STEREOSCOPIC IMAGE QUALITY ASSESSMENT BASED ON THE BINOCULAR PROPERTIES OF THE HUMAN VISUAL SYSTEM

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ABSTRACT

One of the most challenging issues in stereoscopic image quality assessment (IQA) is how to effectively model the binocular behaviors of the human visual system (HVS). The latter has a great impact on the perceptual stereoscopic 3D (S3D) quality. This paper presents a stereoscopic IQA metric based on the properties of the HVS. Instead of measuring the quality of the left and the right views separately, the proposed method predicts the quality of a cyclopean image to ensure that the overall S3D quality is as close as possible to the binocular vision. The cyclopean image is synthesized based on the local entropy of each view with the aim to simulate the phenomena of the binocular rivalry/suppression. A 2D IQA metric is employed to assess the quality of both the cyclopean image and the disparity map. Additionally, the quality of the cyclopean image is modulated according to the visual importance of each pixel defined by the just noticeable difference (JND). Finally, the 3D quality score is derived by combining the quality estimates of the cyclopean image and disparity map. Experimental results show that the proposed method outperforms many other state-of-the-art SIQA methods in terms of prediction accuracy and computational efficiency.

Index Terms— stereoscopic image quality assessment, cyclopean image, binocular rivalry/suppression, just noticeable difference (JND)

1. INTRODUCTION

In the past few years, great efforts in Stereoscopic 3D (S3D) technologies have been made to bring a realistic 3D visual experience to consumers. However, S3D technology development brings some challenges especially to 3D-TVs makers. One of the major challenges is linked to the user's quality of experience (QoE) including comfort and fatigue aspects. In order to achieve this, it's important to develop accurate and reliable IQA metrics for 3D stereoscopic content. While 2D IQA has greatly advanced in the recent years, stereoscopic IQA (SIQA) is only in its infancy. Mainly because 3D perceptual quality can be affected by the characteristics of both monocular and binocular vision. Even though 3D quality can be measured using subjective experiments [1], these are tedious and expensive. Therefore, objective metrics are needed to automatically assess the perceived 3D visual quality.

A stereo pair contains two slightly different views (i.e., left and right views), each of which is projected separately onto the retina. When a S3D image is observed, the human visual system (HVS) merges the two views to yield a single mental view (i.e., cyclopean image) based on the properties of the binocular vision [2]. Thereby, the 3D perceptual quality depends not only on the quality of each individual view [3], but also on the depth information [4] and the binocular characteristics [5]. The idea is to explore how these attributes contribute to the overall 3D quality. Therefore, to design reliable and accurate S3D metrics, it is important to understand and account for the different perceptual processes of the HVS.

In this paper, we propose a new SIQA metric based on the HVS properties, combining the quality scores of the cyclopean image [5] and the disparity map. The major contribution of this work lies in the development of a novel 3D quality metric by modeling the phenomena of binocular rivalry/suppression, and accounting for disparity map quality as well as the monocular spatial sensitivity of the HVS. Besides, we provide a comprehensive experimental evaluation for our proposed method, and an extensive comparison with other SIQA methods. The remainder of the paper is organized as follows. In Sect. 2, we provide a brief review of recent SIQA metrics. Sect. 3 describes the proposed SIQA method. We evaluate and discuss the performance of the proposed metric in Sect. 4. This paper ends with some conclusions and future work.

2. RELATED WORK

In this section, we briefly review the recent SIQA methods. Based on the type and the amount of the information used from stereoscopic views, the SIQA methods can be divided into three categories [6]: (1) stereo-pair-based methods, (2) methods based on stereo-pair and depth information, (3) methods considering the HVS properties.

2.1. Stereo-pair-based methods

The SIQA methods of the first category try to extend the 2D IQA algorithms directly to measure the distortions of S3D images. Most early approaches [7, 8] assess the quality of left and right views separately using state-of-the-art 2D quality metrics, and then combine both scores into an overall 3D quality score. For instance, Campisi *et al.* [7] evaluated the S3D quality by four 2D quality metrics including structural similarity metric (SSIM) [9], universal image quality index (UQI) [10], C4 [11] and reduced-reference QA [12]. However, considering the combination of the qualities for each view as an overall 3D quality does not correlate well with the human quality judgments [13]. This is mainly due to the fact that these 2D metrics do not take into account depth information, which plays an important role on 3D perception.

