Optimal Rendition Resolution Selection Algorithm for Web Streaming Players

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ABSTRACT

In web streaming, the size of video rendered on screen may be influenced by a number of factors, such as the layout of a web page embedding the video, the position and size of the web browser window, and the resolution of the screen. During the playback, the adaptive streaming players, usually select one of the available encoded streams (renditions) to pull and render on the screen. Such selection is typically done based on the available network bandwidth, and also based on the size of the player window. Typically, the logic of matching video stream to be played to the size of the window is very simplistic, considering only pixel dimensions of the video. However, with vastly different video playback devices, their pixel densities and other parameters influencing the Quality of Experience (QoE), the reliance of pixel matching is bound to be suboptimal. A better approach must use a proper QoE model, considering parameters of viewing setup on each device, and then predicting which encoded resolution, given player window and other constraints would achieve best quality. In this paper, we adopt such a model and develop an optimal rendition selection algorithm based on it. We report results by considering several different categories of receiving devices (HDTV, PCs, tablets and mobile) and show that optimal selections in all those cases will be considerably different.

Keywords: ABR Streaming, Encoding Ladders, QoE, Adaptation Logic, Web Streaming, Players, Renditions

1. INTRODUCTION

Adaptive streaming, where the playback is adapted based on the changing network conditions is one of the fundamental technology that has helped in improving the end-user experience. One of the most widely used formats currently by major Over The Top (OTT) services is HTTP Adaptive Streaming (HAS), in which a media segment is encoded and segmented into various renditions (resolution-bitrate pairs). HTTP Live Streaming (HLS)[1] and Dynamic Adaptive Streaming over HTTP (DASH)[2] are two of the most commonly used HAS technology formats with the latter being standardized in 2012. One of the commonly preferred methods to create multiple representations of the video content is to encode the video into multiple resolution-bitrate pairs. Usually, the client (player), depending on that available network throughput and/or buffer status selects the appropriate rendition for playback.[3]

However, in today's world of web streaming, where the video is streamed to web browsers, the video playback is often affected by the embedded video player size.[4] Many factors, such as user preferences and device type often influence the position and size of the web page and hence, the video player size. The player size significantly affects the choices of the streams that are requested and played by the end-user device. This is illustrated in Figure 1 which shows the simplified model of rendition selection logic based on network (left), player size (center) and combination of both (right) developed in Ref. 5. Fig. 1a shows the trend of selection of rendition bitrate, R_i based on the estimated available network bandwidth B. Fig. 1b shows the rendition selection based on player window resolution. In this particular case, the nearest available encoded resolution is chosen. Finally, Fig. 1c illustrates the selection logic when the player's adaptation logic considers both network bandwidth and player size. For model equations and further details on these models, please refer to Ref. 5.

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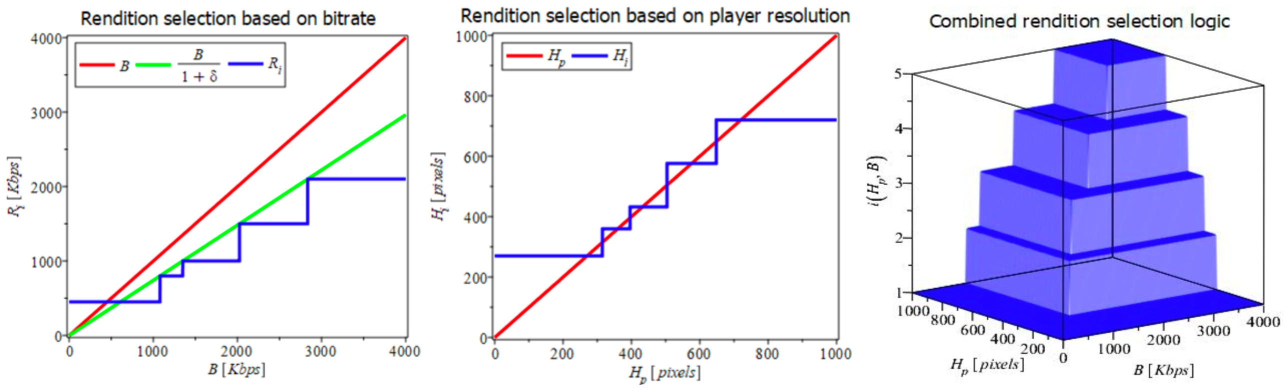


(a) (b) (c)

Figure 1: Streaming client model proposed in related work in Ref. 5. (a) Rendition selection based on the available network bandwidth B. (b) Rendition selection based on player window size H_p. (c) The combined rendition selection logic.

