QOE CONTINUUM DRIVEN HTTP ADAPTIVE STREAMING OVER MULTI-CLIENT WIRELESS NETWORKS

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ABSTRACT

Different from traditional HTTP adaptive streaming (HAS) in which only one client is considered, HAS over multi-client wireless networks faces new challenges. The Quality of Experience (QoE) of users becomes unstable due to users' competition for shared bandwidth. It is thus important to accurately estimate the perceived experience of users and then adapt the streaming process accordingly. Furthermore, the QoE fairness among multiple clients subscribing to the same services shall also be addressed. In this research, we propose a QoE continuum driven HAS adaptation algorithm to address these challenges. We model the QoE continuum as an integrated consideration of cumulative playback quality and playback smoothness. Based on this model, we jointly optimize the quality adaptation of multiple users by considering both QoE history and channel status. Moreover, we propose to use quantization parameter and segment size to represent the video files in a fine-grained fashion, in order to more effectively capture the bandwidth fluctuation. The results from extensive simulations show that the proposed scheme can provide balanced and satisfactory QoE among multiple clients.

***Index Terms*—** QoE continuum, QoE fairness, HTTP adaptive streaming, multi-client, wireless networks

1. INTRODUCTION

With the development of powerful smart phones and tablets, and the growing demand of watching videos from anywhere and at anytime, video streaming over wireless networks has been rapidly booming in the past few years. It is predicted that video traffic will account for over two-thirds of total mobile traffic by the end of 2017. Lately, HTTP adaptive streaming (HAS) has been widely studied to address the bandwidth inefficiency in traditional streaming systems. The video source is pre-encoded in several quality levels and is split into small segments. The client dynamically requests the video segment with different quality at each switching point based on its network and device status. That way, the user is able to watch the video with the highest possible quality while the bandwidth can also be efficiently utilized.

One key objective of HAS is to improve the Quality of Experience (QoE) of users under highly complicated wireless environment. One major challenge is how to precisely measure users' QoE, which is a subjective perception of the entire viewing experience. Users' QoE at a certain moment is impacted by the playback quality of both currently displayed frame and previously displayed frames, as well as the consistency in playback quality [1]. Conventional modeling of QoE simply based on current viewing experience makes HAS adaptation non-optimal. Therefore, QoE measurement shall consider users' viewing experience in a temporally continuous manner. Furthermore, the QoE fairness among different HAS users who have the same service priority should also be guaranteed. According to [2], the time-varying and shared wireless networks lead to unpredictable QoE for every user. Consequently, users may have very different viewing experience due to their different channel status even though they pay for the same service. Another important issue in current HAS systems is the inaccurate representation of the pre-encoded video files. Currently, different video quality levels are usually indicated by video bit-rate. However, since modern videos are all encoded in a variable-bit-rate (VBR) fashion, the real bit-rate of different video segments is significantly different and cannot be accurately represented by an average bit-rate. To overcome all these adversaries, it is imperative to develop a new quality adaptation scheme that incorporates proper QoE modeling and adaptation measures.

1.1. Existing General HAS

Recently, both 3GPP and MPEG have made tremendous efforts towards the standardization of HAS [3]. However, specific adaptation strategies are not part of the standard and are left to future designs. The overview of standardized HAS QoE metrics and QoE-driven adaptation is presented in [3].

Although several commercial HAS solutions, such as Microsoft Smooth Streaming and Apple Live Streaming, have been deployed, experimental results showed that the user experience is negatively impacted when multiple clients compete for the shared wireless bandwidth [4]. Research com-

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munities have also proposed several HAS rate adaptation algorithms [5–7]. However, these algorithms are targeted at single-user and client-side adaptation. They cannot be directly applied to the multi-client wireless networks since they are unaware of QoE fairness. The proposed framework, instead, shifts the adaptation to the base station that can jointly adapt the video quality and optimize the QoE of multiple clients without modifying the standard HAS framework.

