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修士論文

題目：偏好性を考慮したゲーム理論による安定的なレート決定と早期離脱時の評価

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Chapter 1

Introduction

Video distribution services using Hypertext Transfer Protocol (HTTP) streaming have rapidly become popular with the growth of Web platforms. As network traffic increases, video is expected to become a larger percentage of Internet traffic [1] [2] [3] [4]. Because of increases in traffic, delivering higher quality video in a stable manner has become a major issue. Currently, HTTP streaming with Dynamic Adaptive Streaming over HTTP (DASH) is a popular system that can resolve this issue. DASH achieves stable video delivery service by using a technology that dynamically selects bit rates according to network conditions and a method of delivering video files divided into segments of a few seconds [1] [5] [6].

However, at a bottleneck link, the bandwidth available to DASH users is limited, so it is essential that users select an appropriate bit rate. The existing rate-selection methods focus on improving Quality of Service (QoS) to prevent video playback stoppages due to decreased throughput, packet loss, delay, jitter, etc. [7]. In recent years, however, methods that focus on Quality of Experience (QoE), which represent user satisfaction with the quality of video content, have attracted the attention of service providers and network providers [1] [2]. One of the methods proposed is to improve QoE using game theory and the subgradient method [1]. This method improves the QoE of multiple users simultaneously while considering the bandwidth of the bottleneck link. However, the previous study [1] has two issues. First, in general, the subgradient method takes time for the selection rate to stabilize [8], which may degrade the QoE. Second, it does not take specific user characteristics into account. For example, it is known that user preference affects QoE [9] [10]. ”User preference” in this case refers to the types of video that users prefer (e.g., sports, music, etc.). However, the game theory used in that study [1] does not reflect such preferences. In addition, in real networks, some users terminate a video session without watching the video to the end (hereafter referred to as ”early departure”) [11] [12]. However, the previous study [1] did not evaluate the QoE of users in an early-departure environment. In the study reported in this paper, we devised a method to solve those problems. Its contributions are summarized as follows.

- Based on the game theory of the previous study [1], we propose a stable dash rate determination method that does not use the subgradient method.
- We propose a method that takes user preference into account and show that it

improves the user's QoE.
- We show that the proposed method can maintain user QoE even under conditions where early departure occurs.

The structure of this paper is as follows. Chapter 2 describes related studies, Chapter 3 models the proposed method, Chapter 4 evaluates the performance of the stable dash rate determination method that does not use the subgradient method, and Chapter 5 shows the QoE improvement by considering user preference. Chapter 6 presents a numerical analysis in an early departure environment, and Chapter 7 summarizes the results of the study and discusses future issues.

Chapter 2

Related works

There are several rate-selection methods for DASH that take QoS into account [13]. One previous study [14] proposed a rate-selection method that estimates network throughput on the basis of the ratio of segment playback time and the elapsed time between a segment request and download completion. Another study [15] proposed a method to stabilize the user buffer length and segment rate by estimating throughput by using RTT and past throughput values. However, these methods improve QoS, not QoE directly. Some studies [16] and [17] proposed buffer management methods to improve QoE, while others [18] and [19] proposed rate-selection methods that take into account variations in buffer length and throughput. However, these methods do not consider the bandwidth allocation problem on bottleneck links caused by multiple users watching videos. In general, HTTP streaming leads to contention between users for the bandwidth of a bottleneck link [20] [21] [22] [23].

On the other hand, one study [1] proposed a method that maximizes the consumption of the available bandwidth of the bottleneck link while simultaneously improving the QoE of multiple users by using game theory and the subgradient method. This method improves the QoE of users more than previous rate-selection methods can. However, since it uses the subgradient method, it takes time for the rate to stabilize [8], which may cause QoE degradation.

The necessity of considering user characteristics in DASH rate-selection methods has been pointed out [9] [10] [24] [11] [12] [25]. In order to take into account the effect of user preferences on QoE [9] [10], a previous study [24] proposed to fix the existing QoE formula by using MOS values obtained from a subjective test in which users with strong interest in video content and users with weak interest in it are pre-separated. Furthermore, it is known that some users leave early [11] [12]. A previous study [11] showed that the average time a video is watched is about 42.6% of the total video time and that many users leave a video early without watching it to the end.

In this paper, we modify the game theory of the previous study [1] and propose a rate determination method that does not use the subgradient method. In addition, we consider user preference in order to improve QoE. We also show that the proposed method can maintain the user's QoE even under conditions where early departure occurs.

Chapter 3

Game-Theoretic Modeling and Rate-Selection Methods

We propose a novel game theoretic function to avoid using the subgradient method. Figure 3.1 shows that the available bandwidth of a DASH server link is shared by multiple users $\mathscr{N} = \{1, 2, ..., N\}$. Therefore, the sum of the rates of segments delivered to each user may exceed the available bandwidth of the link, making the DASH server link a bottleneck link [1]. The user QoE and user buffer amount are determined by the rate selected for each segment. In DASH, all users choose an appropriate rate at which to share the available bandwidth of the server link to improve QoE and optimize the amount of user buffering. In other words, the rate can be modeled as a strategic game (in game theory) by considering the rate to be selected as a strategy and the user's QoE and buffer amount as gains. In this paper, we use game theory to determine the optimal selection rate $r^*_{i,k}$ in the k ($k \in \mathscr{K} = \{1, 2, ..., K\}$)th segment of the i ($i \in \mathscr{N}$)th user. In particular, we utilize game theory with user QoE to determine $r^*_{i,k}$. We also use the estimated download time for the kth segment, which is obtained from the available bandwidth of the link. The optimal rate $r^*_{i,k}$ is determined by finding the Nash equilibrium, a situation in which all the users individually select an optimal rate relative to the rates selected by other users. Our system can be modeled as

$$G := (\mathscr{N}, \{\boldsymbol{R}_i\}_{i\in\mathscr{N}}, \{f_i\}_{i\in\mathscr{N}}), \tag{3.1}$$

where $\boldsymbol{R}_i = \{r_i^{(1)}, r_i^{(2)}, ..., r_i^{(J)}\}$ denotes the set of rates that can be selected by user i in the kth segment. Without loss of generality, we will assume that $r_i^{(1)} < r_i^{(2)} < ... < r_i^{(J)}$ [26]. Here, f_i denotes the gain function of user i. Here, Nash equilibrium is guaranteed by finding $\{r^*_{i,k}\} = \arg\max_{r_{i,k}\in\boldsymbol{R}_i} f_i(r_{i,k}, \boldsymbol{r}^*_{-i,k}),\ \forall i \in \mathscr{N}$. Let $\boldsymbol{r}^*_{-i,k}$ be an optimal rate vector other than that of user i. We define $\boldsymbol{r}^*_k$ as the rate vector when Nash equilibrium is achieved. Let $\boldsymbol{r}^*_k$ be a rate vector for all the users in the kth segment. The selection rate vector of Nash equilibrium $\boldsymbol{r}^*_k$ in the kth segment is obtained by the gain function of each user. It is important to note, however, that $\boldsymbol{r}^*_k$ does not necessarily correspond to the rate actually chosen by the user. This is because in DASH, the set of rates $\boldsymbol{R}_i$ that user i can request is a discrete set, while the optimal rate $r^*_{i,k}$ obtained from the continuous

