Multimedia Service Discrimination Based on Fair Resource Allocation Using Bargaining Solutions

KwangSup Shin, Jae-Yoon Jung, Doug Young Suh, and Suk-Ho Kang

We deal with a resource allocation problem for multimedia service discrimination in wireless networks. We assume that a service provider allocates network resources to users who can choose and access one of the discriminated services. To express the rational service selection of users, the utility function of users is devised to reflect both service quality and cost. Regarding the utility function of a service provider, total profit and efficiency of resource usage have been considered. The proposed service discrimination framework is composed of two game models. An outer model is a repeated Stackelberg game between a service provider and a user group, while an inner model is a service selection game among users, which is solved by adopting the Kalai-Smorodinsky bargaining solution. Through simulation experiments, we compare the proposed framework for multimedia service discrimination with existing resource allocation methods according to user cost sensitivity. By comparing and contrasting results, it is shown that the proposed framework performs better than existing frameworks in terms of total profit made by the service provider and fairness being ensured for users' utilities.

Keywords: Multimedia service discrimination, resource allocation, quality of service, bargaining game, fairness.

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I. Introduction

Great advances in wireless network technologies, such as WLAN, WCDMA, WiMAX and LTE, have enabled us to access the network from anywhere, at any time. However, a wireless network cannot help causing time-varying quality issues for delay-sensitive, bandwidth-intense, and loss-tolerant multimedia applications due to limited available resources [1]. Therefore, how to effectively utilize limited resources and guarantee the quality of service (QoS) is critical in wireless network management.

So far, many studies on network resource allocations have been conducted. A representative way is to maximize the resource utilization of service providers or maximize utilities of users [2]. Nevertheless, such approaches to globally optimizing total utility have limitations because practices are adopted to remain competitive in the network environment, where users' decisions affect one another. Global optimization can have multiple optimal solutions, called Pareto optima, all of which guarantee the maximum of total utility. In this case, we should also consider "fairness" to users. In practice, resource allocation problems are complicated because utility functions of users are not identical, nor linear, so game theory is often applied to fair resource allocation problems in competitive network environments.

In this paper, we introduce a service discrimination problem, which often appears in practical network services. The resource allocation of service discrimination is more difficult than that of a single service. A service provider offers users multiple services that guarantee different levels of service quality and users can choose one of those services according to the capacities of their devices or the requirements of application services (for example, bandwidth of multimedia stream). The service provider has to fairly allocate limited resources to users based on a price structure created for the different discriminated services, and users can also change their service selections according to their expected utility of each service. The expected utility of each user can be calculated by the utility function of each user considering service quality and cost. The service discrimination problem is of significance in that users lie in different wireless networks (such as WLAN, WCDMA, and WiMAX), use different devices (such as laptops, smartphones, and mobile phones), and require different amounts of network resources (such as different bandwidth sizes of multimedia streams).

The service discrimination problem proposed in this paper is regarded as a combination of two game models. The first game model is a fair resource allocation problem among users who lie in different service conditions. In the model, users can change their service selections according to the expected utility of each service that is decided by the service providers. We adopted the Kalai-Smorodinsky bargaining solution (KSBS) [3], which guarantees fair resource allocations proportional to maximum achievable utilities of users. The second model is a repeated Stackelberg game between a service provider and the user group. The service provider adjusts the quality levels of services according to users' service selections in consideration of total profit and efficiency. Since the decisions of the service provider and users affect others' utilities, the model was designed as a repeated Stackelberg game [4].

To evaluate the performance of the proposed framework, we conduct simulation experiments. By comparing our results with the functioning of the KSBS without service discrimination, the Nash bargaining solution (NBS), and an equal rate allocation scheme (ERAS), we show that our proposed framework obtains better total profit and fairness.

In summary, the proposed framework of multimedia service discrimination has three characteristics:

- Discrimination of wireless multimedia services: To satisfy different customers' needs in wireless networks, we introduce a service discrimination problem and present a solution to the problem in terms of utility and fairness.
- Utility function of users (considering of cost): Existing studies on network resource allocation used to consider only QoS, not price of resource [2]. In the case of service discrimination, cost is a critical factor to in choose choosing one of the discriminated services. It makes the problem more complicated since the utility function considering cost is not monotonously increasing any more.
- Utility function of service providers: Most studies focus on utility functions of users, and they assume that the utility of a service provider is simply the sum of all users' utilities [5]. However, because our approach considers the price of resources in each discriminated service, we directly reflected the profit of the service provider in his/her utility function.

The rest of this paper is organized as follows. The related work and background of bargaining solutions are described in section II. In section III, we discuss the problem of multimedia service discrimination and the overall procedure of the proposed mechanism. A service discrimination strategy is described based on profit and efficiency of a service provider in section IV. Section V presents resource allocation service selection algorithms. Experiment results are explained and illustrated in section VI, and, finally, the paper concludes in section VII.

