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4 authors:

Junyong You
Christian Michelsen Research

Liyuan Xing
Norwegian University of Science and Technology

Andrew Perkis
Norwegian University of Science and Technology

Xu Wang
Shenzhen University

PERCEPTUAL QUALITY ASSESSMENT FOR STEREOSCOPIC IMAGES BASED ON 2D IMAGE QUALITY METRICS AND DISPARITY ANALYSIS

Junyong You[1], Liyuan Xing[1], Andrew Perkis[1], Xu Wang[2]

1 Centre for Quantifiable Quality of Service in Communication Systems (Q2S)[*], Norwegian University of Science and Technology (NTNU); 2 Ningbo University

ABSTRACT

Both compression and transmission errors may degrade the quality of stereoscopic images. Although many two-dimensional (2D) image quality metrics have been proposed that work well on 2D images, developing quality metrics for three-dimensional visual presentations is almost an unexplored issue. This paper investigates the capabilities of some 2D image quality metrics in stereoscopic image quality assessment. Furthermore, disparity has a significant impact on stereoscopic image quality assessment, as an important attribute in stereopsis. A study on the integration of disparity information into quality assessment is presented. The experimental results demonstrate that a better performance can be achieved if the disparity information and original images are combined appropriately in stereoscopic image quality assessment.

Index Terms— Perceptual quality assessment, Stereoscopic, image quality metric, disparity

1. INTRODUCTION

Networked three-dimensional (3D) media services are becoming increasingly feasible through the evolution of digital media, entertainment, and visual communication. Three-dimensional television (3DTV), one of the popular media services, can provide a dramatic enhancement in user experience, compared with the traditional black-and-white and color television. Although David Brewster introduced the stereoscope, a device that could take photographic pictures in 3D, in 1844, it was not until 1980s that experimental 3DTV was presented to a large audience in Europe. However, although various recent technological developments combined with an enhanced understanding of 3D perception have been achieved, many important topics related to 3D technology are almost unexplored [1]. A networked 3DTV service consists of an entire chain from content production and coding schemes for transmitting through communication channels to adequate displays presenting high quality 3D pictures. During this chain, the quality of a 3D presentation may be degraded at each stage. In this work, we will focus on perceptual quality assessment for stereoscopic images based on two-dimensional (2D) image quality metrics and disparity information.

Existing work on perceptual quality evaluation for both video-plus-depth and multi-view video 3D presentation is mostly focused on assessing the quality degradation caused by compression errors. Currently, most 3D compression schemes are developed for stereoscopic images or videos that consist of two views taken from a lightly different perspective in a 3D scene. Since one image (target) in a stereo-pair images can be restored from the disparity information and the other one image (reference), the reference image is in general coded with a traditional 2D compression scheme whereas the target image can be represented by disparity vectors. Stereoscopic coding schemes using the disparity estimation can be classified into: 1) intensity-based methods and 2) feature-based methods [1]. Although many quality metrics for 2D image quality assessment have been proposed, the quality models on stereoscopic images have not been widely studied. Hewage et al. [2] tested the performance of three quality metrics, including peak signal-to-noise ratio (PSNR), video quality model (VQM) proposed by NTIA [3], and structural similarity model (SSIM) [4], with respect to a subjective quality experiment on a series of coded stereoscopic images. The experimental results demonstrated that VQM is better than other two metrics while its performance is still not promising. Similar work has been done in [5]. Four metrics, as well as three approaches, called average approach, main eye approach, and visual acuity approach, were tested for measuring the perceptual quality of stereoscopic images. Further, disparity information was integrated into two metrics for the quality assessment [6]. It was found that the disparity information has a significant impact on stereoscopic quality assessment, while its capability has not been studied adequately. In [7], only absolute disparity was

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used. It was found that added noise on the relatively large absolute disparity has greater influence than on other disparity. Subsequently, a metric called stereo sense assessment (SSA) based on the disparity distribution has been proposed.

