An approach for modeling the effects of video resolution and size on the perceived visual quality

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***Abstract*—Video-telephony and mobile TV are typical multimedia services which are becoming a part of the everyday life due to the increase in bandwidth availability and also viewing devices with larger screen sizes (smartphone, PDA, etc). To ensure high quality, packet-layer parametric quality prediction models for audio-visual services like video-telephony and IPTV video streaming have emerged and are still under development. Those parametric models depend on a set of parameters which have to be tuned for every specific application. In this work, we carry out an experiment to analyze the impact of video resolution and upscaling operation on perceived quality. We could show that the current parametric models can be modified to explicitly integrate the joined effect of resolution and display video size.**

***Keywords*-video display size; visual resolution; parametric quality prediction models**

I. Introduction

Early studies on subjective image quality assessment reveal the importance of physical parameters like image resolution, image absolute size and viewing distance [1][2][3][4]. 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. These studies were mostly realized in a television setup using still images. Several important findings were established: Westerink and Roufs [1] found that at a constant viewing distance the subjective quality of still pictures was influenced independently by both the resolution and the size. Meaning that even if correlated, resolution and size represent two different dimensions. Moreover, Fish and Judd [5] consistent with Westerink and Roufs [1] determined that there is no strong relationship between subjective video quality and viewing distance. Knoche et al. [6], working with mobile devices and viewing distances between 13 and 40cm, found no evidence that viewers actually modify their viewing distance in response to varying video sizes at a constant angular resolution. This confirms the conclusions of Kato et al. [7] who obtained similar results in a study on mobile devices. We will therefore consider the resolution and size as variables of interest but leave out the viewing distance as it doesn't seem to be correlated to the subjective quality in a mobile scenario involving short viewing distances and small resolutions. We thus decide to let this variable up to the viewer preference in the sense that the viewing distance should be felt by the viewer as being optimal.

In this article, we study two aspects which have so far received little attention in the literature, namely the influence of compression distortions with regards to the combination of image resolution and size, as well as the integration of the related degradations into existing parametric quality prediction models.

A recent study was led by Bae et al. [8] on the trade-off between spatial resolution and quantization noise. They used still images encoded by JPEG and JPEG2000 to measure the visibility of compression. The statistical analysis of the results proved that a trade-off exists and that users are ready to accept more visible distortions to get a higher resolution. In [9], Péchard et al. show that whilst comparing HDTV and half-band filtered HD (close to real SDTV), image size is a factor of visual comfort when images are only slightly distorted but becomes a drawback when the distortion level increases. The results presented in those studies can however not be used to predict the trade-off between video resolution and display size for a given level of distortions. Knoche et al. investigated in [10][11] the user preferences on how the videos should be presented in order to maximize the acceptance rate. They provided guidelines regarding the adequate display size for certain resolutions and some limitations on the minimal acceptable angular resolution.

However, there is so far no study reporting results based on subjective quality scores (subjective Mean Opinion Score) that are at integrating the effects of resolution and size in recent parametric quality prediction models. The existing parametric packet-layer video quality prediction models, which we focus on in this study, depend implicitly on the physical parameters. These are, among others, video size and resolution. The impact of these parameters is so far integrated in the models by means of model coefficients with fixed values. These coefficients have to be determined via subjective tests for each specific set of physical parameters. This approach makes the current models case specific and not very modular. A first attempt has been drawn by Joskowicz and Ardao [12] to integrate the effect of resolution into the parametric model for video-telephony standardized as the ITU-T Recommendation G.1070 [13]. They, however, based their analysis on quality ratings provided by an objective metric for video quality [14] that doesn't take into account the absolute video size and the loss of details associated with reducing the size: two different resolutions will automatically lead to the same visual quality saturation value, thus not reflecting any "context effect" [15]. This work, nevertheless, shows that the objective video quality is scalable across different ranges of bit rate depending on the resolution. This comes from the fact that for a fixed encoding bit rate, reducing the resolution increases the bandwidth allocation per pixel and thus the image quality by reducing the amount of encoding artefacts. However reducing the resolution also reduces the amount of visible details which may impact the quality perception in a negative way. The global shape of the quality curves on a given range of bit rates, squeezed or stretched, should in principal remain similar. This observation leads to the idea that it may be possible to find an analytic transformation to model the impact of rescaling on the