The model, presented in Figure 1, was developed by study of several existing practical streaming players, operating on different devices. Importantly, it has shown that while modern generation streaming players do adapt selection of streams to player resolution, such adaptations do not seem to incorporate other factors, such as pixel density, display size, viewing distance, and others - which are fundamental from Quality of Experience (QoE) perspective. This makes such selection algorithm suboptimal. A better approach must use a proper QoE model, considering parameters of viewing setup on each device, and then predicting which encoded resolution, given player window and other constraints would achieve best quality.

Towards this end, we present in this paper a simple algorithm to be implemented in the player adaptation logic, which takes into account the player size and display parameters and will select the optimal rendition resulting in the best perceived picture quality. For quality prediction, we use the Westerink and Roufs (WR) model[6] which predicts the perceived quality directly based on video resolution.[7–9] The rest of the paper is organized as follows. In Section 2 we discuss some of the related works followed by a discussion of the required definitions, symbols and terminologies in Section 3. In Section 4 we introduce and validate the Westerink and Roufs (WR) model using subjective ratings (mean opinions scores) from six recent, third-party open source datasets representing different viewing angles and angular resolutions. Section 5 presents the proposed algorithm to select the optimal rendition using the WR model and then using different device types and settings along with the observations reported in the literature, we demonstrate the results obtained using the proposed algorithm. The paper is concluded in Section 6. The reference algorithm implementation and the dataset files are available in Ref. 10.

2. RELATED WORK

Many early studies on subjective image quality assessment reveal the importance of physical parameters like image resolution, image/display size, and viewing distance.[6,8,11–13] The focus was emphasized on investigating the influence of these physical parameters on the subjective visual quality. The relationship between these parameters was of interest, especially to figure out what the optimal viewing distance should be in order to optimize the perceived visual quality. Catellier *et al*[14] showed that lower-quality content is usually rated slightly higher on displays with high pixels per degree, which is the case for smaller screen devices. In the work of Camara *et al*,[15] the authors studied the effect of different resolutions on end-user quality perception by using three different mobile devices and found that the equivalent resolution in current handheld devices is 720p and any higher resolution is not valued by the users. Such observations have also been reported in other studies.

More recently, the ongoing standardization document, ITU-T Rec. SG12-TD1612[16] provides a draft proposal on methods for optimizing bitrates and transmission resolution by considering display characteristics and available bandwidth. Based on various studies, it is shown that only 40″ TV monitors showed noticeable quality improvement when video resolution was 1080p as compared to 720p, while no noticeable improvement was

Table 1: List of commonly used parameters of video, player, and characteristics of viewing set up used in this work.

Parameter	Parameter Description	Units
W_p	player window width	pixels
H_p	player window height	pixels
w	horizontal image resolution	pixels
h	vertical image resolution	pixels
W	display resolution width	pixels
H	display resolution height	pixels
d	viewing distance	inches
ρ	pixels per inch	-
B	network bandwidth	kbps
R	bitrate	kbps

observed for smaller screen devices. For smaller displays, mobiles and tablets, it is found through a series of experiments, that depending on content type and display type, low bitrates at low resolution can provide equivalent perceptual quality as obtained by 1080p video. Also, considering a 75″ TV and 12 high-quality UHD videos, it is found that for some UHD sequences, the difference between 1080p and UHD video sequences is very small and hence, increasing the bitrate did not provide any significant improvement in perceptual quality.

In one of the closest works to our proposed work here, in Ref. 17 the authors model the perceived image quality as a function of coded image quality using a power-law whose parameters are dependent on the downsampling factor while incorporating the device characteristics in terms of effective-displayed pixels-per-inch (ED-PPI). Similar to this work, the authors in Ref. 18 present a content-independent model of variation of subjective scores across different devices, viewing modes and viewing distances. Using a power-law function, the authors derive a relationship between the subjective scores (MOS and DMOS) and display size and viewing distances using the ratio of the device pixels-per degree (PPD), which is shown to work well on lab and crowdsourced subjective test data. Depending on the end-user, type of application and/or device type used, the actual player size (viewport) is different from that of the actual device resolution. However, none of these works focuses on the selection of optimal renditions considering the effect of player size and viewing setup on different devices, which is the focus of this work.

