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QUALITY PREDICTION OF ASYMMETRICALLY DISTORTED STEREOSCOPIC IMAGES FROM SINGLE VIEWS

Jiheng Wang, Kai Zeng and Zhou Wang

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

ABSTRACT

Objective quality assessment of distorted stereoscopic images is a challenging problem. Existing studies suggest that simply averaging the quality of the left- and right-views well predicts the quality of symmetrically distorted stereoscopic images, but generates substantial prediction bias when applied to asymmetrically distorted stereoscopic images. In this study, we first carry out a subjective test, where we find that the prediction bias could lean towards opposite directions, largely depending on the distortion types. We then develop an information-content and divisive normalization based pooling scheme that improves upon SSIM in estimating the quality of single view images. Finally, we propose a binocular rivalry inspired model to predict the quality of stereoscopic images based on that of the single view images. Our results show that the proposed model, without explicitly identifying image distortion types, successfully eliminates the prediction bias, leading to significantly improved quality prediction of stereoscopic images.

***Index Terms*—** image quality assessment, stereoscopic image, 3D image, asymmetric distortion, SSIM, divisive normalization

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. Nevertheless, recent process on 3D image quality assessment (IQA) remains limited. In the literature, a majority of studies have been focused on extending existing 2D-IQA methods to stereoscopic images. These methods can be grouped into two categories based on whether depth or disparity information is explicitly employed. In [1, 2], 2D-IQA measures are applied to the left- and right-views separately and then combined to a 3D quality score. In [3, 4, 5], disparity maps between left- and right-views are estimated, followed by 2D quality assessment of disparity quality, which is subsequently combined with 2D image quality to produce an overall 3D quality score.

Recent subjective studies suggested that in the case of symmetric distortion of both views, simply averaging state-of-the-art 2D-IQA measures of both views is sufficient to provide reasonably accurate quality predictions of stereoscopic images. In particular, in [6], it was shown that averaging peak-signal-to-noise ratio (PSNR), structural similarity (SSIM) [7] and multi-scale SSIM (MS-SSIM) [8] measurements of left- and right-views performs equally well or better than the advanced 3D-IQA models [2, 3, 4]. Similar results were also observed in [9], where averaging universal quality index (UQI) [10], MS-SSIM [8] and visual information fidelity (VIF) [11] of both views all outperformed advanced 3D-IQA models [2, 3, 4, 5]. Compared with the case of symmetric distortions, quality assessment of asymmetrically distorted stereoscopic images is a much more challenging problem. In [6], 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. Previous studies exhibit somewhat conflict observations and opinions regarding the effect of asymmetric distortions. For image blur, evidence in [12] shows that the quality of asymmetric blurred images is largely dominated by the higher quality view, a result generally agrees with [13]. For image blockiness, it was reported in [14] that 3D quality has a tendency towards the lower quality view, while in [12], it was claimed that it should be approximated by averaging the quality of both views. In [13], it was suggested that the best strategy of asymmetric quality assessment for compressed images should be content and texture dependent.

Subjective data is essential in understanding the impact of asymmetric distortions on the quality of stereoscopic images. Ideally, we would need a complete set of subjective test on an image database that contains both single-views and stereoscopic images, both symmetrically and asymmetrically distorted images at different distortion levels, as well as both single- and mixed-distortion types. Existing 3D databases are highly valuable but limited in one aspect or another. Specifically, IRCCyN/IVC 3D Images Database [4], Tianjin Database [5], Ningbo Database Phase II [15], and LIVE 3D Image Database Phase I [9] only include symmetrically distorted stereoscopic images. Ningbo Database Phase I [13] only includes asymmetrically distorted stereoscopic images. MICT 3D Image Evaluation Database [16] contains both cases but only for JPEG compressed images. The most recent LIVE 3D Database Phase II [6] includes both symmetric and asymmetric cases with five distortion types. Unfortunately, subjective 2D-IQA of single-view images is still missing, making it difficult to directly examine the relationship between the perceptual quality of single-view and stereoscopic images. Moreover, asymmetric distortions with mixed distortion types are missing in all existing databases, making it hard to validate the generalization capability of 3D quality prediction models.