II. Background and Related Work

1. Bargaining Game

Recently, game theory was introduced to effective resource management in telecommunication networks [6], [7]. Although game theory has been applied mainly to economies, management, and social sciences, it has also been disseminated through several research areas, including biology, engineering, political science, computer science, and philosophy, to analyze economic behaviors in wide areas "Game." For instance, van der Schaar and Shankar suggested a new paradigm in which players interact by exchanging information and distributing resources [1].

There are a few bargaining game solutions for fair resource allocation, such as the NBS and the KSBS. The basic definitions and concepts of the KSBS are explained by comparing it with the NBS. Let S be a resource allocation solution guaranteeing utilities of users by fairly allocating Q to n users. The utility of user i is derived from the amount of allocated resource, R_i, given the bargaining power of users α. The solution S can be represented as follows:

$$S = \left\{ \pi_1\left(R_1\left(x_1\right) \mid \alpha\right), \ldots, \pi_n\left(R_n\left(x_n\right) \mid \alpha\right) \right\} \in \mathbb{R}^n \quad . \qquad (1)$$

Because the convexity for any two joint utility points X and Y in S is proved in [3], the feasible solution of our problem S also becomes convex. Therefore, this feasible utility set S is nonempty, convex, closed, and bounded. All properties, except convexity, are straightforward.

For each user to stay in the game, the minimum requirement should be considered. In other words, a user will leave the service if the allocated resource does not reach a certain level of utility [8]. The minimum requirements for utilities $d=(d_1,\ldots, d_n)$ are called disagreement points.

$$d = (d_1, \ldots, d_n) = \left\{ \pi_1(R_1^0), \ldots, \pi_n(R_n^0) \right\} \in \mathbb{R}^n \quad . \qquad (2)$$

Therefore, the service provider should provide the minimum resource requirements R_i^0 to make users stay in the network.

Finally, the resource allocation problem can be defined by the pair of feasible solution set and disagreement points, (S, d). In the problem, since there are many Nash equilibriums, the proper axioms are required to decide the fairest solution among them. Previous research included deep consideration of optimality and fairness [9], [10].

The NBS is characterized by four axioms: Pareto optimality, scale invariance, independence from linear transformation, and symmetricity [11]. However the third axiom was often criticized since it did not consider players' differential receptive capacities. Accordingly, the notion of proportional fairness was introduced in [12] to allocate resources based on the maximum requirements. In the aspect of proportional fairness, the KSBS was compared with the NBS because it applies individual monotonicity instead of the third axiom of the NBS. The optimality conditions of both solutions and differences between the quantitative proportional fairness of the NBS and the qualitative proportional fairness of the KSBS for multimedia services are analyzed in [3]. The KSBS allows choosing a proportional fair solution among the Nash equilibrium if it preserves four axioms: Pareto optimality, symmetry, independence from linear transformation, and individual monotonicity [13].

2. Game Theoretic Resource Allocation

The main objectives of research on the game theoretical resource allocation in a wireless network can be summarized into three issues: avoidance of wasted resources, fairness to users, and maximization of individual and social utility.

The first two issues have been addressed in much of the previous research on effective and fair resource allocation [7]. The naïve way to allocate resources is to equally allocate resources to participating users. It may cause the waste of resources since it does not consider the characteristics of the users and the devices. The NBS is the well-known solution in game theory that can be implemented to assign limited capacity, control the flow on the network, or design the network structure [13]-[16]. Although the proportional fairness policies were also implemented successfully in other works [17], [18], they have not considered the dynamic bandwidth exchanges among collaborative devices and the resulting impact on the multimedia quality for various content-aware and delay-sensitive applications. Thus, they are not suitable for content-aware multimedia applications since they do not explicitly consider the resulting impact on QoS [3].

The last issue, maximizing individual and social utilities, is how to define and maximize service quality or user satisfaction. To apply game theoretical approaches to this problem, it should be assumed that all players rationally make decisions based on their utility function. Although players' rationality assumption is sometimes criticized because players may not be able to measure quantitatively their own utilities [19], the utility function is the most widely applied criteria in making rational decisions. Much research on multimedia service focuses on QoS for developing utility functions. In wireless multimedia networks, QoS can be represented with the degree of user satisfaction from the amount of allocated resource, delay, or the rate of distortion [2], [5], [19].

The second game model of the proposed approach can be considered as a kind of multicriteria game of n-players with strategy interaction [20]. The multicriteria games between service provider and users similar to those proposed in this paper have been utilized to allocate wireless network resources by designing the bid based pricing and negotiation mechanism [21]. In other research, the access control and bandwidth allocation for users in heterogeneous networks are modeled with a bargaining game [22] and a congestion game [23]. Especially in the case of the existence of the strategy interrelationship, the Stackelberg game assumes the sequence of decision making [4]. A leader who has the priority makes a decision first, and then followers make decisions based on the leader's decision. Relay selection and power control mechanisms using the noncooperative Stackelberg game [24] and radio resource allocation using the cooperative manner in heterogeneous wireless networks [25] have been developed.

