i,s} = 1$) is the weight of QoS s on application i reflecting the importance of the QoS for the application.

The degree of satisfaction $q_{i,s}$ of QoS s on application i is derived from the QoS satisfaction ratio $x_{i,s}$ as,

$$q_{i,s} = \begin{cases} \frac{1}{1+\exp(-g_{i,s}\log(x_{i,s}))} & (x_{i,s} > 0), \\ 0 & (x_{i,s} = 0), \end{cases} \tag{20}$$

where $g_{i,s}$ is a gain ($g > 0$) of a sigmoid function. The QoS satisfaction ratio $x_{i,s}$ ($x_{i,s} \geqslant 0$) of QoS s indicates how much each QoS requirement of an application is satisfied by the wireless network allocated to the application. For example, in the case of bandwidth, $x_{i,s}$ is the ratio of the available bandwidth on the allocated wireless network to the required bandwidth. Therefore, $x_{i,s} = 1.0$ means that the required QoS is fully satisfied.

A reason that we introduce a sigmoid function in Eq. (20) is to control the sensitivity of QoS satisfaction ratio to the QoS provided by the allocated wireless network. When the gain $g_{i,s}$ is large, the slope of the sigmoid function around $x_{i,s} = 1$ becomes steep as shown in Fig. 3. With such a function, the QoS satisfaction ratio $x_{i,s}$ remains low as far as, for example, the available bandwidth is less than the required bandwidth. It means that, once a wireless network with the available bandwidth smaller than the required bandwidth is occasionally allocated to an application, the QoS satisfaction ratio drastically decreases. Consequently, the activity decreases, and the application begins to choose a wireless network at random being driven by the noise term. Therefore, a large $g_{i,s}$ leads to the unstable resource allocation. On the other hand, a small $g_{i,s}$ makes the slope gentle. Therefore, the QoS satisfaction ratio $x_{i,s}$ becomes high, even when application i is allocated a wireless network providing insufficient QoS and the QoS requirement of the application is not well satisfied. Furthermore, resource allocation becomes stable and no further improvement is expected, because the activity becomes sufficiently high.

3.6. Algorithm

We show how our proposal determines network for application i in Algorithms 1 and 2, where the function $NormalDistributionRandom(0, \sigma)$ derives the white Gaussian noise with mean zero and standard deviation σ and Δt is the calculation interval.

4. Numerical experiments

In this section, we show and discuss results of numerical experiments using a vehicular application scenario as an example.

Algorithm 1 Calculate $s(\alpha)$ and $d(\alpha)$

Require: $g > 0,\ \beta > 0,\ \gamma > 0$
Ensure: calculate $s(\alpha)$ and $d(\alpha)$
  for all i **do**
    for all s **do**
      derive QoS satisfaction ratio $x_{i,s}$ of QoS s
      $q_{i,s} \leftarrow \frac{1}{1+\exp(-g_{i,s}\log(x_{i,s}))}\ (x_{i,s} > 0), \quad 0 (x_{i,s} = 0)$
    end for
    $\bar{q}_i \leftarrow \sum_{s=1}^{K_i} w_{i,s} q_{i,s}$
    $\sigma_i^2 \leftarrow \sum_{s=1}^{K_i} w_{i,s}(\bar{q}_i - q_{i,s})^2$
    $Q_i \leftarrow \bar{q}_i - \sqrt{\sigma_i^2}$
  end for
  $\bar{Q} \leftarrow \sum_{i=1}^{N} W_i Q_i$
  $\sigma_Q \leftarrow \sqrt{\sum_{i=1}^{N} W_i(\bar{Q} - Q_i)^2}$
  $S \leftarrow \frac{\bar{Q}}{1+b\sigma_Q}$
  $p_l(S) \leftarrow \max(\min(p_l^-, S + \zeta_l), S - \zeta_l)$
  $h_l(p_l(S)) \leftarrow \frac{1}{1+\exp(-gp_l(S))}$
  $\alpha_0^* \leftarrow \frac{1}{P}\sum_{t=1}^{P} h_l(p_l(S))$
  $\alpha \leftarrow \frac{\sum_{t=0}^{T-1}\alpha_t^*}{T}$ (α_t^* is the instant activity of t intervals ago)
  $s(\alpha) \leftarrow \alpha(\beta \times \alpha^\gamma) + \frac{1}{\sqrt{2}}$
  $d(\alpha) \leftarrow \alpha$