Meanwhile, studying the impact of asymmetric distortions on the quality of stereoscopic images not only has scientific values in understanding the human visual system, but is also desirable in the practice of 3D video compression and transmission, where it has been hypothesis that only one of the two views need to be coded at high rate, and thus significant bandwidth can be saved by coding the other view with low rate. However, previously reported testing on this hypothesis has been controversial [17, 14], because of a lack of accurate quality model. It is worth noting that 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/right views should be used. Thus the actual asymmetric distortions in practice could be mixed and complicated.

In this work, we first carry out a subjective quality assessment experiment on a database that contains both single-views and stereoscopic images with symmetric and asymmetric distortion types and levels. This database allows us to directly study the quality prediction performance from single-views to stereoscopic images, for which we observe that simply averaging the quality of both views creates substantial bias on asymmetrically distorted stereoscopic images, and interestingly, the bias could lean towards opposite directions, largely depending on the distortion types. We then develop an information-content and divisive normalization based pooling scheme that improves upon SSIM in estimating the quality of single-views. Furthermore, we propose a binocular rivalry inspired model to account for the bias, which not only results in better quality prediction of stereoscopic images with asymmetric distortion levels, but also well generalizes to the case of asymmetric distortions with mixed distortion types.

2. SUBJECTIVE STUDY

2.1. WATERLOO IVC 3D Image Quality Database

The new Waterloo IVC 3D Image Quality Database is created from 6 pristine stereopairs (and thus their corresponding single-views), all collected from the Middlebury Stereo 2005 Datasets [18]. Each single-view was altered by three types of distortions: noise contamination, blur, and JPEG compression and each distortion type had four distortion levels. The single-views are employed to generate distorted stereopairs, either symmetrically or asymmetrically. Table 1 categorizes these images into seven groups. There are two unique features of the new database when compared with existing 3D-IQA databases. First, this is the only database that performs subjective test on both 2D and 3D images. The inclusion of 2D images allows us to directly examine the relationship between the perceptual quality of stereoscopic images and that of the its single-view images. Second, this is the only database that contains mixed distortion types in asymmetrically distorted images. This provides the potential of a much stronger test on 3D-IQA models on their generalizability.

Table 1. Categories of test images

Group	# of images	Description
Group 2D.0	6×1	Pristine single-view images
Group 2D.1	6×12	Distorted single-view images
Group 3D.0	6×1	Pristine stereopairs
Group 3D.1	6×12	Symmetrically distorted stereopairs with the same distortion type and distortion level
Group 3D.2	6×12	Asymmetrically distorted stereopairs with distortion on one view only
Group 3D.3	6×18	Asymmetrically distorted stereopairs with the same distortion type but different levels
Group 3D.4	6×12	Asymmetrically distorted stereopairs with mixed distortion types and levels

Single stimulus continuous quality scale protocol was adopted in the subjective test. An ASUS 27” VG278H 3D LED monitor with NVIDIA 3D Vision$^{\text{TM}}$2 active shutter glasses is used for the test. Twenty-four naive subjects, 14 males and 10 females aged from 22 to 45, participated in the study. Following previous works [19, 20, 21], the subjects were asked to evaluate four aspects of their 3D viewing experience, including the perception of 3D image quality (3DIQ), depth quality (DQ), visual comfort (VC) and overall 3D quality of experience (3DQoE). The detailed descriptions of each aspects of visual experience are elaborated in Table 2. The rest of the paper focuses on the relationship between single-view image quality and the 3DIQ scores. More detailed descriptions of our database and analysis of the other aspects of the subjective experiments will be reported in future publications.