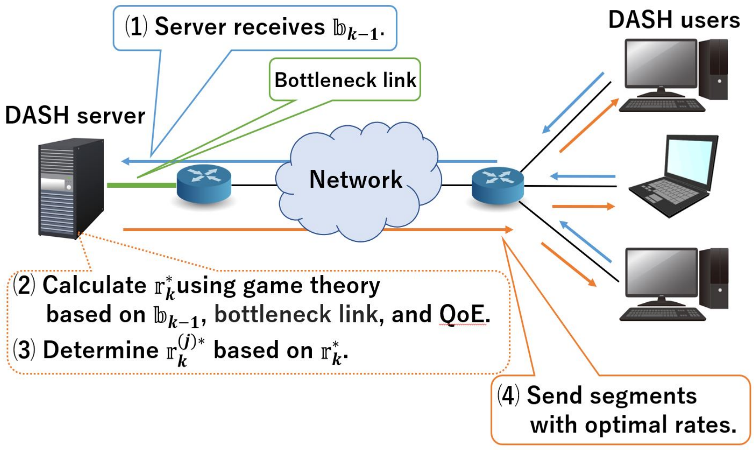

Fig. 3.1: System overview.

function f_i is an arbitrary positive real number. In other words, in this method, the rate $r_i^{(j)^*}(j \in \mathscr{J} = \{1, 2, ..., J\})$ that is closest to $r_{i,k}^*$ obtained by the gain function from among $\boldsymbol{R}_i$ is the rate selected by user i. Thus, the set of rates actually transmitted from the server to each user is $\boldsymbol{r}^{(j)^*}$.

Figure 3.1 and Algorithm 1 show the steps of our system [1]. Essentially, DASH

Algorithm 1 Steps of the proposed system.

Input: $\boldsymbol{b}_{k-1}$
Output: $\boldsymbol{r}^{(j)^*}$

1: **for** $k \Leftarrow 1$ to K **do**
2: Server receives the previous buffer amount $\boldsymbol{b}_{k-1}$ when all users downloaded the $k-1$th segment.
3: Server calculates $\boldsymbol{r}_k^*$ using game theory.
4: Determine $\boldsymbol{r}^{(j)^*}$ based on $\boldsymbol{r}_k^*$.
5: Server sends segments to each user.
6: **end for**

enables users to select their rates. However, in this study, the server selects a rate for each user so that the server computes $r_{i,k}^*$.

The gain function f_i consists of three factors: (A) video quality due to the selection rate, (B) playback stoppage due to buffer underrun, and (C) variation of selection rate. These three factors affect user QoE. Here, f_i is defined as in [1] [24],

$$f_i = \underbrace{q_i(r_{i,k})}_{\text{(A)}} + \underbrace{\mu\Delta b_{i,k}^{\text{est}}(r_{i,k}, \boldsymbol{r}_{-i,k})}_{(B)} + \underbrace{\gamma_i R^{\text{sta}}(r_{i,k})}_{\text{(C)}}. \tag{3.2}$$

where i $(i \in \mathscr{N})$ represents the user number and k $(k \in \mathscr{K} = \{1, 2, ..., K\})$ represents the segment number. μ and γ_i represent weighting coefficients. Moreover, $q_i(r_{i,k})$

is a function for video quality based on user i's QoE for the rate $r_{i,k}$ selected in the k-th segment [1], and $\Delta b^{\text{est}}_{i,k}(r_{i,k}, \boldsymbol{r}_{-i,k})$ is a function for buffer underrun based on the estimated buffer variation of user i [1]. $\boldsymbol{r}_{-i,k}$ is a rate vector other than that of user i. The estimated buffer variation of user i assumes that rate of user i is $r_{i,k}$ when the rates of users other than user i are $\boldsymbol{r}_{-i,k}$. However, this is not enough to achieve a sufficiently high QoE. The reason is that there is no function to prevent the selection rate from varying. In the previous study [1], the subgradient method was used to stabilize the rate. Instead, we use $R^{\text{sta}}(r_{i,k})$ to stabilize the rate more quickly than the subgradient method can. This function $R^{\text{sta}}(r_{i,k})$ prevents QoE degradation due to large rate changes from segment to segment for user i.

Now let us define the above functions. First, $q_i(r_{i,k})$ in the second item (A) of Eq. (3.2) is as follows [27] [26] [16]:

$$q_i(r_{i,k}) = \alpha_{ct} \log(1 + |\beta_{ct}| r_{i,k}). \tag{3.3}$$

where α_{ct} and β_{ct} are values determined when $ct \in C$ of the set of playable video types C is played.

$\Delta b^{\text{est}}_{i,k}(r_{i,k}, \boldsymbol{r}_{-i,k})$ in the second item (B) of Eq. (3.2) denotes the estimated buffer variation of user i when $r_{i,k}$ is selected for the kth segment; it is expressed using the segment length T and the mean throughput θ_i of user i:

$$\Delta b^{\text{est}}_{i,k}(r_{i,k}) = Tr_{i,k} - T\frac{r_{i,k}}{\theta_i} r_{i,k}. \tag{3.4}$$

In Eq. (3.4), $Tr_{i,k}$ represents the amount of data accumulated when user i downloads the kth segment at rate $r_{i,k}$.$T\frac{r_{i,k}}{\theta_i}$ represents the download time. Therefore, $T\frac{r_{i,k}}{\theta_i} r_{i,k}$ is the approximate amount of data consumed. It is difficult to calculate each user's throughput status for each segment with sufficient accuracy [1]. Therefore, we use the available bandwidth of the link on the server side for $\Delta b^{\text{est}}_{i,k}$. If the sum of the selected rates is larger than the available bandwidth of the link, the download time of all the users will increase. Therefore, the download time of each user can be estimated from the sum of the selected rates and the available bandwidth of the link on the server side, B_{W}. There is a correlation between the download time based on this estimation and the actual download time [1]. Therefore, by using B_{W} and the constant ω, we can redefine $\Delta b^{\text{est}}_{i,k}(r_{i,k})$, as shown in Eq. (3.5):

$$\begin{aligned} \Delta b^{\text{est}}_{i,k}(r_{i,k}, \boldsymbol{r}_{-i,k}) &= A_{\text{f}} Tr_{i,k} - \omega Tr_{i,k} \frac{\sum_{i=1}^{N} r_{i,k}}{B_{\text{W}}} \\ &= A_{\text{f}} Tr_{i,k} - \omega T \frac{(r_{i,k}{}^2 + r_{i,k} \sum_{l=1, l\neq i}^{N} r_{l,k})}{B_{\text{W}}} \\ &= A_{\text{f}} \phi(r_{i,k}) - \omega \psi(\boldsymbol{r}_k), \end{aligned} \tag{3.5}$$

where $\phi(r_{i,k})$ is a positive gain due to the amount of data to be stored. When $\phi(r_{i,k})$ is large, buffer underrun is less likely to occur. However, $\psi(\boldsymbol{r}_k)$ represents a negative gain due to the approximate amount of consumed data based on the sum of the selected rates for all users in the kth segment. Here, $\boldsymbol{r}_k$ is the rate vector for all users in the kth segment. When $\psi(\boldsymbol{r}_k)$ is large, buffer underrun is likely to occur. Thus, Eq. (3.5) shows the estimated buffer variation for user i per segment. However, A_f is a function that adjusts the rate to prevent buffer underruns, as follows [28]:

$$A_\mathrm{f} = 2\frac{e^{p(b_{i,k-1}-b_\mathrm{s})}}{1+e^{p(b_{i,k-1}-b_\mathrm{s})}}$$
$$\begin{cases} A_\mathrm{f} > 1 & (b_{i,k-1} > b_\mathrm{s}) \\ A_\mathrm{f} < 1 & (b_{i,k-1} < b_\mathrm{s}), \end{cases}$$

where p is a constant greater than zero, i.e., $p > 0$. Moreover, $b_{i,k-1}$ denotes the buffer amount when the $k-1$th segment is downloaded, b_s represents the buffer reference amount to prevent buffer underrun. Note that each unit of $b_{i,k-1}$ and b_s is in time [s].