3. Limitations and Proposed Approach

In this research, the concept of cost, one of the best ways to model the efforts that users invest to achieve their own goals, is additionally considered to express user satisfaction. Generally users in the network are charged for allocated resources to guarantee the desired QoS. Like the case of utility functions, quantitatively defining unit cost might be a complex issue as well, since cost can include a lot of factors such as the energy consumption, delay, or consumed bandwidth. While quantifying these cost factors, pricing mechanisms should regulate the usage of the limited resources by adjusting the cost. The ultimate goal of users in the multimedia network is to maximize their utility and also minimize cost derived from allocated resources [2].

Other limitations can be found in designing utility functions. Much research has focused on designing user utility functions and assumed that the utility for the service provider and the social utility are simply derived by summing the utilities of all users [5] or counting the number of users who select the network [23]. However, the utility of the service provider should include the efficiency of the resource usage whereas the user utility functions are mainly derived from the amount of allocated resources. In addition, to interpret the utilities in the view of economics, the concepts of investment (cost) and profits should be included during designing utility functions and making decisions of optimal solutions.

Therefore, the objective function of the service provider includes two different criteria: total profit and efficiency of resource utilization. Also, with this assumption, the utility function and decision variable of the service provider become different from the users'. In this paper, the utility function for the service provider has been unified by combining two criteria with the weight factor. Then, for the game of the service provider and the user group, we have adopted the repeated model of the Stackelberg game.

Still, some limitations remain to realize the current wireless multimedia network environment. The majority of the research has assumed the single type or level of service, not discriminated services in terms of different QoS. However, it is general that there are users who want the premium service that guarantees higher QoS even though they should pay more. Morever, it is common that users have different levels of utilities even though exactly the same amount of resources is allocated to them due to the different service environment such as device, network, and multimedia contents. Nevertheless, all users hope to enhance QoS and reduce cost at the same time, but the degree of balance between QoS and cost, called cost sensitivity, differs from one user to another.

To deal with these problems, it is necessary to present discriminated services to enhance the utility of all users simultaneously. In this paper, we utilize the bargaining power that is known to be the effective means to discriminate the service level or amount of allocated resources [3], [11]. With the bargaining power, the KSBS guarantees the same utility penalty relative to the maximum achievable utility [3].

III. Problem Definition and Overall Procedure

In this section, we define the problem of multimedia service discrimination and present the overall procedure for the proposed framework. Figure 1 depicts the general relationship between a service provider and a user group. At first, the service provider presents multimedia services to users, and the services are discriminated by different unit prices for resources. Users with different service requirements select the service that can best guarantee the maximum utility among the services. Based on the result of service selection, network resources are allocated to users. The service provider tries to improve total profit and efficiency of resource utilization determined by the result of resource allocation.

Table 1. Summary of notations.

Notation	Description
N	set of users, $\{1,\ldots, n\}$
M	set of service types, $\{1,\ldots, m\}$
Q	total available resource of the network
β_i	bargaining power of the service type j
c_i	unit price of the service type j
α_i	bargaining power of user i
b_i	available budget of user i
x_{ij}	binary variable indicating whether user i selects service type j
R_i^0	minimum resource requirement of user i
R_i	amount of resources to allocated to user i
$R_i(x_{ij})$	amount of allocated resources when user i selects service type j
X_i	utility function of user i, $\pi_i(R_i(x_{ij}))$

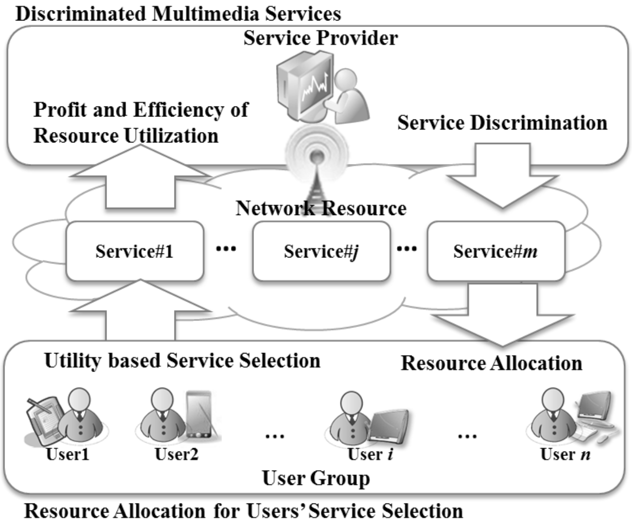

Fig. 1. Relationship between service provider and user group.

The multimedia environment assumed in this research is characterized as follows: 1) multimedia devices have the agent that keeps communicating with a multimedia server and selects one of the discriminated services based on the utility function, 2) a multimedia server informs agents how much resource are expected to be allocated when they select each service type among discriminated services, and the server then waits for the users' decisions, and 3) the expected amount of resource to be declared may be different from the amount finally allocated resource c it depends on other users' decisions. The notations used in the proposed service model are summarized in Table 1.