Table 2. Description of visual experience criteria

Criterion	Description
3DIQ	The image content quality without considering 3D viewing experience
DQ	The amount, naturalness and clearness of depth perception experience
VC	The comfortness when viewing stereoscopic images
3DQoE	The overall 3D viewing experience

2.2. Key Observations

The raw 3DIQ scores given by each subject were converted to Z-scores and the entire data set was rescaled to fill the range from 1 to 100. The mean opinion score (MOS) for each image was then computed after removing outliers. Given the subjective data, the main question we would like to ask first is how the single-view 2D image quality predicts the 3D image quality, for which the most straightforward prediction method is to directly average the MOSs of the left- and right-views. The left column of Fig. 1 shows the scatter plots of using averaging 2D-MOS to predict 3D-MOS for different distortion types. Quantitative measures of Spearman rank-order correlation coefficient (SRCC) can be found in Table 3, which shows that the best prediction occurs when the distortions are symmetric (consistent with the literature [9, 6]). By contrast, the SRCC values drop significantly with asymmetrical distortions. The drops are also reflected in the scatter plots in Fig. 1, where the direct average prediction model generates substantial bias of many stereopairs. Most interestingly, this bias leans towards opposite directions, largely depending on the distortion types. In particular, for noise contamination and JPEG compression, direct average prediction overestimates the 3D quality of many images, while for blur distortion, direct average prediction often underestimates the 3D image quality.

It is interesting to compare our observations regarding distortion type dependency with those published in the literature. For image blur, it was reported in [12, 13] that 3D quality is less affected by the view with lower quality, which is consistent with our result. For image blockiness, [14] and [12] reported somewhat conflicting results. The former concluded that 3D quality is mainly dependent on the view with lower quality, and the latter suggested that averaging the quality of both views is a better choice. These seemingly controversial results are well explained by the scatter plot shown in Fig. 1(g), where 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.

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

We opt to use a two-stage approach in the design of an objective 3DIQ predictor. The first stage aims to evaluate the perceptual quality of single-view images, while in the second stage, a binocular rivalry inspired model is developed to combine 2D image quality of both views into a quality estimation of 3D image quality.