2.2. Methods based on stereo-pair and depth information

Consequently, the second category employs both views of a stereo pair in addition to depth/disparity information to estimate 3D quality. In this category, 2D quality metrics are used to measure the quality of both the stereo-pair and the disparity map. Then, these two quality values are combined to yield a 3D quality score. In an

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early research, Benoit *et al.* [3] proposed a full reference 3D metric that applies SSIM and C4 metrics on left and right images independently, and then combined these 2D scores with the estimate of disparity map distortion. Later, You *et al.* [14] explored the performance of 2D quality metrics used in the context of 3D quality assessment with different ways of combining between the disparity map quality and views' quality. Hwang and Wu [15] developed a 3D quality prediction model that integrates the stereo-pair quality with depth quality and S3D visual saliency. Recently, Wang *et al.* [16] designed a reduced reference SIQA model, considering the quality of both luminance images and disparity map, based on image statistics in the contourlet domain. Since the ground truth depth/disparity maps are not always available, this category of methods estimate the disparity maps by using stereo matching algorithms. Thereby the accuracy of the stereo matching algorithms may affect the performance of 3D quality prediction.

2.3. Methods considering the HVS properties

In fact, the views of a stereo-pair may suffer from an equal amount of distortion (namely symmetric distortion) or different amounts and/or types of distortions (namely asymmetric distortion). Symmetric distortion results in binocular fusion [17], whereas asymmetric distortions lead to either binocular rivalry [18] or binocular suppression [19] depending on the strength of the difference. These latter have a great impact on perceived 3D quality. The SIQA methods of the two above-mentioned categories are quite useful in the case of symmetric distortion, but perform much less effectively for asymmetrically distorted stereo-pairs that are very common in real application such as coding. Thus, to improve the performance of the 3D metric, the third category of SIQA methods consider the monocular and/or binocular visual properties in addition to stereo-pair quality and depth information.

It is known that the human eyes are incapable of perceiving pixel changes below a specific visual threshold namely the just noticeable difference (JND) due to their underlying temporal/spatial sensitivity and masking effects [20]. Some JND models for S3D content (3D-JND) accounting for both monocular and binocular depth cues have been proposed [21]. For instance, a binocular just noticeable difference (BJND) model [22], which investigates the properties of the binocular vision in response to asymmetric noise in a stereo-pair based on HVS characteristics, has been applied in 3D quality estimation [23, 24].

Other SIQA approaches combine left and right views into one cyclopean image, and the final 3D quality is measured by analyzing this merged image. For example, Chen *et al.* [5] developed a SIQA metric by computing the quality of the cyclopean images constructed by a linear model. The weights of this model are derived from the Gabor filter magnitude responses, which simulate the binocular rivalry. Similarly, Fezza and Larabi [25] proposed a full reference SIQA method based on the quality of the test cyclopean image generated by using local entropy and depth information. Besides, Lin and Wu [26] predicted the 3D quality based on both binocular combination and binocular frequency integration. In the following section, we propose a SIQA method that estimates the degradations of cyclopean image and disparity map.

3. THE PROPOSED SIQA METHOD

As mentioned above, the HVS is not sensitive to the quality in the left or right image separately. Instead, it perceives distortions of the cyclopean image as 2D impairments, and depth/disparity distortion as 3D impairment. Thereby our proposed SIQA method is based on the assumption that the overall 3D quality is a combination of the qualities of binocular-based cyclopean image and the disparity map. Figure 1 shows the framework of the proposed SIQA method. This 3D quality prediction model consists of 5 steps:

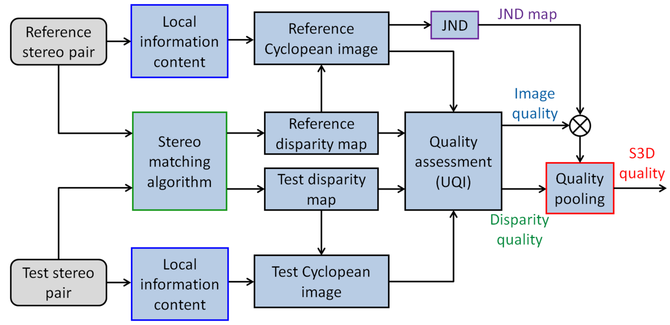

Fig. 1: Framework of the proposed SIQA method.