Only few work has been focused on HAS for multi-client wireless networks. In [4], the authors first identified the issues in multi-client wireless networks and proposed a simple traffic shaping mechanism to improve the experience of two competing users. In [8], the authors enhanced the QoE by maximizing the overall mean opinion score (MOS) that is decided by the selected bit-rate and content of the video. Nevertheless, the QoE model is not accurate enough since only the viewing experience at the adaptation moment is considered.

1.2. Existing QoE-driven HAS

QoE has been studied in the design of several HAS systems. QDASH [1] improved the HAS adaptation by incorporating a intermediate level into the switching process. However, no explicit model is provided for QoE measurement, which limits its application to different HAS systems. In [9], an adaptation proxy located at the edge of the wired network was proposed to maximize user average data rate and minimize the rate variation and delay jitter. However, the algorithm is essentially QoS-driven and the standard HAS framework is modified due to the use of split-TCP. Although the work in [10] revealed the importance of temporal factors for QoE by studying the jitter and local content, the necessity of human intervention makes it difficult to be generally deployed.

1.3. Summary and Contributions

In summary, although aforementioned works have made contributions to the HAS development, none of them thoroughly studies the impacts of *QoE continuum* (namely previous playback quality, current playback quality, and playback quality variation) on HAS quality adaptation, and the *QoE fairness* among multiple clients in wireless environment. The major contribution of this research is that we propose a quality adaptation algorithm that can guarantee both QoE and fairness in one shared cell with multiple clients by exploiting the nature of human perception and video source. Specifically, we model the QoE continuum by considering both *cumulative playback quality* and *playback smoothness*. By exploiting the proposed model, the base station can jointly optimize the video quality levels of multiple HAS users under bandwidth-limited cellular networks, in order to fairly maximize all users' QoE. Moreover, we propose to adopt *fine-grained video representations* that characterize the video quality levels by a tuple of file size and quantization parameter (QP), in order to capture video source characteristics and then execute more efficient quality adaptation. More importantly, the proposed algorithm is standard-friendly since the base station only need to modify the clients' requests to accommodate the QoE and fairness driven adaptation.

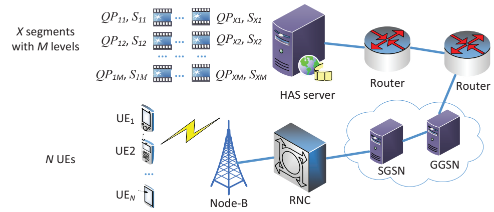


Fig. 1. System Architecture

The rest of this paper is organized as follows. In Section 2, we describe the system models. In Section 3, the proposed quality adaptation algorithm is introduced. We then evaluate the performance of proposed algorithm and present the results in Section 4. Finally we conclude this paper in Section 5.

2. SYSTEM MODEL

2.1. System Architecture

In this research, we consider the system architecture as shown in Fig. 1. The HAS server stores several VBR videos that all have M levels of quality. Each level of video is split into multiple video segments with the same segment length and each segment is characterized by the QP and segment file size, i.e., a tuple (QP, S).

The proposed algorithm is designed for cellular networks, where the base station jointly optimizes the quality adaptation to ensure QoE continuum and fairness. Here we consider 3G High-Speed Downlink Packet Access (HSDPA) network as the underlying cellular network. However, the design principles are generic and the algorithm can be easily extended to other cellular networks such as LTE. We focus on the HAS within one cell, where N users in the cell are managed by Node-B and each user is indexed by $i, i = 1, 2 \cdots N$. We assume that one user can only establish one flow with the HAS server. The proposed algorithm is operated by Node-B and implemented on top of underlying scheduling algorithms. Hence, it is practical to apply it to the modern cellular networks without modifying lower-layer scheduling strategies.