In addition, some special metrics that take into account the advantage of the characteristics of 3D images have been proposed. Boev et al. [8] combined two components: a monoscopic quality component and a stereoscopic quality component, for developing a stereo-video quality metric. A cyclopean image for monoscopic quality, a perceptual disparity map and a stereo-similarity map for stereoscopic quality were defined. These maps were then measured using SSIM in different scales and combined into a monoscopic quality index and a stereoscopic quality index, respectively. The experimental result demonstrated that the proposed method is better than signal-to-noise ratio (SNR). Additionally, an artifact distribution of coding schemes at different depth layers within a 3D image was modeled in a single metric [9]. The metric included three steps. Firstly, a set of 2D image pairs were synthesized at different depth layers using an image based rendering (IBR) scheme. Secondly, pixels that can be discerned to belong to each depth layer were identified. Finally, the image pairs were masked and the coding artifact at each depth layer was evaluated using the multi-scale SSIM. Three coding schemes were studied including two H.264 based pseudo video coding schemes and JPEG 2000. The experimental results showed a high correlation between the coding artifacts and their distribution at different depth layers. Gorley et al. [10] used a new Stereo Band Limited Contrast (SBLC) algorithm to rank stereoscopic pairs in terms of image quality. SBLC took into account the sensitivity to contrast and luminance changes in image regions with high spatial frequency. A threshold for evaluating image quality produced by SBLC metric was found to be closely correlated to subjective measurements.

The rest of this paper is organized as follows. In Section 2, a subjective quality experiment on stereoscopic images is introduced briefly, which provides a solid basis for designing objective quality metrics. Section 3 introduces some well-known 2D image quality metrics and investigates their capabilities in evaluating the stereoscopic image quality; an integration of disparity information into objective quality metrics is proposed based on an intensive analysis of the disparity information on stereoscopic quality evaluation. Finally, concluding remarks and future work are given in Section 4.

2. SUBJECTIVE STEREOSCOPIC IMAGE QUALITY ASSESSMENT

A subjective quality assessment study on the stereoscopic images was conducted at Ningbo University, China [11]. Ten source stereopair images with high resolution and high quality were collected from the Internet [12]. For each pair of source images, the right eye image was degraded with four typical distortion types: Gaussian blurring, JPEG compression, JPEG2000 compression, and white noise, while the left eye image was kept undistorted. The distortion levels in this experiment covered a wide range of image impairments from imperceptible to very annoying. 370 distorted images in total were generated and they were divided into four sessions. Twenty non-expert subjects equipped with polarized glasses participated in the subjective quality assessment using a double-stimulus continuous quality scale (DSCQS) method. Finally, difference mean opinion scores (DMOS) on a scale of 0-100 were obtained from the quality evaluation. Readers can refer to [11] for the details about the subjective quality assessment.

3. STEREOSCOPIC IMAGE QUALITY METRIC BASED ON 2D IMAGE QUALITY METRICS AND DISPARITY ANALYSIS

Accurately predicting stereoscopic quality is an important issue for improving the ability and feasibility of compression and transmission schemes for stereoscopic images. Although many 2D image quality metrics (IQM) have been proposed that work well on 2D images, developing quality metrics for 3D presentations is almost an unexplored issue. It was found that PSNR is not appropriate for evaluating the quality of stereoscopic images in [11]. Therefore, in this section, we will introduce some well-known 2D IQMs and investigate their capabilities in stereoscopic image quality assessment. Furthermore, as disparity is an important attribute of stereopsis, we will try to improve the performance of IQMs on stereoscopic image quality assessment by integrating disparity information into the IQMs. We will mainly focus on the full reference (FR) metrics in this study, which means that the undistorted images are required for evaluating the quality of the distorted images.

Over the years, a number of researchers have contributed significant research in the design of full reference image quality assessment algorithms, claiming to

Table 1 Descriptions of image quality metrics

IQM	Descriptions
PSNR	Peak signal-to-noise ratio
SSIM	Single scale structural similarity
MSSIM	Multi-scale structural similarity
VSNR	Visual signal-to-noise ratio
VIF	Visual information fidelity
UQI	Universal quality index
IFC	Information fidelity criterion
NQM	Noise quality measure
WSNR	Weighted signal-to-noise ratio
PHVS	Modified PSNR based on HVS
JND	Just noticeable distortion model

have made headway in their respective domains [13]. In this study, eleven IQMs that are summarized in Table 1 were employed in the stereoscopic image quality assessment.

