Parametric Quality Models for Multiscreen Video Systems

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***Abstract*—We propose simple parametric models for predicting visual quality scores on different devices in multi-screen systems. As input parameters, the proposed models take the distortion measure for the encoded video and parameters of viewing setup: the resolution of projected video, size of the display, and viewing distance. We derive models for the following distortion measures: PSNR, SSIM, VIF, and VMAF. We validate the proposed models by using datasets corresponding to three different reproduction environments: standard TV sets, UltraHD TV sets, and mobiles. The obtained results confirm the improved accuracy of the prediction of MOS scores by the proposed techniques. The paper also includes introductory material explaining the usefulness of parametric quality for the analysis and optimizations of multi-screen video systems.**

Keywords*—*quality metrics, streaming, multi-screen systems

I. Introduction

A. Quality-related problems in multi-screen systems

Most modern-day streaming services deliver videos on many devices: TVs, PCs, tablets, mobiles, and others. Such devices have different characteristics of their screens and parameters of viewing setups: typical viewing distance, viewing angle, ambient illuminance, etc. Consequently, the same videos encoded at the same resolutions and bitrates may appear differently on different devices, resulting in different MOS scores in the subjective tests. Such differences are critical for understanding of the performance of multiscreen systems and posing the related optimization problems.

To explain this more specifically, let us consider an HLS [1] or DASH [2]-based adaptive bitrate (ABR) streaming system, presented in Figure 1. In this system, an input video (mezzanine) is encoded into n streams, with resolutions $W_1 \times H_1, \ldots, W_n \times H_n$ and bitrates $R_1, \ldots, R_n$, respectively. These streams are subsequently placed on an origin server connected to a CDN. The origin also receives an HLS or DASH manifest file, describing properties of such streams. On the receiving end, we may have k possible devices with different form factors and viewing setup parameters $\xi_1, \ldots, \xi_k$. Such devices may then pull any combinations of segments/chunks from the encoded streams from the CDN, as needed to facilitate continuous playback. In practice, the stream selection logic in players is typically driven by several considerations, such as device capabilities, network conditions, video player sizes, and others. Additional details about operation of ABR systems can be found in [3-9].

In order to measure *codec-introduced distortions* in each encoded streams, it is sufficient to produce n quantities: $D_1, \ldots, D_n$. I.e., one distortion value (e.g., PSNR or SSIM [10]) per each stream. However, since in this system, the receiving devices are different, and we are ultimately interested in Quality