3. DEFINITIONS

3.1 Symbols and Terminologies

The main parameters of video, player, and characteristics of viewing setup that we will use in this paper are summarized in Table 1.

3.1.1 Viewing Angle

Given known video player window size $W_p \times H_p$, display pixel density ρ, and viewing distance d, we can define viewing angle ϕ as follows:

$$\phi = 2\ \arctan\left(\frac{W_p}{2d\rho}\right) \tag{1}$$

This parameter describes the horizontal angular span [in degrees] of video as it is visible to the viewer.

3.1.2 Angular Resolution

Similarly, given all same parameters plus the resolution of the video $w \times h$ [in pixels] that is being played, we can define angular resolution μ of this video as follows:

$$\mu = \left(2\ \arctan\left(\frac{W_p}{wd\rho}\right)\right)^{-1}. \tag{2}$$

Such resolution is now measured in units of cycles per degree (cpd). If effectively describes Nyquist frequency of the video, presented in angular units.

Table 2: Characteristics of viewing setups and resolutions tested for the six different datasets considered in this work.

Characteristic* / Dataset	ITU TV	AVT-VQDB-UHD-1	NFLX	GamingVideoSET	ITU Tablet	ITU Mobile
Display size	75″	65″	24″	24″	9.7″	5″
Display pixel size (pixels x pixels)	3840x2160	3840x2160	1920x1080	1920x1080	1920x1080	1920x1080
Viewing Distance (H: display height)	1.5H	1.5H	3H	3H	18″	14″
Viewing angle	61.3	61.3	33	33	29.3	17.66
Display Nyquist [cpd]	28.272	28.272	28.28	28.28	32.08	53.92
Tested Video Resolutions (resolution -> cpd)	480x360 -> 3.53 960x540 -> 7.07 1280x720 -> 9.42 1920x1080 -> 14.14 3840x2160 -> 28.28	640x480 -> 4.71 1280x720 -> 9.42 1920x1080 -> 14.14 3840x2160 -> 28.28	384x288 -> 5.65 512x384 -> 7.54 720x480 -> 10.60 1280x720 -> 18.85 1920x1080 -> 28.28	640x480 -> 9.42 1280x720 -> 18.85 1920x1080 -> 28.28	1280x720 -> 21.39 1920x1080 -> 32.08	1280x720 -> 35.95 1920x1080 -> 53.92

*Notes: The characteristics of the datasets used in this work (AVT-VQDB-UHD-1,[19] NFLX,[20] GamingVideoSET[21] ITU TV,[16] ITU Tablet[16] ITU Mobile dataset[16]) are based on the information provided in the respective dataset. Parameter H in viewing distance refers to the height of the display in inches. In the absence of any required information, the values are assumed based on usage statistics as reported in Ref. 22.

3.2 Encoding Ladders

A media sequence, in ABR streaming, is encoded into different resolution-bitrate pairs referred to as renditions of the ABR ladder. Let $H_1, H_2, ...H_n$ be the height (in pixels) of the different renditions available for a particular video stream, where n is the number of renditions and can vary from stream to stream. For simplicity, we will assume that the aspect ratio of all the renditions of the ladder for a given video is the same. Therefore, the specification of a single resolution parameter, e.g., height H_i is sufficient to derive the other.

3.3 Video Player Sizes

In a given display of resolution $W \times H$, the player window size can vary as per user choice. Let H_p be the player window height, where H_p can vary, e.g. 240p up to the maximum display height, H. For simplicity, similar to renditions, it is considered that the aspect ratio is fixed for a given video streaming session. Hence, knowledge of one parameter among width and height of the player window size is sufficient.

