AUTOMATED QOE EVALUATION OF DYNAMIC ADAPTIVE STREAMING OVER HTTP

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ABSTRACT

Dynamic Adaptive Streaming over HTTP (DASH) is referred to as a multimedia streaming standard to deliver high quality multimedia content over the Internet using conventional HTTP Web servers. As a fundamental feature, it enables automatic switching of quality levels according to network conditions, user requirements, and expectations. Currently, the proposed adaptation schemes for HTTP streaming mostly rely on throughput measurements and/or buffer-related metrics, such as buffer exhaustion and levels. In this paper, we propose to enhance the DASH adaptation logic by feeding it with additional information from our evaluation of the users' perception approximating the user-perceived quality of video playback. The proposed model aims at conveniently combining TCP-, buffer-, and media content-related metrics as well as user requirements and expectations to be used as an input for the DASH adaptation logic. Experiments have demonstrated that the chosen model enhances the capability of the adaptation logic to select the optimal video quality level. Finally, we integrated all our findings into a real DASH system with QoE monitoring capabilities.

***Index Terms*—** DASH, Quality of Experience, monitoring, content adaptation.

1. INTRODUCTION

Dynamic Adaptive Streaming over HTTP (DASH) [1] is an approach which enables the streaming of high quality multimedia content over the Internet using conventional HTTP Web servers. In order to support interoperability among existing and future HTTP-enabled devices, DASH has been standardized by ISO/IEC MPEG [2]. As a fundamental feature, it proposes an automatic switching of quality levels according to network conditions, user requirements, and expectations. Currently, the proposed adaptation schemes for HTTP streaming mostly rely on throughput measurements and/or buffer-related metrics such as buffer exhaustion and levels. In this paper, we propose to enhance the DASH adaptation logic by feeding it with a perceptual user evaluation, based on a Quality of Experience (QoE) monitoring model, approximating the user-perceived quality of video playback. The proposed model aims at conveniently combining TCP-, buffer-, and media content-related metrics as well as user requirements and expectations to obtain an objective evaluation of the quality experienced by the end user. Traditional QoE approaches, such as the ones described in [3] and [4], are mostly conceived for RTP/UDP transmission of multimedia content over IP networks which are based on common intrinsic metrics such as packet loss ratio, packet error ratio, packet delay variation and packet transfer delay. In our work, we focused at first on HTTP/TCP-related metrics, such as re-buffering events rate and duration, in order to evaluate how they impact the user experience. Then, in order to extend the precision of the QoE model, we combined them with media-related metrics, such as video quantizer, bitrate, and framerate. Finally, we evaluated how the DASH adaptation logic impacts the QoE, for example taking into account the rate of transitions between different quality levels. Through our experiments we have demonstrated the potential of our model to enhance the capability of the adaptation logic to select the optimal video quality level. Finally, we integrated all our findings into a real DASH system with QoE monitoring capabilities.

The reminder of the paper is organized as follows. Section 2 described background and related work. Our QoE model for DASH is provided in Section 3 and experimental results are described in Section 4. The results are further discussed in Section 5 while Section 6 concludes the paper.

2. BACKGROUND AND RELATED WORK

Part 1 of the DASH standard (ISO/IEC 23009-1) specifies how to structure a Multimedia Presentation Description (MPD) and its representation in terms of segments. DASH aims at enabling content adaptation in existing HTTP client-server systems, while maintaining the benefits of traditional HTTP streaming, i.e., reuse of existing Internet infrastructure comprising caches, CDNs, and traversal of NATs and firewalls. It is worth highlighting that the standard is intended to support a multimedia streaming process that is deliberately controlled by the client. This enables existing HTTP servers to support DASH without any extensions or modifications whatsoever. This is the reason why a compliant DASH system requires that a client is able to parse the syntax of a DASH MPD and to behave accordingly. Another fundamental element of the DASH standard is the concept of segment. A segment is a unit of data associated with an HTTP URL that can be optionally associated with a byte range which may be requested individually by DASH clients. A DASH streaming service is therefore built around the concept of the MPD, which is a formalized description of how a given multimedia content is available, i.e., it mainly describes the available qualities, the fragmentation of these qualities, and the temporal dependencies between individual segments. A DASH streaming session will then start with a client retrieving and parsing the MPD and the following content acquisition according to the information found therein. During the decoding process and according to the information retrieved in the MPD, the client will be able to switch among available qualities of the same content that best suit the users' requirements and the (possibly changing) context. The most obvious example is a change in the available bandwidth that may require a lower bitrate encoding in order to avoid service interruption (frozen images in a video presentation).