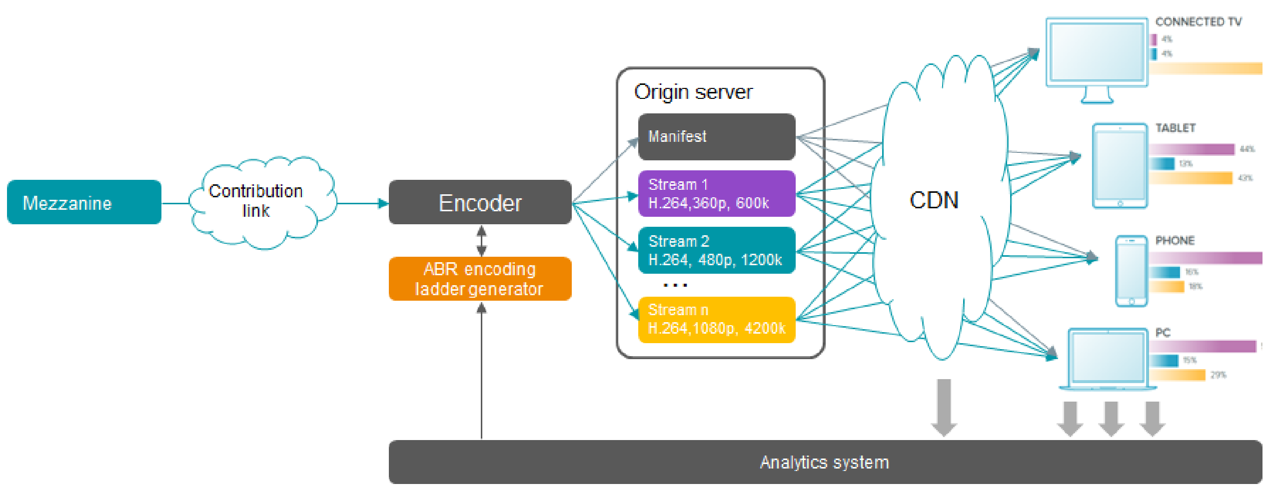

Fig. 1. Example of a multi-screen video delivery system using HTTP-based adaptrive bitrate (ABR) streaming framework.

[1]The work of on this paper was conducted while Rahul Vanam was affiliated with Brightcove, Inc.

of Experience (QoE) and not just distortions, we have to consider *a matrix of* $k \times n$ *parameters*:

$$Q = \begin{bmatrix} Q_{11} & \cdots & Q_{1n} \\ \vdots & \ddots & \vdots \\ Q_{k1} & \cdots & Q_{kn} \end{bmatrix}$$

corresponding to MOS scores, measured for all streams and on all receiving devices. Having such a matrix, we can subsequently express the *average quality* achievable *for each device*:

$$\bar{Q}_i = \sum_{j=1}^{n} p_{ij} Q_{ij}, \ \ i = 1, \dots, k$$

as well as the *average quality across all devices*:

$$\bar{Q} = \sum_{i=1}^{k} v_i \, \bar{Q}_i.$$

The weight factors p_{ij} and v_i in the above expressions correspond to *load probabilities* of each stream on each device, and *relative volume of content* pulled by each device, respectively.

By further noting that quality scores Q_{ij} are influenced by stream bitrate and resolution parameters as well as parameters of reproduction devices:

$$Q_{ij} = Q_{ij}\left(R_j, W_j, H_j, \xi_i\right),$$

we can pose several related optimization problems.

For example, we can pose a problem of the *design of encoding profiles* (choices of bitrates and resolutions for n streams [11,12]), such that the average quality delivered by the system (for given limits on average bitrates $\bar{R}_{\mathrm{max,i}}$) is maximal:

$$\bar{Q}^* = \max_{\substack{R_1,\dots,R_n,\, W_1,\dots,W_n,\, H_1,\dots,H_n \\ \sum_{j=1}^{n} p_{ij} R_i \le \bar{R}_{\mathrm{max,i}}, i=1,\dots,k}} \sum_{i=1}^{k} v_i \sum_{j=1}^{n} p_{ij} Q_{ij}\left(R_j, W_j, H_j, \xi_i\right),$$

An alternative problem can also be posed by considering *relative quality gaps*:

$$\delta_{ij} = \frac{Q_i^* - Q_{ij}}{Q_i^*},$$

where Q_i^* denotes maximum quality achievable on i^{th} device:

$$Q_i^* = Q_{ij}\left(R_j \to \infty, W_j \to \infty, H_j \to \infty, \xi_i\right)$$

Using such relative scores, the problem can be posed as follows:

$$\bar{\delta}^* = \min_{\substack{R_1,\dots,R_n,\, W_1,\dots,W_n,\, H_1,\dots,H_n \\ \sum_{j=1}^{n} p_{ij} R_i \le \bar{R}_{\mathrm{max,i}}, i=1,\dots,k}} \max_i \sum_{j=1}^{n} p_{ij} \delta_{ij}\left(R_j, W_j, H_j, \xi_i\right).$$

In other words, we minimize the worst-case average quality gap across all devices. This setting allows the problem to be posed without exact knowledge of content usage distribution across devices, and without the risk of biasing the solution to benefit the most intensively used device while delivering suboptimal performance on the others.

However, as we can see, in both problem settings, the availability of quality estimates $\mathrm{Q_{ij}}$ specific for each device is essential. Examples of various additional optimizations problems utilizing quality estimates on different devices can be found in [13,14].