Algorithm 2 Select network for application i

Ensure: select j with the largest $m_{i,j}$
  for all j **do**
    $\eta_{i,j} \leftarrow \mathit{NormalDistributionRandom}(0, \sigma)$
    $m'_{i,j} \leftarrow m_{i,j} + \Delta t \times (\frac{s(\alpha)}{1+(\max_{1\leqslant k\leqslant M} m_{i,k})^2 - m_{i,j}^2} - d(\alpha)m_{i,j} + \eta_{i,j})$
  end for
  $\vec{m}_{i,j} \leftarrow \vec{m}'_{i,j}$
  select j with $\max(\vec{m}_{i,j})$

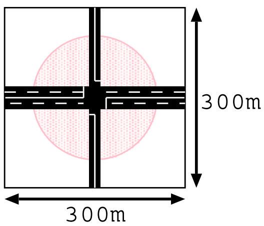

Fig. 4. Road model used in numerical experiments.

4.1. Definitions and settings

Considering resource allocation in a vehicular application scenario, we use the road model illustrated in Fig. 4. The region is 300 m × 300 m large and a torus. There are two roads crossing at the center of the region. The horizontal road has four lanes and the vertical road has two lanes. Car traffic is affected by traffic signals at the intersection.

Wireless Networks

There are four wireless networks available in the region. They are DSRC (ARIB STD-T75 or later protocol), Wi-Fi (IEEE 802.11g), WiMAX, and cellular (3G-HSPA) networks. DSRC, WiMAX, and cellular networks cover the whole region, while the access area of Wi-Fi network is limited within the radius 100 m as shown by a circle in Fig. 4. For simplicity, the distance between a node and a base station or an access point does not affect the communication speed. Therefore, dynamic changes in wireless networks are mainly caused by moving across a Wi-Fi access area and competition among applications and nodes.

Empirically determined characteristics of wireless networks are summarized in Table 1. For instance, the maximum capacity of the DSRC, Wi-Fi, WiMAX, and cellular networks are 4 Mb/s, 20 Mb/s, 40 Mb/s, and 2 Mb/s, respectively. We assume the constant delay jitter of the DSRC, Wi-Fi, WiMAX, and cellular networks as 100 ms, 500 ms, 200 ms, and 100 ms, respectively. Although the transmission cost may be differentiated by price plan, we assume the constant transmission cost, i.e. 10^{-7} unit/b, 10^{-9} unit/b, 10^{-8} unit/b, and 10^{-5} unit/b for the DSRC, Wi-Fi, WiMAX, and cellular networks, respectively,

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Table 1
Characteristics of wireless networks assumed in numerical experiments.

Network	Capacity [Mb/s]	Delay jitter [ms]	Transmission cost [unit/b]
DSRC	4	100	10^{-7}
Wi-Fi	20	500	10^{-9}
WiMAX	40	200	10^{-8}
Cellular	2	100	10^{-5}

Table 2
QoS requirements of applications assumed in numerical experiments.

Application	Bandwidth [kb/s]	Delay jitter [ms]	Transmission cost [unit/s]
Web (1)	300 (0.3)	10,000 (0.1)	0.1 (0.6)
VoIP (3)	64 (0.5)	150 (0.4)	1 (0.1)
Video (2)	3000 (0.6)	1000 (0.1)	0.1 (0.3)

for the sake of simplicity. Although some of them will vary time by time in reality, we assume they are constant for the sake of simplicity in the numerical experiments.

