QUALITY PREDICTION OF ASYMMETRICALLY COMPRESSED STEREOSCOPIC VIDEOS

Jiheng Wang, Shiqi Wang and Zhou Wang

Dept. of Electrical and Computer Engineering, University of Waterloo, Waterloo, ON, N2L 3G1, Canada
Emails: {j237wang, s269wang, zhou.wang}@uwaterloo.ca

ABSTRACT

Objective quality assessment of stereoscopic 3D video is a challenging problem. We carry out a subjective test on symmetrically and asymmetrically compressed stereoscopic videos followed by different levels of low-pass filtering. We observe a strong systematic bias when using direct averaging of 2D video quality of both views to predict 3D video quality. We use a binocular rivalry inspired model to account for the prediction bias, leading to significantly improved quality estimation of stereoscopic videos. The model allows us to quantitatively predict the potential coding gain of asymmetric video compression, and provides new insight on the development of high efficiency 3D video coding schemes.

***Index Terms*—** video quality assessment, stereoscopic video, 3D video, asymmetric compression, HEVC

1. INTRODUCTION

With the fast development of 3D acquisition, communication, processing and display technologies, automatic quality assessment of 3D images and videos has become ever important. Objective quality assessment of stereoscopic images/videos is a challenging problem [1], especially when the distortions are asymmetric, i.e., when there are significant variations between the types and/or degrees of distortions occurred in the left- and right-views. Recent subjective studies suggested that in the case of symmetric distortions of both views, simply averaging state-of-the-art 2D image quality assessment (IQA) measures of both views is sufficient to provide reasonably accurate image quality predictions of stereoscopic images. In particular, in [2], it was shown that averaging PSNR, SSIM [3], MS-SSIM [4], UQI [5] and VIF [6] measurements of left- and right-views performs equally well or better than the advanced 3D-IQA or 3D video quality assessment (VQA) models [7, 8, 9, 10, 11, 12] on LIVE 3D Image Database Phase I. Similar results were also observed in [13], where averaging SSIM and MS-SSIM measurements of both views outperformed advanced 3D-IQA models [7, 9, 10, 14] on LIVE 3D Image Database Phase II. Compared with the case of symmetric distortions, quality assessment of asymmetrically distorted stereoscopic images is much more challenging. In [13], it was reported that there is a large drop in the performance of both 2D-IQA and 3D-IQA models from quality predictions of symmetrically to asymmetrically distorted stereoscopic images on LIVE 3D Image Database Phase II. On the other hand, our previous work [15, 16] revealed a strong distortion type dependent prediction bias when predicting quality of asymmetrically distorted stereoscopic images from single-views.

Studying the impact of asymmetric distortions on the quality of stereoscopic images/videos not only has scientific values in understanding the human visual system, but is also desirable in the practice of 3D video compression and transmission. The distortions involved in 3D video coding/communication are not only compression artifacts. The practical encoder/decoder also needs to decide on whether deblocking filters need to be turned on, and whether mixed-resolutions of the left/rightviews should be used. Mixed-resolution coding, asymmetric transform-domain quantization coding, and postprocessing techniques (deblocking or blurring) may be employed individually or collectively. Previously, the extent of the downsampling ratio that can be applied to a low quality view without a noticeable degradation on 3D quality has been investigated [17, 18, 19, 20]. In [19], symmetric stereoscopic video coding, asymmetric quantization coding and mixed-resolution coding have been compared and the results suggested that mixed-resolution coding achieves the best coding efficiency. However, in the literature, systematic studies on subjective and objective quality assessment of asymmetrically distorted videos are still lacking, making it difficult to directly compare different coding strategies, nor to derive 3D-VQA models that have the potential to be generalized to the case of mixed distortion types and levels to guide asymmetrical 3D video coding.

In this work, we first carry out a subjective quality assessment experiment on a database that contains both symmetrically and asymmetrically compressed stereoscopic videos, as well as videos undergone postprocessing by different levels of Gaussian low-pass filtering. We observe a strong systematic bias when using direct averaging of 2D video quality of both views to predict 3D video quality. We then apply a binocular rivalry inspired model to account for the prediction bias, leading to significantly improved quality estimation of stereoscopic videos. The model allows us to quantitatively predict the potential coding gain of asymmetric video compression, and provides new insight on the development of high efficiency 3D video coding schemes.