B. The problem addressed by this paper

In this paper we propose a set of simple parametric quality models, allowing full matrix of per-device quality values $[Q_{ij}]$ to be easily computed by using a set of n distortion values $D_1, \dots, D_n$ computed once for each stream, and k viewing setup parameters $\xi_1, \dots, \xi_k$ corresponding to each category of receiving devices. In other words, what we propose are model functions:

$$Q_{ij} = Q\left(D_j, \xi_i\right), \qquad i = 1, \dots, k, j = 1, \dots, n.$$

These models effectively reduce the problem of assessment of quality on each device to a simple computation of distortions (e.g., using basic metrics such as PSNR, or SSIM) for each stream, and then applying a formula combining such distortion measures with other quality-influencing factors for each device to arrive at final predicted quality scores.

C. Benefits

The main benefit of the proposed models is reduced complexity. Instead of computing quality scores many times and customarily for each stream and device parameters, and using sophisticated QoE tools (such as e.g., Tektronix PQA [15,16]), the proposed approach enables the distortion measures to be computed only once per each stream, and then reused for arriving at quality estimates for all devices.

The added benefit of the proposed approach are simple mathematical forms of coupling the distortion values with device-specific parameters. These could lead to simplifications in related optimization problems.

The separation of distortion also allows simple modeling of the performance of the encoder. Effectively, the design of models for quality-rate functions $Q_{ij}\left(R_j, W_j, H_j, \xi_i\right)$ is reduced to producing models of operational distortion-rate functions $D_j\left(R_j\right)$, which is a much simpler and better understood problem.

And finally, as we will show, based on our experimental results, the proposed approach allows high accuracy QOE prediction even when using very simple distortion measures, such as PSNR or SSIM. Considering that such metrics are much simpler to compute than more sophisticated models, and that they only need to be computed at encoded video resolutions, and not in the upscaled (as displayed) domain, this makes the proposed approach even more appealing from complexity and ease of use standpoints.

D. Related prior art

Early studies on subjective image quality assessment reveal the importance of physical parameters like image resolution, image/display size, and viewing distance [17-23]. Specifically, Westerink and Roufs [17] have 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. Barten [18,19] has confirmed same effects by using his SQRI method [19]. Most recently, this model was also generalized and validated based on data in modern datasets [24].

Much more sophisticated models, attempting to model different perceptual effects at optical, retinal, and visual cortex levels have also been proposed. They all naturally require parameters of viewing setups for calibrations. Good examples of such models include VPD [25], Sarnoff model [26], the model of Teo and Heeger [27], and others [28]. However, most of these models are pretty complex and have found only limited use in practical applications. Perhaps best known become Sarnoff model [26], due to its inclusion in Tektronix PQA analyzers [15,16].

Fast forwarding to modern practice, we notice that most modern objective quality metrics are purely distortion-based. Good examples are PSNR and SSIM [10]. The both compute summary statistics of differences between pixels in the original and decoded video. VIF [29] is a bit more sophisticated. It looks at logarithmic (information) differences, considering particular statistical models of visual information. But fundamentally, it still measures the differences between the original and reconstructed images.

VMAF [30,31] is another popular modern-era metric, using SVM for turning VIF and several additional metrics into final quality scores. However, as explained in [30], it is trained by using a database [32] with DMOS scores and measured in a single and very specific viewing environment: ITU-R BT-500 [33] setup. In other words, by design, VMAF is meant to predict DMOS in one specific environment, and not MOS scores across different platforms.

As it becomes evident from this review, most metrics that are broadly used in today's practice are simply not appropriate for the analysis of relative quality effects in multi-screen systems. The objective of this paper, therefore, is to bridge the gap between popular metrics that are broadly available and an application that needs device-specific quality assessments.

E. Outline

In Section II, we describe our proposed models and explain the reasoning behind them. In Section III, we conduct the experimental study, assessing the performance of the proposed models on datasets with MOS scores measured on three different categories of receiving devices. In Section IV, we offer conclusions.

