INTERACTIVE MULTIVIEW VIDEO SCHEDULING THROUGH BARGAINING

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ABSTRACT

This paper proposes a multiview video scheduling scheme through asymmetric Nash bargaining for a tradeoff between user satisfaction and view fairness. The interactions of view streams queueing at the scheduler are modeled as a bargaining problem, where packets of different views share the transmission opportunities via negotiation. A utility function based upon the viewing angle is defined to indicate whether a view is desired by a user, then a network utility maximization problem is solved by the Nash bargaining solution (NBS). The impacts of the bargaining powers on both network performance and view fairness are analytically investigated. Simulation results are provided to compare the performances of three scheduling schemes including fair scheduling, symmetric bargaining, and proportional scheduling, which can be achieved by adjusting the bargaining powers.

***Index Terms*—** Interactive multiview video streaming, scheduling, fairness, asymmetric bargaining game

1. INTRODUCTION

Advances in camera and display technologies have enabled three-dimensional (3-D) video applications, such as 3-D television and free viewpoint television, to home and mobile platforms in the near future. Multiview video (MVV) [1], one popular 3-D video format, has recently attracted considerable attention. It consists of multiple video sequences that are captured simultaneously by closely deployed cameras from different viewpoints.

MVV representation requires massive amount of data. The state of the art multiview video coding (MVC) standard [2] compresses MVV efficiently by exploiting both temporal and interview redundancies, its transmission bitrate is still very high. MVC requires to transmit the entire multiview sequence to each user, which is practically unnecessary for the sake that, relying on the head position, the user in a period might be only interested in a subset of the captured views. Interactive MVV streaming [3] is designed to reduce bandwidth utilization by only transmitting the desired views that are currently requested by the users.

Due to users' diverse preferences, the view sequence subset to be injected into the network might be very large. For current bandwidth-constrained infrastructures, it is hard to accommodate such large amount of data. Therefore, view data scheduling or dropping strategy should be employed to avoid congestion. The existing works [4]-[7] on MVV streaming mostly focused on efficient coding techniques and rate allocation schemes. In this paper, we consider the view scheduling problem, which is seldom addressed in the literature.

When network congestion occurs, one scheduling strategy is to satisfy the majority of the users and first transmit view streams requested by the most users (i.e. popular views). This strategy ignores user fairness. On one hand the users who required unpopular views might receive nothing, while on the other hand the users who requested and also received more than two popular views would be excessively satisfied, as two views are sufficient for creating 3-D perception. The other strategy is to schedule all the views fairly. Such strategy does not specifically consider users' requirements and leads to a low network efficiency. It is critical to design a view scheduling strategy that can achieve a high overall system performance while guaranteeing fairness among users.

Bargaining game theory has been extensively used for fairness-guaranteed resource allocation in wireless networks. In this article, we are inspired to model the interactions of the buffered view packets as a bargaining problem, where packets of different views share the transmission opportunities via negotiation. Our main contributions are as follows: We propose an asymmetric Nash bargaining based view scheduling scheme to enable interactive MVV streaming over the current Internet. We investigate the impacts of asymmetric bargaining power on both network performance and view fairness. We show that a tradeoff between user satisfaction and view fairness can be achieved by adjusting the bargaining powers.

The remainder of this paper is organized as follows: Sec. II formulates the view scheduling problem as a bargaining game. Simulation results are discussed in Sec. III. Finally, Sec. IV concludes the paper.

2. VIEW SCHEDULING STRATEGY

2.1. System Architecture

The architecture of the proposed interactive MVV streaming system is shown in Fig. 1. A scene of interest is captured by M cameras from different viewing angles. All the captured view videos then are transmitted to the media server. At the server side, each view is encoded independently, with the encoded view data stored a priori. At the user side, by using autostereoscopic head-tracking display [8], the information of the requested views is sent back to the server periodically. After receiving the view requests of all users, the server selectively sends out the desired view sequences with a particular view scheduling strategy.

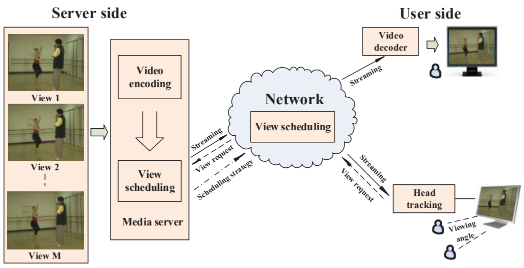

Fig. 1. Architecture of interactive MVV streaming system

View scheduling strategy refers to the decisions made by the scheduler (at the server or intermediate node) that whether packets of a view should be forwarded or dropped. Different scheduling strategies may lead to different results. For example, as shown in Fig. 2, consider that there exist five view video sequences to be transmitted to four users. The view requirements of these four users are $\{1, 2\}$, $\{2, 3, 4\}$, $\{3, 4, 5\}$, and $\{4, 5\}$, respectively. Owing to limited network capacity, only three view sequences can be forwarded by the scheduler. If the scheduler randomly selects view 1, 2, and 3, user 4 would receive nothing. If the scheduler transmits the most popular views 3, 4, and 5, user 1 would receive nothing. If the scheduler transmits view 2, 3, and 4 (or 5), all the users can at least obtain a visual stream. Our goal in this work is to find a view scheduling strategy that addresses issues of network efficiency and user fairness.