The third term (C) of Eq. (3.2) replaces the subgradient method used in the previous study [1] to stabilize the rate $R^{\mathrm{sta}}(r_{i,k})$, This term depends on the difference between $r_{i,k-1}$ and $r_{i,k}$:

$$R^{\mathrm{sta}}(r_{i,k}) = -m(r_{i,k} - r_{i,k-1} + r_i^{(J)})^{-2} 2^{-m(r_{i,k}-r_{i,k-1})}. \tag{3.6}$$

where m is a constant value with $m > 0$. $r_i^{(J)}$ is the highest rate among the set of rates $\boldsymbol{R}_i$ that user i can choose. Moreover, $r_{i,k-1}$ represents the rate of the $k-1$th segment downloaded by user i. This function is such that R^{sta} becomes smaller when the difference between $r_{i,k}$ and $r_{i,k-1}$ becomes larger. Since this is equivalent to a lower gain, R^{sta} can make rate decisions such that the difference between the $k-1$th rate and the kth rate does not increase. Substituting Eqs. (3.3)(3.5)(3.6) for Eq. (3.2), our gain function becomes

$$\begin{aligned} f_i(\boldsymbol{r}_k) &= \alpha_{ct}\log(1+|\beta_{ct}|r_{i,k}) + \mu\left(2\frac{e^{p(b_{i,k-1}-b_\mathrm{s})}}{1+e^{p(b_{i,k-1}-b_\mathrm{s})}}Tr_{i,k}\right) \\ &- \mu\omega T\left(\frac{({r_{i,k}}^2 + r_{i,k}\sum_{i=1,l\neq i}^{N} r_{l,k})}{B_\mathrm{W}}\right) \\ &+ \gamma_i(-m(r_{i,k} - r_{i,k-1} + r^{(J)})^{-2}2^{-m(r_{i,k}-r_{i,k-1})}). \end{aligned} \tag{3.7}$$

Equation (3.7) is for N users, each gain of which is an upward convex function. Thus,

$r^*_{i,k}$ is determined by solving a simultaneous equation consisting of N equations (3.8),

$$\begin{aligned}
&\frac{\partial f_i(\boldsymbol{r}_k)}{\partial r_{i,k}} \\
&= \frac{\alpha_{ct}|\beta_{ct}|}{1+|\beta_{ct}|r_{i,k}} + \mu T\left(2\frac{e^{p(b_{i,k-1}-b_s)}}{1+e^{p(b_{i,k-1}-b_s)}}\right. \\
&\left. -\,\omega\frac{r_{i,k}}{B_W} - \omega\frac{\sum_{i=1}^{N} r_{i,k}}{B_W}\right) + \gamma_i m 2^{m(r_{i,k-1}-r_{i,k})} \\
&\cdot \frac{(m\log(2)(r_{i,k-1}-r^{(J)}-r_{i,k})-2)}{(r_{i,k-1}-r^{(J)}-r_{i,k})^3} \\
&= 0.
\end{aligned} \tag{3.8}$$

Chapter 4

Advantages of the Proposed Method

In this chapter, we compare the method used in the previous study [1], in which the rate is determined by game theory alone without the subgradient method and the game-theoretic rate-determination method using the new gain function (3.6). We show which of the two methods can determine the rate more quickly and stably.

4.1 Numerical Parameters and Analysis Procedure

Assuming that all users watch a 4 minute sports video, we set $\alpha_{ct} = 0.5124$ and $\beta_{ct} = -2.7524$. The value of θ_i is determined according to max-min fairness based on the rate selected by each user [29]. In addition, θ_i caused two variations, as shown in Figure 4.1 and Figure 4.2These variations are similar to ones that occur in a real environment [1] [25]. In particular, staged variations, *variation I*, affect the available bandwidth wherein it increases (or decreases) for several tens of seconds in Fig. 4.1. On the other hand, short-term variations *variation II* are those with repeated temporary changes in Fig. 4.2. Table 4.1 shows the parameters for *variation I* and *variation II*, and Table 4.2 shows the bit rates for the segments.

In this analysis, the rate is determined by algorithm2. DASH provides J discrete rates. However, f_i is a continuous function from which our method cannot directly obtain a discrete variable. Therefore, the rate $r_i^{(j)^*}$ that is closest to the optimal rate $r_{i,k}^*$ from among $\boldsymbol{R}_i$ is selected by user i. In addition, b_{ini} represents the initial buffer amount. We assume $r_i^{(j)^*} = 1.0$ Mbps until $b_{\text{ini}} = 4$ s [30]. The video is not played during this initial period [1] [30].

Table 4.1: Value of parameter.

N	4
T	2 s
B_W	20 Mbps
J	21
μ	3.2×10^{-6}
ω	1.25
γ_i	1.0×10^{20}
p	0.05
m	1.0×10^{-6}

Table 4.2: Bitrates for a segment.

Resolution	Bit rate (Mbps)
480 × 360	0.1, 0.2, 0.3, 0.4
704 × 480	0.5, 0.6, 0.7, 0.9, 1.0
1280 × 720	1.2, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0

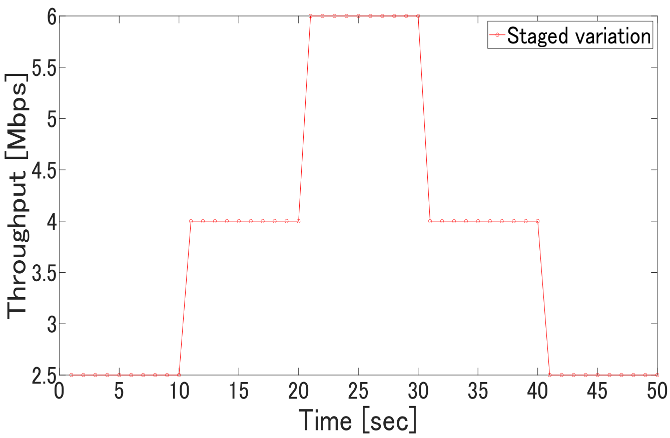

Fig. 4.1: Staged variation (variation I)

4.2 Results of Proposed Method Without the Subgradient Method

Figure 4.3 and Figure 4.5 show that when the subgradient method was not used in the method of the previous study [1], the rate obtained in the early phase was not stable and the lowest rate (0.1 Mbps) was obtained continuously thereafter. On the other hand,