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perceived visual quality. We therefore further extend the study towards an integration of the physical parameters video resolution and size into parametric packet-layer video prediction models.
A straightforward outcome would be to know what the trade-off between resolution and size for a given bandwidth is: Would it be better to watch a video with a smaller resolution but rescaled, thus introducing blurring artefacts, rather than watching a video with a higher resolution but containing more encoding artefacts?
The description of the subjective experiments is given in Section II. The quantitative analysis of the raw results as well as the fitting with two different quality models are presented in Section III. Section IV explains how to integrate the impact of resolution and Section V shows how to extend the modeling to incorporate the effect of size into the quality models. Finally we conclude in Section VI with the possibilities for improvements.

II. Test methodology

We carried out two subjective experiments in a viewing-only setup. Four different video sequences of a total duration of twelve seconds were used. The videos initially of SD resolution (720×576) were first downscaled into several smaller resolutions, namely VGA (640×480), CIF (352×288), QCIF (176×144) and QVGA (320×240). Those videos have then been encoded using the H.264 codec (implementation X264 of the MPEG4-Part10/AVC video codec using the baseline profile) with several bit rates covering different ranges depending on the resolution (see Table 1). Additionally, we produced upscaled versions of the videos in the native resolution. Both downscaling and upscaling operations have been performed using a Lanczos3 filter [16]. The influence of the interpolation method is here out of scope. Let us note that the videos have been downscaled and upscaled whilst conserving the aspect ratio and cropped to operate the resolution change. It has been shown in [17] that the cropping operation (up to 30% reduction of the image width) has a negligible influence on the quality perception compared to the coding degradations. This means that a CIF video upscaled to VGA size will have a slightly different content as the original (around 20 pixels cropped on both sides, that is to say a reduction of 8% of the image width) but we assume that the cropping is very limited and should not have any impact on the quality assessment.
Video quality was evaluated using an 11-point continuous rating scale according to ITU-T Recommendation P.910 [18]. The videos were displayed on a 19 inch LCD monitor with a resolution of 1280×1024. In the following, we will designate as video format the combination of video resolution and size. We used 7 different formats per experiment, five different bit rates per format (covering different ranges) and four different video contents. We used typical TV content that can be watched on a mobile device, i.e. a movie, a soccer game, news, and a music clip. That led to a total of 35 conditions per experiment, resulting in 140 stimuli to be assessed by the test participants (see Table I). The quality descriptions for individual rating categories were given in German. The participants were instructed to base their evaluation on the visual quality only. Twenty four test participants aged between 18 and 40, balanced in gender, took part in the experiment. They were non-experts and were not concerned with multimedia quality as part of their work. The ratings were then linearly mapped to the 5-point ACR category scale. Before actually starting the experiment, the test participants followed a training phase during which they saw and evaluated a set of twelve stimuli of different contents and quality. This set is representative of the full quality range the test participants experienced during this experiment.
Both experiments contain all native resolutions. The difference between both experiments is that the first includes exclusively upscalings to the highest size (size of native VGA) whereas the second includes only intermediate upscalings (for example, native QCIF upscaled to the native size of QVGA). The resolution, usually expressed as the frame width times the height in pixel units will be here considered as the number of effective pixels contained in a video frame to be encoded (i.e. native resolution). The size will refer to the number of pixels over which the video frame is spread, that is to say, the size will always be bigger than the resolution in case of upscaling or will equal it if there is none. Details of the experiments composition are given in Table I.