The capacity of the Wi-Fi network is shared among applications to which it is allocated. The bandwidth available to an application is given by dividing the capacity by the number of applications using the Wi-Fi network. The capacity of DSRC and WiMAX networks are also shared among applications, but the maximum bandwidth a node can use on the WiMAX network is limited to 15 Mb/s. In the case of the cellular network, the available bandwidth to an application varies in accordance with the number of connections. When there is only one application using the cellular network, the available bandwidth to the application is 2 Mb/s. When two or three applications are assigned for the cellular network, each of them can use 1 Mb/s bandwidth. Furthermore, when there are four through six applications, the available bandwidth to each application decreases to 0.5 Mb/s. Finally, when there are seven to twelve applications using the cellular network, an application can use only 0.25 Mb/s for each. When there are twelve applications using the cellular network, an application to which the cellular network is newly allocated cannot establish a connection. Then, the application begins to ignore the cellular network in resource allocation by setting a state value $m_{i,j}$ of the cellular network at zero, until the cellular network becomes ready to accept a new connection again. Similarly, a node out of the access area of Wi-Fi network considers only the DSRC, WiMAX, and cellular networks in resource allocation.

Regarding delay jitter and transmission cost, we use empirical values to make them different from each other while taking into account their general characteristics. For example, since a cellular network is designed for voice communication, delay jitter is set at the lowest among networks. However, it costs the most when we consider per-bit charge of data communication. Such empirical setting implies that we can call them network A, B, C, and D, instead of referring to real network technologies. Since our purpose of numerical experiments is to demonstrate how our proposal can choose an appropriate network for an application in the competitive and dynamically changing environment, those parameter settings do not affect the usefulness of our protocol very much.

At the beginning of a numerical experiment, nodes are randomly placed on the roads while keeping the density of nodes on the horizontal road 2.5 times larger than that on the vertical road. Nodes move along the road where they are initially placed. A node goes in and out an access area of Wi-Fi network. Assuming that the speed of node on the horizontal road is 40 km/h, a node stays in the access area of Wi-Fi network for random duration of time ranging from 18 s to 120 s with consideration of influence of a traffic signal at the intersection. In addition, we assume that a node becomes out of an access area for constant duration of 9 s. On the vertical road, nodes move at the speed of 20 km/h. The durations that a node is in the access area is set at random from 36 to 150 s and the duration of out of access area is 18 s.

Applications

We consider that Web browsing and mail (denoted as Web), VoIP, and video streaming (denoted as Video) applications are running. All nodes use Web. One-tenth of nodes additionally use either VoIP or Video and one-twentieth of nodes use all of three applications. QoS requirements of applications are summarized in Table 2.

As shown in the table, QoS requirements are defined in terms of the required bandwidth, the tolerable delay jitter, and the affordable transmission cost. Numbers in parentheses define the weight values W_i and $w_{i,s}$ of each application i and QoS s on application i, respectively (see 3.5). For example, Web requires the bandwidth of 300 kb/s with the importance of 0.3, the tolerable delay jitter of 10 s with the importance of 0.1, and the affordable transmission cost of 0.1 unit/s with the importance of 0.6. Weight values are identical among nodes and applications. Since weight W_i of application i is normalized as $\sum_{i=1}^{N} W_i = 1$, on a node with Web and VoIP they have weights of 1/4 and 3/4, respectively, for example. Similarly, in a case of a node with all three applications, Web is assigned the weight of 1/6.

We consider that Web concerns the transmission cost most, while it tolerates the large delay jitter. On the other hand, VoIP should maintain the bandwidth of 64 kb/s and the delay jitter smaller than 150 ms for smooth and interactive communication at the sacrifice of cost. Video is an application that requires the bandwidth most. Although Video is a real-time multimedia application, it can tolerate delay jitter to some extent by using a play-out buffer and a pre-fetching mechanism.

Whereas the transmission cost is defined on a per-bit basis in Table 1, it is on a per-sec basis in Table 2. The per-sec transmission cost of an allocated network is derived by multiplying the required bandwidth by the transmission cost of network in Table 1. For example, the per-sec transmission cost of Web on a Wi-Fi network is 300,000 b/s $\times 10^{-9}$ unit/b $= 0.0003$ unit/s, while that on a cellular network is 300,000 b/s $\times 10^{-5}$ unit/b $= 3.0$ unit/s. Therefore, a Wi-Fi network is more appropriate for Web than a cellular network.