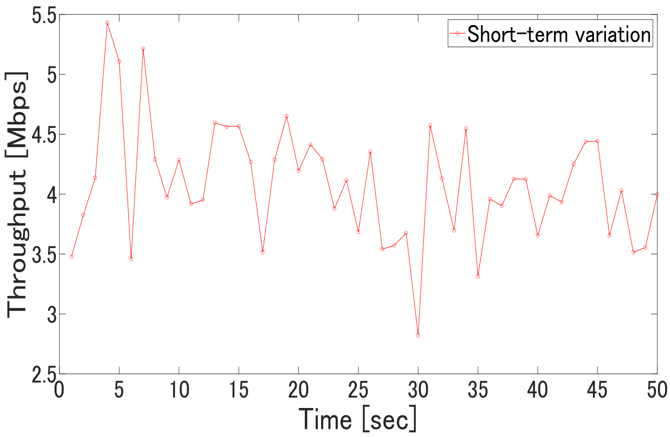

Fig. 4.2: Short-term variation (variation Ⅱ)

Algorithm 2 Proposed rate-determination algorithm

Input: $b_{\mathrm{ini}}, T, k, b_{i,k-1}, \theta_i$
Output: $r_i^{(j)^*}, b_{i,k}$

for $k \Leftarrow 1$ to K **do**
  for $i \Leftarrow 1$ to N **do**
    if $b_{i,k} \leqq b_{\mathrm{ini}}$ **then**
      $r_i^{(j)^*} \Leftarrow 1.0[\mathrm{Mbps}]$
      $b_{i,k} \Leftarrow T \times k$
    else
      Calculate $r_{i,k}^*$ based on (3.7).
      Select $r_i^{(j)^*}$ in $\boldsymbol{R}_i$ that is closest to $r_{i,k}^*$ obtained by the gain function as the rate for user i.
      $b_{i,k} \Leftarrow b_{i,k-1} + T - \frac{Tr_i^{(j)^*}}{\theta_i}$
    end if
  end for
end for

Figure 4.4 and Figure 4.6 show that the proposed method with the new function kept the rate stable. In other words, the method from the previous study [1] is able to make stable rate decisions by combining game theory and the subgradient method, but it is unable to make stable rate decisions using game theory alone. On the other hand, the proposed method can make stable rate decisions using only game theory. In addition, the method from the previous study requires about 50 segment acquisitions for the rate to stabilize, even if the subgradient method is used, whereas the proposed method stabilizes the rate at less than 50 segments. In other words, the proposed method can determine the rate more quickly and stably than the previous one.

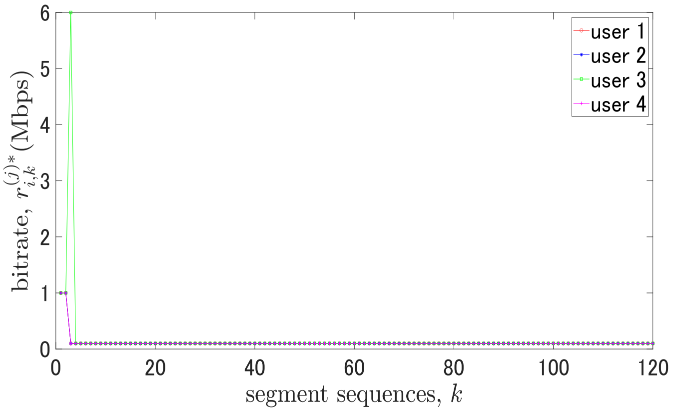

Fig. 4.3: Rate variation of existing method [1] without subgradient method in staged variation I.

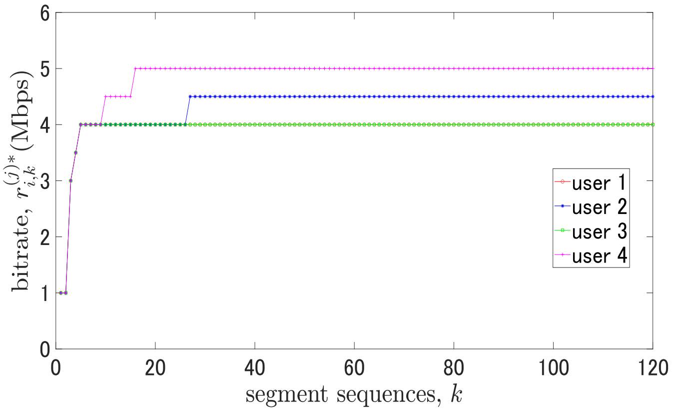

Fig. 4.4: Rate variation of the proposed method in staged variation I.

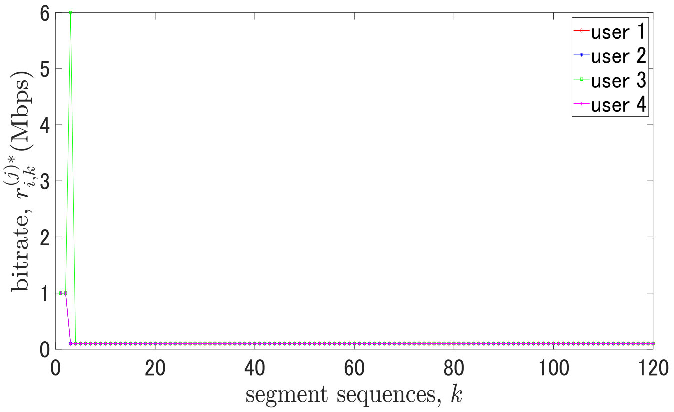

Fig. 4.5: Rate variation of existing method [1] without subgradient method in short-term variation II.

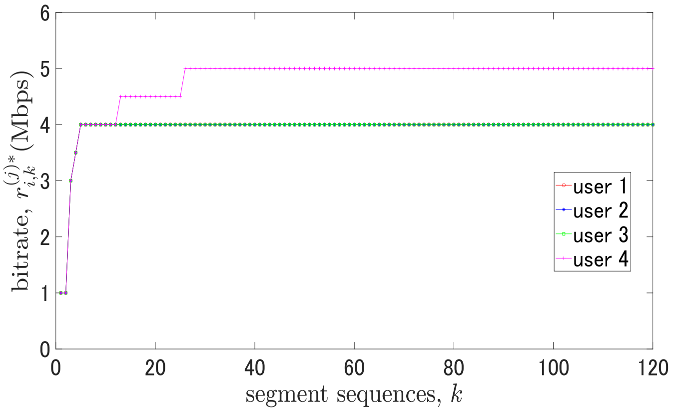

Fig. 4.6: Rate variation of the proposed method in short-term variation Ⅱ.

Chapter 5

Analysis of Methods Considering User Preference

In this chapter and the next, we consider user characteristics. In particular, in this chapter we show that QoE can be improved by allowing the game theory model in chapter 3 to account for user preference.