4. WESTERINK AND ROUFS (WR) MODEL AND ITS VALIDATION ON NEWER DATASETS

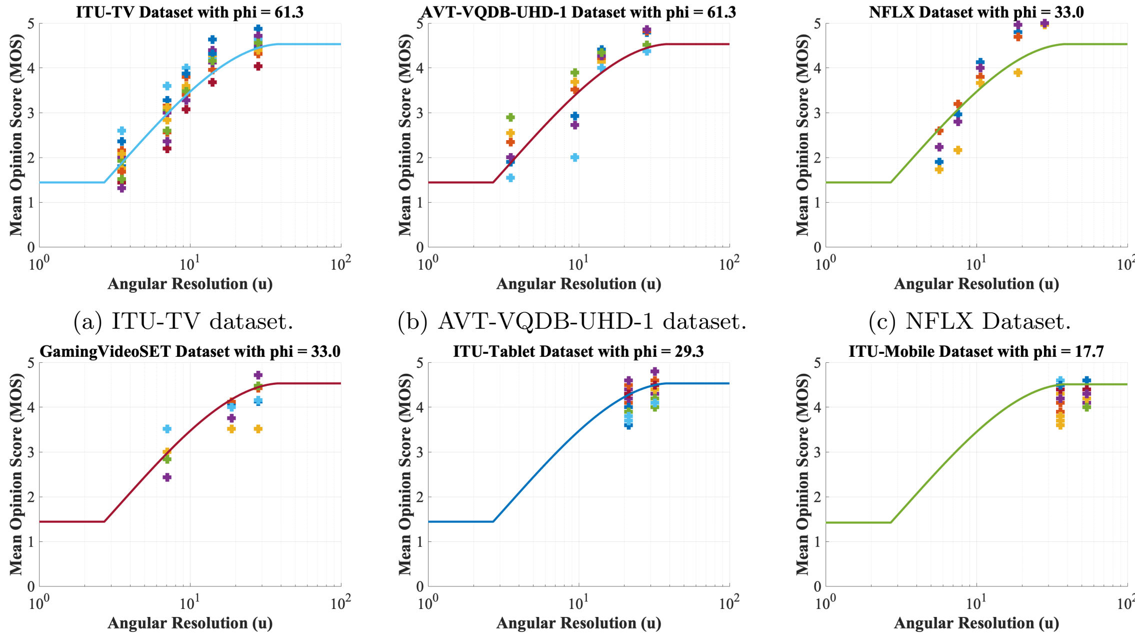
Westerink and Roufs[6] found that at a constant viewing distance the subjective quality of still pictures was influenced independently by both the angular resolution and the size of the displayed picture. Meaning that even if correlated, angular resolution and image/display size represent two different dimensions. Given ϕ is the viewing angle or angular size of the display (in degrees) and μ is the effective angular resolution of the projected video (in cycles per degree, cpd), the perceived picture quality of the video, $Q(\phi,\, \mu)$, can be approximated using the Westerink and Roufs analytic model as:

$$Q\left(\phi,\, \mu\right) = 3.6\ \log_{10}\left(\phi\ \frac{\pi}{180}\right) + 2.9 + 4.6\log_{10}\left(\mu\right)\ + 2.7\left(\log_{10}\left(\mu\right)\right)^2 - 1.7\left(\log_{10}\left(\mu\right)\right)^3 \tag{3}$$

The range of viewing angles (ϕ) used in these tests was from about 2.526 to 18.026 degrees. while the range of angular resolutions μ used was from about 2.7 cpd to 38 cpd. Henceforth, we will refer to the model in Eqn 3 as the WR model and this range of viewing angles and angular resolutions will be referred to as the valid operating range of the model. Also, with an increase in viewing angles, the perceived picture quality Q increases unbounded, while our knowledge of Human Visual System (HVS) indicates that it should rather saturate.[23] Hence, for all calculations used in this work, we cap the values of the viewing angles and angular resolutions to the operating range of the original model.

4.1 Validation of WR model on Newer Datasets

Since the WR model was initially proposed in 1989, one may wonder about its suitability more than 30 years later given newer display technologies. In order to validate the WR model on newer datasets, we collected data



(a) ITU-TV dataset. (b) AVT-VQDB-UHD-1 dataset. (c) NFLX Dataset.

(d) GamingVideoSET dataset. (e) ITU-Tablet dataset. (f) ITU-Mobile dataset.