There are n users who compete for available network resources Q, which are provided by a service provider. A user $i(\in N)$ has utility function $\pi_i(R_i)$, which is derived from the allocated resource R_i. A service provider provides m service types, which guarantee different service levels. A service type $j(\in M)$ has the unit price $c = (c_1,\ldots,c_m)$. A user pays for the allocated resource according to the unit price of the service that they selected. To keep the problem simple, it is assumed that services are ordered by ascending prices, that is, $c_k < c_l$ if $k < l$ for $\forall k, l \in M$. Let x_{ij} be a binary decision variable indicating whether user i selects service type j or not. Also, we assume that a user selects only one service, that is, $\sum_{j\in M} x_{ij}=1$.

The goal of this research is to develop the resource allocation and service discrimination strategy. Algorithm 1 describes the overall procedure of the proposed framework in this research. It includes how a user selects the service types that can guarantee the maximum utility among m service types, how resources are allocated after users' service selection, and how the service provider adjusts bargaining powers of services for effective service discrimination.

In the algorithm, once users select a service, resources are allocated to users by using the KSBS. The utility of user i, $R_i = \pi_i(R_i)$, is calculated based on the expected amount of resources allocated to the user. The order of the users' service selections is determined by the gap between the maximum utilities and the current utilities of the users (X_i^{MAX} - X_i). Each user changes the service selection if another service type guarantees greater utility than the current service type. After services have been selected by the users, the service provider adjusts bargaining powers based on the result of their selections. This procedure is repeated until an equilibrium condition is reached.

Algorithm 1. Discriminated multimedia services

Input : total amount of network resource R^{MAX},
unit prices of m services $c = (c_1, \ldots, c_m)$
Set initial bargaining powers of m services, β^0.
Allow users to select a service.
Repeat
  Repeat at most (n-1) times
  1) Allocate resource to users based on their service selection by KSBS.
  2) Calculate users' utilities (X_i) for the allocated resources.
  3) Create an ordered queue of users SEQ in descending order of users' utility gaps, X_i^{MAX} - X_i.
  4) Update user selections by using elementary stepwise system
  5) Escape the iteration if service selections of users do not change.
  Modify bargaining powers based on users' service selection:
$$\beta^{t+1} \leftarrow \mathrm{mod}(\beta^t | \{R^*\})$$
Until $|\beta^{t+1} - \beta^t| \le \varepsilon$

IV. Discriminated Multimedia Service

In this section, we describe the procedure in which a service provider discriminates service levels by adjusting bargaining powers of each service type. The bargaining powers of m service types are denoted by $\beta=(\beta_1, \ldots, \beta_m)$.

In our framework, the only way for a service provider to discriminate services is to adjust the bargaining powers of m service types. To set bargaining power β_j to service type j can be interpreted as the service provider intending to allocate $\beta_j R^{MAX}$ resource to service type j without knowing how many users will select the service.

1. Profit-Based Discrimination

The total profit (TP) of the service provider can be calculated from the amounts of allocated resources and unit prices as (3):

$$TP = \sum_j c_j \sum_i x_{ij} R_i^* = \sum_j c_j \sum_i x_{ij} \pi_i^{-1}\left(\delta^* \beta_j x_{ij} X_i^{MAX}\right). \tag{3}$$

At this time, as found from the utility function of users defined in section III, the inverse function of the utility function is monotonous increasing with $\beta_j x_{ij} X_i^{MAX}$. Moreover, as the service selection result x_i. and maximum utility X_i^{MAX} are fixed, the expected profit from service type j is proportional to its bargaining power β_j. In addition, the unit price of the service type is the most fundamental and important factor for service discrimination. It is rational to give more priority to users who select more expensive services. Here, we utilize the relative price ($c_j / \sum_{k\in M} c_k$) for the service discrimination.

2. Efficiency-Based Discrimination

The other major issue of the service provider is to allocate limited resources in an economically efficient way. The most general and widely adoptable way is to allocate resources to the users who value them the most [26].

We propose a method that adheres to the fundamental discriminating role of the bargaining power. To allocate resources to users who give more value to them than others do, the economic efficiency is developed as the metric of valuation. Since we assume that users evaluate the allocated resources according to their own utility functions, the economic efficiency of resource allocation can be determined by the utility-resource ratio ($f_i = X_i / R_i$). In this paper, the service provider presents discriminated services that guarantee priority by adjusting bargaining powers. Thus, the result of service discrimination and resource allocation from the standpoint of the service provider can be evaluated based on the average utility-resource ratio of users who select the same service type. The average utility-resource ratio of each service type is simply achieved as (4):

$$\hat{f}_j = \frac{1}{\sum_j x_{ij}}\left(\sum_j f_i \cdot x_{ij}\right) = \frac{1}{\sum_j x_{ij}}\left(\sum_j \frac{X_i}{R_i(x_{ij})} x_{ij}\right). \tag{4}$$

