QoE-aware Video Resolution Thresholds Computation for Adaptive Multimedia

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***Abstract*—Multimedia streaming to mobile devices is one of the main sources of network congestion. As bandwidth requirements are continually increasing and users are becoming more quality-aware, there is a growing need for QoE-aware multimedia adaptation solutions. This paper presents a novel mechanism named ResCompute, which enables to automatically compute threshold values up to which the video resolution can be decreased while still maintaining a predefined QoE level. The mechanism combines full-reference objective VQA metrics and rules for mapping their values to the subjective MOS scale. The results from a subjective study with 60 participants show that mapping rules for full-reference VQA metrics such as PSNR, SSIM and VIFp provide up to 72.22% MOS level match accuracy across different categories of multimedia clips. Moreover, accurate resolution threshold values computation requires careful selection of the VQA metrics mapping rules to balance the under and overestimation of subjective video quality.**

***Index Terms*—Multimedia quality, QoE, objective and subjective quality assessment, content adaptation and scaling.**

I. Introduction

Mobile devices such as smartphones and tablets are becoming more powerful and affordable, and are being used for a multitude of activities including online multimedia applications such as IPTV, VoD, video chat and multimedia-based learning. However, multimedia streaming to mobile devices is a resource intensive task that requires significant network bandwidth, computation and battery power to stream, to decode and to display the content [1]. Although 5G technologies will increase capacity and newer video codecs such as HEVC provide higher video compression efficiency, network providers will continue to struggle with congestion. In fact, the mobile video traffic was estimated to increase 8-fold between 2015 and 2020, and to account for 75% of the total mobile data traffic [2]. At the same time, mobile users are becoming increasingly quality-aware with the proliferation of high-resolution displays and multimedia content.

In this context, there is an increasing need for QoE-aware solutions [3], to enhance or complement existing standards such as MPEG-DASH [4]. While QHD and UHD screen resolutions are increasingly used in mobile devices, previous research has shown that UHD 2160p video resolution has little benefit in terms of user perceived video quality over full-HD 1080p video resolution [5].

This paper presents a novel mechanism (ResCompute) for automatic computation of threshold values up to which the video resolution can be decreased while still maintaining a predefined QoE level. The ResCompute mechanism uses full-reference objective VQA metrics and rules for mapping their continuous values to the discrete subjective MOS scale (i.e., 1 – bad, 2 – poor, 3 – fair, 4 – good and 5 – excellent). Full-reference metrics are used because the ResCompute mechanism is primarily intended for video on demand applications, and the resolution threshold values are computed offline for each multimedia clip. However, the mechanism could be extended to use reduced-reference [6] or no-reference [7] metrics for live streaming application. While a multitude of objective VQA metrics have been proposed, previous research studies have focused on evaluating their performance in terms of correlation after nonlinear regression, without mapping their values to the discrete MOS scale [8], [9]. Moreover, the evaluation was typically done on generic video content databases that consist mainly of natural clips such as news, sports and movies [10]. Non-natural clips that are typically computer generated such as animations were often excluded as they were considered to complicate the metrics' evaluation [9].

This paper also presents objective and subjective results that investigate how choosing different VQA metrics mapping rules, impacts on the resolution threshold computation. The investigation is done for both natural and non-natural multimedia clips. Moreover, the investigation compares six mapping rules corresponding to three full-reference metrics PSNR, SSIM and VIFp. The selected metrics are highly representative as they correspond to different categories: traditional point-based, natural visual statistics-based, and perceptual HVS modelling-based metrics respectively [8].

The rest of the paper is structured as follows. Section II presents an adaptive multimedia framework that incorporates the proposed ResCompute mechanism, and details the procedure used for computing the resolution threshold values. Section III present the setup for the objective and subjective study, while section IV presents the results analysis. section V concludes the paper and presents future work directions.

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II. DQAMLearn Framework Overview

DQAMLearn is an adaptive framework that aims to support educational multimedia content delivery to mobile devices, and to provide learners with a good QoE even in resource constrained situations. The framework will be integrated within the large pan-European learning platform that is curently being built by NEWTON [11], a large scale EU Horizon 2020 project. The platform will integrate and deploy a multitude of novel mechanisms and technologies, including: interconnected fab labs and virtual labs, multi-modal and multi-sensorial media distribution, augmented reality, gamification, game-based learning, and self-directed learning. Additionally, the NEWTON platform will perform personalisation and adaptation to improve the learning process, and to increase the learning outcomes and learner QoE. The following subsections provide more details on the multimedia profiling and the novel ResCompute mechanism incorporated by the framework.