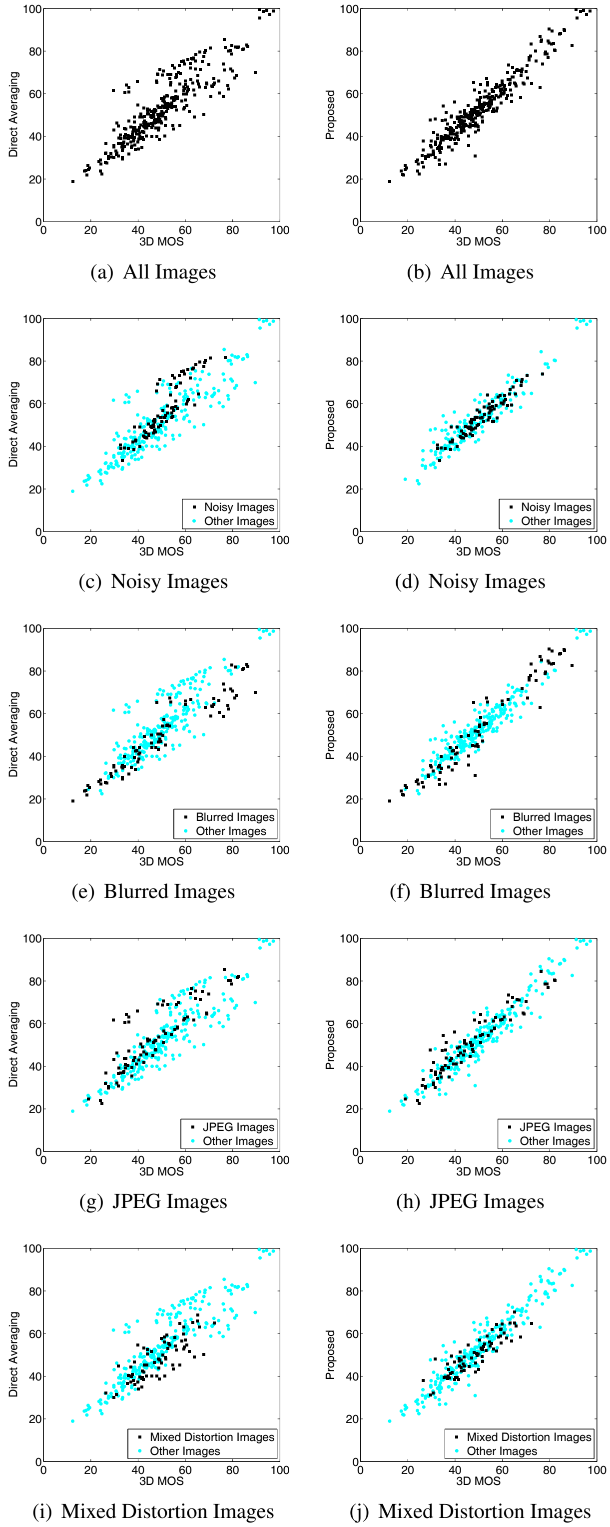

Fig. 1. Scatter plots of 3D image quality MOS score versus predictions from the MOS scores of 2D left- and right-views. Left column, prediction by averaging the MOS scores of both views; right column, prediction by the proposed method.

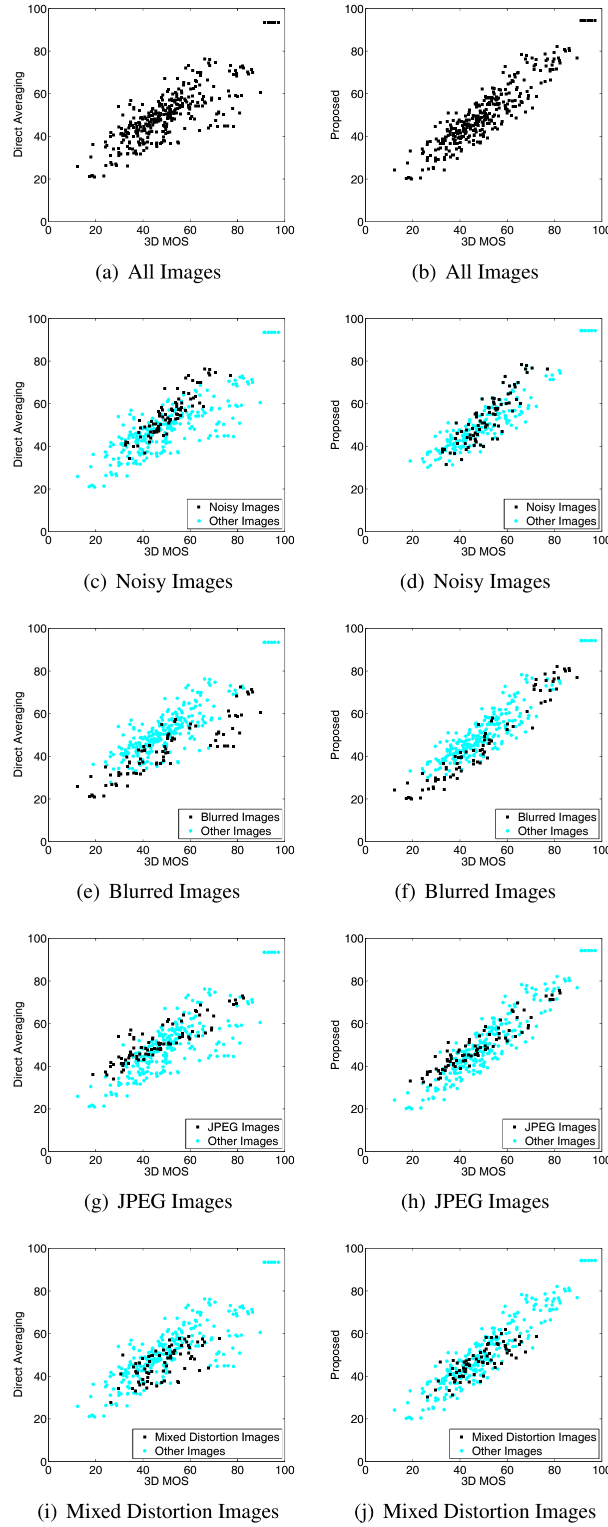

Fig. 2. Scatter plots of 3D image quality MOS score versus predictions from the IDW-SSIM scores of 2D left- and right-views. Left column, prediction by averaging IDW-SSIM of both views; right column, prediction by the proposed method.