3.1. Performance analysis of 2D IQMs on stereoscopic image quality assessment

We performed the 11 IQMs on the stereoscopic images, respectively. As some IQMs use luminance component only, while others can employ color components as well, we transformed all the color images into gray images firstly, and then computed the image quality using these IQMs. After obtaining the metric results, a nonlinear regression between the metric results (*IQ*) and the subjective scores (DMOS) was performed using the following logistic function:

$$DMOS_P = \frac{a_1}{1+\exp(-a_2 \cdot (IQ - a_3))} \quad (1)$$

The nonlinear regression function was used to transform the set of metric results to a set of predicted DMOS values, $DMOS_P$, which were then compared against the actual subjective scores (DMOS) and result in two evaluation criteria: root mean square error (RMSE) and Pearson correlation coefficient. We performed the IQMs on the right eye images in the stereoscopic image quality assessment, as there were no distortions on the left eye images. Actually, we can use a constant as the quality values of the left eye images, e.g. 1, for SSIM, MSSIM, UQI, etc. Then, the significance of the interaction effect between the quality of the left eye image, the right eye image, and the overall quality was tested by performing a two-way ANOVA (ANalysis Of Variance) on the results. The ANOVA results show that the quality of the right eye image dominates the overall quality and there is almost no influence of the left eye image on the overall quality.

Table 2 and Table 3 give the evaluation results on RMSE and Pearson correlation coefficients. According to the evaluation results, the performance of IQMs is promising for stereoscopic images with a same distortion type, while the robustness to the changes of the distortion type is weak. Furthermore, we have also performed these IQMs on 2D image data sets. The experimental results demonstrated that the robustness of these IQMs to the changes of distortion type in stereoscopic image quality assessment is much worse than that in 2D image quality assessment, and the performance of these IQMs on the entire distortion types in 2D image quality assessment is much better than that in stereoscopic image quality assessment. In our opinion, the reason is that the perceived quality is not only affected by image contents, but other attributes of stereopsis, such as disparity. For example, we think that the disparity information has significant influence on the quality evaluation of stereoscopic images.

Table 2 RMSE of IQMs on stereoscopic images

IQM	Blurring	JPEG	JPEG2000	Noise	All
PSNR	1.97	5.97	5.09	2.74	7.64
SSIM	3.00	7.70	8.91	2.43	9.28
MSSIM	1.91	4.94	4.97	2.51	7.62
VSNR	2.58	5.71	5.42	3.54	8.63
VIF	1.84	4.39	6.45	3.41	7.78
UQI	1.89	3.96	6.44	4.06	7.13
IFC	1.78	3.55	6.37	3.98	8.61
NQM	2.17	3.53	4.23	4.36	8.70
WSNR	2.02	6.74	6.09	3.85	9.07
PHVS	2.10	5.62	5.27	2.65	8.06
JND	2.18	6.97	5.73	3.55	8.58
Average	***2.13***	***5.38***	***5.91***	***3.37***	***8.29***

Table 3 Pearson correlation coefficient of IQMs on stereoscopic images

IQM	Blurring	JPEG	JPEG2000	Noise	All
PSNR	0.939	0.882	0.950	0.978	0.795
SSIM	0.851	0.793	0.824	0.983	0.677
MSSIM	0.943	0.920	0.948	0.981	0.797
VSNR	0.893	0.893	0.948	0.962	0.731
VIF	0.947	0.938	0.916	0.966	0.788
UQI	0.943	0.950	0.913	0.950	0.825
IFC	0.951	0.962	0.929	0.954	0.734
NQM	0.925	0.961	0.963	0.942	0.726
WSNR	0.935	0.846	0.924	0.955	0.696
PHVS	0.930	0.896	0.949	0.979	0.769
JND	0.924	0.836	0.937	0.961	0.738
Average	***0.926***	***0.898***	***0.927***	***0.965***	***0.752***

3.2. Perceptual stereoscopic quality assessment based on disparity information

Human eyes are horizontally separated by about 50-75 mm (interpupillary distance) depending on each individual. Thus, each eye has a slightly different view of the world. This can be easily seen when alternately closing one eye while looking at a vertical edge. At any given moment, the lines of sight of the two eyes meet at a point in space. This point in space projects to the same location (i.e. the center) on the retinae of the two eyes. Because of different viewpoints observed by the left and right eyes however, many other points in space do not fall on corresponding retinal locations. Visual binocular disparity is defined as the difference between the points of projection in the two eyes and is usually expressed in degrees as the visual angle. The brain uses binocular disparity to extract depth information from the two-dimensional retinal images in stereopsis. In computer stereo vision, binocular disparity refers to the same difference captured by two different cameras instead of eyes. Generally, one image of stereo-pair images can be restored from the disparity and the other one image. Therefore, we believe that the disparity between the left eye image and right eye image has an important impact on visual quality assessment.