Among the existing HTTP streaming technologies the most popular include Apple HTTP Live Streaming (HLS), Microsoft Smooth Streaming and Adobe HTTP Dynamic Streaming (HDS). All these technologies share the same approach of fragmenting the content in chunks to be independently downloaded, rearranged, and decoded at the client side. This enables the distribution of the same content among several sources in order to support scalability, error resilience, bandwidth throttling, and overload management. A second fundamental aspect of these technologies is the support of content encoding at different qualities (and bitrates) which enables dynamic adaptation of the presentation according to various parameters. With respect to these approaches, DASH is the first attempt to standardize the concept of media segmentation for dynamic HTTP streaming so as to support wider interoperability among different vendors' applications and devices.

The term Quality of Experience has been extensively discussed in research literature and may refer to the user satisfaction during service consumption, i.e., the subjective quality perceived by the user when consuming audio-visual content (Perceived QoS or PQoS) [3]. In [5] the QoE is additionally affected by environmental, psychological, and sociological factors such as user expectations and experience. Recently, [6] proposes to define QoE as “the degree of delight or annoyance of the user of an application or service”.

Two basic approaches exist for assessing the QoE:

- **Subjective assessment** as formalized by the ITU-R Rec. BT.500-13 [7] which suggests experimental conditions such as viewing distance and conditions (room lighting, display features, etc.), selection of subjects and test material, assessment and data analysis methods. The tests are performed by employing a panel with evaluators, assessing the quality of a series of short video sequences according to their own personal opinion. The output is the quality of the sequences as seen by an average observer and is usually expressed as a Mean Opinion Score (MOS typically ranging from 1 – bad – to 5 – excellent);
- **Objective assessment** is being widely adopted in the industry since the preparation and execution of subjective tests is costly and time consuming. The objective evaluation methods involve the use of algorithms and formulas, measuring the quality in an automatic, quantitative, and repeatable way, based on either signal processing algorithms or network-level quantitative measurements.

Most of existing solutions for real-time services are conceived for traditional VoIP and video streaming applications, which are built on UDP as a transport level protocol, and rely on RTP/RTCP for the transfer of real-time data, both favouring timeliness over reliability. However, due to the recent success of HTTP as a protocol for providing multimedia transmission, the content providers are being increasingly interested in evaluating the quality of TCP/HTTP-based services. For such services, the traditional QoS/QoE models are not suitable anymore, due to the different transmission model. For example, QoS parameters such as packet loss rate and packet delay do not apply to TCP-based services. On the contrary, parameters such as buffer underflow/overflow, filling rate, initial delay, etc. have to be taken into account. Moreover, most of the traditional models, such as the one described in [4], do not address the problem of measuring QoE in the case of adaptive bitrate video, i.e., switching among different media representations has in fact an impact on the QoE [8]. Hence, new challenges face the QoE monitoring in order to address the TCP/HTTP-based services.

This paper aims at defining and validating a new QoE model particularly suited for HTTP streaming, based on the collection and combination of TCP and media QoS parameters in order to automatically compute the subjective quality.

3. QOE MODEL FOR DASH

For DASH-based services, one of the most interesting applications is the implementation of intelligent clients that can dynamically change the content representation according to the ongoing user experience. Such intelligent systems are of great interest for both academia and the industry; specifically, how a dynamic content adaptation according to metrics related to the user experience can actually improve the content delivery effectiveness. This section aims at identifying a meaningful set of factors that have an impact on the QoE and - based on these parameters - a QoE model for DASH-based services is established.