Table 3. SRCC performance of 2D-to-3D quality prediction models on WATERLOO IVC 3D database

	All images	Symmetric	Asymmetric
2D-MOS with direct average	0.8765	0.9657	0.8471
2D-MOS with proposed weighting	0.9484	0.9657	0.9405
You [3]	0.5968	0.7517	0.5706
Benoit [4]	0.5852	0.7275	0.5766
Yang [5]	0.6106	0.6668	0.6108
Proposed	0.8836	0.9462	0.8846

3.1. Objective 2D Quality Assessment

In the literature, the SSIM index [7] and its derivatives [8, 22] have demonstrated competitive performance in 2D objective IQA tests [22]. An advantage of the SSIM approach is that it provides a quality map that indicates the variations of image quality over space [7]. It was shown that spatial pooling built upon the quality map based on information-content or distortion weighting further improves the performance [22]. When testing SSIM and its derivatives on the 2D image datasets of our new database, we find although they have high correlations with subjective quality on images with the same distortion types, their performance drops when all distortion types are mixed. Therefore, here we build our 2D-IQA model upon SSIM, but improve it further by incorporating an information-content and divisive normalization based pooling scheme. A general form of spatially weighted pooling is given by

$$Q_{2D} = \frac{\sum_{i=1}^{N} w_i q_i}{\sum_{i=1}^{N} w_i}, \tag{1}$$

where q_i and w_i are the local quality value (e.g., local SSIM value) and the weight assigned to the i-th spatial location, respectively. The assumption behind information-content weighted pooling is that the spatial locations that contain more information are more likely to attract visual attention, and thus should be given larger weights. Let $\mathbf{x}_i$ and $\mathbf{y}_i$ be the local image patches extracted around the i-th spatial location from the reference and the distorted images, respectively. Following the information content evaluation method in [23], we compute the weighting factor by

$$w_{(ic),i} = \log\left[\left(1+\frac{\sigma_x^2}{C}\right)\left(1+\frac{\sigma_y^2}{C}\right)\right], \tag{2}$$

where σ_x and σ_y are the standard deviations of $\mathbf{x}_i$ and $\mathbf{y}_i$, respectively, and C is the noisy visual channel power. Another useful pooling strategy is distortion-weighted pooling, which is based on the intuitive idea that the spatial locations that contain more distortions are more likely to attract visual attention, and thus should be given more weights. Since the local quality has been gauged by q_i (e.g., the SSIM value at location i), we can easily obtain a local distortion measure, for example, by $d_i = 1 - \mathrm{SSIM}_i$. Divisive normalization has been recognized as a perceptually and statistically motivated non-linear transformation [24]. We apply divisive normalization to the local distortion map and define a normalized distortion based weighting factor by

$$w_{(d),i} = \frac{d_i}{\sqrt{\sum_{j\in\mathcal{N}_i} d_j^2 + D_0}}, \tag{3}$$

where $\mathcal{N}_i$ denotes the set of neighboring pixels surrounding the i-th spatial location, and D_0 is a stability constant. The final weighting factor is obtained by combining information content and divisive normalization-based distortion weighting factors

$$w_i = \max\{w_{(ic),i}^2, w_{(d),i}^2\}. \tag{4}$$

Applying this weighted pooling approach to the SSIM map, we obtain an information-content and distortion weighted SSIM (IDW-SSIM) measure. This has led to significant performance improvement when tested using the single-view images in our new database. Specifically, the SRCC with respect to the MOS scores has been improved from 0.4800 for PSNR and 0.7066 for SSIM to 0.9381 for IDW-SSIM.

3.2. 2D-to-3D Quality Prediction Model

The competition between binocular fusion and binocular rivalry [25] provides a potential theory to develop 2D-to-3D quality prediction models. When the left- and right-views are consistent, they are fused in the visual system to a single percept of the scene, known as binocular fusion. On the other hand, when the two views are inconsistent, instead of being seen superimposed, one of them may dominate or two views may be seen alternately, known as binocular rivalry [25]. Although there is a rich literature on binocular fusion and rivalry in biological vision science [25], how to apply the principle to 3D-IQA remains an active research topic. Since in 3D-IQA we need to work on complicated scenes and distortions, simplifications are essential to create practical solutions.