3. Bargaining Powers of Service Types

We present the way to determine bargaining powers of service types by considering both profit-based and efficiency-based service discrimination strategies. By combining the total profit of a service provider and the average utility-resource ratio of users, the bargaining power of service type j can be determined while satisfying $\sum_{j\in M} \beta_j = 1$ as (5):

$$\beta_j = \frac{1}{m\psi + 1}\left(\psi + \zeta\left(\frac{c_j}{\sum_i c_i}\right) + (1-\zeta)\left(\frac{\hat{f}_j}{\sum_i \hat{f}_i}\right)\right). \tag{5}$$

In this equation, a service provider can adjust gaps between service types by varying a factor ψ ($0<\psi$) and adjusting the relative weights of the profit to the efficiency by varying a factor ζ ($0\leq\zeta\leq1$). In addition, this predetermined factor (ψ), determined by the service provider, can be interpreted as a damping factor because it does not vary while updating bargaining powers, whereas other components in (5) vary according to the result of the users' service selection. Since a positive damping factor accelerates the convergence [27], it can be said that Algorithm 1 reaches an equilibrium.

V. Resource Allocation for Users' Service Selection

In this section, we explain how users select the best service type based on their utility functions and how a service provider allocates resources according to their service selections.

1. Utility Function

There are many studies of defining utility functions of multimedia service. An approach considered sophisticated was to join encoder and channel rate control with the goal of achieving consistent video quality in terms of the peak signal-to-noise ratio (PSNR) for every frame [28]. The problem of minimizing the total distortion for a video sequence subject to network channel constraints was explored [29]. The same problem was studied using a windowed technique for real-time implementation [30]. Yet, it is hard to say that these utility functions implemented in these works precisely represent how much users are satisfied with the allocated resources since it depends on the factors, such as data types transmitted through the allocated bandwidth. Even the sensitivity to delay can vary dramatically from case to case [6]. Several utility functions like distortion rate models for wavelet video coders were proposed [31], [32], and the distortion rate model in [33] is known to be well suited for the average rate-distortion behavior of the state-of-the-art video coders [9]. Thus, we adopt a PSNR-based QoS metric for the utility function of users. In particular, the simplified equation devised in [3] and [33] is adopted for the QoS metric for the convenience of calculation as follows:

$$QoS_i\left(R_i\left(x_{ij}\right)\right)=\frac{k\left(R_i\left(x_{ij}\right)-R_i^0\right)}{D_{0i}\left(R_i\left(x_{ij}\right)-R_i^0\right)+\omega_i}\quad, \tag{6}$$

where R_i is the rate for the video sequence and ω, k, R^0 and D_0 are the parameters that are dependent on the video sequence characteristics (spatial and temporal resolutions and delay). Note that ω is positive and D_0 are nonnegative.

In the meantime, a lot of studies focus on designing pricing mechanisms. Usually the pricing mechanisms used by the service providers are very coarse-grained since operators tend to charge the unit price for resources based on their investment, or the pricing strategy of their competitors, not on the instantaneous congestion of a wireless network [6]. Although research has revealed variations defining unit cost for network resources, it is common to charge according to the amount of allocated resources [19]. In [34] and [35], the combination of flow control and pricing was suggested. Kelly assumes that users state their prices and the network allocates the bandwidth accordingly [12], while the network manager charges a price based on user bandwidth demands [19]. Therefore, considering the utilities for users and a service provider, a pricing and resource allocation mechanism should be able to maximize the profit of each game player [16]. In addition to QoS, cost is also considered, which is derived from the unit price of a service type and the amount of allocated resource to the user as follows:

$$Cost\left(R_i\left(x_{ij}\right)\right)=R_i\left(x_{ij}\right)\sum_j c_j x_{ij}\quad. \tag{7}$$

Finally, the utility function of user i is defined as the weighted sum of QoS and cost terms.

$$X_i=QoS_i\left(R_i\left(x_{ij}\right)\right)+\tau_i Cost\left(R_i\left(x_{ij}\right)\right)\quad. \tag{8}$$

Parameter τ_i is the user cost sensitivity coefficient that represents the degree to which a user values cost compared to QoS. The cost sensitivity coefficient should have a negative value in the utility function.

$$\begin{gathered}\frac{\partial}{\partial R_i}QoS_i\left(R_i\right)>0\,,\ \frac{\partial^2}{\partial R_i^{\,2}}QoS_i\left(R_i\right)<0,\\ \frac{\partial}{\partial R_i}\left(\tau_i R_i\sum_j c_j x_{ij}\right)=\tau_i\sum_j c_j x_{ij}\end{gathered}\quad. \tag{9}$$

The first derivate of QoS is positive and the second one is negative. In addition, the first derivate of the cost factor is constant, as described in (9). Therefore, we can say that utility function $\pi_i(x_{ij})$ has a maximum value. The maximum value of a utility function is considered the maximum utility of user i, R_i^{MAX}. Example utility functions are depicted in Fig. 2.