The new metrics have been categorized as follows:

- **Buffer overflow/underflow:** thresholds in the buffer filling level have to be defined to avoid image freezes or

Table 1: Video parameters affecting the QoE.

Parameter	Description	Symbol
Video Bitrate	Indicates the video bit rate Scale: actual bits per second (bps) Range: 0 to infinity	BR
Video Frame rate	Indicates the video frame rate Scale: actual frames per second (fps) Range: 0 to 60 fps	FR
Video Quantization Parameter	Video quantization parameter Scale: average value of AVC QP Range: 0 to 51	QP

packet losses. TCP is supposed to provide a reliable packet delivery to the application layer.

- **Frequency and amplitude of quality switches:** this metric is composed by the frequency of change of content representation according to a predefined logic and the related amplitude. In case this logic depends on a few parameters such as the available bandwidth, the switch rate and amplitude can impact the QoE [9].
- **Objective content quality level (media parameters):** these are some parameters related to the actual media encoding algorithms and mechanisms that can provide information on the actual content presented to the user [10]. They are briefly summarized in Table 1.

Together with these objective parameters, the following factors with impact on the QoE have been taken into account:

- Re-buffering event frequency (RER)
- Re-buffering event average duration (RED)
- Representation quality switching rate (RQSR)

The main goal of the paper is to find an automated mechanism to extract an Estimated Mean Opinion Score (eMOS) from the above mentioned Quality of Service (QoS) parameters. The algorithm embodying this automated calculation follows a *psychometric model* because it aims at mimicking and quantifying the psychological reactions of human beings confronted to a given multimedia presentation. The model is based on a non-linear function as shown in Equation (1):

$$\boldsymbol{eMOS} = \sum_{i=0}^{N-1} a_i * x_i^{k_i} \qquad (1)$$

Where

- $\{x_0 \dots x_{N-1}\}$ are the measured values of the selected metrics as described above,
- $\{a_0 \dots a_{N-1}\}$ and $\{k_0 \dots k_{N-1}\}$ are coefficients used to fine-tune the final eMOS calculation in order to closely follow the results of subjective testing.

For each x_i the actual meaning and value range of a_i and k_i will change according to the specific nature of the metrics. The weighting factors and exponents can be adapted, via off-line configuration, to the service and the terminal targeted by the application. For example, re-buffering-related factors can be modified according to the decoder buffer model.

The authors privileged the exponential relationship among parameters because previous works [14] showed that such models outperform logarithmic ones when trying to link QoS parameters with QoE measurements. Additionally, the validity of such a model has been proven through subjective tests performed to evaluate the correspondence between the eMOS values and the user perception, according to standard subjective validation procedures.

4. EXPERIMENT SETUP AND PSYCHOMETRIC MODEL TUNING

4.1. Experimental Setup

The experiments described in this section have been performed using an adapted version of a MPEG-compliant video player with QoS/QoE monitoring capabilities, also called *QoE Monitoring Tool*, including an MPEG-4 AVC/SVC decoder, developed by the company *bSoft* (http://www.bsoft.net/). Such software solution is composed by a set of C/C++ libraries supporting:

- elementary media streams processing (Video: H.264/MPEG-4 AVC) and SVC, MPEG-4 part 2 Simple Profile, H.263; Audio: AAC, AMR, G.723, G.729);
- file format reading (MP4, 3GPP, AVI);
- transport and session protocols (RTSP and RTP/RTCP).

The above module has been integrated with *libdash* [11][12], a C++ open source implementation of a DASH client developed by the company *bitmovin* (http://www.bitmovin.net/). The tests run to produce the results listed below took place on Windows and Linux according to the availability of respective tools such as network bandwidth throttle (Linux) or the GUI for the parameters tuner (Windows).