The quality adaptation is proceeded as follows. Initially, the HAS server sends out the media presentation description so that Node-B and clients will have the knowledge of available video representations. At each adaptation period whose length equals to segment length, clients request a specific video segment at a certain quality level based on a simple throughput calculation, which requires very low complexity. Such operation is only used to be compatible with current DASH standards. Hence, no local hardware or operating system optimization is needed. Rather than directly forwarding the requests, however, Node-B in the proposed system will intercept the requests and modify the adaptation decisions based on the proposed algorithm, where both low-layer link status (such as channel quality indicator (CQI)) and high-layer QoE and encoding information (such as current cumulative playback quality) are utilized to guarantee balanced QoE continuum for all users. Such information are embedded in the periodic feedback from clients. Note that this is feasible since 3GPP DASH standard has standardized the quality metrics reporting process for clients. It uses a HTTP POST as the reporting protocol. Thus users are able to enjoy the video with optimized QoE while neither the client nor the HAS server is aware of the adaptation done by Node-B. Therefore, the proposed algorithm can be friendly implemented in current HAS standard framework.

2.2. QoE Continuum Model

We have identified that the QoE of HAS shall be measured in a timely continuous fashion. In this section, we introduce two factors that impacts QoE continuum, i.e., cumulative playback quality (CPQ) and playback smoothness.

2.2.1. Cumulative Playback Quality

It has been discovered by psychological research that human memory demonstrates an exponential decay with respect to time, which is called as forgetting curve effect. Such effect has been suggested by ITU standard [11] to be applied in continuous quality evaluation. Hence, we exploit this effect to model the CPQ. In [12], we have derived Q_k, the CPQ at frame k, as the summation of instantaneous playback quality over all displaying moments until the measure moment, i.e.,

$$Q_k = \gamma Q_{k-1} + (1-\gamma) q_k \tag{1}$$

where Q_{k-1} is the CPQ at the previous frame, q_k is the instantaneous playback quality at frame k, and γ is the characterization constant of the memory strength. Q_k, q_k and γ all belong to (0,1]. That way, we can capture the QoE from previous displaying moments until the current moment.

At a particular displaying moment of HAS systems, the video player can either playback one frame normally or freeze at a certain previous frame. Note that transmission distortion is disregarded in this research since HAS is virtually loss free due to the underlying TCP mechanisms. For the moment with normal playback, the instantaneous playback quality is dictated by the image quality of that frame. Thus we can predict image quality from QP using a linear model and estimate the instantaneous playback quality $q_{k,play}$ as

$$q_{k,play} = aQP_k + b \tag{2}$$

where a and b are content-specific parameters.

When the bit-rate of the streamed video for a user exceeds the user's available bandwidth and the selected video has not been downshifted to a lower quality, playback interruption may occur due to the client's re-buffering. In this case, the video player's screen will stall at the most recent displayed image and consequently the user will undergo certain loss of expected visual information. Thereby, we can reliably model and validate the instantaneous playback quality for an interruption moment $q_{k,stall}$ as the visual information loss L scaled by the instantaneous user expectation E [12], i.e.,

$$q_{k,stall} = L_k E_k. \tag{3}$$

where E_k is signified by the playback quality of the last displayed frame j, i.e., $E_k = q_{j,play}$. Besides, L_k represents the residual norm between expected frame and frame j in pixel domain, which is linearly approximated by $\frac{r_{j,play}}{\eta}$, where $r_{j,play}$ is the bit count of the last displayed frame j and η is the compression ratio. To further describe the logarithmic relation in rate distortion theory, we apply a logarithmic operation and then bound L_k in (0,1] as follows,

$$L_{k|j} = -\frac{\log(\min(r_{j,play}, r_{QP})) + c}{\log(r_{QP}) + c} \tag{4}$$

where r_{QP} is the upper bound of frame size with the specific QP, and $c = \log(\eta)/2$ is a model constant. The value of r_{QP} can be calculated online based on previous streaming information of decoded bits assuming that the size of frames with a fixed QP is governed by a Laplace distribution. This assumption is reasonable given the independent identically distributed property of compressed frames.