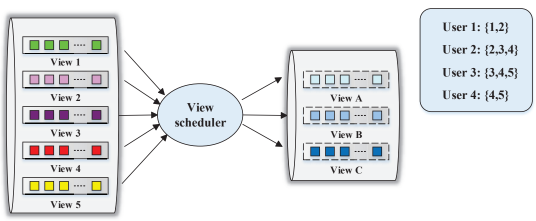

Fig. 2. Example of view scheduling strategy

2.2. Bargaining Game Model

Assume that there are M queues at a scheduler. Each queue m is used for buffering packets of view m. When bandwidth is insufficient, packets in the queues compete for limited transmission opportunities. In the bargaining framework, the players in our problem are M queues (or views) that negotiate with each other on the use of bandwidth resource.

Scheduling strategy: Scheduling strategy $\mathbf{X} = \{x_1, \ldots, x_M\}$ represents the decision of the scheduler that which view is selected for transmission. That is,

$$x_m = \begin{cases} 1, & \text{if view } m \text{ is selected for transmission;} \\ 0, & \text{otherwise.} \end{cases}$$

Since the scheduler can not select more than one view at the same time, we have $\sum_{m=1}^{M} x_m = 1$.

View demands: The demands for a view can be calculated by using the angle between the user and the view as in [10]. Let $\vec{O}_m$ denote the orientation of view m given by the normal of its image plane, and the user view is represented by its orientation $\vec{O}_n$, then user n's demands for view m is

$$d_m^n = \cos\theta_m^n, \tag{1}$$

where θ_m^n is the angle between $\vec{O}_m$ and $\vec{O}_n$. Generally, view m is supposed to be desired by user n, if d_m^n is larger than a pre-defined threshold T, $0 \le T \le 1$.

We now define a utility function $u_{n,m}$ as:

$$u_{n,m} = \begin{cases} 1, & d_m^n \ge T; \\ 0, & d_m^n < T. \end{cases} \tag{2}$$

Given a scheduling strategy $\mathbf{X}$, the utility of view m is

$$u_m(\mathbf{X}) = x_m \cdot \sum_{n=1}^{N} u_{n,m}, \tag{3}$$

where $\sum_{n=1}^{N} u_{n,m}$ is the number of users who requested view m, which we call it *view popularity* in this paper.

To find a scheduling strategy that provides network utility maximization with guaranteed fairness, we formulate the optimization problem as:

$$\begin{aligned} \max & \prod_{m=1}^{M} (x_m \cdot \sum_{n=1}^{N} u_{n,m} - u_m^{\min})^{\delta_m} \\ \text{s. t.} & \quad \sum\nolimits_{m=1}^{M} x_m = 1, \\ & x_m = \{0, 1\}, \quad m = 1, ..., M, \\ & x_m \cdot \sum_{n=1}^{N} u_{n,m} \ge u_m^{\min}, \quad m = 1, ..., M, \end{aligned} \tag{4}$$

where δ_m is view m's bargaining power that is normalized as $\sum_{m=1}^{M} \delta_m = 1$.

The value of the minimum utility $u_m^{\min}$ has a great impact on the outcome of the bargaining game. To schedule the popular views first, we let $u_m^{\min}$ of view m proportional its popularity.

$$u_m^{\min} = \varepsilon \cdot (\sum\nolimits_{n=1}^{N} u_{n,m})^2, \tag{5}$$

where $\varepsilon \le \varepsilon_0$ is a positive constant, and ε_0 is the positive root of the equation $\varepsilon \cdot \sum_{m=1}^{M} \sum_{n=1}^{N} u_{n,m} = 1$.

The optimization problem in (4) is an integer programming problem. Its solution is usually achieved by an exhaustive search that has a high computational complexity. To efficiently solve the problem, we relax the constraint $x_m = \{0, 1\}$ to continuous values with $0 \le x_m \le 1$, as in [11]. Then, x_m can be viewed as the probability that view m is selected by the scheduler. Correspondingly, the outcome $\mathbf{X}$ of the game becomes a probability vector.