Figure 2: MOS vs Angular resolution (cpd) plot for six different datasets. The fitted line is the perceived picture quality (Q) scores as predicted by the WR model. The marker colours in each plot represents a particular video sequence.

from different new and open-source datasets which have been designed considering different display sizes, viewing distances and resolutions representing different content types (gaming and non-gaming), different compression standards (H.264 and HEVC), display settings (UHD TV, PC monitor, Tablet and Mobile). The datasets (ITU-TV, ITU-Mobile and ITU-Tablet,[16] AVT-VQDB-UHD1,[19] NFLX[20] and GamingVideoSET[21]) and their respective settings and parameters are summarized in Table 2. It can be observed that these data sets cover a diverse range of use cases – from QCIF (video conferencing) to HD and UHD type of experiences and viewing setups. We also note that these data sets are also exhibiting a variety of distortions – such as codec noise and/or artifacts introduced by different up-sampling algorithms. No efforts were also made to post-process results accounting for differences in scores based on content. However, in order to minimize the codec noise (distortion introduced due to compression) and/or scaling artefacts (due to upscaling or downscaling of video to a resolution other than the original video resolution), for each dataset, if multiple renditions for a particular resolution are available, we only consider the subjective quality (MOS) score corresponding to the maximum encoded bitrate representation. However, since there are a lot of different contents, there will still exist a broad variation of MOS scores and hence, one should not expect a perfect fit.

Figure 2 presents the results of the MOS vs Angular resolution (log scale) for the six considered datasets. Here, for angular resolution values outside the valid operating range of the WR model, we cap the viewing angle and angular resolution values for the calculation of $Q(\phi, \mu)$ which is shown in the figure as the fitted curve. The only model parameter that was adopted between these datasets/test cases was the angular size (or viewing angle ϕ), which in the case of ITU-T TV and AVT-VQDB-UHD-1 datasets was approx. 61.3 degrees, for NFLX and GamingVideoSET dataset it was 33.0 degrees, for the ITU-T Tablet dataset 29.3 degrees and for ITU-T Mobile dataset was approx 17.66. Since the perceived quality (Q) as estimated by the WR model can be unbounded, we have used a linear fitting function $\alpha + \beta x$ to fit the Q values to the MOS scores (1-5), using generalized parameters obtained using data from all six datasets. Table 3 shows the "goodness of fit" in terms of RMSE scores for each dataset. One can observe that, even when considering the newer datasets, the fit is quite good, demonstrating that the WR model still holds. The average RMSE score over all six datasets is 0.27 which considering the scale (1-5) is a very reasonably good score.

Table 3: RMSE scores representing the "goodness of fit" of the Westerink and Roufs model on new datasets.

Dataset	**RMSE**
ITU-TV	0.17
AVT-VQDB-UHD-1	0.29
NFLX	0.43
Gaming	0.19
ITU-Mobile	0.34
ITU-Tablet	0.20
Average	**0.27**

5. PROPOSED ALGORITHM AND EVALUATION RESULTS

Having now established that the WR model works in principle, we present in this section an algorithm to be implemented at the player side for selecting the best available rendition. As explained earlier, in this work, we present a very simplistic form of the algorithm considering only the available rendition resolutions and assume that each rendition is of the "best" possible quality, thus allowing us to minimize the effect introduced due to compression or scaling artefacts.

5.1 Player Rendition Selection Algorithm

Algorithm 1 describes the selection of the best rendition so as to maximize the end user perceived quality. It is assumed that the player size $W_p \times H_p$ cannot exceed the available display size. Only display, player and video rendition height are considered with the assumption that the display aspect ratio (DAR, W/H) is fixed. For simplicity, in this study, we assume that the aspect ratio is 16:9 which is a reasonable assumption considering most of the commonly used display sizes[24] as well as recommended renditions[25] are of 16:9 aspect ratio. A reference implementation of the proposed algorithm is available in the open-source dataset.[10]

Algorithm 1: Optimal Rendition Resolution Selection Based on Player Size

Data:

Viewing angle ϕ

Angular resolution μ

Available video rendition heights, $H_{renditions} = H_1, ...H_n$, such that $H_1 \leq .. \leq H_n$

Player Window Height H_p

Distance from the display d

Effective pixel density of the screen, ρ

Result: Best rendition height, H_{best}

$MOS_{best} = 0$;
$best_{rendition-index} = 0$;
for $i \leftarrow 1$ **to** n **do**
    Calculate Viewing angle ϕ
    Calculate Angular resolution μ
    Calculate MOS $Q(\phi, \mu)$; `/* Using Eqn 3 */`
    if $MOS\ is \leq best_{mos}$ **then**
        $MOS_{best} = MOS$;
        $best_{rendition-index} = i$;
    end
end
$H_{best} = H_{renditions}(best_{rendition-index})$

Table 4: Display parameters of the four different devices.