A. Multimedia Profiling

The DQAMLearn framework overcomes the multitude of mobile devices users may have by grouping them into a manageable number of device classes based on their screen resolution. Each device class is associated a video profile that would provide an 'excellent' user-perceived video quality level for that particular device class. A video profile is represented by triples of reference values for the video resolution, framerate and bitrate, the three most important encoding parameters affecting the video quality. A particular video profile is represented conceptually as in (1), whereas the set of video profiles associated to the X number of mobile device classes is represented as in (2).

$$VideoProfile_x = \langle RefRES_x, RefFR_x, RefBR_x \rangle \tag{1}$$

$$V = \left\{ VideoProfile_x;\ x = \overline{1, X} \right\} \tag{2}$$

Based on each video profile, the framework creates a reference multimedia clip version $RefMov_x^i$ by transcoding the original multimedia clip $OrgMov^i$, as in (3). The set of reference clip versions that are created is represented as in (4).

$$OrgMov^i \xrightarrow[VideoProfile_x]{Transcoding} RefMov_x^i \tag{3}$$

$$M = \left\{ RefMov_x^i;\ x = \overline{1, P^i};\ P^i \leq X \right\} \tag{4}$$

where i is the clip index, while P^i is the number of reference versions created for that particular clip. P^i can be lower than the number of device classes X because a reference clip version is created only if the video resolution for that profile is lower or equal to the video resolution of the original clip.

The DQAMLearn framework builds on our preliminary research work, that proposed multimedia profiling recommendations in terms of video and audio encoding characteristics for five classes of mobile devices covering a broad range of display resolutions, that were proposed for the wireless streaming scenario in [12].

B. QoE-aware Resolution Threshold Values Computation

Due to various resource constraints such as limited network bandwidth, in often situations it may not be possible to efficiently stream the reference clip version $RefMov_x^i$ that would provide an excellent quality level for a particular mobile device. The DQAMLearn framework would continuously monitor the network performance, and if necessary it will switch to another reference clip version having a lower resolution value, $RefMov_y^i$ where $y < x$.

To avoid streaming a clip version whose video quality would be too low to support a good QoE, the framework incorporates the novel ResCompute mechanism. ResCompute enables to compute threshold values indicating how much the video resolution can be decreased from the reference value while still maintaining a predefined user-perceived video quality level named MOS threshold ($ThMOS$). A MOS threshold is specified on a discrete 5-point scale with subjective meaning for each level (i.e., 1 – bad, to 5 – excellent). The resolution threshold values corresponding to $ThMOS$ are computed separately for each reference clip version $RefMov_x^i$, and for each multimedia clip to account for video content complexity.

The ResCompute makes use of full-reference objective VQA metrics to estimate the video quality of the lower resolution clip version $RefMov_y^i$ relative to the quality of the reference version $RefMov_x^i$. Multiple VQA metrics could be combined in order to increase the overall quality estimation performance [13], as in (5). The weights for the different VQA metrics could be assigned based on training data from public VQA databases [10], by taking into account the performance of each metric for different video content and resolution.

$$EMOS_y^i = \sum_{n=1}^{N} W_{VQAM_n} \cdot MOS_{VQAM_n,y}^i \tag{5}$$

where $MOS_{VQAM_n,y}^i$ is the quality estimated with the $VQAM_n$ metric, W_{VQAM_n} is the weight associated to this metric in the overall score, while N is the number of metrics.

Objective VQA metrics express video quality on continuous scales with no meaning (e.g., 0 – 100 for PSNR, 0 – 1 for SSIM and VIFp), thus the objective values are mapped to equivalent MOS scores on the subjective 5-point scale, as in (6).

$$Q_{VQAM_n,y}^i \xrightarrow{Mapping\ Rule} MOS_{VQAM_n,y}^i \tag{6}$$

Since video quality is non-linear, the conversion of objective values to equivalent MOS scores is done based on predefined mapping rules. Despite the multitude of VQA metrics, very few papers have proposed mapping rules to interpret the objective values. Table I presents mapping rules that were identified in the literature for the PSNR and SSIM metrics [14], [15]. Additionally, the table presents mapping rules for the three metrics that were automatically generated based on data from public VQA databases, by making use of the novel VQAMap mechanism proposed by us in [16], [17]. The mapping rules for the same VQA metric are different as they were generated based on different content.