2.2.2. Playback Smoothness

Subjective tests have shown that users prefer consistently low-quality video over the video that fluctuates between high quality and low quality [1]. By using the cumulative playback quality model in (1), the playback smoothness can be effectively characterized in this research. Suppose one has been enjoying the video with decent quality for a while (e.g., $Q_{k-1} = 0.9$), the sudden quality degradation of the current frame (e.g., $q_k = 0.6$) could lead to a decreased current CPQ Q_k. Such degradation would be accumulated and eventually cause annoy experience after the playback of an entire segment. The larger difference between the previous CPQ and the instantaneous playback quality, the worse the current CPQ would be. That way, the proposed algorithm places a constraint on the quality adaptation so that abrupt quality change is avoided and QoE continuum is improved. More importantly, due to the smooth quality variation of some users, resources can be saved for the other users who need them.

3. PROPOSED QUALITY ADAPTATION

In this section, we introduce the novel framework to exploit the nature of QoE continuum and fine-grained video representations in order to fairly enhance the perceived experience of users. We formulate the adaptation optimization problem and propose an effective solution to achieve improved QoE continuum and QoE fairness.

3.1. Formulation of the Optimization

The QoE of HAS systems is critically decided by whether or not the data volume of the streamed segment is larger than the currently available bandwidth. It is necessary to incorporate the channel condition into quality adaptation process, especially considering the time-varying nature of wireless channel. In typical HSDPA implementations, wireless resources are divided into Transmission Time Intervals during which one user can receive its data packets. The maximum number of data bits that can be received by user i per second, denoted as $R_{i,max}$, is essentially determined by the CQI of link i. At a given switching point, we employ the mean CQI of link i during the last adaptation period to estimate $R_{i,max}$ during the next period by using the look-up table in 3GPP standard [13]. Note that the mean CQI shall not be calculated based on a time interval that is too brief since it may not reflect the average channel status in the next updating period. Similarly, conservative mean CQI calculation using a long time interval may lead to slow adaptation to channel variation. Thus the resource sharing of user i, denoted by φ_i, is given by

$$\varphi_i = \frac{S_i}{TR_{i,max}} \tag{5}$$

where we approximate the bit-rate of the selected video segment as the ratio between the file size and the segment length. Hence, the available channel resource constraint for the proposed HAS system is $\sum_{i\in\mathcal{N}} \varphi_i \leq 1$, where $\mathcal{N}$ is set of HAS users. Such joint consideration of shared bandwidth will make the quality selection fair and reliable, and thus enhance QoE continuum. This definitely cannot be accomplished by individually blind client-side adaptation.

According to the estimated maximum data rate, Node-B is able to estimate the CPQ at the next switching point $Q_{i,t+T}$ when a video quality level $l_{i,t+T}$ is considered. Node-B first analyzes the adaptation-related information, such as current CPQ $Q_{i,t}$ and buffer status, as feedback received from clients. Then $Q_{i,t+T}$ can be recursively calculated according to (1) by predicting whether the player is playing or stalling at each display moment from t to $t+T$. If user i is not re-buffering at t, $Q_{i,t+T}$ will be estimated from $Q_{i,t}$ by first considering the normal playback of the remaining frames (quality level $l_{i,t}$) in the buffer and then considering the normal playback of the selected level $l_{i,t+T}$ for the rest of the period. If the user is re-buffering, $Q_{i,t+T}$ will be first calculated by assuming that the player is frozen until the buffer size reaches the playback threshold. The interruption time is decided by the estimated $R_{i,max}$. Then $Q_{i,t+T}$ will be further updated by assuming the normal playback of video with level $l_{i,t+T}$. That way, we can accurately estimate the cumulative user experience at next switching point and assign the most satisfactory and fair adaptation decision to users accordingly. Note that interruption may happen in reality during the playback of level $l_{i,t+T}$ due to the channel estimation error.