In this work, we do not intend to study the estimation methods of disparity map between a stereo-pair images and their impact on the quality assessment. We chose a belief propagation based method to estimate the disparity map

[14]. Because of the distorted regions, the disparity of the original stereo-pair images is different from that of the distorted stereo-pair images, even though the relative positions of objects in the image pair do not change at all. Because the real objects in the image do not change during the distortion process, changes between two disparity images (one is original disparity and another is the disparity between the left eye image and the distorted right eye image) are usually located at those positions where the distortions are clearly visible, such as noise added regions, regions with blockiness. Consequently, we can compare the disparity images to obtain a quality prediction for distorted stereoscopic images.

As explained above, the disparity refers to the difference in location of an object seen by the left and right eyes. Thus, the disparity image has quite different modality compared to the original images. First, we tested three simple metrics: global correlation coefficient (GCC), mean square error (MSE), and mean absolute difference (MAD). We performed the same fitting operation, as in Equation (1), between the computed results obtained by these metrics and the DMOS values on the whole distortion types, and then the Pearson correlation coefficient and RMSE were calculated. Second, we also validated the performance of the IQMs on the disparity images, even though these IQMs were supposed to be developed for predicting the quality of natural images. Table 4 gives the evaluation results of the Pearson correlation coefficient and RMSE using these metrics.

According to the evaluation results of the IQMs on the disparity images, the performance is much better than that on the original images. This observation probably indicates that disparity information is more important than original images for perceptual quality assessment, even though the disparity image does not contain any real objects. The big differences between two disparity images usually appear in the regions where the distortions are greatly annoying. Thus, even a very simple metric on the disparity images, such as MSE, performs better than a complicated IQM on the original images. Additionally, we found that SSIM and UQI have the best performance within all the IQMs. We believe that this is because these two metrics are based on comparing the structural information, and the disparity can express such structural information of the original images.

Since the disparity images have significant influence on stereoscopic image quality assessment, we naturally suppose

Table 4 Evaluation results of image quality metrics on disparity images

Criteria	GCC	MSE	MAD	PSNR	SSIM	MSSIM	VSNR
RMSE	7.11	7.09	7.22	6.86	6.40	6.99	6.85
Pearson	0.83	0.83	0.82	0.84	0.86	0.83	0.84
Criteria	**VIF**	**UQI**	**IFC**	**NQM**	**WSNR**	**PHVS**	**JND**
RMSE	8.31	6.37	8.08	7.94	7.20	6.87	7.59
Pearson	0.76	0.86	0.77	0.78	0.82	0.84	0.82

that the combination of the disparity images and the original images can perform better than using either the disparity or the original images solely. Subsequently, we used three approaches to combine the disparity and original images to compute the stereoscopic image quality.

The first approach, called global combination, was to compute two quality values of the distorted image and the distorted disparity firstly, denoted as *IQ* and *DQ*, respectively. *IQ* was computed by IQMs on the original images, and *DQ* by GCC, MSE, MAD, and the IQMs. Then, an overall quality (*OQ*) that was taken as the quality of the stereoscopic image was calculated using the following function with different parameters ($a \sim e$):

$$OQ = a \cdot IQ^{d} + b \cdot DQ^{e} + c \cdot IQ^{d} \cdot DQ^{e} \qquad (2)$$

In this study, we employed the Levenberg-Marquardt algorithm to find the optimum parameters in Equation (2). Although the optimum parameters may change if different initial values were used, we found that the highest correlation coefficient between *OQ* and DMOS values is *0.899*. For example, one set of the optimum parameters is a=3.465, b=0.002, c=-0.0002, d=-1.083, and e=2.2. In this experiment, we used the direct correlation between *OQ* and DMOS values while the fitting operation in Equation (1) was not performed because we have performed an optimization operation between *OQ* and DMOS values in Equation (2). We report the highest correlation for different combinations in Table 5 while the corresponding optimum parameters are omitted in the sake of clarity.