2. SUBJECTIVE STUDY

The new Waterloo-IVC 3D Video Quality Database Phase I is created from 4 pristine multi-view 3D videos, i.e., Balloons, Book, Kendo and Lovebird, which are commonly used 3D HEVC testing sequences. The details of the test videos are given in Table 1. The format of all videos is YUV4:2:0. Each single-view video was compressed using an HEVC encoder by five levels of transform-domain quantization with QP = {25, 35, 40, 45, 50} in low-delay main profile. The single-view videos are employed to generate compressed stereoscopic videos, either symmetrically or asymmetrically. There are 11 different kinds of combinations as listed in Table 3. The lower and higher QP views are assigned to the left-view or the right-view randomly. Moreover, for each QP combination, four levels of Gaussian low-pass filtering with $\sigma = \{0, 3.5, 7.5, 11.5\}$ are applied to the higher QP (lower quality) views. Altogether, there are totally 176 3D videos in the database.

There are two important features of the current database when

Table 1. Details of the test videos

	Resolution	Length	Frames/Second	Views
Book	1024×768	6s	16.67	View 6 & View 8
Balloons	1024×768	10s	30.00	View 1 & View 3
Kendo	1024×768	10s	30.00	View 1 & View 3
Lovebird	1024×768	10s	30.00	View 4 & View 6

compared with existing publicly known 3D-VQA databases. First, the current database contains both symmetrically and asymmetrically compressed stereoscopic videos with various QP combinations, which allows us to directly examine the impact of asymmetric compression [21, 22, 23]. Second, the current database contains asymmetrically compressed stereoscopic videos followed by different levels of low-pass filtering, which allow us to study the combined effect of asymmetric compression and postprocessing [24].

The subjective test was conducted in the Lab for Image and Vision Computing at University of Waterloo. The test environment has no reflecting ceiling walls and floor, and was not insulated by any external audible and visual pollution. An ASUS 27" VG278H 3D LED monitor with NVIDIA 3D Vision™2 active shutter glasses is used for the test. The default viewing distance was 3.5 times the screen height. In the actual experiment, some subjects did not feel comfortable with the default viewing distance and were allowed to adjust the actual viewing distance around it. The details of the viewing conditions are given in Table 2. Twenty-two näive subjects, 12 males and 10 females aged from 22 to 35, participated in the study. A 3D vision test was conducted first to verify their ability to view stereoscopic 3D content and no one failed the vision test. As a result, a total of twenty-two subjects proceeded to the formal test. While a visual acuity test was not performed in this study, a verbal confirmation was obtained prior to the experiment and subjects were asked to use their eyeglasses or contact lenses to correct their visual acuities.

Table 2. Viewing conditions of the subjective test

Parameter	Value	Parameter	Value
Subjects Per Monitor	1	Screen Resolution	1920 × 1080
Screen Diameter	27.00"	Viewing Distance	45.00"
Screen Width	23.53"	Viewing Angle	29.3°
Screen Height	13.24"	Pixels Per Degree	65.5 pixels

The subjects were asked to evaluate their overall 3D viewing experience − 3D Video Quality (3DVQ) in this study. Since to visualize every 3D stereoscopic video, the subjects need to readjust their eyes so as to adapt to the content of the scene and establish 3D perception, using a double stimulus approach leads to interruptions of the viewing experience. To reduce this effect, we chose to use the single stimulus procedure using an 11-grade numerical categorical scale (SSNCS) protocol. A general introduction was given at the beginning of the whole test, and more specific instructions and training session were given afterwards. The rating strategy was introduced and the subjects were required to rate training videos until they fully understood the criteria and the strategy. We use three types of videos in the training phase: pristine videos, moderately compressed videos, and highly-compressed videos. The subjects were told to give scores at the high end (close to 10 pts) to the pristine videos, at the mid-range to the moderately compressed videos, and at the low end (close to 0 pts) to the highly-compressed videos.