II. Parametric Quality Models

A. Distortion metrics used as input

In this work, we will assume that the amount of codec-introduced noise (distortion) in each stream is measured by either PSNR, SSIM, VIF or VMAF metrics. In all cases, we will further assume that such metrics are computed at same resolutions as video is encoded, and hence they only characterize the code-added noise (distortion) aspects, and not the effects of scaling.

B. Viewing setup parameters

We will further assume, that for each reproduction device we may know its *resolution* $W_d \times H_d$ [in pixels], and *relative viewing distance* η, expressed in display heights. If instead of relative distance η, we know the absolute *viewing distance* d [in inches], then *display pixel density* ρ [in pixels per inch] or physical dimensions of the screen [in inches] will also be needed to construct the model.

In order to define quality model, we will use two *angular parameters*:

- *viewing angle* ϕ [in degrees] – capturing the horizontal angular size of video, as seen by the viewer on the screen, and
- *angular resolution* u [in cycles per degree] – expressing the highest possible spatial frequency that may be present in the encoded video. This is effectively translation of Nyquist frequency reproducible by the video to cycles per degree units.

We provide formulae connecting the above angular parameters to standard parameters of viewing setup in Table I.

TABLE I. Relationships Between Parameters of Viewing Setup

Parameter	Notation / formula	Units
Height of encoded video	H	Pixels
Width of encoded video	W	Pixels
Height of displayed video	H_p	Pixels
Height of displayed video	W_p	Pixels
Display pixel density	ρ	Pixels per inch
Viewing distance in inches	d	Inches
Viewing distance in display heights	$\eta = \frac{d\rho}{H_p}$	Display heights
Horizontal viewing angle	$\phi = 2\arctan\left(\frac{W_p}{2d\rho}\right) = 2\arctan\left(\frac{W_p}{2\eta H_p}\right)$	Degrees
Maximum horizontal spatial frequency (Nyquist) reproducible by the display	$u_d = \left(2\arctan\left(\frac{1}{d\rho}\right)\right)^{-1} = \left(2\arctan\left(\frac{1}{\eta H_p}\right)\right)^{-1}$	Cycles per degree
Maximum horizontal spatial frequency (angular resolution) that can be present in encoded video	$u = \left(2\arctan\left(\frac{W_p/W}{d\rho}\right)\right)^{-1} = \left(2\arctan\left(\frac{W_p/W}{\eta H_p}\right)\right)^{-1}$	Cycles per degree

C. Quality model based on viewing setup parameters

As basic model of perceived quality based on the parameters of viewing setup, we will use the well-known model of J. Westerink and J. Roufs [17]. The specific formula that we will use in our work comes from [24]:

$$Q_{WR}(\phi, u) = \ln\left(a + b\left(1 + \left(\frac{\phi}{\phi_s}\right)^{-k}\right)^{-\frac{c}{k}}\left(1 + \left(\frac{u}{u_s}\right)^{-l}\right)^{-\frac{d}{l}}\right), \quad (1)$$

where $a = 2.718$, $b = 145.69$, $c = 1.55$, $d = 2.12$, $k = 6.01$, $l = 2.11$, $\phi_s = 35.0$, and $u_s = 16.93$ are the constants. This model predicts how the parameters of viewing setup (and specifically, viewing angle ϕ, and angular resolution u) impact the perceived quality of videos projected on the screen.

D. Quality models based on distortion measures

We are now ready to introduce parametric models proposed in this paper. In the most general form, they can be expressed as:

$$Q(D,\phi,u) = \alpha + \beta\big(1+\gamma Q_{WR}(\phi,u)\big)\, Q_D(D) + \delta Q_{WR}(\phi,u), \quad (2)$$

where $Q_{WR}(\phi,u)$ is a Westerink-Roufs model, $Q_D(D)$ is a fitting function for translating distortion scores to MOS domain, and where α, β, γ, and δ are the calibration constants.