TABLE I
RULES FOR MAPPING THE VALUES OF PSNR, SSIM AND VIFP FULL-REFERENCE OBJECTIVE VQA METRICS TO THE SUBJECTIVE MOS SCALE.

MOS	**PSNR**$^{(K)}$ [14]	**PSNR**$^{(Z)}$ [15]	**PSNR**$^{(M)}$ [16]	**SSIM**$^{(Z)}$ [15]	**SSIM**$^{(M)}$ [16]	**VIFp**$^{(M)}$ [16]
5 (Excellent)	≥37	≥45.0	≥36	≥0.99	≥0.93	≥0.56
4 (Good)	≥31 & <37	≥33.0 & <45.0	≥29 & <36	≥0.95 & <0.99	≥0.85 & <0.93	≥0.40 & <0.56
3 (Fair)	≥25 & <31	≥27.4 & <33.0	≥24 & <29	≥0.88 & <0.95	≥0.76 & <0.85	≥0.27 & <0.40
2 (Poor)	≥20 & <25	≥18.7 & <27.4	≥20 & <24	≥0.50 & <0.88	≥0.62 & <0.76	≥0.16 & <0.27
1 (Bad)	<20	<18.7	<20	<0.50	<0.62	<0.16

Algorithm 1: Resolution threshold computation algorithm.

Input:
$ThMOS$ — Predefined threshold level for the estimated user-perceived video quality;
RES_x^i — Set of reference resolution values that are lower or equal with the resolution of $RefMov_x^i$ reference clip version.

Output:
$ThRES_x^i$ — Resolution threshold value corresponding to $ThMOS$ and the $RefMov_x^i$ reference clip version.

Procedure:

begin
  // Initialisation
  $FoundTh =$ FALSE ; // threshold not found
  $w = x - 1$; // check lower resolution values in decresing order
  // Threshold computation
  while $(w \geq 1)$ **and** $(FoundTh =$ FALSE$)$ **do**
    Compute $EMOS_y^i$ as in (5) ;
    if $(EMOS_y^i < ThMOS)$ **then**
      $w = w + 1$;
      $ThRES_x^i = RefRES_y$; // threshold is set to previous value
      $FoundTh =$ TRUE ;
    else // proceed to check next resolution
      $w = w - 1$
    end if
  end while
  if $(FoundTh =$ FALSE$)$ **then**
    $ThRES_x^i = RefRES_{y=1}$; // threshold is set to lowest resolution value
  end if
end

Algorithm 1 illustrates the procedure used by the ResCompute mechanism to compute the resolution threshold value $ThRES_x^i$ for the reference clip version $RefMov_x^i$. Along with $ThMOS$, the mechanism takes as input the set of reference resolutions RES_x^i that are lower and equal with $RefRES_x$, represented as in (7).

$$RES_x^i = \left\{RefRES_y, y = \overline{1,x}\right\} \tag{7}$$

ResCompute gradually iterates through the reference resolutions in a decreasing order, estimates the user-perceived quality of each lower resolution version $EMOS_y^i$, and compares this against the $ThMOS$ threshold taken as input. The set of estimated user-perceived quality values for all the lower resolution clip versions, is represented as in (8).

$$EMOS_{RES_x^i} = \left\{EMOS_y^i,\ y = \overline{1,x-1}\right\} \tag{8}$$

The resolution threshold value computation process stops when QuTComute encounters a clip version for which the estimated user-perceived quality $EMOS_y^i$ is lower than the predefined user-perceived quality threshold $ThMOS$. In this case the resolution threshold value $ThRES_x^i$ is taken as the last resolution value for which $EMOS_y^i \geq ThMOS$. Alternatively, the process stops after checking all lower resolution clip versions, in which case the resolution threshold is set as the lowest reference resolution value $RefRES_{y=1}$.