The psychometric model has been developed at the system level of the MPEG player in order to have direct access to the metrics collected by a series of software monitoring probes, placed at the media (audio, video codecs), transport (HTTP, buffering), and DASH (MPD) levels. The software ran on a Wintel laptop equipped with WiFi and 3G wireless connectivity which enabled the emulation of a user roaming across several networks and bandwidth conditions.

The test procedure has been defined by determining a set of quality affecting factors/parameters, which may have an impact on the perceived quality such as quantization parameter, framerate, re-buffering events, adaptation switching rate, together with the related set of values. A set

Table 2: Media parameters for test sequences.

ID	QP	Bitrate	Frame Rate	Resolution
1	12	*variable*	30	720p
2	20	*variable*	30	720p
3	28	*variable*	30	720p
4	36	*variable*	30	720p
5	48	*variable*	30	720p
6	*variable*	500kbps	30	720p
7	*variable*	1Mbps	30	720p
8	*variable*	2Mbps	30	720p
9	*variable*	4Mbps	30	720p
10	*variable*	8Mbps	30	720p
11	32	*variable*	7	720p
12	32	*variable*	10	720p
13	32	*variable*	15	720p
14	32	*variable*	30	720p

Table 3: Representation quality metrics.

ID	Re-buffering Frequency	Re-buffering Duration
15	0.1/minute	3 sec.
16	0.2/minute	3 sec.
17	1/minute	1 sec.
18	1/minute	3 sec.
19	1/minute	5 sec.

of parameters is referred to as a configuration and several configurations are defined. Once the configurations have been defined, a set of 'impaired samples' has been built using a configurable MPEG-4 AVC encoder, as described in the next Section. This means that samples resulting from the transmission of the original media over the network under the different chosen configurations are taken.

4.2. Test Sequences

The sequences "Big Buck Bunny" and "Ducks takeoff" provided by *Xiph.org* (http://media.xiph.org/video/derf) were used as reference content for the objective and the subjective tests. The MPEG-4 AVC encoder, including DASH encoding (MPD generation) capabilities, developed by the company *bSoft*, has been used. Concerning the media encoding parameters used to generate the impaired samples, the sequences were encoded in AVC byte stream format with the settings listed in Table 2.

In order to test the impact on the QoE of events related to the media representation (re-buffering frequency and average duration, representation quality switch rate) the combinations of impairments listed in Table 4 have been taken into account.

As opposed to the media coding parameters mentioned above, where the impact on the QoE can be considered continuous and evaluated in quasi real-time with frequencies measurable in seconds, the impact of re-buffering and quality switches has been evaluated on larger intervals of time. Re-buffering events have been measured on intervals of 10 minutes and the related impact added as contribution to the psychometric model calculation. The eMOS

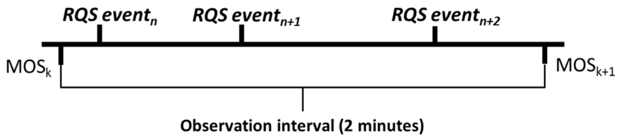

Figure 1: Calculation of rate quality switch (RQS) events on the eMOS.

Table 4: Representation quality switch rate dataset.

ID	QP0	QP1	Representation Quality Switch Rate
20	12	16	0.5/sec (2 secs)
21	12	32	0.5/sec (2 secs)
22	12	48	0.5/sec (2 secs)
23	12	16	0.25/sec (4 secs)
24	12	32	0.25/sec (4 secs)
25	12	48	0.25/sec (4 secs)
26	12	16	0.125/sec (8 secs)
27	12	32	0.125/sec (8 secs)
28	12	48	0.125/sec (8 secs)
29	12	16	0.0625/sec (16 secs)
30	12	32	0.0625/sec (16 secs)
31	12	48	0.0625/sec (16 secs)
32	16	32	0.5/sec (2 secs)
33	16	48	0.5/sec (2 secs)
34	16	32	0.25/sec (4 secs)
35	16	48	0.25/sec (4 secs)
36	16	32	0.125/sec (8secs)
37	16	48	0.125/sec (8secs)
38	16	32	0.0625/sec (16 secs)
39	16	48	0.0625/sec (16 secs)
40	32	48	0.5/sec (2 secs)
41	32	48	0.25/sec (4secs)
42	32	48	0.125/sec (8secs)
43	32	48	0.0625/sec (16 secs)

fluctuations due to these events are therefore much slower than those related to the media parameters.