We note, that in a special case when both parameters $\gamma = \delta = 0$, the model (1) turns into a direct mapping of distortion scores to MOS:

$$Q(D) = \alpha + \beta\, Q_D(D). \quad (3)$$

In a case when $\gamma = 0$, but $\delta > 0$, the proposed model (1) treats the impacts of distortion (D) and viewing factors (ϕ, u) as additive terms in the overall quality expression:

$$Q'(D,\phi,u) = \alpha + \beta\, Q_D(D) + \delta\, Q_{WR}(\phi,u).$$

Finally, when $\delta > 0$, but $\gamma \gg 1$, the model uses multiplicative coupling of effects of distortion and viewing-related factors:

$$Q''(D,\phi,u) \sim \alpha + \beta\gamma\, Q_{WR}(\phi,u) \cdot Q_D(D).$$

In other words, by using two fitting parameters γ and δ these models can exploit both additive and multiplicative effects in combinations of distortion-based and viewing-based factors.

For translation of PSNR, SSIM and VIF scores to MOS, we will use the standard logistics function:

$$Q_D(D) = f(D,\varepsilon,\zeta) = \frac{1}{1+\exp(-\varepsilon(D-\zeta))}, \quad (4)$$

where ε defines the slope, and ζ defines the mid-point of this function. For translation of VMAF scores to MOS, we will use linear model:

$$Q_D(D) = D, \quad (5)$$

since it is known that by design, VMAF is trained to operate at DMOS scale.

The full set of models and their parameters that we will be considering in this paper is presented in Table II.

TABLE II. PROPOSED QUALITY MODELS

Quality models	**Distortion metric D**	**Function $Q_D(D)$**	**Model formula**	**Model Parameters**
WR+PSRN2MOS	PSNR	$f(D,\varepsilon,\zeta)$	(2)	$\alpha,\beta,\gamma,\delta,\varepsilon,\zeta$
WR+SSIM2MOS	SSIM	$f(D,\varepsilon,\zeta)$	(2)	$\alpha,\beta,\gamma,\delta,\varepsilon,\zeta$
WR+VIF2MOS	VIF	$f(D,\varepsilon,\zeta)$	(2)	$\alpha,\beta,\gamma,\delta,\varepsilon,\zeta$
WR+VMAF2MOS	VMAF	D	(2)	$\alpha,\beta,\gamma,\delta$
PSNR2MOS	PSNR	$f(D,\varepsilon,\zeta)$	(3)	$\alpha,\beta,\varepsilon,\zeta$
SSIM2MOS	SSIM	$f(D,\varepsilon,\zeta)$	(3)	$\alpha,\beta,\varepsilon,\zeta$
VIF2MOS	VIF	$f(D,\varepsilon,\zeta)$	(3)	$\alpha,\beta,\varepsilon,\zeta$
VMAF2MOS	VMAF	D	(3)	α,β
xPSNR2MOS	$\uparrow$ PSNR	$f(D,\varepsilon,\zeta)$	(3)	$\alpha,\beta,\varepsilon,\zeta$
xSSIM2MOS	$\uparrow$ SSIM	$f(D,\varepsilon,\zeta)$	(3)	$\alpha,\beta,\varepsilon,\zeta$
xVIF2MOS	$\uparrow$ VIF	$f(D,\varepsilon,\zeta)$	(3)	$\alpha,\beta,\varepsilon,\zeta$
xVMAF2MOS	$\uparrow$ VMAF	D	(3)	α,β

The top 4 models in Table II are our main parametric models translating distortions and viewing factors to MOS scores. These models use full set of parameters according to formula (2). We name them as *"WR+<distortion>2MOS"*, where distortion metric can be either PSNR, SSIM, VIF, or VMAF. In all cases, the distortion metrics are assumed to be computed at encoded video resolutions.