In the formal test, all stimuli were shown once. The order of stimuli was randomized and the consecutive testing stereoscopic videos were from different source contents. Around 60 stereoscopic videos were evaluated in one session. Each session was controlled to be within 20 minutes and sufficient relaxation periods (5 minutes or more) were given between sessions. Moreover, we found that repeatedly switching between viewing 3D videos and grading on a piece of paper or a computer screen is a tiring experience. To overcome this problem, we asked the subject to speak out a score between 0 and 10, and a customized graphical user interface on another computer screen was used by the instructor to record the score. All these efforts were intended to reduce visual fatigue and discomfort of the subjects.

3. KEY OBSERVATIONS

The raw 3DVQ scores given by each subject were converted to Z-scores and the mean opinion scores (MOS) for each 3D video was then computed.

Given the subjective data, the first question we would like to ask in the current paper is how single-view 2D video quality predicts 3D video quality, especially for the case of asymmetrically distorted 3D videos. The most straightforward 2D-to-3D quality prediction method is to average the qualities of the left- and right-view videos. Table 4 reports Spearman's rank-order correlation coefficient (SRCC) between 3D MOS and the average of 2D-IQA/VQA predictions including PSNR, SSIM, MS-SSIM, IW-SSIM [25], and VQM [26] by different test groups. Higher SRCC value indicates better consistency with human opinions of quality. From Table 4, it can be observed that accurate predictions are obtained in the category of symmetrically compressed 3D videos. By contrast, the performance drops significantly for asymmetrically compressed 3D videos. In [15, 16], we reported that for JPEG compression, average prediction overestimates 3D quality (or 3D quality is more affected by the poorer quality view). More importantly we found that for blockiness, the bias of the averaging prediction model increases with the level of distortions, and thus whether the bias is pronounced depends on the quality range being investigated. With respect to blockiness created from HEVC compression, this overestimated prediction bias is still pronounced, but not as strong as JPEG compression, which is probably due to the reduction of blocking artifacts in HEVC.

From Table 4, it can be observed that the direct averaging model performs well for 3D videos without postprocessing (by Gaussian blurring). By contrast, the SRCC values drop significantly for videos with postprocessing. The left column of Fig. 1 shows the corresponding scatter plots, where the simple averaging prediction model generates substantial bias on many stereoscopic videos. In [15, 16], we reported that for blurriness, average prediction often underestimates 3D quality (or 3D quality is more affected by the better quality view). Here the same kind of prediction bias is clearly observed as direct averaging of state-of-the-art 2D-IQA/VQA metrics always underestimates 3D video quality for these post-processed videos.

The second question we would like to ask is how the Gaussian low-pass post-filtering affects the perceptual 3D quality of asymmetrically compressed stereoscopic videos. Table 3 reports 3D MOS changes after applying different levels of Gaussian low-pass filtering with respect to different QP combinations and different blurring levels. From Table 3, it can be observed that for symmetrically compressed 3D videos, blurring reduces perceptual 3D video quality in most cases. By contrast, for asymmetrically compressed 3D videos, blurring on the higher QP (lower quality) views improves the perceptual 3D video quality in almost all cases. Generally, the improvement increases with the level of blurring and with the difference between QP_l and QP_h. This preliminary analysis verifies that the adoption of certain postprocessing techniques such as blurring could improve the efficiency of stereoscopic video coding.