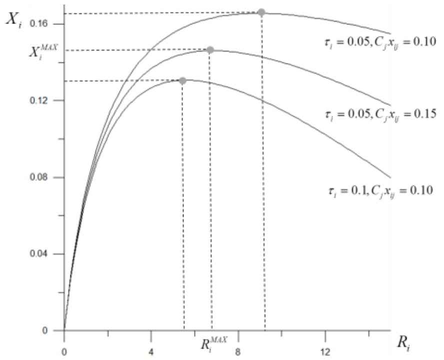

Fig. 2. Example of utility functions.

2. Resource Allocation Using KSBS

In this research, the KSBS is adopted because the solution can effectively reflect proportional fairness based on the maximum utilities of the users shown in Fig. 2.

We first explain the resource allocation using the KSBS for the fixed bargaining powers of services, β. Bargaining powers are generally used as coefficients that represent the priority upon the resources and have effect on the amount of allocated resources. We assume that equal bargaining powers should be allocated to users who select the same service type. Therefore, the bargaining power of a user is determined by that of the service type that the user selected. Bargaining powers of users, $\alpha=(\alpha_1,\ldots,\alpha_n)$, are calculated as equation (10) to meet the condition, $\sum_{i\in N}\alpha_i=1$. The service provider can adjust gaps of bargaining powers among users by parameter ξ.

$$\alpha_i = \frac{1}{(n\cdot\xi+1)}\left(\xi+\frac{\sum_j \beta_j x_{ij}}{\sum_i\sum_j \beta_j x_{ij}}\right) \quad \text{for } \forall i\in N \;\; \forall j\in M \tag{10}$$

If the disagreement point d is assumed to be the origin, the generalized KSBS is on the line L defined by (11) [3].

$$L=\left\{X \,\middle|\, \frac{X_1}{\alpha_1 X_1^{MAX}}=\cdots=\frac{X_n}{\alpha_n X_n^{MAX}}, X_i>0, \sum_{i=1}^{n}\alpha_i=1, \alpha_i\geq 0, \forall i\right\} \tag{11}$$

We can obtain the solution in the n-th degree polynomial time by using simple numerical methods such as the bisection method [36]. By adopting the upper bound (u=Q) and the lower bound (l=R_i^0) of resource allocation, the bisection method can be easily applied. The method then requires exactly $\lceil log_2((u\text{-}l)/\varepsilon)\rceil$ iterations [3].

Since a service provider has limited resources Q and users have a certain level of budgets, b, the optimal solution should meet the following four feasibility conditions, which are defined to model the network conditions of the proposed framework.

$$\sum_{i\in N} R_i\left(x_{ij}\right)\leq Q \tag{12}$$

$$R_i\left(x_{ij}\right)\sum_{j\in M} c_j x_{ij}\leq b_i, \forall i\in N \tag{13}$$

$$R_i^0\leq R_i\left(x_{ij}\right)\leq R_i^{MAX}, \forall i\in N \tag{14}$$

$$\sum_{j\in M} x_{ij}=1, x_{ij}\in\{0,1\}, \;\forall i\in N \tag{15}$$

The first constraint represents that the total amount of allocated resources to users cannot exceed the total amount of resources that the service provider has. In the second constraint, the total cost incurred by a user cannot be larger than his/her budget. The third constraint is the rationality of users, which represents that the amount of allocated resources must be between the maximum and the minimum requirements. The last constraint is that users can select only one service type.

3. Service Selection Algorithm

Users make primitively their minds based on the utilities derived from the amount of allocated resources. If multiple users are assumed to be able to change their service selections at a time, the resource allocation plan cannot be determined as discussed in previous research [37]-[39]. They assume that only one user can change his/her decision at a time and then the problem can be implemented by the Elementary Stepwise System (ESS), where only one user can select a service type at each step. Since it has already been proven that ESS converges to a Nash equilibrium [38], we can say that the required number of service changes for n users to reach a Nash equilibrium is at most n-1, which is linear to the number of users [8].

In the rest of this subsection, we describe how to apply ESS to our problem. The order of users who can change their service selections is determined by utility gaps of users, which are derived from the difference between the maximum achievable utility and current utility, $\rho_i(x_{ij})=X_i^{MAX}\text{-}X_i^*$. Hence, the bigger utility gap a user has, the earlier the user can change the service selection. The overall procedure of the proposed ESS is described in Algorithm 2.

Algorithm 2. ESS for service selection

Input:

Ordered queue of users, *SEQ*

Service selection $x=(x_i)$, $\forall i\in SEQ$

Repeat

1) Retrieve the user who has the biggest utility gap in *SEQ*.
   $u = SEQ.pop()$
2) Suppose user u selected a service type w. (that is, x_{uw}=1). If any service type can offer larger utility than w, user u changes service selection to the new one.
   $$s^* = \arg\max_{j\in M}\left(\pi_u\left(R\left(x_{uj}\right)\right)\right)$$
   $$\text{if } \pi_u\left(R\left(x_{uw}\right)\right)<\pi_{s^*}\left(R\left(x_{us^*}\right)\right), x_{uw}\leftarrow 0 \text{ and } x_{us^*}\leftarrow 1.$$

Until *SEQ* is empty

VI. Experiments

In this section, we first present the results of simulation experiments to show how the proposed service discrimination framework works according to user cost sensitivity. We then show that the proposed framework has better performance in allocating resources by comparing it with three resource allocation frameworks: the KSBS without service discrimination, the NBS, and an ERAS.