According to the experimental results, it was found that appropriate combinations of the image quality and the disparity quality perform better than using the quality of either the original images or the disparity images solely. In addition, we also found that the combination of SSIM and MAD, i.e. SSIM was used to compute *IQ* and MAD was used to compute *DQ*, always obtains the best performance within all the possible combinations. Furthermore, SSIM has a promising performance in the combinations either for measuring the original image quality or for computing the disparity image quality. This result indicates that a good metric for predicting the stereoscopic image quality can be developed if appropriate methods are found to combine the original image quality and the disparity image quality.

The second approach is called local combination. Some IQMs, e.g. PSNR (based on MSE), SSIM, MSSIM, UQI, PHVS, and JND, compute a quality map between the reference image and the distorted image to depict the distribution of quality degradation at image pixels directly or indirectly, and the overall quality of the distorted image is usually computed as a mean over all the pixels in the quality map. Furthermore, we can also compute a quality map of the disparity image which can reflect an approximate distribution of the degradation on the distorted disparity image. In this study, four methods were used to compute the quality map on the disparity image as following:

Table 5 Evaluation results of global combination between image quality and disparity quality on stereoscopic image quality assessment

DQ	IQ										
	PSNR	SSIM	MSSIM	VSNR	VIF	UQI	IFC	NQM	WSNR	PHVS	JND
GCC	0.869	0.867	0.840	0.830	0.831	0.835	0.836	0.837	0.828	0.833	0.839
MSE	0.887	0.878	0.838	0.830	0.828	0.844	0.843	0.829	0.847	0.828	0.846
MAD	0.888	**0.899**	0.853	0.828	0.825	0.841	0.833	0.829	0.838	0.830	0.851
PSNR	0.876	0.887	0.848	0.836	0.837	0.847	0.874	0.842	0.840	0.839	0.829
SSIM	0.858	0.859	0.870	0.862	0.858	0.870	0.861	0.866	0.856	0.859	0.866
MSSIM	0.857	0.865	0.837	0.832	0.836	0.846	0.853	0.833	0.840	0.834	0.815
VSNR	0.850	0.842	0.844	0.841	0.837	0.860	0.834	0.838	0.833	0.845	0.863
VIF	0.817	0.819	0.804	0.741	0.779	0.826	0.730	0.732	0.730	0.766	0.778
UQI	0.855	0.859	0.865	0.862	0.858	0.868	0.863	0.868	0.855	0.857	0.864
IFC	0.814	0.807	0.793	0.764	0.775	0.822	0.760	0.762	0.760	0.778	0.780
NQM	0.847	0.856	0.829	0.770	0.784	0.827	0.774	0.764	0.763	0.796	0.775
WSNR	0.865	0.878	0.852	0.817	0.831	0.838	0.840	0.821	0.818	0.823	0.818
PHVS	0.853	0.879	0.845	0.813	0.818	0.843	0.823	0.817	0.813	0.818	0.825
JND	0.839	0.876	0.827	0.833	0.806	0.852	0.795	0.836	0.827	0.815	0.839

$$DQ\_map = \begin{cases} (D-\overline{D})^2 \\ \left|D-\overline{D}\right| \\ 1-\dfrac{\sqrt{D^2-\overline{D}^2}}{255} \\ IMQ(D,\overline{D}) \end{cases} \tag{3}$$

where D and $\overline{D}$ denote the original disparity image and the distorted disparity image, respectively, and $IMQ(D,\overline{D})$ denote the quality map using the corresponding IQMs (including PSNR, SSIM, MSSIM, UQI, PHVS, and JND) between the original disparity image and the distorted disparity image. After computing the quality maps of the original image and the disparity image, Equation (2) was used to pool each pixel pair on the quality maps, and then a mean over all pixels was taken as the overall quality of the stereoscopic image. Table 6 gives the Pearson correlation coefficients between the quality values and the DMOS values by using the local combination, where the highest correlation coefficients were reported.