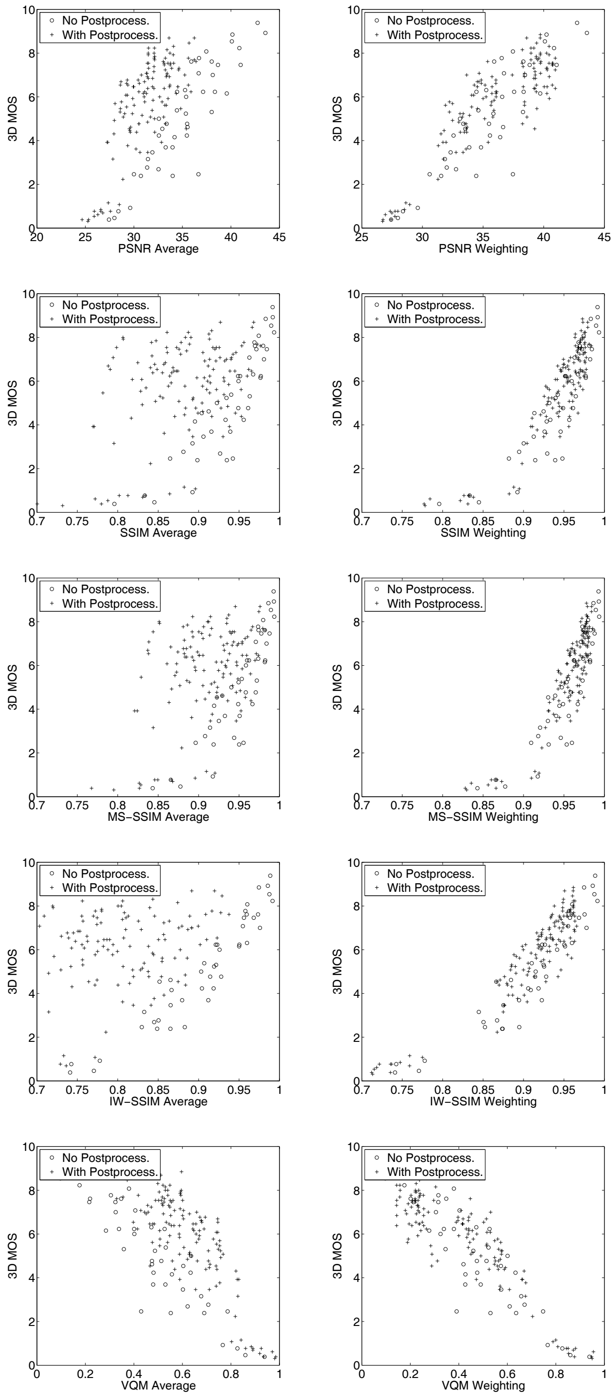
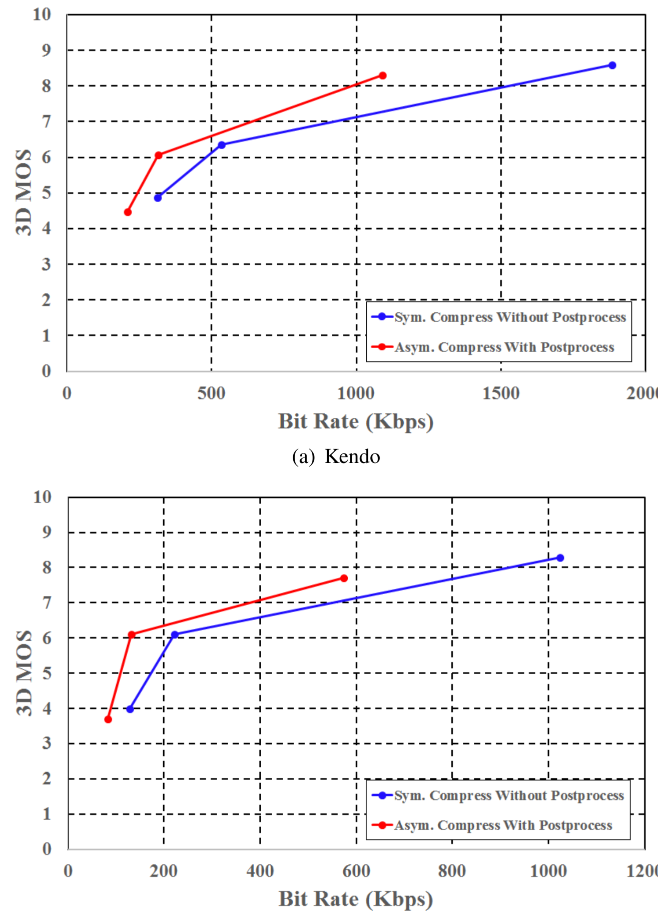


Fig. 1. 3D MOS versus predictions from 2D PSNR, SSIM, MS-SSIM, IW-SSIM, and VQM of single-views. Left column: direct averaging of left- and right-views; Right column: proposed weighting scheme.