Our work is motivated by existing vision studies on binocular rivalry [26, 27], where it was found that for simple ideal stimuli, an increasing contrast increases the predominance of one view against the other. Also note that in complicated scenes the contrast of a signal increases with its signal strength measured using energy. This inspires us to hypothesize that the level of view dominance in binocular rivalry of stereoscopic images is monotonically increasing with the relative energy of the two views. The diagram of the proposed method is shown in Fig. 3. Let ($I_{r,l}$, $I_{r,r}$) and ($I_{d,l}$, $I_{d,r}$) be the left- and right-view image pairs of the reference and distorted stereoscopic images, respectively. We first create their local energy maps by computing the local variances, i.e., the variances of local image patches extracted around each spatial location from the reference or the distorted images are computed, for which a sliding Gaussian window with standard deviation of 1.5 is employed. The resulting energy maps are denoted as $E_{r,l}$, $E_{r,r}$, $E_{d,l}$ and $E_{d,r}$, respectively. Assume that the reference stereopair has perfect quality with strong 3D effect, where binocular fusion prevails. When at least one of the single-view images is distorted at some spatial locations, the distortion may affect the consistency between the image structures from the two views, and thus binocular rivalry prevails. As a result, one view may dominate the other at any time instance. Based on our hypothesis, we compute the local energy ratio maps in both views:

$$R_l = \frac{E_{d,l}}{E_{r,l}} \quad \text{and} \quad R_r = \frac{E_{d,r}}{E_{r,r}}. \tag{5}$$

The energy ratio maps provide useful local 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. To emphasize on the importance of high-energy image regions, we adopt an energy weighted pooling method given by

$$g_l = \frac{\sum E_{d,l} R_l}{\sum E_{d,l}} \quad \text{and} \quad g_r = \frac{\sum E_{d,r} R_r}{\sum E_{d,r}}, \tag{6}$$

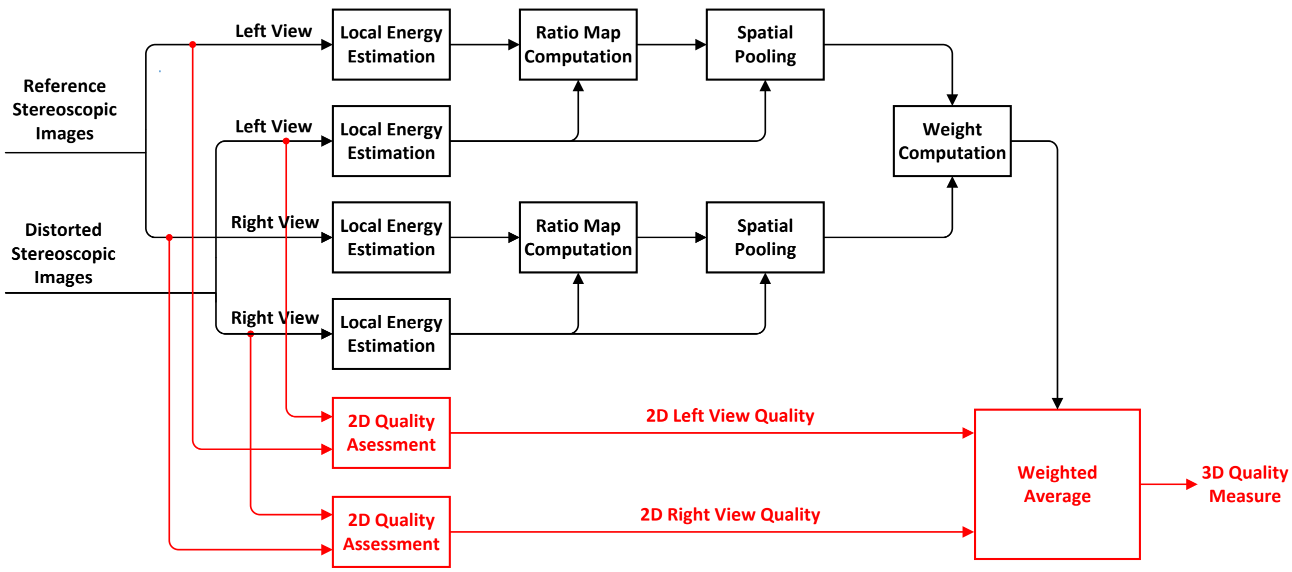

Fig. 3. Diagram of the proposed 2D-to-3D quality prediction model.