III. TEST SETUP

Objective and subjective testing was conducted to investigate how the performance of ResCompute mechanism is influenced by choosing different mapping rules for the PSNR, SSIM and VIFp metrics. As Table I shows, the mapping rules for the same metric vary considerably. Selecting between different mapping rules can have practical implications, as it may lead to under or overestimation of user-perceived video quality. For example, a PSNR value of 40 dB corresponds to 'excellent' quality level according to [14] and [16], but only to 'good' level according to [15].

A. Multimedia Test Sequences

Six high-quality clips were used for the objective and subjective testing. Three clips are natural (i.e., ArtOfBook, NitrogenIceCream and ProjectPlanning), while three clips are non-natural (i.e., AtomSize, CoralsIntro and PhotoEditing). The clips correspond to six different categories of educational multimedia clips as detailed in [18].

A 4 min long continuous test sequence was extracted from each multimedia clip. Five versions were created for each multimedia test sequence in order to illustrate the principle of the ResCompute mechanism. The reference clip version for threshold values computation had a video resolution of 1280×720 pixels, while the resolution of the lower quality versions were: 848×480, 640×360, 427×240 and 320×180 respectively. The reference framerate value was 30 fps for all five versions. The reference video bitrate values providing an excellent quality level for the five resolutions were selected as: 1800, 1000, 550, 300 and 165 kbps. These were based on the multimedia profiling recommendations for wireless streaming of H.264 encoded videos to mobile devices presented in [12]. Apart of video resolution and bitrate all other video and audio encoding settings were maintained constant.

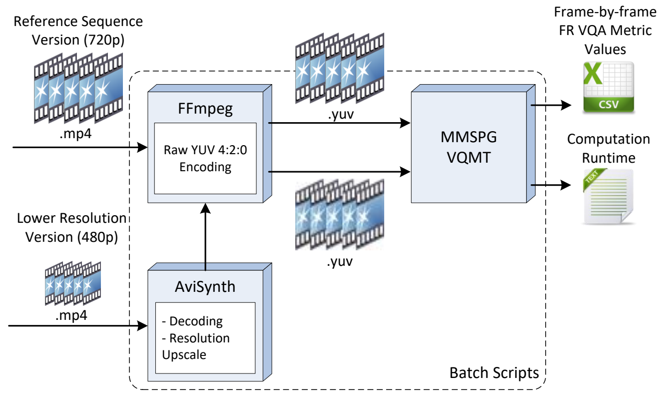

Fig. 1. Procedure used for measuring the PSNR, SSIM and VIFp full-reference objective VQA metrics for the lower resolution versions.

B. Objective VQA Metrics Measurement Procedure

Fig. 1 illustrates the batch processing procedure used for measuring the full-reference objective VQA metrics by considering the 720p reference sequence and a corresponding version with lower resolution such as 480p, both compressed with H.264 video codec in .mp4 format. AviSynth [19] nonlinear video editor was used for performing on-the-fly video editing without the need for recompression. Since full-reference VQA metrics require spatio-temporal synchronisation, the resolution of the lower quality version was upscaled to the 720p value of the reference sequence version using the `BicubicResize()` function from AviSynth.

The MMSPG Video Quality Measurement Tool (VQMT) [20], was used to compute the PSNR, SSIM and VIFp objective metric values. The tool requires as input uncompressed files, thus the reference version and the corresponding upscaled version were converted to raw YUV format using FFmpeg [21]. The tool computes the specified metric for each frame and saves the values in a .csv file. The metric value for a particular test sequence is then computed as the average across all frames.

C. Subjective Testing Procedure

The subjective study was conducted with 60 non-expert volunteer participants (37 males, 23 females), aged between 20 to 53 years old. For the subjective study each quality level corresponding to the reference and lower resolution values was displayed for a 15 sec interval of the 4 min long test sequence. The participants were asked to view the test sequences and continuously rate their perceived video quality.

The subjective study followed the standardised Single Stimulus Continuous Quality Evaluation (SSCQE) procedure, and used a calibrated 0 – 100 continuous scale with annotated discrete MOS levels (i.e., 0 – 19 'bad' to 80 – 100 'excellent') [22]. The rating was done using an on-screen slider displayed over the video player. The viewing and rating of the test sequences was done on a tablet device, having a 7 inch screen size and 1280×800 resolution.