5.1 Gain Function to Account for User Preference

To account for user preference, we incorporate a coefficient of (D) in the gain function, Equation (3.2).

$$f_i = \underbrace{t_i}_{\text{(D)}} q_i(r_{i,k}) + \mu \Delta b^{\mathrm{est}}_{i,k}(r_{i,k}, \boldsymbol{r}_{-i,k}) + \gamma R^{\mathrm{sta}}(r_{i,k}). \tag{5.1}$$

In Eq. (5.1), i ($i \in \mathcal{N}$) represents the user number and k ($k \in \mathcal{K} = \{1, 2, ..., K\}$) represents the segment number. t_i is the coefficient to reflect user preference [24]; it is composed of a general function Q_{mean} to represent the user's QoE and a function $Q_i^{\mathrm{preference}}$ for QoE focusing only on users with strong (weak) interest in video. That is, Q_{mean} does not take user preferences into account and represents the average QoE obtained when users watch a video with the j ($j \in \mathcal{J} = \{1, 2, ..., J\}$)th highest rate $r_i^{(j)} \in \boldsymbol{R}_i$, regardless of preference. Q_{mean} can be expressed as a logarithmic function of $r_i^{(j)}$ [27] [26]:

$$Q_{\mathrm{mean}}(r_i^{(j)}) = \alpha_{ct} \log(r_i^{(j)}) + \beta_{ct},$$

where α_{ct} and β_{ct} are values determined when $ct \in C$ of the set of playable video types C is played. However, in DASH, each user has the same set of rates to choose from, which means that $r_1^{(j)} = r_2^{(j)} =, ..., = r_N^{(j)}$. The QoE of a user i who is strongly (or weakly) interested in the video is defined as in [16],

$$Q_i^{\mathrm{preference}}(r_i^{(j)}) = \begin{cases} \alpha^{\mathrm{P}}_{i,ct} \log(r_i^{(j)}) + \beta^{\mathrm{P}}_{i,ct} & \text{(Strong interest)} \\ \alpha^{\mathrm{NP}}_{i,ct} \log(r_i^{(j)}) + \beta^{\mathrm{NP}}_{i,ct} & \text{(Weak interest)}. \end{cases}$$

where $\alpha^{\mathrm{P}}_{i,ct}$, $\beta^{\mathrm{P}}_{i,ct}$ and $\alpha^{\mathrm{NP}}_{i,ct}$, $\beta^{\mathrm{NP}}_{i,ct}$ are values determined by ct and user i's preference. Thus, we can derive t_i by using $Q_{\mathrm{mean}}(r_i^{(j)})$, $Q_i^{\mathrm{preference}}(r_i^{(j)})$, and the number of rate types J, as in [24],

$$t_i = \frac{1}{J}\sum_{j=1}^{J}\{Q_i^{\mathrm{preference}}(r_i^{(j)})/Q_{\mathrm{mean}}(r_i^{(j)})\}.$$

5.2 Numerical Parameters and Analysis Procedure

We evaluated the user's QoE by using equation (5.2) from three perspectives: the average rate of acquired segments, playback stoppage time, and rate variation [25]:

$$\begin{aligned} Q_i = \frac{1}{K_i}\Bigg(&\sum_{k=1}^{K_i} Q_i^{\mathrm{preference}}(r_{i,k}) \\ &- \sum_{k=1}^{K_i}\eta\frac{\exp(-a + bT_{\mathrm{f}}[k])}{1+\exp(-a+bT_{\mathrm{f}}[k])} \\ &- \sum_{k=2}^{K_i}\epsilon\frac{\zeta|r_{i,k}-r_{i,k-1}|}{r_{i,k}}\Bigg). \end{aligned} \tag{5.2}$$

We set users with strong interest in a video to $\alpha^{\mathrm{P}}_{i,ct} = 0.4483$, $\beta^{\mathrm{P}}_{i,ct} = -1.6794$, and users with weak interest to $\alpha^{\mathrm{NP}}_{i,ct} = 0.7935$, $\beta^{\mathrm{NP}}_{i,ct} = -6.9912$ [16] [31] [25]. In Equation (5.2), K_i is the total number of segments acquired by user i at the time of evaluating QoE. In this analysis, only the QoE at the time when all segments are acquired is evaluated, so it is $K_i = K$. $T_{\mathrm{f}}[k]$ represents the playback stoppage time during viewing of the $k-1$th segment. a, b, and ζ are constants, each set to 1, while η and ϵ are weighting factors set to $\eta = 8$ and $\epsilon = 5$, respectively [25]. The first term in the equation represents the QoE obtained from the average rate per requested segment, the second term represents the degree of degradation in QoE due to playback stoppage, and the third term represents the degree of degradation in QoE due to the difference in rate between the kth acquired segment and the $k+1$th acquired segment. As shown in Table 5.1, the ratios of users who are strongly interested in video (P users) and those who are not (NP users) can be divided up into three patterns. For each pattern, we performed ten simulations and checked the average value $\overline{Q_i}$ obtained by Equation (5.2).

5.3 Effect of Considering User Preference

As shown in Figure 5.1–Figure 5.6, for any pattern of user headcount ratio and throughput variation, the QoE was higher for the method considering user preferences. When the QoE is greater than 5, users are considered to have little or no perception of poor video quality [24] [26]. The advantage of considering user preferences is thus confirmed.

Table 5.1: Ratio of users.

	Pattern A	Pattern B	Pattern C
P user	user 1, user 2	user 1, user 2, user 3	user 1
NP user	user 3, user 4	user 4	user 2, user 3, user 4

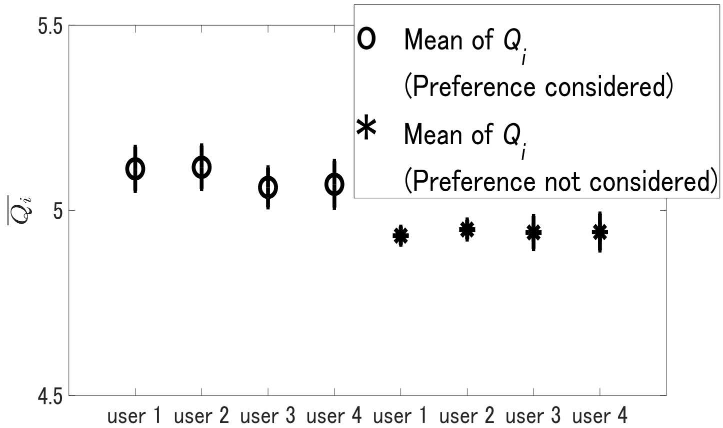

Fig. 5.1: Mean and 95 % CI of Q_i for pattern A (variation I).

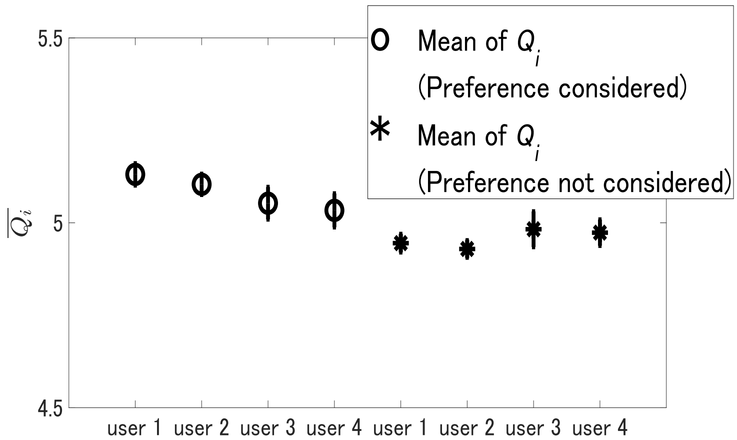

Fig. 5.2: Mean and 95 % CI of Q_i for pattern A (variation II).