Based on the above analysis, we now can formulate an optimization to find the optimal level of video segment, which is indicated by a tuple (QP, S), for each user at switching point t. We model the QoE continuum as a joint consideration of the playback quality and playback smoothness, i.e., the CPQ model in (1). The objective of the optimization is to maximize the average QoE continuum of all users at the next switching point $t+T$, subject to the wireless resources constraint. i.e.,

$$\begin{array}{ll} \max_{(\mathbf{QP},\mathbf{S})} & \frac{1}{N}\sum_{i\in\mathcal{N}} Q_{i,t+T} \\ \text{s. t.} & \sum_{i\in\mathcal{N}} \varphi_i \leq 1 \end{array} \tag{6}$$

The wisdom of adaptation behind (6) is that higher quality level is generally given to those users who currently possess a lower QoE continuum value and a better channel condition, while significant quality variation shall also be avoided. For example, when users are currently enjoying the same level of video and the same channel condition, higher quality is assigned to the user with a lower current QoE continuum because such adaptation will attain a maximum increase of the average QoE continuum. In other words, when a user enjoys good experience for a long time, his/her satisfaction will rise less than the one with bad previous experience if the video quality is raised. Consequently, we can enhance not only the QoE but also the fairness of users. Additionally, the penalty on playback variations avoids the sudden big change and keeps the playback smooth. This shall also inherently improve fairness since one's potential resources for big quality upgrading can be conserved for the others who need them.

3.2. Greedy Optimization

The objective of (6) is nonlinear due to the involved logarithmic and minimum operation, as well as the recursive calculation process of $Q_{i,t+T}$. Therefore, finding the optimal solution is complicated and time-consuming. We propose a greedy algorithm, shown in Algorithm 1, to efficiently solve the optimization and approximate the optimal solution. When the algorithm initiates, Node-B collects users' CPQ at t and starts the greedy search at users' current levels l_t. At each subsequent step, if $\sum_{i\in\mathcal{N}} \varphi_i < 1$, a small amount of resources that gain one-level quality improvement are assigned to the user who can accomplish maximum $\Delta_{i,in}$, the increase of average QoE continuum per unit data. If $\sum_{i\in\mathcal{N}} \varphi_i > 1$, the user having the lowest decrease of average QoE continuum per unit data ($\Delta_{i,de}$) will be degraded one level. This process repeats until all the resources are allocated or no further change can be seen in average QoE continuum. The formulated problem is a generalization of bounded knapsack problem, which is NP-hard. The greedy heuristic is adopted to solve the problem in polynomial time with $O(MNlogN)$.

Algorithm 1 Greedy Quality Adaptation Algorithm

```
procedure ADAPT(Q, B, l_t)                          ▷ B:buffer status
    l_{i,opt} ← l_{i,t}, ∀i ∈ N
    if Σ_i φ_i < 1 then                             ▷ quality upgrading
        while Σ_i φ_i < 1 & objective in (6) changed do
            for i ∈ N do
                Update Δ_{i,in}, Δ_max, max_ue
            l_{max_ue,opt} = min(l_{max_ue,opt} + 1, M)
    else                                            ▷ quality degradation
        while Σ_i φ_i ≥ 1 & objective in (6) changed do
            for i ∈ N do
                Update Δ_{i,de}, Δ_min, min_ue
            l_{min_ue,opt} = max(l_{min_ue,opt} − 1, 1)
    return l_opt                                    ▷ i.e., l_{i,t+T}, i ∈ N
```

Table 1. Simulation Parameters

	l_1	l_2	l_3	l_4	l_5
Seg 1 bytes	13644	26952	52778	104951	141714
Seg 2 bytes	13534	27166	53250	108734	148416
Seg 3 bytes	11066	53250	46748	43365	133706
Seg 4 bytes	16027	31211	59114	3028	151288
Seg 5 bytes	25156	50353	98568	3284	253683
q_{play}	0.85	0.88	0.92	0.94	0.95