From the above conditions, we expect that Web mainly uses a Wi-Fi or WiMAX network for their low transmission cost and large bandwidth. A DSRC or cellular network is expected to be allocated to VoIP. Video should use any other network than a cellular network, since it requires the large bandwidth. Nevertheless, preference of each candidate network is different since different characteristics of the candidate networks lead different values of the degree of satisfaction of node. As we mentioned in the previous section, we design the degree of satisfaction of node to describe how much each QoS requirement of an application is satisfied by the wireless network allocated to the application. Since the bandwidth is most considerable factor for Video from Table 2, the best network for Video is Wi-Fi, which has 20 Mb/s of the bandwidth. Wi-Fi is the best for Video also from the point of view of the per-sec transmission cost, which is also considerable factor for Video. The second candidate is WiMAX, which has 15 Mb/s of the bandwidth on a node and low per-sec transmission cost, and DSRC is the last, which has 4 Mb/s of the bandwidth and affordable per-sec transmission cost. The maximum number of nodes that the system can accommodate while providing them with satisfactory QoS is 99.

Comparison

For a purpose of comparison, we consider another method where each node adopts the optimal allocation using the locally available information, i.e. the characteristics of wireless networks [4,18,19]. At regular intervals identical to the proposal, i.e. 1 s, a node obtains the information about the remaining bandwidth, delay jitter, and cost of networks available to the node. Then, the node solves the optimization problem to maximize the degree of satisfaction of node under given conditions of wireless networks. We should note here that the maximum bandwidth available to an application is considered the same as the reminder of the capacity. In reality, there is the possibility that the amount of bandwidth that an application can use when it is assigned is larger than the reminder of the capacity at the timing of solving the optimization problem. A reason for such a pessimistic assumption is that a node does not know the number of applications, which are using the wireless network and their characteristics and it cannot estimate the amount of bandwidth to become available on allocation. On the contrary, our proposal updates state values and decides resource allocation based only on the degree that applications are satisfied with the currently allocated networks.

We change the number of nodes from 10 to 120. If there are more than more than 99 nodes, there is no resource allocation, which satisfies all of them for the shortage of network resources. The following figures are obtained from 10 numerical experiments with the duration of 20,000 s for each of the number of nodes. For our proposal, we set parameters as $\beta = 8$, $\gamma = 3$, $\sigma = 1$, and the gain of sigmoid function $g_{i,s} = 10$ for all i and s. The window of moving average in derivation of activity α is set at $T = 10$. The number of play hysterons P is 100, the hysteresis gain of sigmoid function g is 5 in Eq. (13), and b is 0.4 in Eq. (14).

4.2. Results and discussion

We first show a summarized result of comparison from viewpoints of the mean degree of satisfaction of node and its mean variance in Fig. 5. The mean degree of satisfaction of node is shown by a solid line for our proposal and a dashed line for the compared method. The variance is indicated by plus signs for our proposal and crosses for the compared method. We derived the mean degree of satisfaction of node as follows. First, we take a sample average of the degree of satisfaction of node among nodes at each second of an experiment. Next, we average sample averages over the whole time and get a time average of an experiment. Finally, the mean degree of satisfaction of node is obtained by averaging time averages of all 10 experiments for each number of nodes. Derivation of the mean variance is as follows. We first derive the variance of the degrees of satisfaction of node among nodes at each second of an experiment. Next, we average the obtained per-second variance over the whole time of an experiment. Finally, the mean variance of degree of satisfaction of node is obtained by averaging the per-experiment variance among 10 experiments for each number of nodes.