Table 3. 3D MOS changes after applying different levels of Gaussian blurring as postprocessing

QP_l	QP_h	$\sigma = 0$	$\sigma = 3.5$	$\sigma = 7.5$	$\sigma = 11.5$	Average
25	25	0.00%	-12.50%	-18.43%	-12.72%	-14.55%
25	35	0.00%	-1.72%	-4.07%	-0.78%	-2.19%
25	40	0.00%	+12.43%	+10.12%	+10.82%	+11.12%
25	45	0.00%	+3.63%	+30.22%	+25.60%	+19.82%
25	50	0.00%	+45.30%	+90.79%	+80.56%	+72.22%
35	35	0.00%	+0.47%	- 9.82%	-5.78%	-5.04%
35	45	0.00%	+30.20%	+31.83%	+41.35%	+34.46%
35	50	0.00%	+38.53%	+82.64%	+98.89%	+73.35%
40	40	0.00%	-5.86%	+1.68%	-1.80%	-1.99%
40	50	0.00%	+29.01%	+63.15%	+73.84%	+55.33%
50	50	0.00%	+31.67%	+17.92%	-13.75%	+11.95%
Average		0.00%	+15.56%	+26.91%	+26.93%	+23.13%



(a) Kendo

(b) Lovebird

Fig. 2. R-D performance comparison in terms of 3D MOS.

In addition, the rate-distortion (R-D) performance in terms of the 3D MOS for the symmetric compression without postprocessing and asymmetric compression with postprocessing is demonstrated in Fig. 2. It can be observed that a significant bit rate reduction is achieved for the asymmetric compression with postprocessing method, which further verifies the effectiveness of asymmetric compression with postprocessing in improving the efficiency of stereoscopic video coding.

Table 4. SRCC Performance comparison of 2D-to-3D quality prediction models on Waterloo-IVC 3D video database

Method	Sym. Compress.	Asym. Compress.	No Postprocess.	With Postprocess.	Direct Average	Proposed Weighting
PSNR	0.9543	0.8226	0.8799	0.6469	0.5469	0.8100
SSIM	0.9470	0.7960	0.9063	0.2668	0.3128	0.8531
MS-SSIM	0.9470	0.7990	0.9049	0.2727	0.3209	0.8453
IW-SSIM	0.9617	0.9017	0.9529	0.3129	0.2961	0.8870
VQM	0.9529	0.8283	0.8953	0.7103	0.6463	0.8378

4. 2D-TO-3D QUALITY PREDICTION METHOD

Let $(I_{i,r,l},\ I_{i,r,r})$ and $(I_{i,d,l},\ I_{i,d,r})$ be the i-th left and right frames of the reference and compressed stereoscopic videos, respectively. We first create their local energy maps by computing the local variances at each spatial location, i.e., the variances of local image patches extracted around each spatial location, for which an 11×11 circular-symmetric Gaussian weighting function $\mathbf{w} = \{w_i | i = 1, 2, \cdots, N\}$ with standard deviation of 1.5 samples, normalized to unit sum ($\sum_{i=1}^{N} w_i = 1$), is employed. The resulting energy maps are denoted as $E_{i,r,l}$, $E_{i,r,r}$, $E_{i,d,l}$ and $E_{i,d,r}$, respectively. We then compute the local energy ratio maps in both views:

$$R_{i,l} = \frac{E_{i,d,l}}{E_{i,r,l}} \quad \text{and} \quad R_{i,r} = \frac{E_{i,d,r}}{E_{i,r,r}} . \tag{1}$$

The energy ratio maps provide useful local binocular rivalry information, which may be combined with the qualities of single-view images to predict 3D image quality. A pooling stage is necessary for this purpose. High-energy image regions are likely to contain more information content. If the ultimate goal of visual perception is to efficiently extract useful information from the visual scene, then the high-energy regions are more likely to attract visual attention, and thus should be given more importance. To emphasize on the importance of high-energy image regions in binocular rivalry, we adopt an energy weighted pooling method [27] given by

$$g_{i,l} = \frac{\sum E_{i,d,l} R_{i,l}}{\sum E_{i,d,l}} \quad \text{and} \quad g_{i,r} = \frac{\sum E_{i,d,r} R_{i,r}}{\sum E_{i,d,r}} , \tag{2}$$

where the summations are over the full energy and ratio maps. Here $g_{i,l}$ and $g_{i,r}$ are estimations of the level of dominance of the i-th left and right frames, respectively. Given the values of $g_{i,l}$ and $g_{i,r}$, the weights assigned are given by