The remaining models define direct mappings between distortion metrics and MOS scores. They are defined by using simplified model formula (3). We will use them for comparison purposes. There are 2 sets of such models. The first set uses names *"<distortion>2MOS"*, with all same distortion metrics and their meanings as in first 4 models. The second set uses names *"x<distortion>2MOS"*, where prefix "x" implies that distortion is computed not at resolution as encoded, but rather in upscaled form, where both the original video and decoded one are upscaled to match the anticipated resolution of the display, and then distortion is computed by comparing such larger videos.

III. EXPERIMENTAL STUDY OF THE PROPOSED MODELS

A. Devices and datasets

The parameters of target devices and data bases that we used in our work are summarized in Table III. These datasets come from several sources [30,34,35], and they all have been used extensively in studies on visual quality topics in the past.

TABLE III. DEVICES AND DATASETS USED IN THIS WORK

Parameter	**UHDTV**	**HDTV**	**Mobile**
Dataset name & reference	AVT-VQDB [34]	Netflix [30]	Mobile VQDB [35]
User devices	55" and 65" UHTVs	Consumer-grade TVs	6.39" smartphones
Viewing distance	1.5H	3H	3.67H
Display resolution	3840x2160	1920x1080	2340x1080
Display area used	Full screen	Full screen	1920x1080
Viewing angle [degrees]	61.3	33	27.2
Display Nyquist [cpd]	28.28	28.28	34.6
Resolutions of encoded videos [pixels→cpd]	480x360→4.71 1280x720→9.42 1920x1080→14.1 3840x2160→28.3	384x288→5.65 512x384→7.54 720x480→10.60 1280x720→18.85 1920x1080→28.3	1920x1080→34.6
Color space / dynamic range	BT.709 / SDR	BT.709 /SDR	BT.709 /SDR
Number of videos	30	70	128

As shown in Table III, our datasets include devices with a broad range of form factors: from 6" mobiles to 65" UHDTVs. The gap in relative viewing distances is also considerable: from 1.5 to 3.67 heights. The smallest encoded resolutions are 288p, the highest 2160p. All videos in datasets are progressively scanned, have 16:9 DAR, BT.609 colors and SDR transfer functions. The data sets include many files with broad variety of visual content and artifacts introduced by transcoding them at different bitrates and resolutions.

For our study, we have used absolute MOS scores (not relative or DMOS scores) as reported in the datasets. We did, however, recomputed all objective distortion metrics for videos in datasets. This was done to ensure consistency of our data. To compute all metrics, we used FFmpeg tool [36]. In computation of scaled metrics, Lanczos3 filter was used for upscaling. For PSNR and SSIM we have used Y-PSNR and Y-SSIM metrics as reported by FFmpeg. For VIF we used the averages of 4 VIF scores as reported by FFmpeg. For computation of VMAF we used libvmaf v2.3.0, integrated in the FFmpeg. Both upscaled and non-scaled versions of all 4 metrics have been computed.

B. *Fitting of models to dataset MOS scores*

For fitting our models, a combined pool of data points was created, including all data points from Mobile data set, plus 2x replicated points from HDTV dataset, and 4x replicated data points from UHDTV dataset. These replication factors have been chosen to ensure that in the combined set, we have a balanced representation of data from each category of receiving devices. For finding model parameters $(\alpha, \beta, \ldots, \zeta)$ we have used MAPLE computer algebra tool [37], and specifically its *Minimize* function. The sum of square differences between model-predicted and actual MOS scores in the combined pool was used as an objective function for minimization.

C. *The results*

The values of optimal parameters found for each of our models are summarized in Table IV.