As shown in the figure, the compared method achieves the mean degree of satisfaction of node higher than 0.9 when the number of nodes is small. However, once the number of nodes exceeds 60, the performance considerably and suddenly deteriorates to about 0.28. A reason is as follows. When there are 60 nodes, 8 among them use Video. The required bandwidth of one Video is 3 Mb/s and it amounts to 24 Mb/s in total. Once all Video applications are assigned for a Wi-Fi, which has 20 Mb/s of the bandwidth, the Wi-Fi runs out of bandwidth and the degree of satisfaction of applications assigned for the Wi-Fi considerably deteriorates. The degree of satisfaction of node is captured at this moment. Then, the allocated network of such unfavored applications is changed to another network. For example, Video and Web are assigned for a WiMAX, which has 15 Mb/s of bandwidth per node and the lowest per-sec transmission cost except the Wi-Fi. Since the reallocation is done on many nodes at a time, the WiMAX becomes tight of bandwidth and the Wi-Fi returns to the best media for the applications, which are changed their resource allocation. The degree of satisfaction of node is also captured at this moment. Then, the Wi-Fi runs out of bandwidth again. For the above reason, the mean degree of satisfaction of node is about 0.28 in the case of the number of nodes exceeds 60.

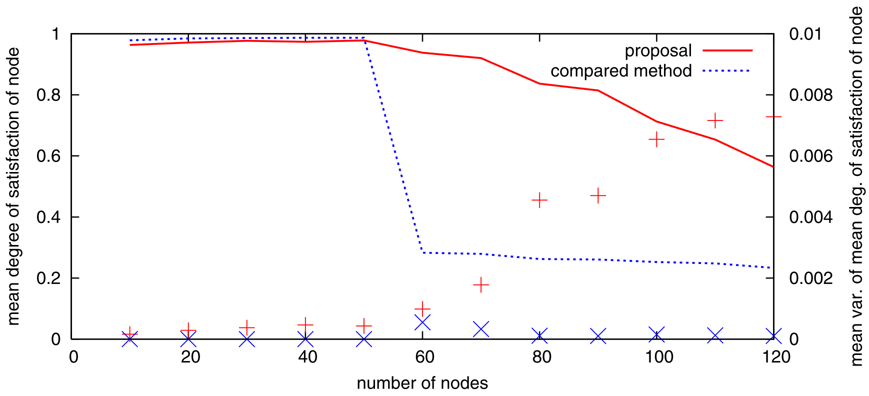

Fig. 5. Mean and variance of degree of satisfaction of node against different number of nodes.

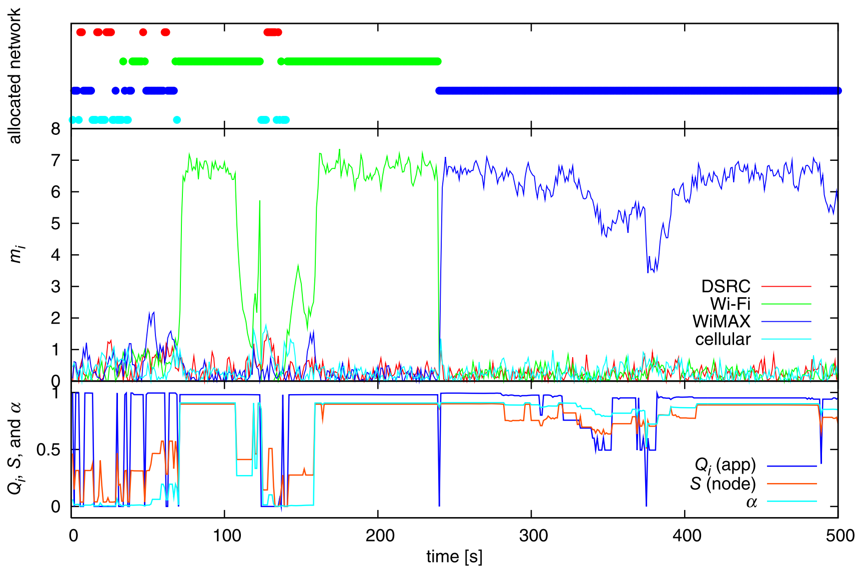

Fig. 6. Time variation of allocated network, state values, degrees of satisfaction of application and node, and activity of Video with proposal (60 nodes). (For interpretation of the colors in this figure, the reader is referred to the web version of this article.)