$$w_{i,l} = \frac{g_{i,l}^2}{g_{i,l}^2 + g_{i,r}^2} \quad \text{and} \quad w_{i,r} = \frac{g_{i,r}^2}{g_{i,l}^2 + g_{i,r}^2} , \tag{3}$$

respectively. The prediction of 3D image quality of the i-th frame is calculated by a weighted average of the left- and right-view image quality:

$$Q_i^{3D} = w_{i,l} Q_{i,l}^{2D} + w_{i,r} Q_{i,r}^{2D} , \tag{4}$$

where $Q_{i,l}^{2D}$ and $Q_{i,r}^{2D}$ denote the 2D image quality of the left and the right frames, respectively. Finally, the overall prediction of 3D video quality is calculated by averaging the prediction of each frame:

$$Q^{3D} = \frac{1}{N} \sum_{i=1}^{N} Q_i^{3D} , \tag{5}$$

where N denotes the frame number of the entire 3D video sequence.

In the case of the frame-based video quality assessment method is not available (for example, VQM [26] is not producing frame-level quality scores), the level of dominance can be estimated with respect to the entire video sequence:

$$g_l = \frac{1}{N} \sum_{i=1}^{N} g_{i,l} \quad \text{and} \quad g_r = \frac{1}{N} \sum_{i=1}^{N} g_{i,r} , \tag{6}$$

where g_l and g_r denote the level of dominance of the left- and right-view, respectively. Given the values of g_l and g_r, the weights assigned to the left- and right-view videos are given by

$$w_l = \frac{g_l^2}{g_l^2 + g_r^2} \quad \text{and} \quad w_r = \frac{g_r^2}{g_l^2 + g_r^2} , \tag{7}$$

respectively. Similarly, the overall prediction of 3D video quality is calculated by

$$Q^{3D} = w_l Q_l^{2D} + w_r Q_r^{2D} , \tag{8}$$

where Q_l^{2D} and Q_r^{2D} denote the 2D video quality of the left- and right-view videos, respectively.

The proposed 2D-to-3D quality prediction model is tested on all 3D videos in the new database. The SRCC values between 3D MOS and the predicted Q^{3D} value are given in Table 4. The corresponding scatter plots are shown in the right column of Fig. 1. From Table 4 and Fig. 1, it can be observed that the proposed model outperforms the direct averaging method significantly with respect to all tested 2D-IQA/VQA approaches. For different levels of compressions and Gaussian blurring, the proposed method, which does not attempt to recognize the distortion types or give any specific treatment, removes or significantly reduces the prediction biases. It is worth noting that with respect to PSNR, SSIM, MS-SSIM and IW-SSIM, both frame-based and sequence-based weighting are tested and the performance in each case is quite similar. Thus Table 4 and Fig. 1 are reported using the sequence-based weighting results, making it consistent with the VQM case which does not allow for frame-based weighting.

5. CONCLUSION AND DISCUSSION

The major contributions of the current paper are as follows: First, we create a new subjective 3D-VQA database and carry out a subjective test on symmetrically and asymmetrically compressed stereoscopic videos followed by different levels of low-pass filtering. Second, we observe a strong systematic bias when using direct averaging of 2D video quality of both views to predict 3D video quality. Third, we use a binocular rivalry inspired model to account for the prediction bias, leading to significantly improved quality estimation of stereoscopic videos. The model allows us to quantitatively predict the potential coding gain of asymmetric video compression.

Asymmetric and mixed-resolution coding has been hypothesized to be able to significantly reduce the required bandwidth in transmitting stereoscopic 3D videos, but subjective and objective quality assessment studies that support the hypothesis is lacking in the literature. Our current work is in favor of this hypothesis, but how mixed-resolutions of the left/right-views should be used and how to control deblocking and postprocessing filters are yet to be further investigated. We are currently building WATERLOO-IVC 3D Video Quality Database Phase II, which includes various stereoscopic 3D videos obtained from mixed-resolution coding, asymmetric transform-domain quantization coding, their combinations, and multiple choices of postprocessing techniques. More detailed descriptions will be reported in our future publications.

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