Table I
Experimental settings

Video codec		H264 Baseline Profile	
Video format (*)the notation QCIF_VGA means original QCIF upscaled to VGA's size		Experiment 1	Experiment 2
		VGA, CIF, QVGA, QCIF, QCIF_VGA(*) QVGA_VGA, CIF_VGA	VGA, CIF, QVGA, QCIF, QCIF_QVGA, QCIF_CIF, QVGA_CIF
Key frame interval (sec)		1	
GOP Pattern		IPPPP	
Video Bit rate (kbs)	VGA	128, 256, 512, 768, 1024	
	QVGA, CIF, QVGA_CIF, QVGA_VGA, CIF_VGA,	64, 128, 256, 512, 1024	
	QCIF QCIF_QVGA QCIF_CIF QCIF_VGA	32, 64, 128, 256, 512	
Frame rate (fps)		25	
Viewing Distance (cm)		50	
Video Content		Interview, Football Movie, Music clip	

III. Qualitative Analysis and model fitting

A. Analysis of the raw results

The first step of the data analysis was to check the coherence of the ratings. We computed the Cronbach's alpha value to measure the internal consistency which is of 0.986. The value being high, no exclusion of subjects from the data set was necessary. The narrow confidence intervals at 95% showed that the results were accurate and consistent. Let's note that the quality scores have been averaged over the differents video contents for both experiments.
The quality curves from the first experiment are shown on Fig. 1. By comparing the different resolutions to their upscaled versions, we observe that upscaling leads to a systematic quality drop. Towards low bit rates and until a certain threshold, resolutions below VGA systematically lead to a better quality than VGA, which is the highest resolution of this study. However lower resolutions saturate faster and the saturation values increase with the resolution. An interesting result is that upscaled versions are rated generally worse than the original ones they were derived

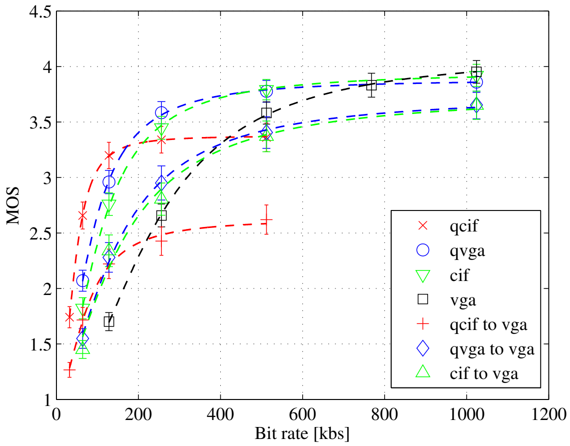

Figure 1. Perceived quality as a function of bit rate for experiment 1. The dashed line represents the data fitting using the parametric model ITU-T Rec. G.1070

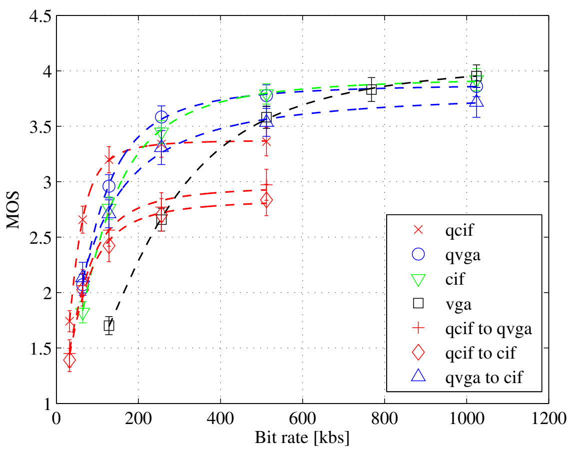

Figure 2. Perceived quality as a function of bit rate for experiment 2. The dashed line represents the data fitting using the parametric model ITU-T Rec. G.1070

from. This behavior is consistent across the different formats under investigation in this experiment, and implies that in the case of coding degradations, upscaling has always a negative impact on quality. Such results are in line with the findings of Garcia et al. [17] where they compare native SD resolution (Standard Definition) and SD rescaled to HD (High Definition) with native HD.

In terms of quality optimization, we denote a direct gain in being able to predict these quality curves for bandwidth saving. For example, in the case where the display size and bandwidth are fixed, such quality curves (in Fig. 1) enable one to predict the optimal resolution in which the video should be streamed for maximizing perceived visual quality.