On the other hand, our proposal can sustain the mean degree of satisfaction of node at the moderate level even when there are 120 nodes in the region. Since our proposal takes a probabilistic approach in finding a good solution as biological systems do, an application is occasionally assigned for the second best network. Such allocation results in the sub-optimal resource allocation as indicated by the lower mean degree of satisfaction of node in the case of small number of nodes in Fig. 5. However, at the same time, it enables nodes to find the moderate solution at the sacrifice of the degree of satisfaction of applications to some extent in the environment where the optimal solution to satisfy all applications does not exist.

It is also a reason why the mean variance of degree of satisfaction of node increases as the number of nodes increases with our proposal in Fig. 5. On the contrary, the mean variance remains small with the compared method. It is because that all nodes solve the same optimization problem to maximize the degree of satisfaction of node under the same given condition, including characteristics of available networks and accommodating applications.

Next, we show time variations in resource allocation, state values, degrees of satisfaction, and activity of Video on a certain node on the horizontal road in one numerical experiment with 60 nodes in Fig. 6. In the top and middle graphs, dots and lines colored with red, green, blue, and aqua correspond to DSRC, Wi-Fi, WiMAX, and cellular networks, respectively. At the top, a wireless network allocated to the application is indicated by dots. The middle is for the time series variation of state values $m_{i,j}$. At the bottom is the graph for the degree of satisfaction Q_i of the application (blue line), the degree of satisfaction S of node (orange line), and the activity α (aqua line).

Until 70 s, a wireless network allocated to Video keeps changing since the activity is low. During the course of random allocation, there are some instants when either of a Wi-Fi or WiMAX network is selected. As a result, the degree of satisfaction of Video increases to 1 (see the blue line in the bottom graph of Fig. 6). However, although not shown in the figure, other applications are not satisfied with the assigned networks, which disturb the degree of satisfaction of node from increasing. Consequently, the activity does not increase enough. Then at 70 s, occasionally all applications are assigned for

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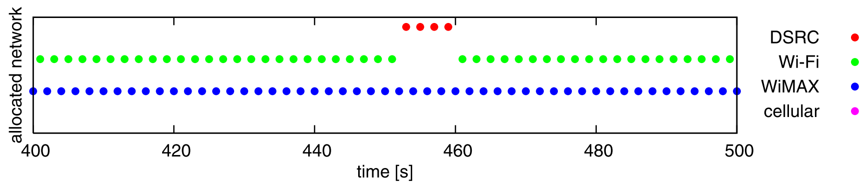

Fig. 7. Time variation of allocated network of Video with compared method from 400 s to 500 s (60 nodes).

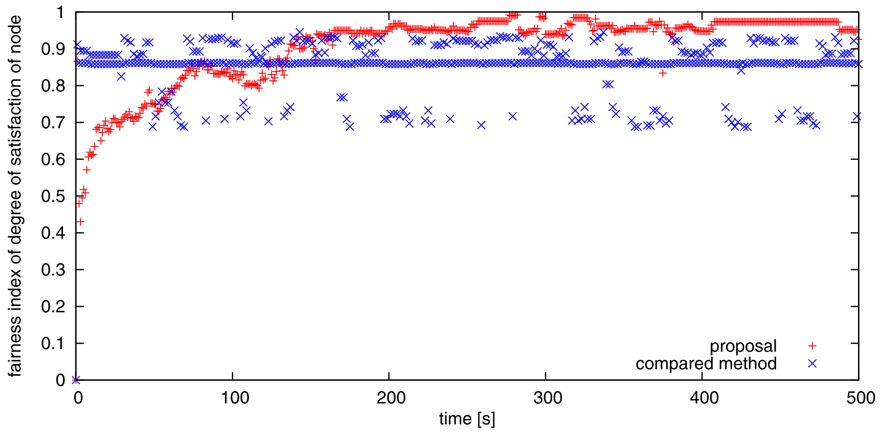

Fig. 8. Fairness index of the degree of satisfaction of node (60 nodes).

appropriate networks as a result of random walking. The activity increases to 0.90 and the resource allocation becomes stable. At 108 s, the activity decreases to 0.41 by being affected by resource allocation at other node. However, resource allocation does not change, because the condition of networks resumes soon.

