Study of User QoE Improvement for Dynamic Adaptive Streaming Over HTTP (MPEG-DASH)

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***Abstract*—Video streaming over HTTP is becoming the de facto dominating paradigm for today's video applications. HTTP as an over-the-top (OTT) protocol has been leveraged for quality video traversal over the Internet. High user-received quality-of-experience (QoE) is driven not only by the new technology, but also by a wide range of user demands. Given the limitation of a traditional TCP/IP network for supporting video transmission, the typical on-off transfer pattern is inevitable. Dynamic adaptive streaming over HTTP (DASH) establishes a simple architecture and enables new video applications to fully utilize the exiting physical network infrastructure. By deploying robust adaptive algorithms at the client side, DASH can provide a smooth streaming experience. We propose a dynamic adaptive algorithm in order to keep a high QoE for the average user's experience. We formulated our QoE optimization in a set of key factors. The results obtained by our empirical network traces show that our approach not only achieves a high average QoE but it also works stably under different network conditions.**

***Index Terms*—QoE, Adaptive Algorithm, DASH, ExoPlayer**

I. Introduction

Today, video streaming over the Internet has been causing major network traffic [1]. Many video providers are facing a great chanllenge in order to keep a high QoE for their subscribers. Many recent studies have elaborated on the traffic crisis and proposed new approaches to mitigate this situation. MPEG-DASH [2], as one of the promissing solutions, has caught significant attentions by both industrial and academic researchers.

DASH uses an adaptive bitrate streaming (ABR) schema. The ecosystem toward DASH utilizes HTTP/TCP as its transporting protocols. This enables a large deployment in current network infrastructure. DASH video segments are stored under various bitrates with different playback lengths. By delivering appropriate bitrate segments, user QoE can be guanranteed. A high user-perceived QoE is a combination of many factors: available bandwidth, available video bitrates, and rebuffers. The key is to keep a balance among those factors.

DASH primarily uses a client pull based paradigm for fetching video segments from the server. Many efforts focus on designing a client side ABR algorithm. In this work, we argue that a DASH user has high expections for a smooth streaming experience, especially in a quite unstable network condition such as using a mobile data plane or an undesirable Wi-Fi environment. Users' concerns include, but are not limited to (1) if there is any buffering period during playback; and (2) the overal bitrate quality, which includes video bitrate switchover magnitude and frequency. Given limited bandwidth resources, the key to achieve such a goal is to understand how a DASH client detects changes in a network channel as well as how to properly respond. Our primary focus is that we collect a set of fine-grained streaming QoE metrics, and conduct real network traces and data collection using our testbed. We take an average QoE approach and propose a dynamic, moving average algorithm.

In this work, we propose a dynamic bitrate adaptive algorithm and try to improve an average QoE. Our work is inspired by the existing adaptive approach with DASH. By designing our video streaming QoE metrics, we can improve QoE in many dimensions under various network conditions. In the rest of this paper, we first give a brief overview of the related work in Section II, then introduce our system model, QoE metrics and problem formulation in Section III. Section IV describes our proposed algorithm. Section V presents our test environment, considered use cases, and empirical evaluation results. We conclude the paper in Section VI.

II. Related Work

Providing a high standard of user streaming QoE towards DASH falls in to two research areas: (1) how to define a set of QoE metrics and (2) how to optimize the client side ABR algorithm.

Users' perspectives of a high quality of experience can vary by each individual. However, in a nutshell it can be quantified by a combination of many metrics. For example, rebuffer is the most undesirable case based on [3]. A high bitrate will provide the user a better streaming quality. However, if the bitrate changes frequently from a higher bitrate to a lower one, a sudden bitrate improvement can not represent a smooth experience. However if the bitrate switches gradually inside one quality catagory, such as between a standard definition range or a high defintion range, it might not cause a noticeable difference for the user. Similar findings are in [4]–[8].

Recent work shows that client side ABR algorithm development takes two different approaches: bandwidth-based and buffer-based. The representatives of the bandwidth-based approach are PANDA [9], Elastic [10], and Festive [11]. The performance of this approach can be affected by its bandwidth estimator's accuracy. Bandwidth estimation and prediction are known to be tough tasks [12], [13]. A buffer-based approach such as the recent BOLA [14] proposal and others in [15],

[16] avoid the inaccuracy of bandwidth estimation and use a system buffer as a main factor for bitrate switching. Most proposed buffer-based algorithms assume that the buffer size is relative large, and thereby makes it unsuitable for short videos. Except that BOLA [14] uses a buffered-based approach to gain a average user experience and provide theoretical proof.