1. Disparity estimation for both reference and distorted stereo pairs;
2. Formation of the cyclopean image for each stereo pair based on local entropy;
3. Quality assessment of the cyclopean image and disparity map separately using the UQI metric;
4. Weighting the cyclopean image quality with the JND map of the reference cyclopean image;
5. S3D quality estimation by combining the quality of the JND-based cyclopean image with the qualiy of disparity map.

The first step is to form the cyclopean images. According to a linear model proposed in [5,27], by modeling the rivalry/suppression when a stereo stimulus is presented, we synthesize the cyclopean image as follows:

$$I_c(i,j) = W_l(i,j) \times I_l(i,j) + W_r(i,j-d_l) \times I_r(i,j-d_l), \quad (1)$$

where I_l and I_r represent the left and right images respectively, and I_c is the cyclopean image. W_l and W_r are the weighting coefficients for their corresponding images, and used to describe the rivalry process, thus $W_l + W_r = 1$. Moreover, i and j are the pixel coordinates, and $d_l(i,j)$ represents the disparity value of the pixel (i,j) of left image that corresponds to the horizontal shift of one pixel from the left to the right image. To determine the disparity map, we propose to use a stereo matching algorithm recently proposed by Lee *et al.* [28]. This algorithm efficiently achieves high performance in disparity estimation and deals with the issues of occlusion and depth discontinuities.

As described in [27], the experience of binocular rivalry is correlated to the relative stimulus strength of each view instead of absolute stimulus strength. Moreover, the studies in [5] [13] found that the 3D human perception is dominated by the view of high contrast or rich contours. In other words, the perceptual 3D quality follows the quality of the view containing a higher amount of information. Therefore, the local information content is used to determine the relative stimulus strengths W_l and W_r of two views, where $W_l(i,j)$ and $W_r(i,j)$ are defined by:

$$W_l(i,j) = \frac{EN_l(i,j)}{EN_T(i,j)}, W_r(i,j-d_l) = \frac{EN_r(i,j-d_l)}{EN_T(i,j)}, \quad (2)$$

$$EN_T(i,j) = EN_l(i,j) + EN_r(i,j-d_l), \quad (3)$$

where $EN_l(i,j)$ and $EN_r(i,j)$ are the left and right local entropy of the pixel (i,j) in the left and right views respectively. The image entropy is related to the amount of information that can be coded in the compression process. For instance, a low entropy image contains very little contrast. The entropy of a pixel computed based on 11-by-11 neighborhood with specific shape around this pixel [29] is described as follows:

$$EN(i,j) = -\sum_{s=g_{min}}^{g_{max}} p(x_s) \times \log_2(p(x_s)), \quad (4)$$

where g_{min} and g_{max} are minimum and maximum values respectively in the corresponding neighborhood pixels. $p(x_s)$ denotes the probability that the difference between two adjacent pixels is equal to s. Based on equations 2, 3 and 4, our SIQA method simulates the binocular rivalry/suppression. For example, different local entropies in two views lead to binocular rivalry/suppression, and the 3D quality is more affected by the view containing higher local entropies.

Given the cyclopean images (I_{rc}, I_{dc}) and the disparity maps (Dp_r, Dp_d) of the reference and distorted stereo pairs, we independently measure the quality of the cyclopean image and the disparity map by using 2D IQA metric. In [14], You *et al.* found that UQI performs the best for 3D quality prediction among all the tested 2D IQA metrics. On the other hand, UQI metric has the best performance for IQA on the disparity map. Actually, UQI used in disparity quality estimation is based on comparing the structural information, and the disparity can express such information of the original images. Thereby we propose to employ UQI to predict the quality of the stereo pair and disparity map independently:

$$Q_c(i,j) = UQI(I_{rc}, I_{dc}), Q_d = UQI(Dp_r, Dp_d), \quad (5)$$

where Q_c is the UQI index map of the test cyclopean image, and Q_d denotes the quality score of the disparity map. In order to improve the SIQA performance, we used the visual importance of the pixel to weight the cyclopean quality score [23]. The visual importance, which corresponds to monocular spatial sensitivity of HVS, is described by JND thresholds [30] of the reference cyclopean image. Accordingly, the JND-based cyclopean quality Q_c^{JND} is calculated by:

$$Q_c^{JND} = \frac{\sum_{i,j}^{N}\left[\frac{1}{JND(i,j)} \times Q_c(i,j)\right]}{\sum_{i,j}^{N}\frac{1}{JND(i,j)}}, \quad (6)$$

where N is the number of pixels in the cyclopean image. High value of the JND in a pixel means that this pixel can tolerate a large degradation, and thus has a low visual importance in the perceptual quality. Finally, the S3D quality score Q_{3D} is calculated by a linear model:

$$Q_{3D} = \alpha \times Q_c^{JND} + \beta \times Q_d \quad (7)$$

where α and β are the weights of the 2D JND-based cyclopean quality and the disparity quality respectively, with $\alpha + \beta = 1$. In our implementation, we assume that the 2D quality has more importance than disparity quality, thus we fixed $\alpha = 0.6$ and $\beta = 0.4$.

4. EXPERIMENTAL RESULTS

In this section, we evaluate the performance of the proposed SIQA method on the publicly available LIVE 3D IQA database (phase II) [34]. LIVE 3D IQA database is composed of 8 original images and 360 distorted stereo pairs with symmetric and asymmetric distortions, including additive white gaussian noise (WN), gaussian blur (Gblur), JPEG, JPEG 2000 compression (JP2K) and fast fading (FF). We compare the proposed method with four other SIQA methods [5,23–25]. For the SIQA methods, we used the same stereo matching algorithm [28] to estimate the disparity maps to ensure a fair comparison. In addition, we evaluate the performance of SIQA methods using only 2D metrics including SSIM, MS-SSIM [31], FSIM [32], VIF [33] and UQI. For these 2D-based SIQA methods, we estimated the 3D perceptual quality by averaging the quality predicted from the left and right views. The performance of the 3D quality metrics has been evaluated using three well-known measures: the Linear Correlation Coefficient (LCC), the Spearman Rank Order Correlation Coefficient (SROCC) and RMSE. Three measures were computed between DMOS and the predicted scores after a nonlinear regression with a five-parameter logistic function described in [35]. All tests were performed by running MATLAB code on a portable computer (Inter Core i7-2630 QM Processor at 2.00 GHz, 4 GB RAM, Windows 7).

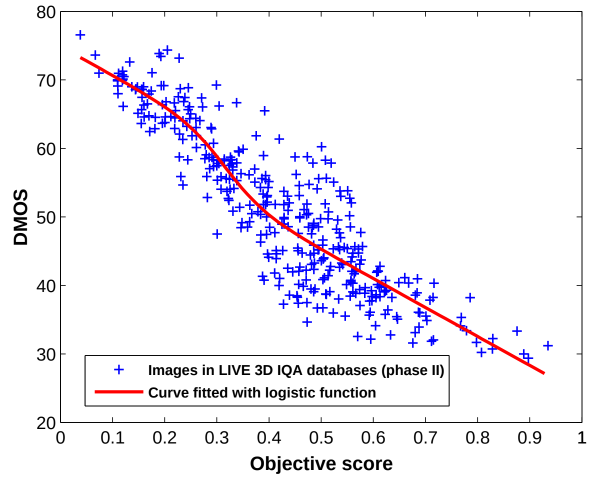

Fig. 2: Scatter plots of DMOS versus predicted scores obtained by proposed SIQA method.

4.1. Overall performance

Table 1 shows the performance of SIQA methods on LIVE 3D IQA database. These results demonstrate that the proposed method outperforms the others methods except Chen's method for the cases of symmetric and asymmetric distortions. Actually, the proposed method is quite similar to Chen's method [5] in terms of overall performance, but the proposed method is obviously much faster than Chen's method. To summarize, our proposed method achieves high performance with low computational costs. On the other hand, most of 2D-based SIQA methods are as efficient as the 3D IQA methods for the symmetrically distorted stereo pairs, but they generally give bad performance than 3D IQA methods for asymmetric distortions. This is mainly due to the fact that 2D-based SIQA methods evaluate the S3D quality without considering neither the depth/disparity information nor the characteristics of the binocular vision. It should be noted that the method using UQI metric performs best within all 2D-based SIQA methods.