The representation quality switch rate (RQSR) impact deserves a dedicated discussion due to its specificity to the DASH media streaming model where the switching among various representations of the same content is a crucial feature and also since its contribution to the overall QoE is more articulated than the other events and parameters. In fact the impact on the QoE depends on both the actual content quality displayed to the user and to the entity of the quality switch (a wider difference will be more noticeable for the user). The contribution of the RQSR on the eMOS calculation has been calculated with the following iterative process, also depicted in Figure 1:

1. An observation period is defined (2 minutes in the experiments);
2. The quality switches occurrences are recorded together with their width in terms of eMOS variation;
3. At the end of the observation period the contribution of each switch event is added to the new RQSR component of the Psychometric Model.

The emulation of the representation quality switches have been performed by setting the encoder in variable bitrate mode (i.e., constant quality) and varying the quantization parameter (QP) among the different representations ranging from 12 to 48, by successive steps of various durations, forth and back, as shown in Table 4.

4.3. Subjective Evaluation

A pool of 10 participants (four female and six male aged between 22 and 53) has been confronted with the test sequences in compliance with the ITU Rec. BT.500-13 [7]. This is slightly less than the size of 15 individuals that is recommended by ITU-T Rec. P.910 [13], but this has been deemed adequate in the context of this work where the goal is the validation of the idea of an automated MOS calculation rather than a precise implementation of a final solution. We selected the Double Stimulus Impairment Scale (DSIS) method and the participants had both technical and non-technical background and a medium-high education level.

According to the DSIS method, reference content has to be submitted to the audience together to the one encoded by the system under evaluation. The assessor has been presented with the reference content and then with the impaired one, later during the evaluation session (which lasted 25 minutes) impaired and reference content has been randomly presented to assessors who were required to rate the presented content at regular intervals (1, 5, 10, 15, 20, 25 minutes). At the end of each session the mean score for each test sequence and impairment combination is calculated among all the subjects.

4.4. Objective Evaluation

The objective evaluation consisted in submitting the *psychometric model* to a self-learning process of adjustment of the coefficients and exponents in order to progressively reduce the gap with the scores provided by the subjective tests.

The next step will be the final model validation, which can be performed using regression statistical modeling tools, such as LSE and MSE, like the one described in [14]. For the scope of this paper the authors decided to focus on the GUI solution and leave the statistical validation for future work, in order to better appreciate the contribution and the dynamic of each single component of the model and better drive the development phase. By means of sliders the authors were able to evaluate in real-time the impact of each coefficient or exponent change on the overall eMOS. The coefficients tuning consisted in iterating over the widest possible range of values combinations so as to closely mimic the results obtained from the subjective tests described in the next section.

The authors went through the test sequences and configurations listed in Table 2, Table 3 and Table 4 and adjusted each component of the psychometric model so as to achieve meaningful and realistic values for the calculated eMOS. This first iteration aimed at obtaining a first coefficient set for the psychometric model that generated eMOS fluctuations among the desired values (1 to 5) with reasonable values or the displayed content quality. The sliders are used to fine-tune (up to the 5th decimal digit) the values of coefficients and exponents in the psychometric model formula.

Once meaningful results for the eMOS calculation have been obtained for the first test sequence (i.e., Big Buck Bunny), the defined coefficient values have been validated against the subjective evaluations of the second test sequence (i.e., Ducks take off). The panel of 10 subjects provided their subjective MOS evaluation for the selected test sequences and the coefficients of the psychometric model previously defined were further tuned so as to minimize the differences between the average subjective MOS and the average eMOS. The results of these iterations are shown and discussed in the next section.