The DASH client also plays an important roles for a smooth playback. Players such as DASHIF [17], Akamai [18], and others in [19]–[21] aim to provide a smooth video rendering feature and a flexible interface for programmers.

Stream QoE optimization has been investigated in a wide range of proposals. HTTP-based adaptive streaming optimization in [22]–[25] has defined a wide range of QoE metrices. Our work in this paper is inspired by the previous proposals and by taking an moving average approach to achieve a high streaming experience using our QoE metrics with a bandwidth-based approach. By running emirpical network traces, we can prove that our proposed dynamic algorithm can provide a high average user-received QoE.

III. Video Streaming QoE Metrics

Our approach toward an average QoE focuses on both the DASH server and client sides. We consider the situation where a client fetches video segments from a DASH server using the HTTP-GET protocol. The communication channel between client and server uses a configurable network environment. The user's QoE is measured by a set of defined variables; see Table I.

TABLE I
QoE Metrics

QoE Metrics Name		Definition
Bitrate Switch Count	ρ, Avg. Change Frequency	$\sum(N_{not}/N)$
	m, Avg. Change Magnitude	$\sum(M_i/N)$, $i = 1,2,3..N$
rebuffer Count	T_{fi}, Count	$T_{fi} \in 0,1,2,...$
	T_R, Duration	$T_R = \sum T_{fi}$, $i \in 0,1,2,...$
Estimated Bitrate	r, Single Bitrate	r_i, $i \in 0,1,2,...$
	γ, Avg. Bitrate	$\sum r_i/N$
Video Quality	Q_{sd}, Avg. SD	$\sum(Q_{si}/N)$
	Q_{hd}, Avg. HD	$\sum(Q_{hi}/N)$
	Q_{total}, Avg. Total	$Q_{sd} + Q_{hd}$
Buffer Status	T_B, Buffered Time	$T_q * t_i$,$t_i \in 1,2,.4..$
	T_q, Buffered Queue	$T_q \in 1,2,3,..$

DASH client. The DASH client is responsible for fetching the proper video bitrate based on current network discrete bandwidth r and captures QoE metrics when streaming a video over the channel. We define N as the total downloaded video segments. The bandwidth moving average γ is refreshed for each download. The playback video segment duration $t_i(s) \in 1,2,4,...T$. Each downloaded segment falls into a bitrate quality catagory that either belongs to Q_{sd} or Q_{hd}, where Q_{sd} represents the average of the standard definition video count and Q_{hd} represents the average of the high definition video count. We define Q_{sd} equals $\sum(Q_{si}/N)$, where Q_{si} is the total standard definition video count at download number i ($\in 0,1,...N$). Q_{total} is the average of the total video segment quality. The bitrate switchover is captured in two levels: average change frequency $\rho = \sum(N_{not}/N)$, where N_{not} is the number of unchanged bitrates, and the average change magnitude $m = \sum(M_i/N)$, where M_i is the average magnitude after each download. Both ρ and m represent the smoothness of the video playback. The client buffer status is represented by T_B, which is the buffered time, and T_q, which is the buffered queue size. The total buffered time equals $\sum(T_q * t_i)$, where t_i represents the video segment length.

The rebuffer is measured by the rebuffer frequency T_{fi} and the rebuffer duration T_R for each T_{fi}, where $i \in \mathbb{Z}^+$. The system buffered time T_B and queue size T_q are important indicators of rebuffer occurance. Given an available bandwidth, the QoE optimization problem can be expressed as follows:

$$Minimize \begin{cases} \text{Bitrate Switchover: } \rho, m \\ \text{rebuffer: } T_f, T_R \end{cases} \quad (1)$$

and

$$Maximize \begin{cases} \text{Buffer: } T_B, T_q \\ \text{Quality: } Q_{total} \end{cases} \quad (2)$$

Network Profile. We design various network profiles based on available bandwidth to simulate different network on-off patterns. The bandwidth r is simulated by the increasing and decreasing percentage P_i where $i \in (1,2,...,N_p)$, and N_p is the bandwidth change frequency. The bandwidth changing magnitude $P_{diff} = (P_i - P_{i-1})$ represents the stable of the given available bandwidth at a specific time T. The combination of N_p and P_{diff} represents a network profile.

IV. Proposed Dynamic Average QoE Algorithm

Our dynamic average QoE adaptive algorithm takes a bandwidth based approach. The estimated bandwidth is captured by the weighted sliding window based bandwidth estimator: Sliding Percentile (SP). A overview of how SP runs is elabrated in Algorithm 1. The performance of SP shows a slow convergence when P_{diff} and N_p are relatively large and frequent. The percentile p for each captured bandwidth r and recycle bin size B can be altered to be suited for an unstable network.