The results of the second experiment differ significantly from the first one. The main difference is that the resolution does not seem to play such an important role. When considering the native resolutions, we can observe that there is no clear ascending order of the saturation values for the different resolutions. Native VGA and QCIF resolutions have approximately the same saturation value which is smaller than the ones of CIF and QVGA. Moreover, the VGA resolution leads to the lowest quality on the studied bit rate range compared to the other original resolutions. The effect of size however seems to be similar as in experiment 1: upscaling the videos systematically degrades the quality and the degradation is growing with the magnitude of the upscaling. As the goal of this study is to investigate the joint influence of the resolution and size, we decide to choose experiment 1 as the reference because it seems to have grasped both effects in a balanced way; experiment 2 mainly reflects the size effect. We therefore normalize the data of experiment 2 to experiment 1 using the normalization procedure presented in [19] where a linear regression in used between the anchor points of both experiments. For a better accuracy, we applied the normalization resolution-wise. The normalized results of experiment 2 are shown on Fig. 2. The details of the normalization and the raw results of experiment 2 can be found in [20]. Figures 1 and 2 both represent the normalized results of the subjective experiments which will be used for the modeling.

B. Data fitting using parametric quality models

1) ITU-T Recommendation G.1070: ITU-T Recommendation G.1070 [13] describes a parametric quality model for video-telephony applications. It has been developed for image sizes ranging from QQVGA to VGA displayed on terminal devices like desktop PC, laptop PC, PDA and mobile phones. The model includes a video quality estimation function that has been developed for video codecs used in multimedia applications like H.264 or MPEG4-part2 but is also valid for older codecs like MPEG2 [21] for instance. The video quality estimation function, excluding the degradations due to the frame rate or to packet loss, follows the formula:

$$Vq = 1 + v_3 \cdot \left(1 - \frac{1}{1 + \left(\frac{Br}{v_5}^{v_4}\right)}\right) \tag{1}$$

where V_q is the predicted video quality, Br the encoding bit rate and v_3, v_4, v_5 are model coefficients. We perform a data fitting per format over all the contents (using a non-linear least-square-based regression algorithm) in order to determine the parameters v_3, v_4 and v_5. For each format we get a high correlation between observed and predicted values, see Table II.

2) TV-MODEL: The TV-Model [22] is a non-intrusive parametric model for multimedia streaming that aims at describing the audiovisual quality for SDTV and HDTV. This model takes the form of a sum where each term, called impairment factors, accounts for a certain type of degradation. So far, impairment factors have been derived to include coding artefacts and packet loss occurring on the network (taking into account different packet loss concealment strategies). The video quality estimation function is the following:

$$\begin{aligned} Vq &= Qv0 - Icod - Inet \quad (2) \\ Icod &= a_1 \cdot exp(a_2 \cdot Br) + a_3 \quad (3) \end{aligned}$$

Where Vq being the predicted video quality, $Qv0$ represents the highest subjective rating, $Icod$ is the impairment factor for coding degradations, $Inet$ is the impairment factor for degradations occurring at the network layer ($Inet = 0$ as we do not consider the case of packet loss degradations), Br the encoding bit rate and a_1, a_2, a_3 are model parameters. In the following, a_3 will be left out as it turns out to not improve the data fitting. The first column in Table II summarizes the modeling prediction accuracy per video format.