Table 4. SRCC performance of 2D-to-3D prediction models

Database	2D-IQA Method	Direct Average	Proposed
Waterloo IVC	2D-MOS	0.8765	0.9484
	PSNR	0.5213	0.5240
	SSIM	0.5976	0.6580
	IDW-SSIM	0.7761	0.8967
LIVE Phase II	PSNR	0.7303	0.7638
	SSIM	0.7925	0.8560
	IDW-SSIM	0.7886	0.9145

where the summations are over the full energy and ratio maps. The weights assigned to the left- and right-views are then given by

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

Finally, the overall prediction of 3D image quality is calculated by a weighted average of the left-view and right-view image quality:

$$Q_{3D} = w_l Q_{2D}^l + w_r Q_{2D}^r \,, \tag{8}$$

where Q_{2D}^l and Q_{2D}^r denote the 2D image quality of the left- and right-views, respectively.

3.3. Testing

We use two 3D image quality databases to test the proposed algorithm, which are our WATERLOO IVC 3D database and the LIVE 3D Phase II database [6]. The latter is a most recent database that contains both symmetrically and asymmetrically distorted images. Note that the parameters of the proposed method is selected empirically when working with our new database, but are completely independent of the LIVE database. Due to space limit, only SRCC results are reported here, but highly consistent results are also obtained in our analysis based on Pearson linear correlation coefficient and Kendall rank-order correlation coefficient.

Table 5. SRCC performance of 2D-to-3D quality prediction models on LIVE 3D Phase II database

	All images	Symmetric	Asymmetric
You [3]	0.7924	0.8030	0.7721
Benoit [4]	0.7436	0.6959	0.7474
Yang [5]	0.7210	0.7608	0.6960
Chen [6]	0.8800	0.9180	0.8340
Proposed	0.9145	0.9190	0.9030

We test the proposed 2D-to-3D quality prediction model by applying it to different base 2D-IQA approaches on both databases. The comparison results with the direct averaging method are shown in Table 4, where it can be seen that the proposed method significantly improves most base 2D-IQA methods. The only exception is PSNR, which might be due to its poor performance in 2D image quality assessment, and thus merely changing 2D to 3D prediction method would not lead to any meaningful result. By comparing the left and right columns of Figs. 1 and 2, we observe how the proposed 2D-to-3D prediction model affects each image distortion type, for the cases of using 2D-MOS and IDW-SSIM as the base IQA methods, respectively. Most importantly, for different distortion types, although the direct averaging method produces different levels of quality prediction biases towards different directions, the proposed method, which does not attempt to identify the distortion types or give any specific treatment for any specific distortion type, removes or significantly reduces the prediction biases for all distortion types. Moreover, the mixed distortion case provides the strongest test on the generalization ability of the model, for which the proposed method maintains consistent improvement.

We have also compared the proposed method with state-of-the-art 3D-IQA approaches [3, 4, 5, 6] using both databases, and the results are shown in Tables 3 and 5, respectively. The proposed method achieves the best performance in both databases among all full objective IQA methods. The highly competitive performance in the LIVE database is a more convincing result because the test is blind in the sense that no parameter has been determined using the LIVE database. Another important observation is that there is a large performance drop in all other objective methods from symmetric to asymmetric distortions. The drop is much smaller in the proposed method, which creates the most significant performance gain in the asymmetric case.

4. CONCLUSION

The major contributions of the current paper are as follows: First, we created a new subjective 3D-IQA database that has two unique features (the inclusion of both 2D and 3D images, and the inclusion of mixed distortion types). Second, we observe strong distortion type dependent bias when using the direct average of 2D image quality of both views to predict 3D image quality. Third, we develop an information-content and divisive normalization based pooling scheme that improves upon SSIM in estimating the quality of single-views. Fourth, we propose a binocular rivalry inspired model to predict the quality of stereoscopic images from the quality of its single-views. Our results show that the proposed model, without explicitly identifying image distortion types, successfully eliminates the prediction bias, leading to significantly improved quality prediction of stereoscopic images. The performance gain is most pronounced in the case of asymmetric distortions.

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