Our proposed algorithm is in Algorithm 2. In order to smooth the estimated bandwidth and allow fast convergence in the case of dramatic network changes when using SP as the bandwidth estimator, we add bandwidth history R_{his} to keep track of bandwidth change. R_{avg} is the moving average of the estimated bandwidth. Immediate bandwidth change $\alpha = R_{his}[-2]/R_{his}[-1]$ is utilized in order to enable and accurately detect network changes and avoid false positive bandwidth estimations. Together $\Delta = R_{avg}[-2]/R_{avg}[-1]$ and α will decide how the bandwidth changes as well as the changing magnitude. To mitigate the SP slow convergence problem, compensators: ω and ϵ are being added to the SP algorithm.

Buffered time based threshold indicators, T_{in} and T_{de}, are also used for returning the final bitrate R_{next} for downloading

Algorithm 1: SlidingPercentile

```
input     : MaxWeight W, percentile p, SampleSet Set,
            SampleSize Set_s, Recycle Bin B, BinSize B_s
output    : A weighted Bandwidth r
parameter : Download ByteSize D_s
// Save data into Set_s and Keep it under W
for i ⊂ D_s do
    if B_s > 0 then
        Set.add(B[-1]) ;
    else
        Set.add(√i) ;
    while Set_s >= W do
        excessWeight ← Set_s − W;
        if excessWeight >= Set[0] then
            Set_s −= Set[0];
            Set_s.remove(0);
            for j ← B_s do
                B.add(Set[0]);
        else
            W −= excessWeight
// Return Weighhted Bandwidth r
for i ← Set do
    if ∑i >= Set_s * p then
        return r_i;
```

where T_{in} and T_{de} represent the threshold for bitrate upgrades and downgrades, respectively. By allowing R_{next} to follow R_{avg} and with constraints of buffer threshold indicators, it can mitigate the rebuffering occurance and improve average QoE.

V. Implementation and Empirical Evaluation

In this section, we conduct our empricial network traces using our dynamic algorithm to evalute the QoE metrics. Google ExoPlayer [26], as the first Android-based mobile DASH player, is being used as our reference player. We compare our algorithm performance with ExoPlayer's reference bitrate adaptive algorithm.

TestBed Setup. We run our network traces in a controlled network environment. Video sources are stored in an Apache Server running Ubuntu 14.04 LTS. A network shaper is also deployed at the server side to simulate different network profiles. Fig. 5 shows the reference network profile recommended by Chrome's [27] web browser. The ExoPlayer will download video segments from the server while the network shaper tries to control the server side bandwidth throughput.

The video source used in our trace is from "Big Buck Bunny" [28] and has 20 video representations, see Table II. The duration of each video segment is 4s. The quality of each downloaded video segment is grouped into standard (Q_{sd}) and high (Q_{hd}) definitions based on the segment bitrate and resolution. In our definition, Q_{sd} includes a segment that has a bitrate less than $0.783mbps$ and the resolution is less than $1280 * 720(720p)$. Q_{hd} includes a segment that has a bitrate greater than and equal to $0.783mbps$ and a resolution that

Algorithm 2: Proposed Dynamic Average QoE Algorithm

```
input  : Estimated Bandwidth r, Buffer Time T_B, BitRate
         Increase Threshold T_in, BitRate Decrease
         Threshold T_de Aviable Bitrate R_mpd, current
         Bitrate R_current, percentile p, Recycle Bin B,
         BinSize B_s, Bandwidth History R_his, Immediate
         Bandwidth Change α = R_his[−2]/R_his[−1],
         Bandwidth Moving Average R_avg,
         BandwidthChangePencentage
         Δ = R_avg[−2]/R_avg[−1], BandwidthState
         R_state, Bandwidth factor ζ, Percentile factor ω,
         Bin factor ε
output : Next Bitrate R_next
System Initialization;
for each r evaltion cycle do
    Recalculate R_avg, R_his, α, Δ;
    // Calculate R_next
    ;
    if Δ > 1 and α > 1 ± ζ then
        R_state is in decreasing mode;
        p = 0.1 ± ω, B_s = 2 ± ε;
        for i ← R_mpd do
            if R_current <= i then
                Return R_next = i ± 1 ∼ 2;
    else if (Δ > 1 and α < 1 ± ζ) or ( Δ < 1 and
    α < 1 ± ζ) then
        R_state is in increasing mode;
        p = 0.5 ± ω, B_s = 5 ± ε;
        Return R_next <= R_avg[−1];
    // Double Check if R_next = i is The proper
       One Based on T_B
    if R_next > R_current then
        if T_B >= T_in then
            Return R_next
        else
            Return R_current
    else if R_next < R_current then
        if T_B >= T_de then
            Return R_next
        else
            Return R_current
    else
        return R_next
```

is greater than and equal to $720p$. We argue that high Q_{hd} represents one important factor of a user's QoE.