After a few seconds, the node goes out of the Wi-Fi access area. It triggers re-allocation of wireless networks for the decline of the activity. Although the node enters the Wi-Fi access area at 133 s, the activity is small until 159 s. It is because that the node is trying to adapt to the appearance of the Wi-Fi network during this period. At 240 s, the node goes out of the Wi-Fi access area again. In this case, the node could successfully allocate the WiMAX network to Video. The resource allocation is stable and does not change until 1220 s. In this way, our proposal can allocate wireless network resources adaptively and stably to applications on a node.

On the contrary, allocated networks flip-flop greatly in the compared method as shown in Fig. 7. From 400 s to 452 s, a node alternately allocates Wi-Fi and WiMAX networks to Video. From 452 s to 460 s, the node is out of the Wi-Fi access area and DSRC and WiMAX networks are allocated alternately. It is because that the compared method determines resource allocation in a greedy manner and as such multiple nodes switch wireless networks at the same time, even if timing of control is not synchronized. Now, assume that no application on the node is assigned for a Wi-Fi network. Because of vacancy, multiple nodes consider that the Wi-Fi network can provide an application with the plenty of bandwidth. Therefore, they decide to allocate the Wi-Fi network to one or more bandwidth-consuming applications. Once resource allocation is performed based on the derived optimal solution, the Wi-Fi network becomes fully congested and the degree of satisfaction of application considerably deteriorates. At the same time, a wireless network that those applications used before becomes empty. Then, nodes will switch from the Wi-Fi network to the former network at the next control timing. With our proposal, a similar phenomenon can be observed during the random allocation phase, but nodes eventually can find the globally appropriate solution and resource allocation converges.

Finally, we evaluate the fairness of resource allocation by using the fairness index [20]. The fairness index ϕ of n nodes is derived by the following equation.

$$\phi = \frac{(\sum_{k=1}^{n} S_k)^2}{n \sum_{k=1}^{n} S_k^2}, \tag{21}$$

n is number of nodes and S_k is the degree of satisfaction S of node k ($1 \leqslant k \leqslant n$). The fairness index of 1.0 means that the degree of satisfaction of node is identical among nodes. Fig. 8 illustrates results of the case of 60 nodes. Although the fairness index is low at the beginning, it gradually increases and becomes as high as 0.9 (average is 0.97) with our proposal. On the other hand, the average of fairness index is about 0.85 and it greatly fluctuates with the compared method. As conclusion, nodes can fairly share the limited network resources by using our proposal.

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5. Conclusion

In this paper, we propose a novel resource allocation mechanism where each node autonomously determines wireless network resources to assign to each of networked applications running on it under dynamically changing environment. Our proposal employs the attractor composition model, which is based on an autonomous and adaptive behavior of biological systems. Since adaptation requires the certain duration of random walk phase, a vehicular network is one of tough applications of our proposal. However, as shown in the results, our proposal could adaptively and stably allocate wireless network resources to applications with consideration on their QoS requirements and fairly share network resources among nodes. It also is shown that our mechanism superiors to a mechanism where a node determines resource allocation by solving an optimization problem.

In general, it is said that biological models are insensitive to parameter setting. Next, we need to confirm this statement by conducting additional simulation experiments by changing the number of wireless networks and their characteristics, QoS requirements of applications, and mobility using more realistic simulation scenarios. Another direction is to extend our proposal to fit to the actual environment. For example, Web browsing can tolerate instantaneous interruption of connection. Therefore, it is possible to keep assigning a Wi-Fi network to a Web application whereas a Wi-Fi network provides intermittent connectivity to a fast moving node. Finally, we plan to build a prototype and perform realistic experiments in the future.

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