TABLE IV. MODEL PARAMETERS

Quality models	α	β	γ	δ	ε	ζ
WR+PSRN2MOS	-6.906	6.130	-0.048	1.476	0.228	23.83
WR+SSIM2MOS	-7.181	7.662	-0.089	1.753	7.492	0.777
WR+VIF2MOS	-12.09	12.117	-0.137	2.763	4.846	0.416
WR+VMAF2MOS	-7.682	0.0753	-0.122	2.01		
PSNR2MOS	0	3.86			0.216	23.49
SSIM2MOS	1.106	2.863			11.751	0.789
VIF2MOS	0.831	2.941			8.124	0.408
VMAF2MOS	1.164	0.0286				
xPSNR2MOS	0	4.14			0.212	25.38
xSSIM2MOS	0	6.414			4.963	0.865
xVIF2MOS	0.305	5.461			4.127	0.598
xVMAF2MOS	0.523	0.0428				

The resulting RMSE accuracy values are provided in Table V. These values are provided separately for each dataset, as well as compound average RMSE value as computed across all sets. The lowest RMSE values in each category are shown in bold.

D. *Discussion*

Based on results presented in Table V, we observe that the proposed combined distortion + viewing factors metrics achieve much higher accuracy of matching MOS scores than metrics that rely on distortion alone. The differences are particularly dramatic for simple metrics, such as PSNR and SSIM. E.g. we see that WR+PSNR2MOS reports 0.466 overall RMSE, while PSNR2MOS reports 0.908. Similarly, WR+SSIM2MOS reports 0.441, while SSIM2MOS reports 0.893.

TABLE V. RMSE ACCURACY RESULTS ACROSS DATASETS

Quality models	UHDTV	HDTV	Mobile	Average
WR+PSRN2MOS	0.384	0.396	0.618	0.466
WR+SSIM2MOS	0.369	0.423	0.532	0.441
WR+VIF2MOS	0.356	0.389	**0.362**	0.369
WR+VMAF2MOS	0.303	**0.375**	0.382	**0.354**
PSNR2MOS	0.886	1.105	0.734	0.908
SSIM2MOS	0.891	1.139	0.649	0.893
VIF2MOS	0.901	1.170	0.583	0.885
VMAF2MOS	0.830	1.103	0.629	0.854
xPSNR2MOS	0.859	0.884	0.710	0.818
xSSIM2MOS	0.839	0.842	0.592	0.757
xVIF2MOS	0.418	0.739	0.470	0.543
xVMAF2MOS	**0.286**	0.422	0.396	0.364

We also note that our proposed metrics *outperform metrics relying on upscaling of videos* to display resolution. As expected, upscaling shows somewhat improved performance, but the combination of non-scaled metrics using our parametric approach seems to work even better. This can be easily followed noting that RMSE for WR+PSRN2MOS ~ 0.466 vs xPSNR2MOS ~ 0.818, or that for WR+SSIM2MOS ~ 0.441 vs xSSIM2MOS ~ 0.757.

However, the most surprising is that all above improvements seem to stay in place not only for simple metrics such as PSNR and SSIM, but also for much more complex ones – VIF and VMAF, which both exploit multi-scale processing, and statistical models. We notice that WR+VIF2MOS achieves RMSE of 0.369, easily beating upscaled VIF: xVIF2MOS ~ 0.543, and that WR+VMAF2MOS, computed without upscaling, achieves overall RMSE of 0.354, which is also better than overall RMSE of upscaled VMAF xVMAF2MOS ~0.364.

The only case, in which regular upscaled VMAF has performed better than our WR+VMAF2MOS, was in fit to UHDTV dataset. It seems that characteristics of this device are simply closer to the training dataset that was used in the design phase of VMAF. But then performance of scaled VMAF on other devices is worse, as well it is slightly worse overall.

These findings confirm the merits of our proposed technique of incorporating parameters of viewing setups for improved predictions of MOS scores on different devices.

IV. CONCLUSIONS

Several parametric models for predicting visual quality scores on different devices have been proposed. The proposed models utilize basic distortion metrics (PSNR, SSIM, VIF, or VMAF) and also use parameters of viewing setup to arrive at final predicted scores. The effectiveness of proposed models has been validated by using datasets with MOS measurements on standard TV sets, UltraHD TV sets, and mobiles. The obtained results confirm the improved accuracy of the prediction of MOS scores by the proposed techniques. Other practical benefits and applications of the proposed techniques are also discussed.

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