Understand QoE Metrics Collection with an Example. QoE metrics collection while playback is presented here by runnning a network trace example. We use a sample video source that is 150s long. Since we desire to test our dynamic algorithm within a relatively unstable network condition, we simulated the bandwidth in a steep on-off pattern. Fig. 3 shows that the available bandwidth starts with 5mbps for 10s, then drops to 2G for 35s, and continues a similar pattern until the playback stops. By keeping a low available bandwidth for a relative longer time, we try to create rebuffer cases.

Fig. 4 (a) shows the system buffer detail. Both the buffered time and queue size show the state of the client. If either the

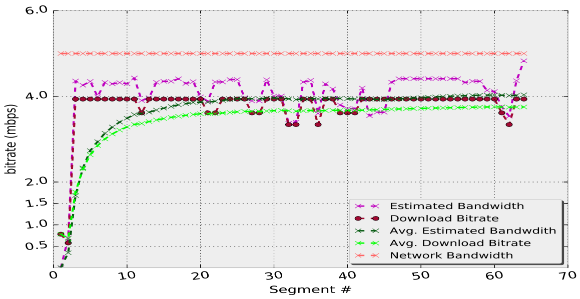

Fig. 1. BenchMark sample run

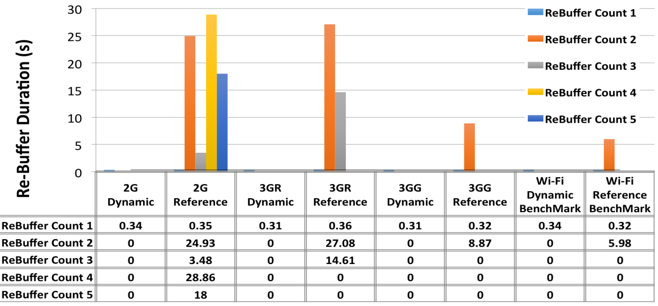

Fig. 2. Rebuffer comparison for various network profiles

buffered time or queue size drops to and near 0, the player stops playing and rebuffering happens. For each downloaded segment, the video quality is stored in a buffered queue in bitrate. Fig. 4 (b) captures the bitrate as Q_{sd} and Q_{hd}. In this run, T_{in} is set to 10s and T_{de} is 25s, which means the next downloadable bitrate will not: (1) increase to a higher bitrate if T_{in} is less than 10s (2) decrease to a lower bitrate if T_{de} is greater than 25s.

TABLE II
TEST VIDEO BITRATE INDEX

Index	Bitrate (mbps)	Resolution	Index	Bitrate (mbps)	Resolution
0.1	0.045	320x240	1.1	0.783	1280x720
0.2	0.089	320x240	1.2	1.0	1280x720
0.3	0.129	320x240	1.3	1.2	1280x720
0.4	0.177	480x360	1.4	1.5	1280x720
0.5	0.218	480x360	1.5	2.1	1920x1080
0.6	0.256	480x360	1.6	2.4	1920x1080
0.7	0.323	480x360	1.7	2.9	1920x1080
0.8	0.378	480x360	1.8	3.3	1920x1080
0.9	0.509	854x480	1.9	3.6	1920x1080
1.0	0.578	854x480	2.0	3.9	1920x1080