4. PERFORMANCE EVALUATIONS

In this section, we compare the performance of the proposed algorithm with reference algorithms through simulations. We first implement the algorithm in [4] (referred as *Baseline*) because it is the first HAS adaptation scheme for multi-client wireless networks. We also implement a typical algorithm (referred as *InstRate*) that covers the logic behind many existing works, in which the adaptation maximizes the utility function dictated by selected instantaneous bit-rate, subject to the channel constraint. One example of InstRate-like algorithms is [8], where utility is the MOS mapped from bit-rate.

We focus on the architecture shown in Fig. 1. The HAS server provides the test sequence "Stefan" with 5 levels of video whose QP is 47, 42, 37, 32, and 30 respectively. The segment length T is 2 seconds and the frame rate is 30 fps. The sequence has 300 frames and these 5 segments are repeatedly streamed. The file size of each segment for each level l is shown in Table 1. We use EURANE for ns-2 [14] to implement the underlying HSDPA network. We consider two users subscribing the same services but having different channel status as in [4]. The typical wired and wireless network parameters shown in [14] are used. Regarding the parameters of cumulative playback quality model, we inherit them from [12], wherein the accuracy of the model is validated by both objective and subjective tests. The memory strength γ is set to be 0.71. To show the impacts of a and b, we directly present the instantaneous playback quality q_{play} of different levels in Table 1. Since the initial buffering can be regarded as a special case of playback stalling, the instantaneous playback quality during initial buffering is calculated using (3) with constant $L_{ini} = -0.5$. The initially selected quality level are level 3 for all users. The playback threshold of buffer size is 4 seconds. The simulation runs 200 seconds.

4.1. Playback Smoothness

We employ the number of quality level changes (NoC) and the playback smoothness (PS), a metric inherited from [7], to evaluate the video consistency. PS is defined as the expected length of one playback round without level change, i.e., PS $= \sqrt{\sum_{p=1}^{P}(n_p^2)/P}$. Here the continuous playback of one level is defined as one round and it consists of n_p frames. There are P rounds in total. Level 0 represents the playback stalling.

From Table 2, we can see that the proposed algorithm demonstrates the least NoC and highest PS. Besides, both users enjoy smooth playback. However, for the reference algorithms, video playback of one user is usually unfairly smoother than the other user.

Table 2. Playback Smoothness

Metrics	UE1/UE2		
	Baseline	InstRate	Proposed
NoC	41/43	44/36	30/32
PS	251.82/149.87	171.96/247.23	289.06/273.98

Table 3. Playback Quality

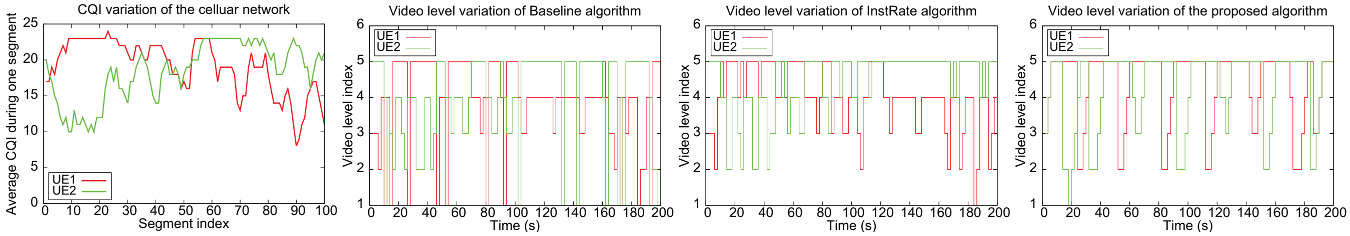
Metrics	UE1/UE2		
	Baseline	InstRate	Proposed
APQ	4.09/3.84	4.03/4.39	4.35/4.26
CPQ	0.94/0.81	0.89/0.93	0.93/0.93
PoI	0/2.23	0/4.30	0/0
NoI	0/1	0/2	0/0