Device Type	Display Diagonal (inches)	Display Resolution (pixels)	Viewing Distance (inches)	Display Pixel Density (ppi)
HDTV	47	1920x1080	3H (69.12)	47
PC	22	1920x1080	24	96
Tablet	9	2048x1536	18	265
Mobile	5.5	1920x1080	14	400

5.2 Simulation Results

5.2.1 Test Conditions

For each device type, we obtain the viewing angle from the display characteristics. For each player size, the angular resolution is calculated. The values of the viewing angle and the angular resolutions were capped to the operating range as used in the original Westerink and Roufs model (ϕ : $[2.526, 18.026]$ degrees and μ : $[2.7, 38]$ cpd).

5.2.2 Available Renditions

We consider that a total of 13 different renditions are available irrespective of the considered device type. Also, it is assumed that the renditions are proper in that the resolutions are non-decreasing such that $0 < H_1 \leq ... \leq H_n$ for all renditions in the ladder. The resolutions of the considered renditions are the recommended resolution values in the DVB Bluebook A168.[25] These values are typical of any streaming solution varying from very low resolution (192×108) to UHD (3840×2160) and hence will allow us to obtain realistic performance figures.

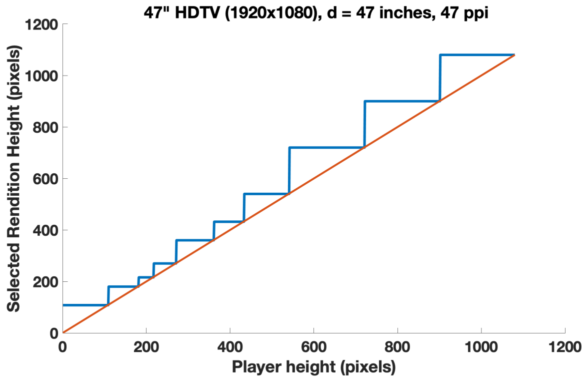
5.2.3 Player Size

For the simulations, we vary the player window height from 0 to maximum player window height (which is the same as the maximum height of the display resolution). For simplicity, we will also assume that the player size has the same aspect ratio as the video (16:9 in this case), and therefore specification of only player height H_p is sufficient. The player dimensions along with the display parameters are then used to calculate the viewing angle and the angular resolution, which are then used to calculate the perceived picture quality (Q) as described in Algorithm 1.

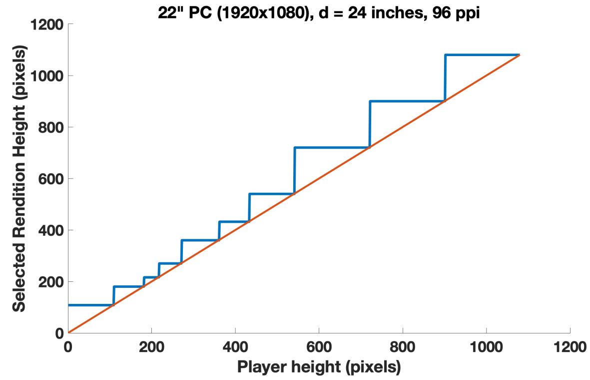
5.3 Results

We now present the results for selected renditions considering four different device types and viewing parameters. Table 4 summarizes the different values of viewing distance, display size (diagonal length), typical pixel density values and display resolution considering four different device types: High Definition TV, PC, Tablet and Mobile. The median values of the viewing setup are obtained from the Adaptive Streaming Playback Statistics Dataset[22] which consists of statistics of several large-scale real-world streaming events, delivering videos to different devices (TVs, desktops, mobiles, tablets, etc.), and over different networks (2.5G, 3G, 5G, broadband, etc.). Hence, the median values represent typical parameters for each device type as would be the case in real-world applications, and, in the absence of knowledge of the exact device parameters, without loss of generality, the respective values can instead be used for the calculation of the perceived picture quality, Q.