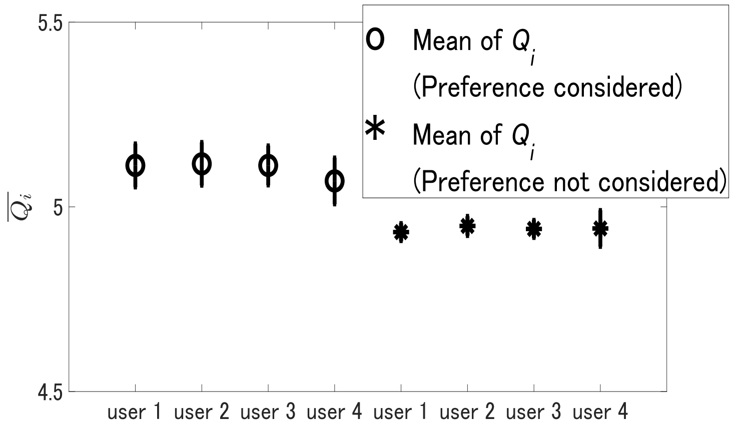

Fig. 5.3: Mean and 95 % CI of Q_i for pattern B (variation I).

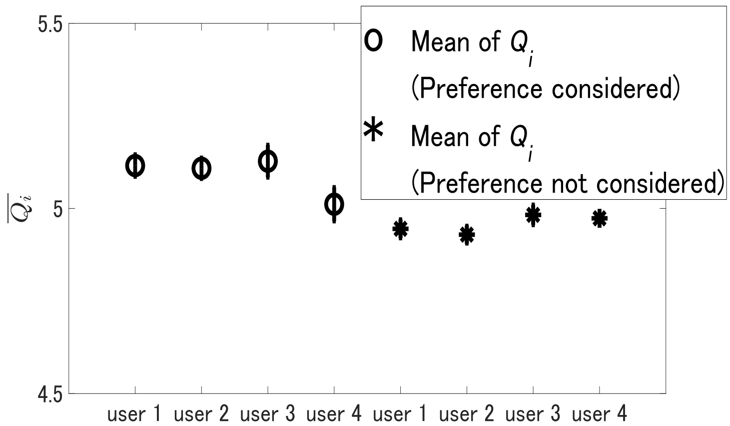

Fig. 5.4: Mean and 95 % CI of Q_i for pattern B (variation II).

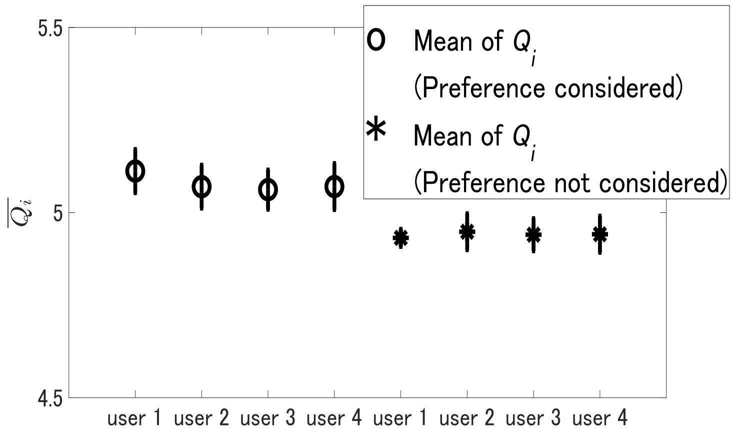

Fig. 5.5: Mean and 95 % CI of Q_i for pattern C (variation I).

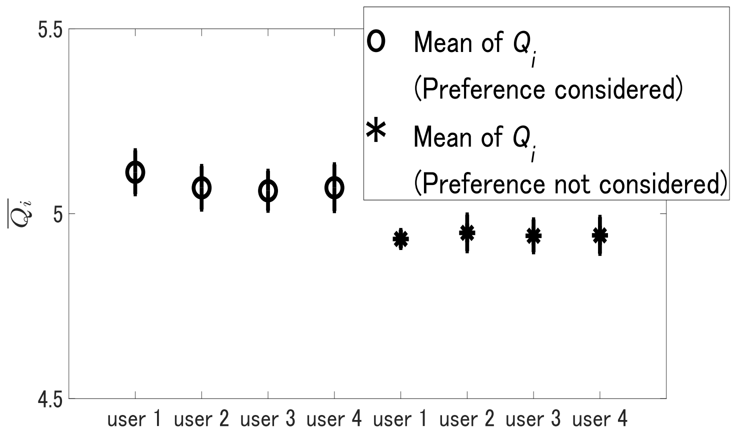

Fig. 5.6: Mean and 95 % CI of Q_i for pattern C (variation II).

Chapter 6

Analysis of When Early Departure Occurs

Here, we show that the method modeled in chapter 5, which takes user preference into account, can appropriately determine rates in the case of early departure of users.

6.1 Numerical parameters and analysis procedure

First, it is necessary to identify which users leave early in order to perform the analysis under conditions where early departure occurs. Therefore, as a preliminary preparation, we conducted an analysis to identify users who leave early. The causes of users stopping watching early are considered to be the average bit rate of the video and the playback stoppage time [12]. In general, the average bit rate and playback stop time affect QoE [32]. Therefore, in the preliminary analysis, we examined the time variation of users' QoE. We assumed that users with low QoE to be those who leave early.

The time variation of QoE was analyzed using Algorithm 3. The algorithm can check the time variation in QoE by determining Q_i each time the user's rate $r^{*'}_{i,k}$ is determined. As in chapter 5, we ran the simulation ten times to check the average time variation of $\overline{Q_i}$, which is the average QoE. Moreover, as in chapter 5, we conducted an analysis for each of the headcount-ratio patterns in Table 5.1.

6.2 Preliminary Preparation Results

Figure 5 shows the average time variation of Q_i when the rate determination method of the proposed method is used for Variation I and Variation Ⅱ. For all three patterns with different ratios of users P user who are more interested in videos to those NP user who are less interested in videos in the two variations, we found that the $\overline{Q_i}$ of NP user is always lower than that of P user. For videos lasting 5 minutes or less, the probability of a user leaving is about 50% regardless of which part of the video is playing between 0 and 5 minutes [11]. Therefore, we can assume that the average number of users who stop watching a 4-minute video before it finishes playing is 2. Hence, we assumed that

Algorithm 3 Algorithm to analyze time variation of QoE

Input: $b_{\mathrm{ini}}, T, k, b_{i,k-1}, \theta_i$
Output: $r_i^{(j)^*}, b_{i,k}, Q_i$
for $k \Leftarrow 1$ to K **do**
  for $i \Leftarrow 1$ to N **do**
    if $b_{i,k} \leqq b_{\mathrm{ini}}$ **then**
      $r_i^{(j)^*} \Leftarrow 1.0[\mathrm{Mbps}]$
      $K_i \Leftarrow k$
      Calculate Q_i based on (5.2).
      $b_{i,k} \Leftarrow T \times k$
    else
      Calculate $r_{i,k}^*$ based on (3.7).
      Find the value closest to $r_{i,k}^*$ in $\boldsymbol{R}_i$, and set it to $r_i^{(j)^*}$.
      $K_i \Leftarrow k$
      Calculate Q_i based on (5.2).
      $b_{i,k} \Leftarrow b_{i,k-1} + T - \frac{T r_i^{(j)^*}}{\theta_i}$
    end if
  end for
end for

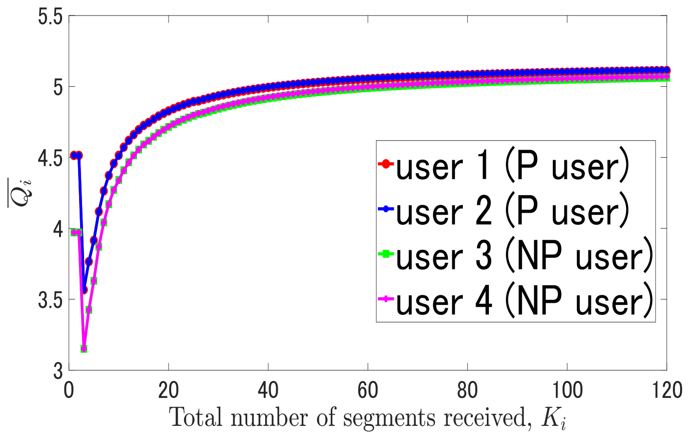

Fig. 6.1: Time variation of Q_i for pattern A (variation I).

the two NP users are users who depart early in Pattern A. In Pattern B, two of the three NP users with low Q_i are users who depart early, while in Pattern C, one of the NP users and one of the three P users with low Q_i are users who depart early.