Using long test sequences with changing quality level enables a real-world like multimedia viewing experience, and was preferred to displaying the same short sequence with different quality level multiple times. To minimise the impact of factors such as fatigue the six test sequences were displayed in random order across the participants.

IV. Test Results

A. Objective Results Analysis

The objective analysis was conducted in order to investigate how the estimated user-perceived quality and the resolution threshold values computed by ResCompute would be impacted by choosing a different VQA metric mapping rule.

Fig. 2 presents the objective video quality assessment results. The plots present the average PSNR, SSIM and VIFp values for each lower resolution test sequence version (i.e., 480p, 360p, 240p and 180p), computed relative to the corresponding 720p reference version. The greyscale bands in the plots indicate the equivalent QoE levels on the 5-point MOS scale (i.e., 1 – 'bad' to 5 – 'excellent'), based on the six mapping rules from Table I.

The results show that the three metrics considered exhibit a slightly different behaviour. In particular, the PSNR and VIFp decrease approximately linear with the decrease in video resolution, while SSIM presents a more concave decrease. The three metrics also differ in terms of the range of values covered. The objective VQA metric values cover approximately 20% of the first half of the scale 0 – 100 scale for PSNR, the top 20% of 0 – 1 scale for SSIM, and the middle 50% of the 0 – 1 scale for VIFp. The results also show that the PSNR, SSIM and VIFp values depend on the video content, with the lines corresponding to the different clips being stacked and with few intersections. Moreover, the VQA metrics present lower values for clips with high spatial index such as ProjectPlanning and PhotoEditing, confirming that more detailed clips are more sensitive to the resolution decrease.

Analysing the objective results in terms of equivalent MOS scores, the results show that the resolution threshold value computed by ResCompute would depend not only on the content characteristic but also on the particular VQA metric and the mapping rule used. The $MOS^{(Z)}_{PSNR}$ and $MOS^{(Z)}_{SSIM}$ equivalent scores range from 'good' to 'poor', while the $MOS^{(M)}_{PSNR}$ and $MOS^{(M)}_{SSIM}$ scores range from 'excellent' to 'fair'. As opposed, the $MOS^{(K)}_{PSNR}$ and $MOS^{(M)}_{VIFp}$ range from 'excellent' to 'poor'.

For example, taking as input a $ThMOS$ of 5 – excellent the resolution threshold value computed by ResCompute for the AtomSize test sequence would be: 360p based on $MOS^{(K)}_{PSNR}$, $MOS^{(M)}_{PSNR}$ or $MOS^{(M)}_{VIFp}$, 720p based on $MOS^{(Z)}_{PSNR}$ and $MOS^{(Z)}_{SSIM}$, or 240p based on $MOS^{(M)}_{SSIM}$. The objective results analysis confirm the importance of identifying both accurate VQA metrics and mapping rules, in order to enable accurate computation of the resolution threshold values.