1.Optimal Service Discrimination Policy

In the first experiment, for a given user's cost sensitivity τ,, we find the best policy that a service provider can take through cost differentiation rate K and service provider preference ζ. In this experiment, we investigate the impact of the unit price

Table 2. Parameters for experiments.

Network Parameters		User Parameters	
Para.	Values	Para.	Values
Q	5,600	b_i	$\infty, \forall i$
n	50	R_i^0	$0, \forall i$
m	4	κ_i	$\kappa_i \in \{10.0, 10.1, 10.2, 10.3\}$
c^0	1.0×10^{-4}	D_{0i}	$D_{0i} \in \{0.01, 0.015, 0.02, 0.025\}$
K	$[0, 1.0\times10^{-4}]$	ω_i	$\omega_i \in \{5.0, 5.1, 5.2, 5.3\}$
ΔK	1.0×10^{-5}	τ_i	$-1\times(\mu_\tau + \upsilon_i)$
ζ	[0.0,1.0]	μ_τ	$[0.0, 1.5\times10^{-4}]$, $\Delta\mu_\tau=1.0\times10^{-5}$
$\Delta\zeta$	0.1	υ_i	$\upsilon_i \in \{0.001, 0.002, 0.003, 0.004, 0.005\}$

increment, service provider preference, and user cost sensitivity on the total profit and the average utility. The experiment results can help the service provider establish the optimal service discrimination policy when the user cost sensitivity is acquired by a market survey or the long-term analysis of user behavior.

The experiment environments are designed to characterize and simplify the circumstances of practical video sequence streaming on the WiMAX network. It was assumed that the network has a maximum resource of 5,600 Kbps and presents four different service types. Unit prices of service types increase from the minimum value c^0 by unit price increment K, which varies from 0.0 to 1.0×10^{-4} by 1.0×10^{-5}. Service provider preference ζ increases from 0.0 to 1.0 by 0.1. It is assumed that there are 50 users in the network. The value of user cost sensitivity τ_i is randomly selected in the corresponding set, in which the average cost sensitivity increases from 0.0 to 1.5×10^{-4} by 1.0×10^{-5}. The other parameters for constructing a user utility function, D_{0i}, κ_i, and ω_i, are also randomly selected in the corresponding sets. All parameters and their setting are summarized in Table 2.

Table 3 shows the optimal policy for a given user's cost sensitivities. The optimal policy,which is composed of a unit price increment and a service provider preference, is selected to guarantee the maximum total profit of the service provider is based upon a given user's cost sensitivity.

Figure 3 shows the result of service selection. In the experiment, users nearly move from SVC#4 to SVC#1 as the user cost sensitivity increases. Three regions were found according to users' service selections. In Region II, users selected different service types. In Region I, all users selected the highest price service SVC#4, while in Region III all users selected the lowest price service SVC#1. Thus, although a service provider changes the policy to differentiate service types, the total profit has not been changed.

2. Comparison with Existing Frameworks

The performance of the proposed framework should be compared with three existing frameworks: the KSBS without service discrimination, the NBS and an ERAS. The first framework, the KSBS without service discrimination, assumes that only a single service type is provided and resources are allocated to users by using the KSBS. The second framework, the NBS, can be obtained by utilizing the bisection algorithm just as the KSBS does [3]. The last framework, an ERAS, intuitively allocates exactly equal amounts of resources (Q/n) to n users.

To evaluate the performance of resource allocation, the total profit of the service provider ($TP=\sum R_i \sum c_j x_{ij}$), the average of user utilities ($\mu_X=\sum X_i/n$) is utilized. In addition, fairness is evaluated with the fairness index that was developed in [27]. The fairness index is applied to users' utilities to evaluate the absolute extent of user satisfaction as (16):

$$FI = \left(\sum_{i=1}^{n} X_i\right)^2 / n\sum_{i=1}^{n} X_i^2 \qquad (16)$$

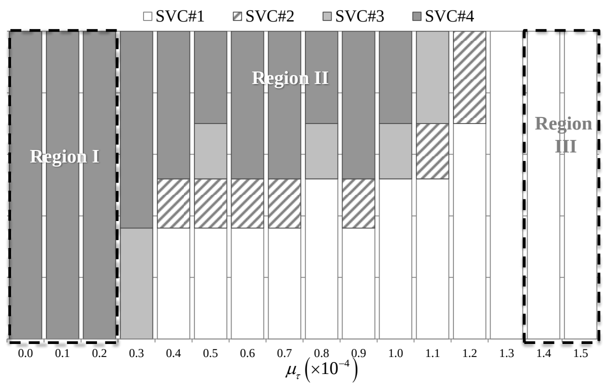

Fig. 3. Result of service selection according to user cost sensitivities.