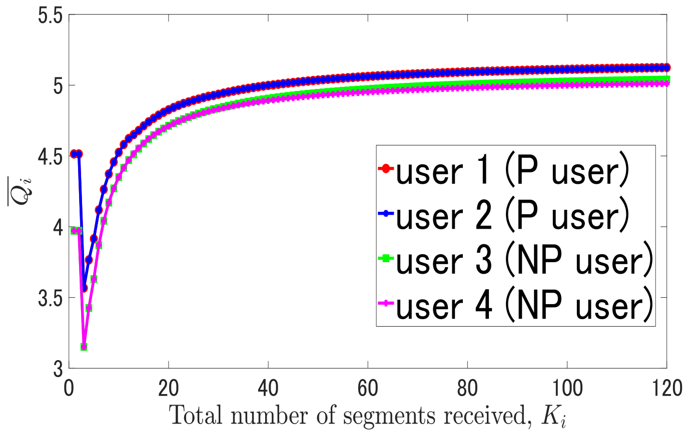

Fig. 6.2: Time variation of Q_i for pattern A (variation II).

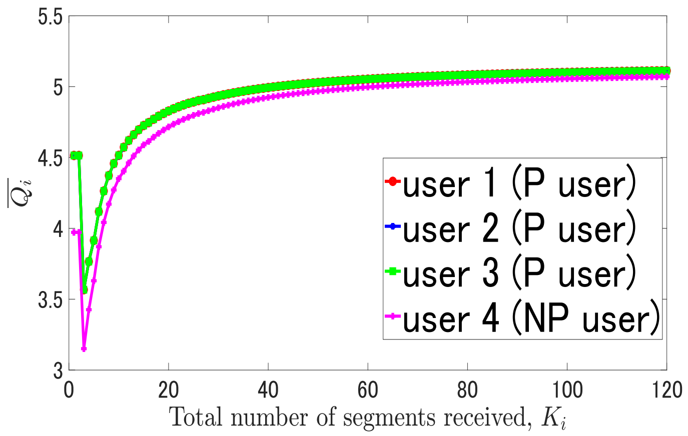

Fig. 6.3: Time variation of Q_i for pattern B (variation I).

6.3 Results for When Early Departure Occurs

Next, we analyzed the situation in which users who were determined to be early deserters according to the results in Figure6.1–Figure6.6 actually leave while watching a video. Then, we checked the average value of Q_i, which is $\overline{Q_i}$, of the remaining users who did not leave the video and finished watching it to the end ($K_i = K$). In addition, the value of the second term in Eq. (3.5) becomes smaller each time the number of users N decreases due to early departure, which makes it harder to prevent buffer underruns. Therefore, we adjusted the weighting factor ω according to the number of users, as shown in Table 6.1. The average time that a video of 5 minutes or less continues to be viewed is approximately 53.5% of the total video time [11]. Therefore, we let two users leave so that the average time that the four users watched the video would be 53.5% of the 4

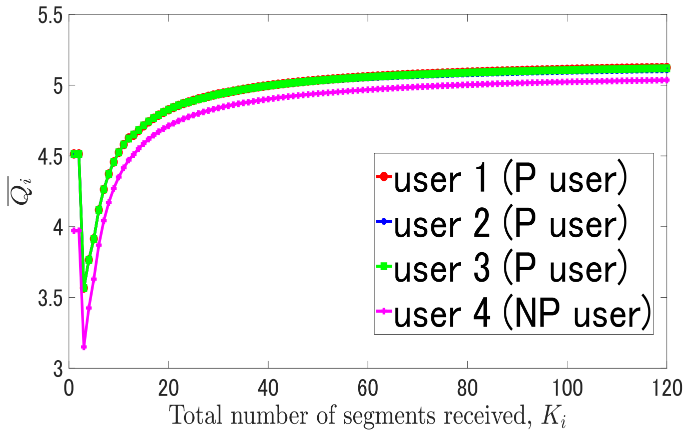

Fig. 6.4: Time variation of Q_i for pattern B (variation Ⅱ).

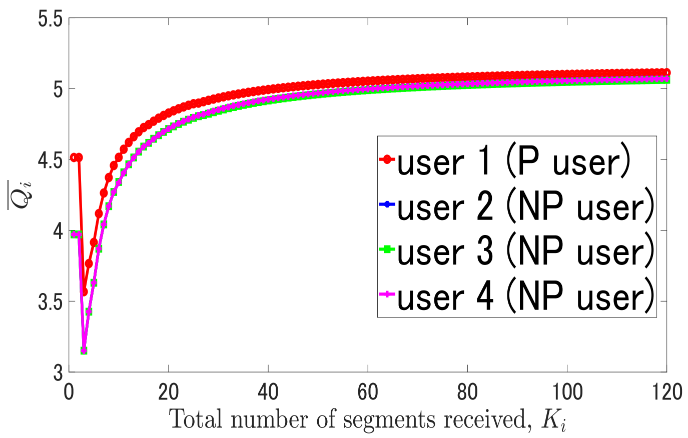

Fig. 6.5: Time variation of Q_i for pattern C (variation I).

Table 6.1: Adjustment of ω.

	$N = 4$	$N = 3$	$N = 2$
ω	1.25	1.72	2.50

minutes of video duration.

Figure6.7–figure6.12 show the $\overline{Q_i}$ of users with and without early departure in Variation I and Variation Ⅱ. Only the $\overline{Q_i}$ of users who did not leave early are compared. Figure6.7–figure6.12 show that $\overline{Q_i}$ did not change significantly from Pattern A to Pattern C in the absence of early departure and in the presence of early departure. This indicates that the proposed rate determination method is stable even in an early-departure environment.

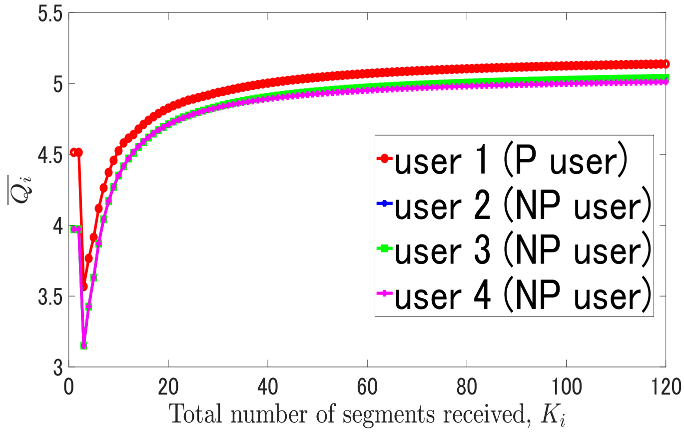

Fig. 6.6: Time variation of Q_i for pattern C (variation II).