According to the evaluation results, it was found that the performance improvement by using the local combination is not as significant as if the global combination was performed. Some combinations even reduced the correlation between the overall quality values and the subjective DMOS values. However, we found that SSIM and UQI algorithms on the original images and disparity images have the best performance for local combination, regardless of what kinds of combination are used. For example, let *IQM* and *DQM* be quality maps of the original image and disparity image computed by UQI and SSIM, respectively, and the combination at each pixel pair be $OQM = \sqrt{IQM} + \sqrt{DQM} + \sqrt{IQM \cdot DQM}$, the Pearson correlation coefficient between the predictive qualities and the subjective results is *0.899*. Therefore, not all metrics are suitable for the local combination, and an appropriate method is needed to explore the relationship between the image quality map and the disparity quality map.

Finally, the third approach was to integrate the local combination into the global combination by the following three steps:

- Two quality maps were computed firstly using appropriate metrics on the original image and disparity image, respectively;
- These two maps were combined locally and the mean was taken as an intermediate quality of the distorted image;
- The final step was to combine the intermediate quality and the quality of the disparity image and then obtained the overall quality of the stereoscopic images.

In our experiment, the highest correlation coefficient

Table 6 Evaluation results of local combination between image quality map and disparity quality map on stereoscopic image quality assessment

DQ	IQ					
	PSNR	SSIM	MSSIM	UQI	PHVS	JND
$(D-\overline{D})^2$	0.866	0.832	0.776	0.833	0.837	0.770
$\left\|D-\overline{D}\right\|$	0.840	0.849	0.743	0.853	0.806	0.803
$1-\frac{\sqrt{D^2-\overline{D}^2}}{255}$	0.807	0.792	0.815	0.898	0.815	0.795
PSNR	0.799	0.805	0.786	0.842	0.776	0.782
SSIM	0.799	0.821	0.800	**0.899**	0.832	0.816
MSSIM	0.762	0.801	0.774	0.859	0.769	0.802
UQI	0.798	0.822	0.831	0.895	0.841	0.839
PHVS	0.795	0.826	0.804	0.846	0.765	0.728
JND	0.804	0.823	0.781	0.835	0.774	0.807

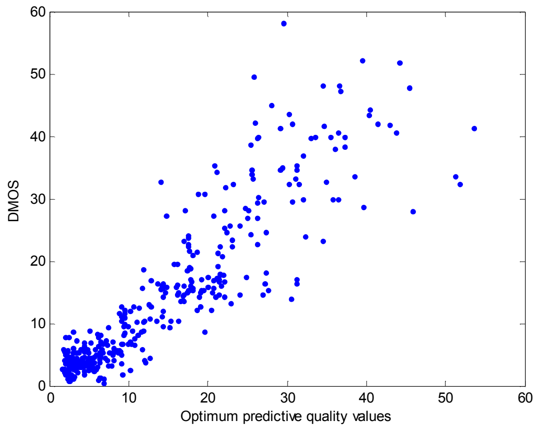

Figure 1. Scatter plot of DMOS versus optimum predictive quality values

(*0.91*) was achieved when UQI was used in computing the quality maps of the original image and disparity image, and the local combination on the quality maps was then combined with the MAD of the disparity image again. Figure 1 gives the scatter plot of the subjective DMOS values versus the optimum predictive quality values. According to the experiment results, the proposed model has better performance on predicting perceptual quality of the stereoscopic images with low impairments than that on the images with high impairments. Therefore, improving the robustness of the quality metric to different impairment levels is also an important task in the future work.

4. CONCLUSIONS

In this work, we have investigated the capabilities of some well-known 2D image quality metrics, including SSIM, MSSIM, VSNR, VIF, UQI, IFC, NQM, WSNR, PHVS, and JND model, in the stereoscopic image quality assessment. The experimental results indicated that 2D image quality metrics can not be adopted in evaluating the stereoscopic image quality directly. Furthermore, as an important factor in stereopsis, the disparity was taken into account in stereoscopic image quality assessment. The experimental results demonstrated the promising performance by using the disparity information in evaluating the stereoscopic quality, and the best performance can be achieved when the disparity information and the original image are combined appropriately.

Although some tentative work on developing objective quality metrics for stereoscopic images has been done in the literature and this work, we are still a long way from 3D quality metrics that are widely applicable and universally recognized. The future work is to understand the fundamental of 3D presentation impact on the human visual and perceptual system and explore the relationship between the original image, the disparity information, and the quality assessment in depth. Determining how to model such impact and the relationship between the characteristics of 3D presentations and quality assessment is another critical issue for evaluating the quality of visual experience in 3D visual presentations.

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