Table 1: Performance of SIQA methods on LIVE 3D IQA database (phase II). The symbols AS and S are respectively the asymmetric and symmetric distortions. CT denotes the computational runtime (in second) for all images. Italicized entries are 2D quality metrics, while the best performance are bolded.

Method	LCC			SROCC			RMSE			CT
	S	As	Total	S	As	Total	S	As	Total	Total
SSIM [9]	*0.852*	*0.767*	*0.802*	*0.826*	*0.736*	*0.793*	*6.543*	*6.510*	*6.736*	***30***
MS-SSIM [31]	*0.927*	*0.719*	*0.795*	*0.912*	*0.684*	*0.777*	*4.694*	*7.047*	*6.851*	*49*
FSIM [32]	*0.929*	*0.731*	*0.808*	*0.912*	*0.684*	*0.786*	*4.623*	*6.913*	*6.654*	*919*
VIF [33]	*0.928*	*0.777*	*0.837*	*0.916*	*0.732*	*0.819*	*4.653*	*6.383*	*6.184*	*684*
UQI [10]	***0.940***	*0.794*	*0.863*	***0.938***	*0.755*	*0.841*	***4.223***	*6.159*	*5.685*	*38*
Wang [23]	0.862	0.743	0.771	0.826	0.696	0.771	6.334	6.787	7.188	82
Fezza [24]	0.788	0.713	0.751	0.778	0.676	0.734	7.685	7.104	7.453	163
Fezza [25]	0.930	0.820	0.871	0.921	0.796	0.862	4.576	5.801	5.553	1410
Chen [5]	0.939	**0.878**	**0.909**	0.927	**0.858**	**0.904**	4.277	**4.846**	**4.700**	14089
Proposed	**0.940**	0.875	0.906	**0.938**	0.839	0.893	4.272	4.903	4.795	2392

The performance of Wang's method [23] and Fezza's method [24] are lower than the proposed approach despite their use of binocular properties. This may be explained by the fact of predicting 3D quality separately of left and right views, and failing in accounting for the binocular properties. Thereby the methods based on cyclopean image (i.e., Chen's [5], Fezza 's [25] and our proposed method) achieved better performance than other 3D IQA methods. In addition to the performance comparison mentioned above, we provide in Figure 2 the scatter distributions of DMOS versus predicted scores obtained with the proposed method, as well as the non-linear fitting curve.

4.2. Discussion about the proposed strategy

In this section, we show the advantages of considering both JND and quality assessment for disparity map in our SIQA method. We compare the performance and the influence of each component of the proposed metric (see Figure 1). The performance of the four SIQA methods on one database are shown in Table 2. SIQA method without JND does not use the JND map to weight the quality of reference cyclopean image, whereas the SIQA method without quality assessment for disparity map (DQA) does not consider the quality of disparity map. From the results, we can notice that the proposed SIQA method (i.e, with JND and DQA) gives the best performance among all strategies. However, the proposed method slightly outperforms method without JND in terms of LCC. In addition, SIQA method without JND performs better than SIQA method without DQA. This can be explained by the fact that the depth information is more important than the sensitivity of HVS for 3D quality prediction. In summary, the results of Table 2 mean that 3D quality prediction performance can be improved by accounting for both JND and disparity quality estimation. We also explored the performance of proposed method for different types of distortions. Our method performs quite well for both GBlur and FF distortion. We cannot show here due to page limitation.

Table 2: Performance of the proposed SIQA method on LIVE 3D IQA database (phase II).

Strategies	LCC	SROCC	RMSE
without JND	0.902	0.883	4.870
without DQA	0.889	0.864	5.163
without JND and DQA	0.887	0.866	5.178
with JND and DQA	**0.906**	**0.893**	**4.795**

5. CONCLUSION

In this paper, we proposed a quality assessment method for stereoscopic images based on HVS properties. Our method models the human stereo vision by fusing the left and right views to generate a cyclopean image, and taking into account the disparity information as well as the monocular spatial sensitivity of HVS. The experimental results showed that the proposed method outperforms well-known 2D-based SIQA methods and 3D IQA methods in terms of prediction accuracy and computational costs. In future works, the performance of the proposed method will be evaluated on other databases. In addition, other reliable approaches modeling the process of binocular rivalry will be considered to improve the performance of our method.

6. ACKNOWLEDGMENT

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