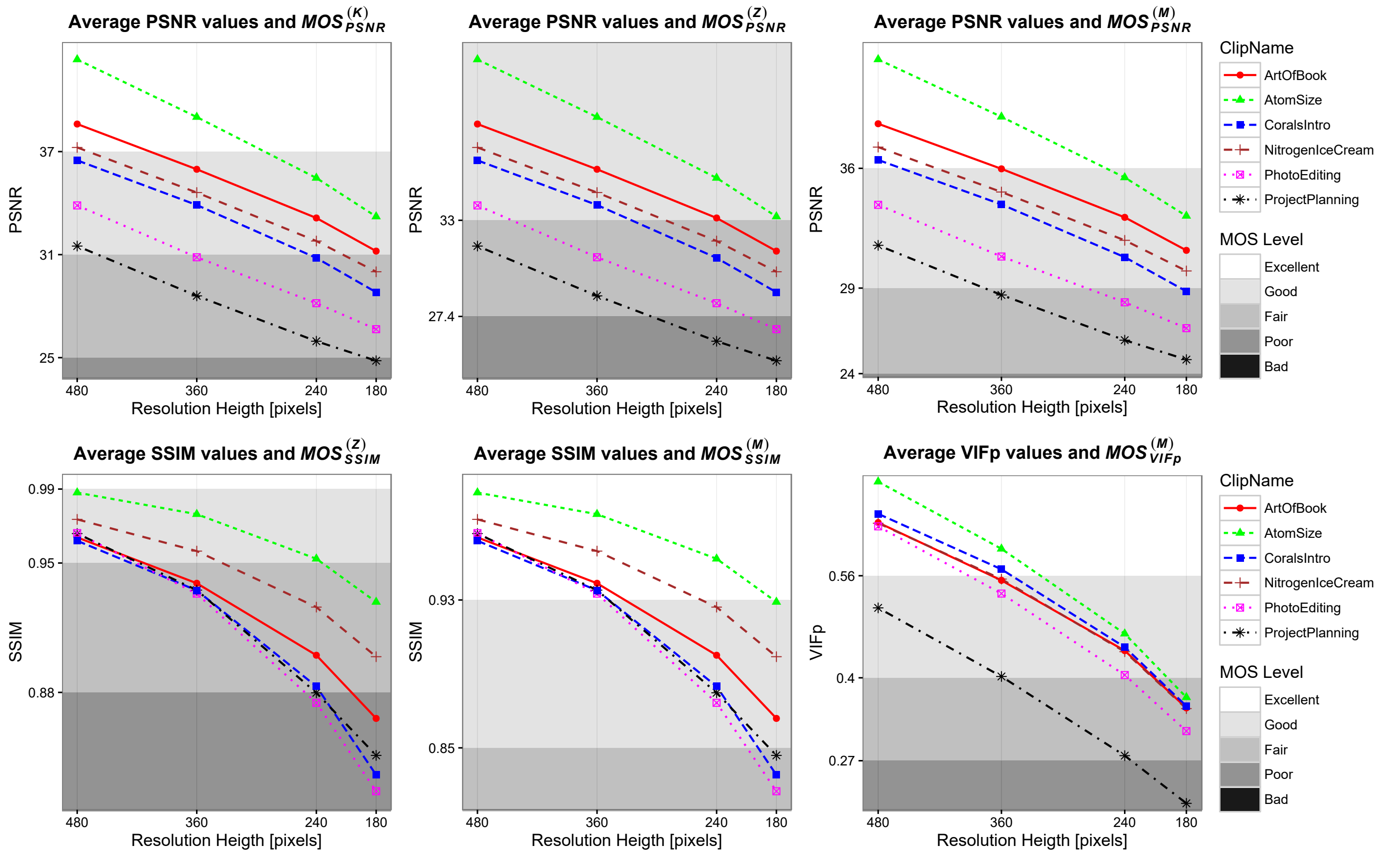

Fig. 2. Average PSNR, SSIM and VIFp values and equivalent MOS scores, for the lower resolution test sequence versions.

B. Subjective Results Analysis

Fig. 3 presents the subjective MOS estimation accuracy results of the six mapping rules for PSNR, SSIM and VIFp metrics. The subjective MOS scores were obtained by averaging the ratings across all 60 participants and across the 15 seconds corresponding to each video resolution. The continuous MOS scores expressed on the $0-100$ scale, were then converted to discrete MOS scores on the $1-5$ scale as in [22] (i.e., $0-19$ to 'bad', $20-39$ to 'poor', $40-59$ to 'fair', $60-79$ to 'good', and $80-100$ to 'excellent').

Fig. 3 present the percentage distributions for three possible cases: exact match (e.g., $MOS^{(K)}_{PSNR} = MOS$), overestimation (e.g., $MOS^{(K)}_{PSNR} > MOS$), and underestimation (e.g., $MOS^{(K)}_{PSNR} < MOS$) of subjective user-perceived video quality. The results are presented separately for the natural clips (i.e., ArtOfBook, NitrogenIceCream and ProjectPlanning), non-natural clips (i.e., AtomSize, CoralsIntro and PhotoEditing), as well as across all six clips.

The subjective results show that the $MOS^{(M)}_{SSIM}$ mapping rule presents the highest accuracy of 72.22%, with the subjective MOS being overestimated for 22.22% and underestimated for 5.58% of test cases (i.e., where a test case represents one quality level for one clip). Moreover, this provides the same performance for both natural and non-natural multimedia clips. The $MOS^{(Z)}_{PSNR}$ and $MOS^{(Z)}_{SSIM}$ mapping rules present the lowest MOS estimation accuracy of 44.44% and 41.67% respectively across all clips. The two mappings tend to underestimate the subjective MOS and the results are consistent when looking separately for natural and non-natural clips.