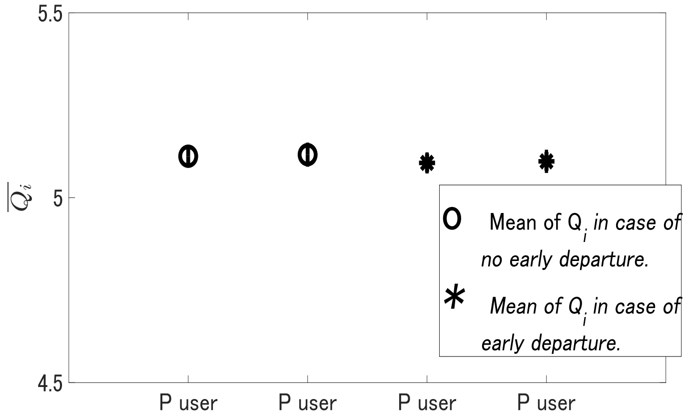

Fig. 6.7: Mean and 95 % CI of Q_i for pattern A when early departure occurs (variation I).

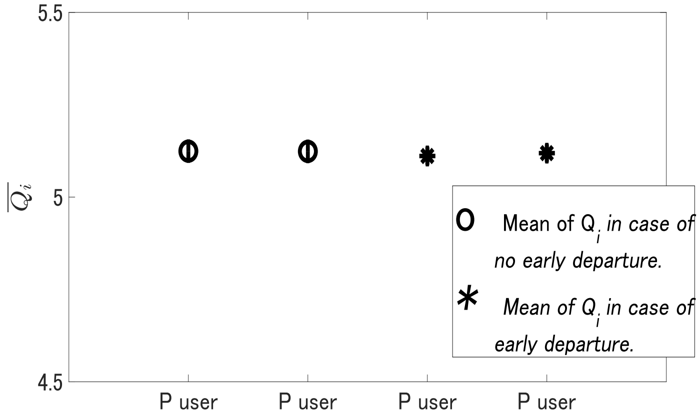

Fig. 6.8: Mean and 95 % CI of Q_i for pattern A when early departure occurs (variation II).

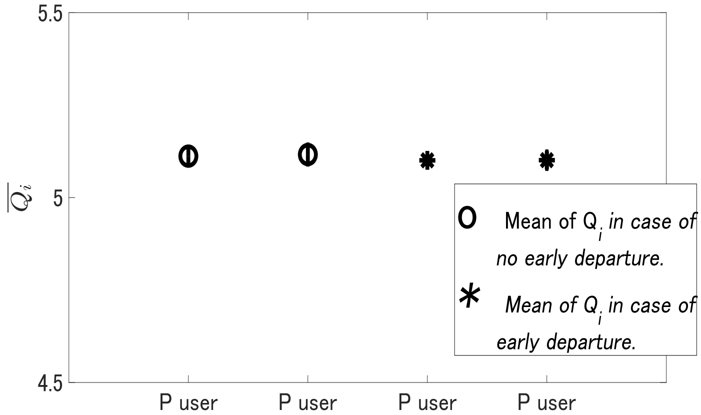

Fig. 6.9: Mean and 95 % CI of Q_i for pattern B when early departure occurs (variation I).

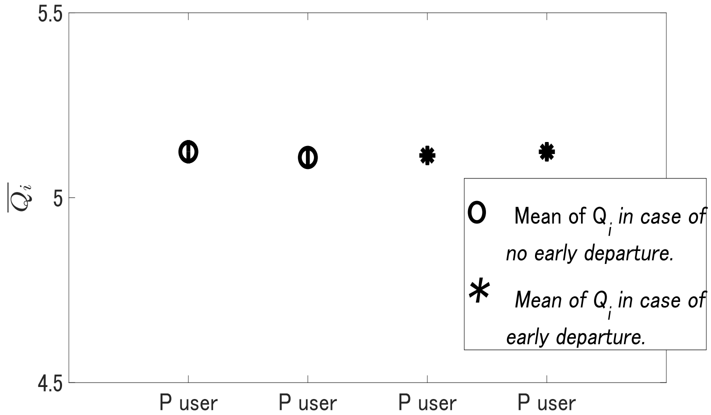

Fig. 6.10: Mean and 95 % CI of Q_i for pattern B when early departure occurs (variation II).

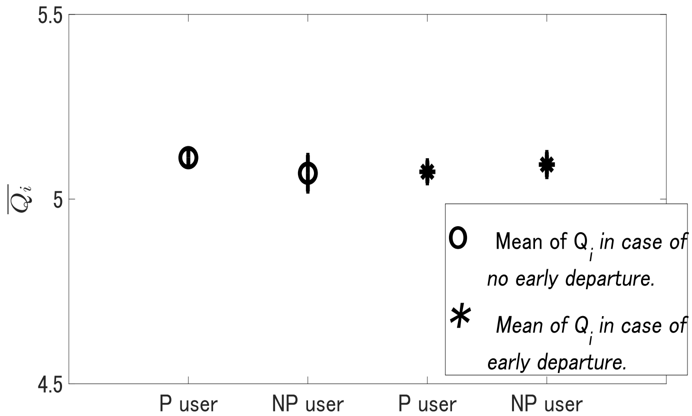

Fig. 6.11: Mean and 95 % CI of Q_i for pattern C when early departure occurs (variation I).

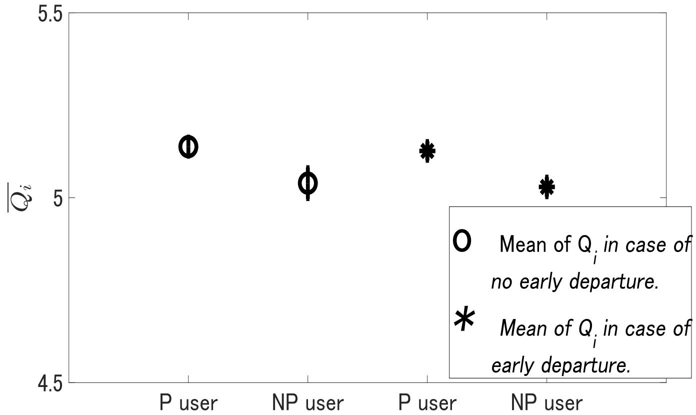

Fig. 6.12: Mean and 95 % CI of Q_i for pattern C when early departure occurs (variation Ⅱ).

Chapter 7

Summary and Future Work

We proposed a new game-theoretic rate determination method that does not use the conventional subgradient method to achieve faster and more stable rate determination for DASH. We focused on user characteristics and showed that a rate determination using game theory and takes user preferences into account improves QoE. Furthermore, we found that the proposed method works well even in situations where users depart early in the middle of a video viewing session.

In our study, we only examined situations in which multiple users watch the same genre of content (e.g., sports or music) at the same time. In other words, we did not analyze cases where multiple users watch videos of different genres. Moreover, we did not analyze the case where a new user joins a bottleneck link contention in the middle of the process. Further research is needed to resolve these issues.

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Research Achievements

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