The problem in (4) with the continuous relaxation is a convex optimization problem [12]. Its solution or the Nash bargaining solution (NBS) is given by

$$x_m^* = \delta_m (1 - \varepsilon \cdot \sum_{m=1}^{M} \sum_{n=1}^{N} u_{n,m}) + \varepsilon \cdot \sum_{n=1}^{N} u_{n,m}. \quad (6)$$

As the view request information of all the users are submitted to the server, the players (or the queues) in our game do not need to mutually bargain for an optimal outcome. Instead, the server can play the game for these players in a centralized manner. Thus, the computational complexity and communication overhead of our scheme is very low.

2.3. Impact of Bargaining Powers

It can be seen from Eq. (6) that x_m is a strictly increasing function with respect to δ_m. Therefore, we can adapt our scheduling strategy to different scenarios by adjusting the bargaining power settings. Here we consider three cases.

Case 1: symmetric bargaining. In this case, all the views have the same bargaining power, i.e., we have $\delta_m = 1/M$ for all m. View m's scheduling probability is therefore given by

$$\begin{aligned} x_m &= \frac{1}{M}(1 - \varepsilon \cdot \sum_{m=1}^{M} \sum_{n=1}^{N} u_{n,m}) + \varepsilon \cdot \sum_{n=1}^{N} u_{n,m} \\ &= \frac{1}{M} + \varepsilon \cdot (\sum_{n=1}^{N} u_{n,m} - \frac{1}{M} \cdot \sum_{m=1}^{M} \sum_{n=1}^{N} u_{n,m}). \end{aligned} \quad (7)$$

This is a typical symmetric bargaining case in which the view fairness and utility performance are both taken into account. The first term in Eq. (7) guarantees the fairness by assigning equivalent scheduling probability to all the views, while the second term can be regarded as an offset determined by the gap between a view's demands and the average demands of all the views.

Case 2: fair scheduling. By setting

$$\delta_m = \frac{1/M - \varepsilon \cdot \sum_{n=1}^{N} u_{n,m}}{1 - \varepsilon \cdot \sum_{m=1}^{M} \sum_{n=1}^{N} u_{n,m}}, \quad (8)$$

our scheme becomes an absolutely fair scheduling where each view is scheduled with the same probability $x_m = 1/M$, regardless of its specific demands.

Case 3: proportional scheduling. When view m's bargaining power is set to

$$\delta_m = \frac{\sum_{n=1}^{N} u_{n,m}}{\sum_{m=1}^{M} \sum_{n=1}^{N} u_{n,m}}, \quad (9)$$

the proposed scheme turns into a proportional scheduling. In this case, the fairness is ignored and view m's scheduling probability is determined only by its popularity, i.e.,

$$x_m = \frac{\sum_{n=1}^{N} u_{n,m}}{\sum_{m=1}^{M} \sum_{n=1}^{N} u_{n,m}}, \quad (10)$$

3. SIMULATION RESULTS

The simulations are conducted on a 8-view "Racel" sequence. Each view is encoded independently with 640x480 resolution by using H.264/AVC reference software. The average bitrate and peak signal noise ratio (PSNR) for each view is shown in Table I. In simulations, 8 views are equally spaced between each other with the angles θ_m from 20 to 160 degrees. We consider two user classes. Class 1 are the users with normal viewing position, whose viewing angles θ_n are uniformly distributed on the interval $[45°, 135°]$. The users in Class 2 are viewing with special posture, whose viewing angles are uniformly distributed within either $[0°, 45°]$ or $[135°, 180°]$. Correspondingly, the views requested by Class 1 are likely to be popular views, while those desired by Class 2 are possibly unpopular views. Assume that all the requested view streams are queuing at the scheduler.

Table 1. Average bitrate and PSNR value of each view

View No	Bitrate (Kbps)	PSNR (dB)
1	1831.11	38.75
2	1721.26	38.94
3	1788.82	38.80
4	1623.92	39.06
5	1262.65	39.95
6	1176.61	40.42
7	2058.77	38.08
8	1737.20	38.78

We introduce two metrics *view fairness* and *user satisfaction*. View fairness, measured by a fairness index $\mathcal{F}$, reveals the fairness among the views in terms of their scheduling probabilities. Based upon the Jain's fairness index [13], we have

$$\mathcal{F} = \frac{\left(\sum_{m=1}^{K} x_m\right)^2}{K \cdot \sum_{m=1}^{K} {x_m}^2}, \quad (11)$$

where $K \le M$ is the number of the queueing views. The value of $\mathcal{F}$ ranges from 0 to 1. It is maximum when all the views are scheduled at the same probability, and decreases with the increase of the disparity of the scheduling probabilities.