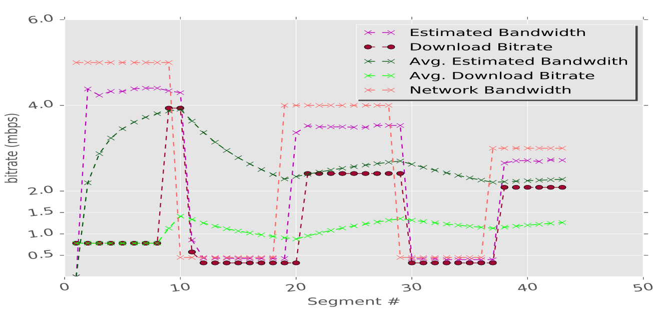

Fig. 3. A sample run of network traces using our dynamic algorithm

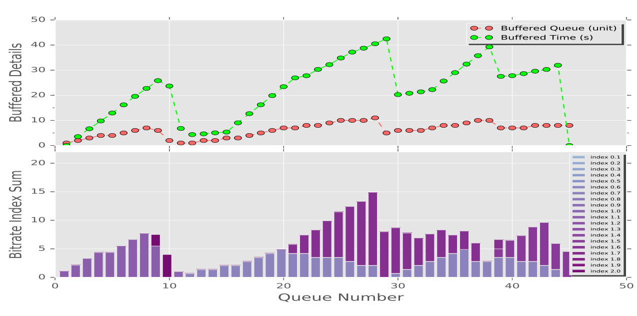

Fig. 4. System buffered details: (a) Buffered time and queue size (b) Buffered bitrate quality and queue number

Empiricial Result. We compared our dynamic algorithm with ExoPlayer's reference adaptive algorithm. We implemented our proposed algorithm in ExoPlayer. Our approach for achieving a high average QoE is described in Section III. A benchmark scenario (Fig.1) is created for the purpose of giving a best case scenario for a playback. In the benchmark use case, the network shaper simualtes a constant 5mbps bandwidth using the same video source in Table II. The achieved QoE is expected to be higher compared with our simulated network profiles.

After a 150s playback, a rebuffer metric comparison is shown in Fig. 2. With our dynamic algorithm, no rebuffering occurs in any network condition except in the initial buffering stage ($\sim 0.35s$) that happens on each case. The worst case happened in a 2G network profile using ExoPlayer's reference adaptive algorithm. Rebuffer T_f occured 5 times and the total duration was 76s, represented by $T_R = \sum T_{fi}$, where $i \in \{1, 2, 3, 4, 5\}$. In the same network profile, our dynamic algorithm only had an intital buffer. When we improved the network condtion from 2G to 3G, the reference algorithm reduced the T_f and T_R, accordingly. However, rebuffering still occured for each case. Even under the benchmark test, the reference algorithm still remained in two rebuffer cases. That happened because even though the network condition was stable, the reference player greedily downloaded the highest bitrate with no concern for TCP protocol's on-off nature (see in Fig. 1). Our dynamic algorithm kept a moving average approach and gradually increased or decreased to the next downloadable bitrate and remained a smooth playback.

The bitrate changing metric is shown in Fig.6. The reference algorithm always has a higher bitrate switchover frequence ρ and change magnitude m compared with our dynamic one in the same network profile. For example, in a 2G network profile, dynamic $\rho = 0.2 <$ reference $\rho = 0.28$ and dynamic $m = 0.28 <$ reference $m = 0.64$.

The average downloaded high definition video quality Q_{hd} also keeps a higher number compared with the referenced algorithm. The video quality increases more slowly when the network profile changes from 2G to 3GR because the bandwidth changes (in a relative small range) from 0.45mbps to 0.75mbps. Video quality quickly improves when the network profile changes to 3GG since bandwidth increases to 1.5mbps.

Network Profile	Delay (ms)	Download (mbps)	Upload (kbps)
2G	150	0.45	0.15
3G Regular (3GR)	100	0.75	0.25
3G Good (3GG)	40	1.5	0.75
Wi-Fi BenchMark (BM)	2	5	5

Fig. 5. Network Profile for Testing Environment [27]

	Avg. Bitrate				Video Quality			
	Dynamic		Reference		Dynamic		Reference	
	ρ	m	ρ	m	Q_{sd}	Q_{hd}	Q_{sd}	Q_{hd}
2G	0.2	0.28	0.28	0.64	3.12	1.7	3.02	0.56
3GR	0.19	0.26	0.37	0.62	3.13	1.74	1.16	1.11
3GG	0.13	0.15	0.28	0.44	0	5.14	0	2.05
Wi-Fi BM	0.04	0.04	0	0.08	0	5.35	0	2.87

Fig. 6. Comparsion in Video Bitrate Switchover Frequence, Magnitude and Video Quality between propose dynamic and ExoPlayer Reference Algorithm

But in any case, our dynamic algorithm keeps a higher video quality in terms of the average number of high definition video segments (Q_{hd}), lower average bitrate switchover rate (ρ) and change magnitude (m).

VI. Conclusion and Future Work

Our main contributions are summarized by (1). We propose a generic dynamic bitrate adaptive algorithm that can be utilized in both bandwdith and buffer based approachs (2). Investigate the average QoE approach for improving DASH performance under various network profiles. In the future, we will test our algorithm with various network topologies using mulitple clients and video sources.

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