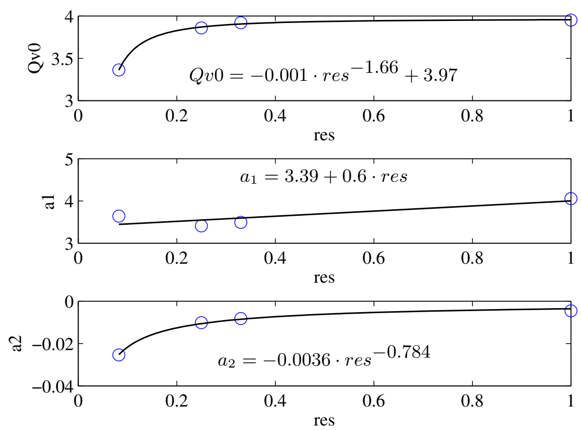

Figure 3. TV-Model parameters for different resolutions

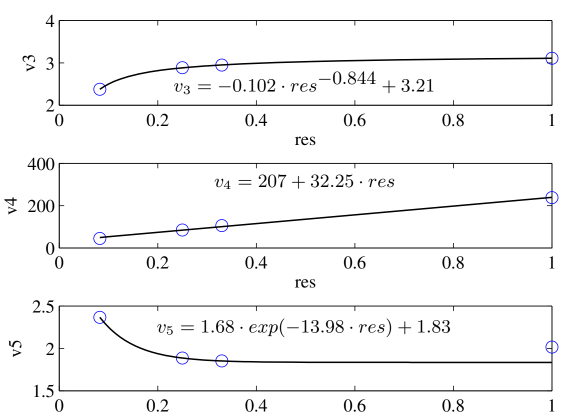

Figure 4. G.1070 model parameters for different resolutions

IV. Modeling the impact of resolution and size on the perceived visual quality

A. Dependency of the models' parameters on the compression resolution

Following the qualitative analysis of the raw results, we here propose a method to model the impact of resolution on the perceived visual quality. We have used in the previous section two different models in order to model the quality curves resolution wise. This resulted in one set of parameters per resolution and per model. Therefore, the chosen approach is to model the evolution of the parameters depending on the actual resolution. We display in Fig. 3 and Fig. 4 the plots of the parameters versus the normalized resolution expressed as follows:

$$res = \frac{num\_pix_{resolution}}{num\_pix_{VGA}} \quad (4)$$

with res being expressed as the ratio between the number of pixels for a given resolution ($num\_pix_{resolution}$) and the number of pixels for the VGA resolution (num_pix_{VGA})
We can see that each parameter can be modeled with a good accuracy using simple analytic functions. The correlation between the raw MOS ratings and the predicted MOS values at this stage is still very good. This modeling approach does not follow an impairment based logic where we would have an additional term reflecting the degradations from the resolution on the overall quality. It rather aims at determining the direct influence of the resolution on the already existing parameters. Thus, the integration function of the quality models can be expressed in a generic way as follows:

$$Vq_{res}(res, Br) = Vq(param_1(res)..., param_N(res), Br) \quad (5)$$

with res being the resolution expressed in equation (4). The correlation coefficients as well at the RMSE (root-mean-square error) values are gathered in Tables II. We can see that the predicted data accounting for the impact of resolution are equally well correlated with the raw data compared to the predicted data directly fitted on the quality models. We however notice an increase in the RMSE caused by the dispersion due to the modeling errors.

Table II
Performance per format for the models G.1070 and TVModel

	data fitting to quality model		modeling impact of resolution		modeling impact of resolution and size	
	corr	RMSE	corr	RMSE	corr	RMSE
QCIF	0.99/0.99$^{(*)}$	0.005/0.01	0.99/0.99	0.076/0.04	0.99/0.99	0.077/0.042
QCIF_QVGA	0.99/0.99	0.037/0.065	-	-	0.99/0.98	0.138/0.21
QCIF_CIF	0.99/0.99	0.042/0.058	-	-	0.99/0.98	0.134/0.201
QCIF_VGA	0.99/0.99	0.032/0.047	-	-	0.98/0.97	0.171/0.236
QVGA	0.99/0.99	0.013/0.033	0.99/0.99	0.016/0.042	0.99/0.97	0.016/0.588
QVGA_CIF	0.99/0.99	0.031/0.048	-	-	0.99/0.99	0.123/0.536
QVGA_VGA	0.99/0.99	0.028/0.05	-	-	0.98/0.99	0.373/0.202
CIF	0.99/0.99	0.018/0.050	0.99/0.99	0.046/0.048	0.99/0.97	0.051/0.6
CIF_VGA	0.99/0.99	0.097/0.109	-	-	0.98/0.99	0.293/0.34
VGA	0.99/0.99	0.011/0.025	0.99/0.98	0.055/0.23	0.99/0.98	0.055/0.23

$^{(*)}$: for each couple of values, the first refers to the model G.1070 and the second to the TVModel