As opposed, the $MOS^{(K)}_{PSNR}$, $MOS^{(M)}_{PSNR}$ or $MOS^{(M)}_{VIFp}$ present over 60% accuracy across all clips, and tend to be less consistent. When not perfect match, these mapping tend to overestimate the subjective MOS for natural clips and underestimate it for non-natural clips. However, linking back to the objective results, the 360p resolution threshold indicated by these three mappings for the AtomSize clip would strike the balance between the 240p threshold value underestimated by $MOS^{(M)}_{SSIM}$, and the 720p threshold overestimated by $MOS^{(Z)}_{PSNR}$ and $MOS^{(Z)}_{SSIM}$.

V. Conclusions

As users are becoming more quality-aware, and network resources more constrained there is a growing need for QoE-aware multimedia adaptation solutions. This paper presented a novel mechanism for automatic computation of threshold values up to which the video resolution can be decreased while still maintaining a predefined QoE level. The mechanism uses full-reference objective VQA metrics and rules for mapping their values to the subjective MOS scale.

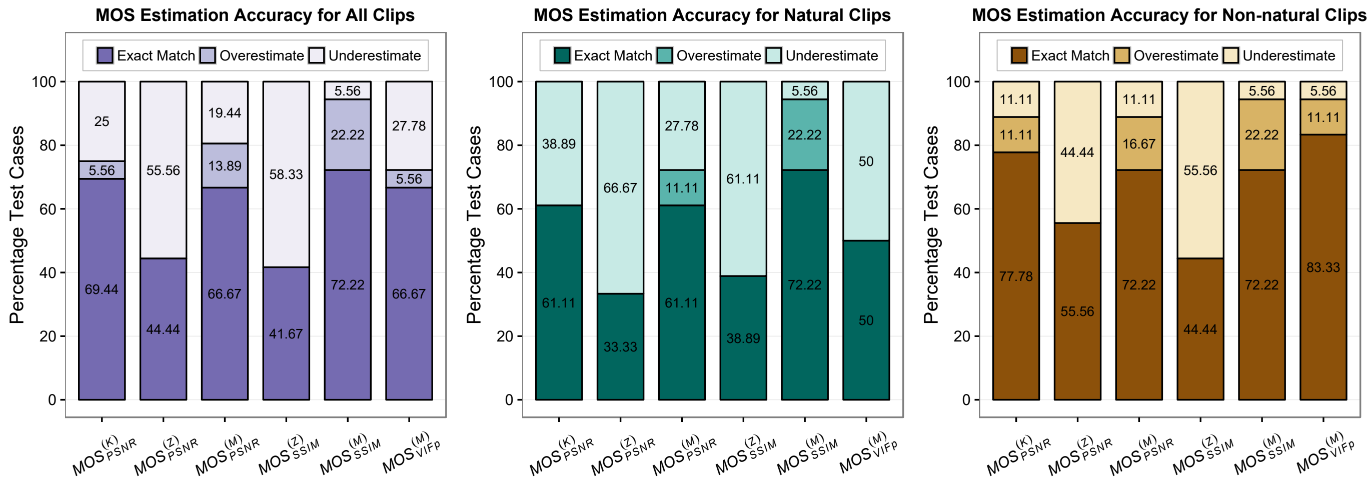

Fig. 3. Subjective MOS estimation accuracy of different PSNR, SSIM and VIFp mapping rules for natural, non-natural and all clips.

The research also investigated how the resolution threshold values computation is influenced by choosing different mapping rules for the PSNR, SSIM and VIFp metrics. The objective results analysts has shown that the VQA metric values are dependant on video content characteristics, and in particular of spatial information when decreasing the video resolution. Therefore, it is necessary to compute the resolution threshold values individually for each multimedia clip.

Moreover, the subjective results analysis has shown that the mapping rules provide good QoE estimation performance with up to 72.22% MOS level match accuracy. However, even for the same VQA metric it is important to carefully choose the mapping rule to find a good balance between underestimating and overestimating the subjective user-perceived quality.

Future work will enhance the proposed multimedia adaptation framework by considering other video characteristics such as bitrate and framerate. Further objective and subjective video quality assessment and data analysis will also be conducted.

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