In order to demonstrate the quality adaptation wisdom behind the proposed algorithm, we show the trend of channel variation and quality level variation in Fig. 2. It is clear that the proposed algorithm outperforms the reference algorithms with smoother quality change. Besides, the proposed scheme does not simply capture the channel variation as is the case in InstRate algorithm. Instead, the proposed algorithm is regulated by the smoothness penalty constraint and is less aggressive than reference algorithms, in which the highest possible quality video is always assigned to users.

4.2. Playback Quality

We use CPQ after simulation ends and the average playback quality (APQ) inherited from [7] to evaluate playback quality viewed by users. APQ is defined as the weighted sum of the level index, i.e., APQ $= \sum_{p=1}^{P}(n_p \times l)/\sum_{p=1}^{P} n_p$. We also evaluate the playback quality by exploring the interruption history, i.e., number of interruption (NoI) and percentage of interruption (PoI) that is defined as the interruption time divided by total time.

We show the evaluation results in Table 3. It can be seen that the proposed algorithm generally has better playback quality than the reference algorithms. This is because the proposed algorithm attempts to enhance the QoE continuum of all users by assigning reasonably higher quality video to those users who suffered from the previously bad experience. Thus those users can quickly recover from the bad experience while keeping smooth playback, as shown in Fig. 2d. Nevertheless, the aggressiveness in reference algorithms may result in interruption due to the estimation error of transmission rate. We present the buffer status of UE2 as an example in Fig. 3. The proposed algorithm can quickly respond to the channel variation. For example, at around the 160th second, the channel status of UE2 is suddenly becoming bad (as shown in Fig. 2a). The proposed scheme can appropriately choose the level to match such channel variation since we use a fine-grained representation of the video files. However, the reference algorithms fail to respond to this change and finally



(a) (b) (c) (d)

Fig. 2. (a) Channel CQI versus segment index; (b-d) The video quality level variation versus time.

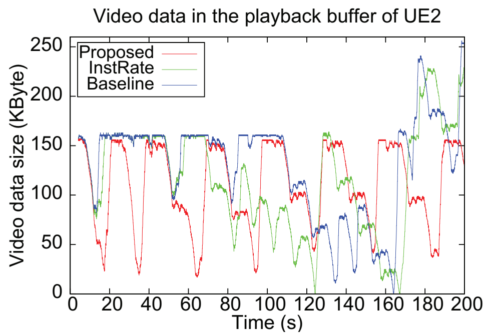


Fig. 3. UE2's buffer size versus time

Table 4. Normalized Difference Between Users

Metrics	UE1 and UE2		
	Baseline	InstRate	Proposed
APQ	6.14%	8.24%	2.04%
PS	40.48%	30.44%	5.22%

undergo stalling at around the 165th second.

4.3. QoE fairness

We have implicitly shown the QoE fairness in the results presented earlier. Now we evaluate the QoE fairness using the normalized difference of a certain metric between the two users, i.e., the difference of two values divided by the larger value. The normalized difference of APQ and PS is shown in Table 4. We observe that the proposed algorithm shows the least QoE difference between two users and thus guarantee the QoE fairness. This is because higher priority is given to users with previously bad experience and that resources can be saved from one user when the variation penalty is adopted.

5. CONCLUSION

In this paper, we propose a QoE continuum driven quality adaptation algorithm to overcome the challenges resulting from imprecise QoE monitoring, unfair QoE, and inaccurate video representation in multi-client wireless HAS. By employing the unaggressive, fair, and fast-responding adaptation logic, the proposed algorithm outperforms existing works and achieves satisfactory QoE and fairness. Future work shall be focused on extending the algorithm to larger-scale systems, wherein downlink scheduling can also be incorporated. Besides, the framework parameters need to be optimized in order to further enhance the overall system performance.

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