B. Integration of the size effect

The observation of the effect of size on visual quality depending on the bit rate reveals that the MOS scores seem to be generally impacted in the same fashion. An example for the QCIF resolution is given on Fig. 5 which shows the plots of the MOS values for

Table III
COEFFICIENTS VALUES FOR $Isize_{res}$ AT DIFFERENT RESOLUTIONS

	a_{res}	b_{res}	c_{res}
QCIF	1.11	-4.6	2.61
QVGA	8.2	-14.73	3.65
CIF	2.07	-0.23	2

different sizes indexed by the bit rates values. The normalized size is expressed as follows:

$$size = \frac{num\_pix_{format}}{num\_pix_{VGA}} \quad (6)$$

where $size$ is the ratio between the number of pixels for a given video format (num_pix_{format}) and the number of pixels for the VGA resolution (num_pix_{VGA}). As noticed during the qualitative analysis of the raw results it appears that for all resolutions the magnified versions always yield a lower quality than the original version. There is also a clear rank order between the different upscalings: the greater the upscaling, the more blurring artefacts thus leading to poorer quality. The decrease in terms of MOS doesn't seem to be correlated with the bit rate. The curves are separated by an offset and the magnitude of this offset depends on the bit rate. This allows us to follow an approach similar to the one described by Inazumi et al. in [23]. We assume that the variables size and MOS are independent. This assumption is, of course, a simplification with limits but has the advantage to greatly simplify the problem without generating significant prediction errors. These assumption permits to realize a complete mapping of the space $\{bitrate, resolution, size, MOS\}$. The final predicted MOS, noted as $Vq_{res,size}$will be expressed as follows:

$$Vq_{res,size} = Isize_{norm}(size, res) \cdot Vq_{res}(res, Br) \quad (7)$$

$$Isize_{norm}(size, res) = \frac{Isize_{res}(size)}{max(Vq_{res}) \cdot max(Isize_{res})} \quad (8)$$

$$Isize_{res}(size) = a_{res} \cdot exp(b_{res} \cdot size) + c_{res} \quad (9)$$

$Isize_{norm}(size, res)$ accounts for the degradation of size. It takes the form of a decreasing exponential as expressed in equation (9). As we made the assumption of independence, we compute the data fitting only for the greatest bit rate (512 kbs for QCIF and 1024 kbs for QVGA and CIF). The results from the fitting of the experimental data using equation (9) are resumed in Table III. $Vq_{res}(res, Br)$ represents the quality function accounting for the resolution and was calculated in Section III. It is therefore valid for both models. Applying equation (7) to our dataset provides quality surfaces as depicted in Fig. 6. The final performance of the modeling can be found in the last column of Table II.

V. RESULTS ANALYSIS

A single dataset was available in this study to develop the model, therefore it had to be split in two reduced non-overlapping datasets (no overlap between the test participants nor between the video contents) in order to check the validity of the model. This latter was thus trained using the training dataset and its performance evaluated

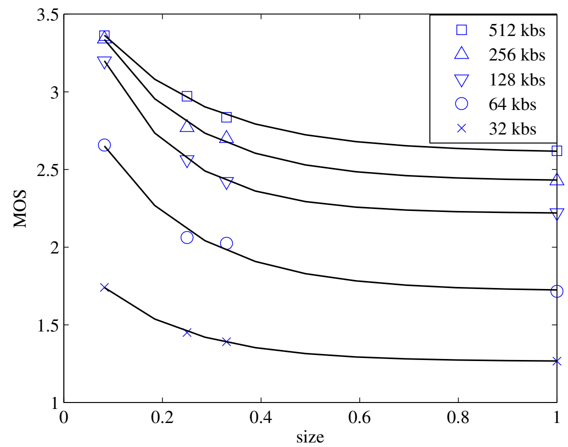

Figure 5. Degradations due to the size depending on the bit rate for the QCIF resolution