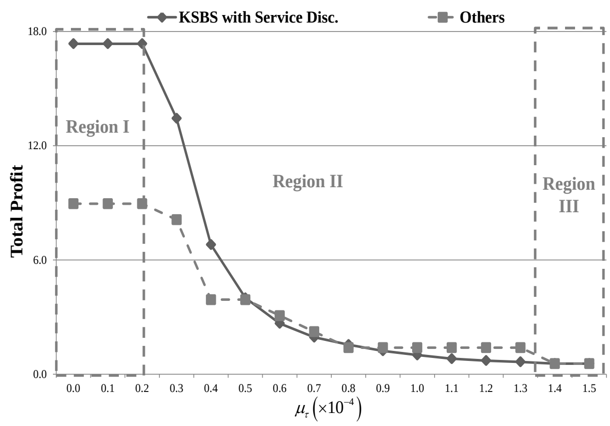

Fig. 4. Comparison result for total profit.

Table 3. Optimal service discrimination policies.

$\mu_\tau(\times 10^{-4})$	$K(\times 10^{-3})$	ζ	$\mu_\tau(\times 10^{-4})$	$K(\times 10^{-3})$	ζ
0.0	1.0	0.7	0.8	0.2	0.9
0.1	1.0	0.6	0.9	0.1	1.0
0.2	1.0	0.4	1.0	0.1	1.0
0.3	0.9	0.0	1.1	0.1	1.0
0.4	0.4	0.1	1.2	0.1	0.0
0.5	0.4	1.0	1.3	0.1	0.2
0.6	0.3	1.0	1.4	0.1	0.6
0.7	0.2	1.0	1.5	0.1	0.6

Figure 4 shows the result of comparing the proposed framework (that is, the KSBS with service discrimination) and three existing frameworks for total profit. We assume that existing frameworks (the KSBS without service discrimination, the NBS and an ERAS) hold a singular unit price p since they do not adopt service discrimination. Hence, if all resources of the service provider (Q) are allocated to users, the total profits of three existing frameworks are $p \times Q$. On the other hand, in the case of the KSBS with service discrimination, the total profit varies according to the users' service selection.

In the figure, when user cost sensitivities are relatively small, total profits of the KSBS with service discrimination are greater than those of the others. However, as the cost sensitivity increases, the gap in total profits becomes smaller. The reason is that as user cost sensitivity increases, most users gather the lowest price service SVC#1, and the total profit of each framework is similar. In that sense, Fig. 4 also illustrates what range of cost sensitivity of the service discrimination is meaningful.

Figure 5 shows the result of comparing the proposed framework and three existing frameworks using the fairness index. The two resource allocation frameworks, the proposed framework and the KSBS without service discrimination, are fairer than the NBS and an ERAS under all cost sensitivities. Note that the fairness values of the proposed framework and the KSBS without service discrimination must be exactly the same

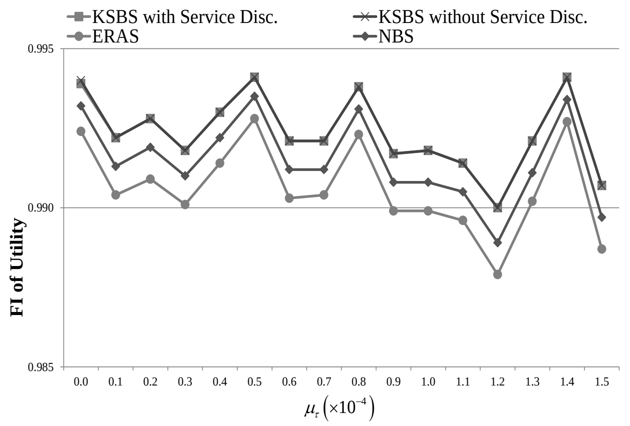

Fig. 5. Comparison result for fairness index.

because these two utilize the same resource allocation schema, the KSBS.

According to the results for total profit of the service provider and fairness index for user utility shown in Figs. 4 and 5, it is proven that the proposed framework performs better than the other frameworks in the aspects relevant to both the service provider and the users.

VII. Conclusion

In this paper, we introduced a service discrimination framework for wireless multimedia services. We suggested an efficient resource allocation algorithm by considering the standpoints of both the service provider and users in the service discrimination framework. To implement the service discrimination framework, we presented the algorithms for fair resource allocation, service selection, and service discrimination strategy. Different from prior related research, we assumed the service provider could actively provide multiple discriminated service types. In addition, we also considered the cost of resources as well as the QoS in the utility function of users.

Numerical simulation results were presented to illustrate how the proposed framework can be utilized. By analyzing the quantitative metrics of resource allocation and comparing the information with that of existing resource allocation frameworks, it was shown that the proposed algorithm could generate more profit for the service provider while guaranteeing more fairness for user utility than can existing frameworks. It is expected that the optimal service discrimination strategy that satisfies both the service provider and users can be developed.

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