User satisfaction, measured by a satisfaction index $\mathcal{S}_n$, indicates the satisfaction of user n with the views selected by the scheduler. Similarly, $\mathcal{S}_n$ assumes values in [0,1]. It reaches maximum when all the desired views of user n have been forwarded by the scheduler. On the contrary, if none of the requested views have been scheduled, $\mathcal{S}_n$ becomes zero. Let $\mathbf{V}_n = \{v_1, \cdots, v_{K_n}\}$ be the set of views requested by user n, then the satisfaction index of user n is defined as:

$$S_n = \frac{1}{K_n} \sum_{m=1}^{K_n} \gamma_{n,m}, \tag{12}$$

where

$$\gamma_{n,m} = \begin{cases} 1, & \text{if view } m \text{ is selected by the scheduler,} \\ 0, & \text{otherwise.} \end{cases}$$

Fig. 3 compares the view fairness of fair scheduling, symmetric bargaining, and proportional scheduling. For fair scheduling, as its fairness is always equal to 1, thus is not shown in Fig. 3. It is observed that symmetric bargaining has a better performance than proportional scheduling. When Class 2 users share a small percentage (e.g. 10%) of the overall users, symmetric bargaining obviously outperforms proportional scheduling as it considers the scheduling of the unpopular views . Then, the difference of these two strategies reduces with the increase of Class 2 users. When Class 2 users account for 50%, the fairness index of these two strategies are both very close to 1. The reason lies in that, once the share of Class 2 equals to Class 1, each view is likely to equally demanded by the users, thus becoming very similar to fair scheduling.

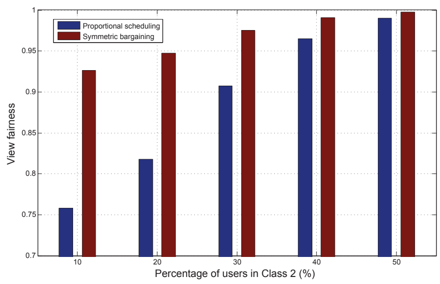

Fig. 3. View fairness vs. percentage of Class 2 users

Fig. 4 shows the satisfactions of the users, where the percentage of Class 1 users is 0.8. It is found that the user satisfaction of fair scheduling goes relatively smooth as it focuses on the fairness and considers each user's requirement. In contrast, proportional scheduling causes large satisfaction disparities among different users. For example, user 20 and 33 who asked for the popular views have a high satisfaction. While the satisfactions of user 13 and 25 are very low, since all their required views are unpopular ones, most of which might be dropped by the scheduler due to insufficient bandwidth.

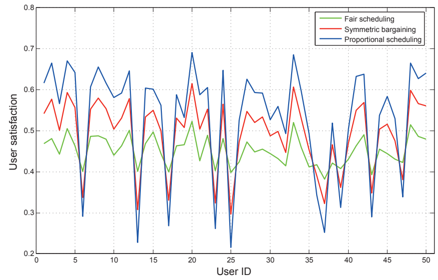

Fig. 4. Performance of user satisfaction

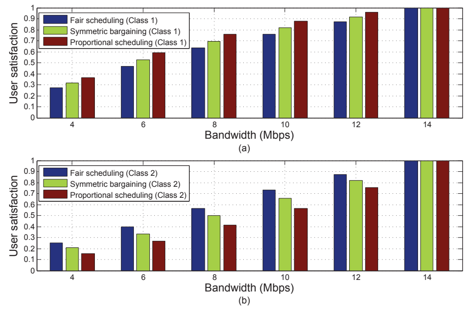

Fig. 5. Average user satisfaction vs. available bandwidth. (a) Users in Class 1 (b) Users in Class 2

Fig. 5 shows the impact of the available outgoing bandwidth on user satisfaction, where the percentage of Class 1 users is 0.8. It is seen that the average user satisfactions of both classes under all three strategies increase with the available outgoing bandwidth, as more views would be forwarded by the scheduler with the increasing bandwidth. In Class 1, proportional scheduling always has the highest user satisfaction, because it chooses the most popular view first so as to satisfy the majority of the users. The proportional scheduling guarantees the forwarding of popular views at the cost of unpopular views, thus resulting in its lowest user satisfaction in Class 2. Compared with proportional scheduling, fair scheduling treats each view the same and obtains completely reverse results. When the available bandwidth reaches 14 Mbps that is enough for accommodating all the views, all users' demands can be fully satisfied whatever strategy is used.

4. CONCLUSION

This paper presented an asymmetric Nash bargaining solution for scheduling the requested view streams, where each view is assigned a bargaining power indicating its scheduling priority. A simple centralized solution was proposed in which the server instead of the view players plays the game and implements the view scheduling. By using different bargaining power settings, a flexible compromise between the utility and the fairness performance can be achieved.

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