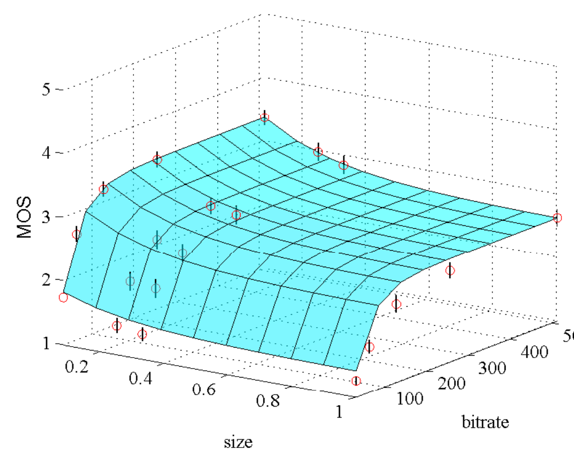

Figure 6. Perceived quality as function of bit rate and size for the QCIF resolution. Modeling using the G.1070 model

on the validation dataset. In Table IV, the results for both datasets and models are presented including all formats. Considering the G.1070 model, we observe that the correlation remains high and the RMSE between the training and validation datasets is similar. The model tends however to slightly underestimate the predicted quality scores for the validation dataset (see Fig. 7). For the TVModel, the prediction error increases at the second stage of the modeling (impact of resolution) where the prediction error is much higher on the training dataset compared to the G.1070 model. Including the effect of size in the modeling makes the performance drop significantly both in terms of correlation and RMSE (the correlation coefficient drops from 0.97 to 0.76 and the RMSE value is three times greater). A finer analysis shows that this drop is due to the greater sensitivity of the models' parameters to the prediction error whilst modeling the impact of resolution.

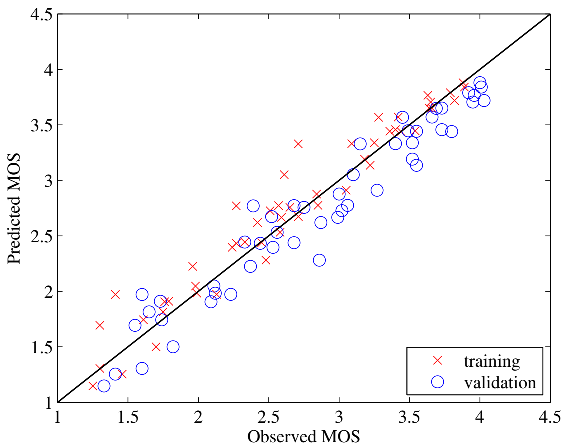

Figure 7. Performance of both training and validation datasets for the G.1070 model

Table IV
PERFORMANCE FOR THE TRAINING AND EVALUATION DATA FOR THE MODELS G.1070 AND TVMODEL

dataset / quality model	data fitting to quality model		modeling impact of resolution		modeling impact of resolution and size	
	corr	RMSE	corr	RMSE	corr	RMSE
training / G.1070	0.99	0.072	0.99	0.085	0.97	0.20
validation / G.1070	0.98	0.24	0.98	0.25	0.97	0.23
training / TVModel	0.99	0.086	0.97	0.21	0.76	0.62
validation / TVModel	0.99	0.23	0.99	0.26	0.82	0.67

VI. CONCLUSION

In this study we have shown the impact of video resolution and size on the perceived visual quality. It has been observed that a trade-off between resolution and size for a given bandwidth could be predicted in order to optimize the video quality. We presented a modeling method to integrate into parametric quality prediction models the degradations caused by the loss of resolution (less details) and also due to the size (upscaling leading to blurring artefacts and magnifying encoding artefacts) with regard to the bandwidth. It was found that the resolution itself could be used as an additional variable in the quality models. The effects of size are gathered in a new term that modulates the initial visual quality estimation function. This modeling aims at enhancing the flexibility of the current parametric models to make them more explicit, i.e. replacing the model's coefficients, which are usually derived from subjective tests, by explanatory terms. The results on the validation dataset show a good correlation with a low RMSE for the G.1070 model whereas modeling the effect of size makes the prediction error increase significantly for the TVModel. The next step involves the validation of the modeling approach against various video contents, different upscalings and additional factors of influence.

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