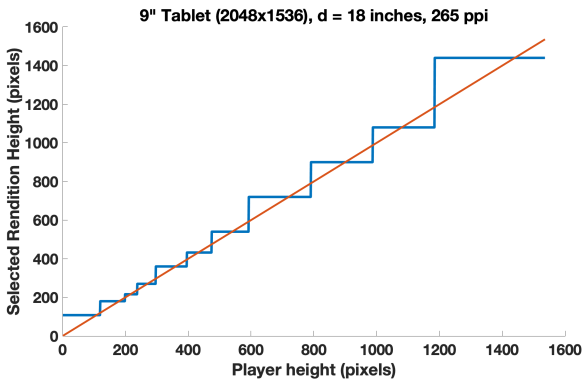
Figure 3 presents the plot of selected rendition height vs player window height along with a line showing the ideal linear fit. It should be noted that the variation along the x-axis is the player window height (pixels) and not the display resolution (which is fixed). Looking at Figure 3, it is clear that given a common set of available renditions for the player to select from, the selected rendition resolutions are different for different devices. Hence, the existing algorithms where selection is based on just nearest player window resolution will result in delivery of sub-optimal quality renditions to the end user. We observe that in general, for larger display devices such as (PC and TV), fetching a slightly higher resolution and downscaling it at the player side will result in higher perceived picture quality. However, for a smaller Tablet device, either upscaling or downscaling



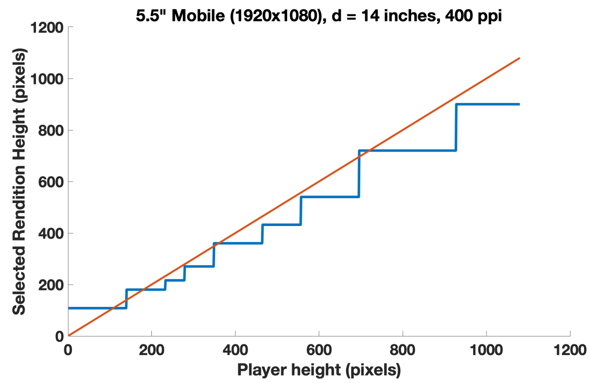
(a) 47″ HDTV (1920x1080), d = 69.12″(3H), 47 ppi.



(b) 24″ PC (1920x1080), d = 22″, 96 ppi.



(c) 9″ Tablet (2048x1536), d = 18″, 265 ppi.



(d) 5.5″ Mobile (1920x1080), d = 14″, 400 ppi.

Figure 3: Rendition selection for four different devices types using typical resolution and viewing distance settings.

the nearest available rendition can result in the optimal perceived picture quality. Considering mobile device type, on the other hand, a slightly lower resolution video upscaled to the player display size will result in higher perceived quality by the end-user. This is in line with many similar observations reported in other literary works such as Ref. 15 and Ref. 16 which found that there does not exist any significant difference between 720p and 1080p resolution videos in terms of subjectively perceived quality for small screen devices such as mobiles and tablets, and hence, lower resolution video should be streamed instead of higher resolution renditions. The proposed algorithm, hence when integrated with more complex player adaptation logic can result in fetching of optimal renditions thus increasing the end-user quality of experience and/or reducing the required bandwidth.

6. CONCLUSIONS

We presented a simple and practical algorithm for rendition selection, improving QoE by considering video player resolution and other device-specific parameters affecting viewing setup. This algorithm relies on the use of Westerink and Roufs QoE model, which we further validated by using six modern datasets. Based on our simulations, we have shown that the proposed algorithm works in principle, selecting different renditions for different devices. We have analyzed the observed effects and noted that they all are in agreement with effects previously known and reported in the literature. The results presented in this paper also establish the importance of device related parameters such as form factor and viewing distance in the design of a perceptual image or video quality metric design.

While we assumed that the available renditions are optimal by considering the highest possible encoded representation for each resolution, the proposed model can be further extended to consider the amount of codec noise introduced during the encoding process and a more holistic design of rate selection in streaming clients. Such combined metric can be particularly important in operating with streams produced by different codecs. Some preliminary results in this direction can be found in references 26–28. Our future work will include extending this work to consider the effect of encoding artefacts and different rescaling filters to either select and/or generate optimal renditions for a given application.

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