5. RESULTS AND DISCUSSION

In this section a comparison is performed between the set of MOS produced by the subjective tests and the eMOS calculated with the psychometric model.

Figure 2 shows the comparison between values of eMOS calculated with the psychometric model and the average values from the panel of subjects (subjective MOS). In an ideal case the values should be on the diagonal line.

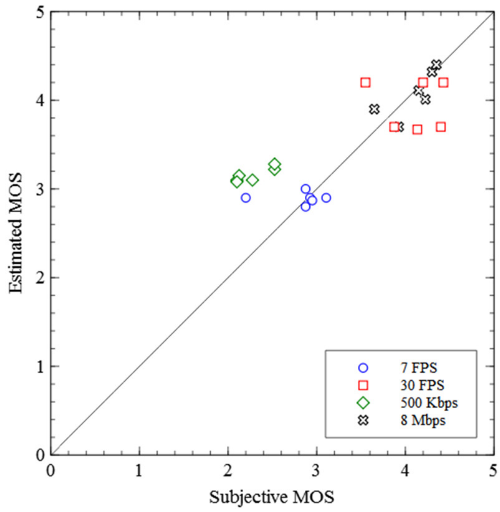

Figure 2: Subjective and automated MOS comparison for sequences at 7 and 30 fps and for 500 kbps and 8 Mbps.

The largest divergence between the estimated and the subjective MOS is for the sequence running at 500 kbps where the eMOS is providing lower scores than the subjective MOS. This is probably due to the fact that subjects are used to low quality images for Web-based video streaming as long as the video presentation runs smoothly (no freezes). For the other three sequences the eMOS never diverges for more than 0.4 points and in some cases they coincide with the average subjective MOS (points on the diagonal line).

These results confirm that the automated calculation of the MOS for a multimedia presentation can effectively rely on the contribution of two classes of metrics. That is, metrics related to the actual media encoding and metrics related to the overall content consumption experience and the events that can impact the end user. These two classes of metrics present fundamental differences both in terms of measurement and calculation of the impact on the QoE. In fact, while media related parameters affect the presentation at intervals that can be measured in seconds, events such as re-buffering or quality switches will impact the QoE over wider intervals. In particular, the representation quality switch rate, which is the most DASH-specific metric in our model, required a "recursive" approach where the eMOS is calculated based on previous eMOS variations in order to take into account the entity of the quality switch in addition to the rate. A previous eMOS calculation, made at a finer time granularity (5 seconds in the experiments) and, hence, mostly influenced by media parameters, becomes then a contribution to a new eMOS calculation, made at a larger time granularity (10 minutes in the experiments). The resulting eMOS might be used to enhance the effectiveness of content adaptation policies on a larger time scale, e.g., by dynamically modifying the adaptation reactivity, according to both content and network characteristics and user mobility (which might lead to sudden and significant quality variations). The definition of possible adaptation policies adopting our QoE model is out of the scope of this paper, but it is a promising perspective for future investigations.

6. CONCLUSIONS

This paper showed that an automated calculation of the MOS (Estimated MOS - eMOS) for digital multimedia content is possible for DASH-based services. The results presented here demonstrated that existing QoS/QoE evaluation systems mostly relying on packet loss (which is absent in case of HTTP streaming), jitter and bitrate can be enhanced by taking into account additional parameters and appropriately weighing them. In particular, DASH specific metrics such as the impact of the representation quality switch rate has been taken into account and quantified together with the contribution of actual media encoding parameters. The results show that this model appropriately mimic the evaluation of human subjects with divergence that amount to less than 0.5 points in the worst case. Further tuning of the psychometric model will be possible by, for example, applying self-learning algorithms to the tuning of the coefficients and exponents that build the model. The most interesting applications for such an automated QoE monitoring system are in the realm of adaptive multimedia streaming in heterogeneous networks supporting mobile terminals.

7. ACKNOWLEDGMENTS

This work was supported in part by the EC in the context of the ALICANTE (FP7-ICT-248652), and QUALINET (COST IC 1003) projects.

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