3D Image Quality Assessment Based on Local Entropy and Disparity Map

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Abstract

The aim of full reference objective quality assessment methods is to deduce a perceptual model that can delicately estimates the quality of a distortion image in a manner likely to human opinion. In this article, we have studied the efficacy of using robust features extracted from 3D stereoscopic image, to present a full-reference (FR) objective image quality assessment (IQA) model. The essential concept of the proposed objective quality assessment model is based on exploiting the statistical and spatial features of 3D stereoscopic image. More specifically, the extracted features are local entropy values and disparity map information. The proposed quality assessment model namely ED-QA was tested on LIVE 3D stereoscopic image database and compared to other full-reference (FR) objective quality assessment methods. The performance evaluation of ED-QA model was achieved by applying it over symmetrical and asymmetrical distorted images with three types of distortions (JPEG, Gaussian Blur and Fast Fading). Based on the experimental results, ED-QA model demonstrates an efficient and

accurate quality measurement of 3D stereoscopic images under all the distortion types utilized in this work.

تقييم جودة الصورثلاثية الابعاد أعتمادا عل الخصائص الانتروبي المحلي و خارطة التباين

المستخلص

ان الهدف من خوارزميات تقييم الجودة الموضوعي للمرجع الكامل هو لاستنباط موديل ادراك حسي يمكن ان يخمن مباشرة جودة الصورة المشوهة باسلوب مشابه لرأي البشر. في هذه الدراسة ، قمنا بدراسة أمكانية استخدام خصائص قوية تستخرج من الصور ثلاثيه الابعاد المجسمة لغرض تقديم موديل تقييم الجودة الموضوعي للمرجع الكامل. ان المفهوم الاساسي لموديل تخمين الجودة الموضوعي المقترح يستند على استغلال الخصائص الاحصائية والمكانية للصور الثلاثية الابعاد المجسمة. وبشكل اكثر تحديدا، الخصائص المستخرجة هي عبارة عن الانتروبي المحلي ومعلومات خارطة التباين. ولقد تم اختبار موديل تقييم الجوده المقترح على قاعدة البيانات LIVE وتمت مقارنته مع موديلات اخرى لقييم الجودة الموضوعية للمرجع الكامل. تم أنجاز مرحله تقييم الاداء للموديل المقترح من خلال تطبيقه على صور مشوهة بطريقة تناظرية وغير تناظرية لثلاثة انواع من التشوهات (JPEG, Gaussian Blure, Fast Fading) . وبناء على النتائج التجريبية، اظهر الموديل المقترح تقييم جودة كفوء ودقيق للصور الثلاثيه الابعاد المجسمة وتحت كل انواع التشوهات المستخدمة في هذا العمل.

1. Introduction

The rapid development of 3D media transmission and processing such as 3D remote education, 3D robot navigation, and 3D medical imagery, has caused a decisive demand for image quality assessment IQA algorithms that can assess the quality of

3D imagery. Stereo imagery system indicates to multiple images taken simultaneously using two or more cameras, which are collectively construct the stereo pair images [1]. The stereoscopic image is composed of two different views (left and right) as shown in Fig. 1. The straightforward way to evaluate perceived visual quality is to use the subjective test (subjective quality assessment) to measure human opinion [2]. Obviously, the subjective quality assessment has two main bugs, which makes it unsuitable for practical applications. First bug, the procedure of subjective quality assessment is expensive and time-consuming in order to obtain meaningful results. Second bug, it is difficult to apply subjective quality assessment process of given object into real-time systems [2]. The objective quality assessment methods are referred to the automated evaluation of visual quality with the assistance of an algorithm. In general, the visual signal is perceived by human (the end user receiver), so, the performance of any image quality assessment method should be correlated tightly with subjective quality assessment obtained by human opinions. Generally, image quality assessment methods are categorized into three main types based on the amount of information available to be utilized for computing the quality score; full-reference (FR), reduced-reference (RR) and no-reference (NR) [2][3]. Full reference methods need the original image to be available in order to evaluate the distorted image. Reduced reference methods estimate the image quality according to presence raw features vector extracted from the original image.

Finally, no-reference methods differ from the previous methods in its ability to predict image quality without needing to have knowledge about the original image [3].

The most ideal way to predict the quality of a 3D image is based on applying 2D QA algorithms on each individual view, then pooling the scores into one quality measurement [4]. The presented work in [5], build the Binocular Energy Quality Metric (BEQM) based on the construction of binocular energy of stereoscopic image. The most frequently assessment tools of IQA method is PSNR metric, as well as Structural Similarity Index Measure SSIM [6] that performs the quality assessment based on similarity measure between reference image and distorted image. P. Gorley et al. in [7] investigated a quality assessment index based on matched points between stereoscopic pair image using SIFT [8] features and RANSAC [9] method. The submitted work by J. Yang [10], proposed an image quality metric using PSNR metric as well as the intensity differences between stereo pairs. In [11], Ko et al. presented a binocular perception index termed structural distortion parameter SDP in order to estimate the overall quality assessment of stereoscopic image.

The framework of this article aims to present a feasible full-reference objective model to evaluate the quality of 3D stereoscopic images at end user receiver based on extracting relevant features from the distorted image. These relevant features are local entropy and disparity variation of stereo pair images. The rest of this article is organized as follows: in section 2, the workflow of the proposed quality model is presented. The disparity map generation and local entropy feature are illustrated in sections 2.1, 2.2 respectively. The experimental results are stated and analyzed in section 3. Finally, the discussion and conclusions of this article are described in section 4.

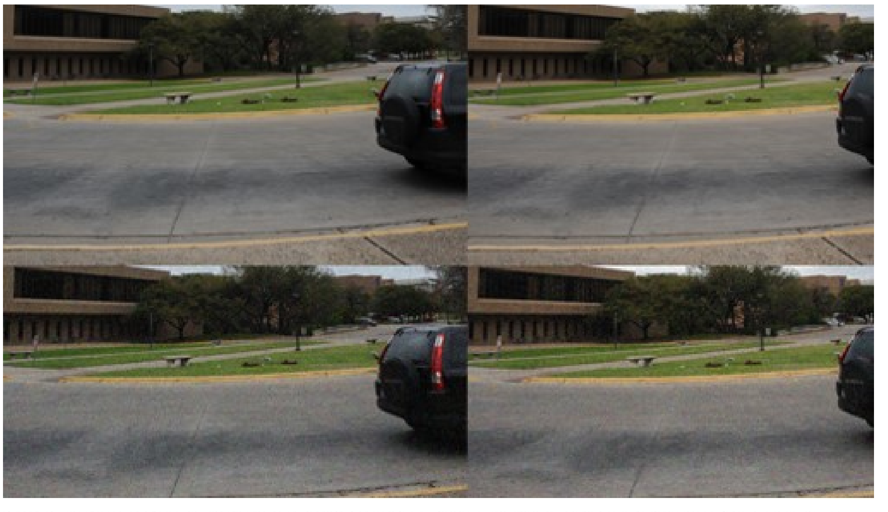

Figure 1: Two samples of 3D stereoscopic images taken from LIVE 3D image database: top image has high quality in both views; bottom image has low quality

2. Workflow of ED-QA Model

The major assumption that we have adopted in this work to predict the FR objective quality assessment of 3D stereoscopic images is; the quality assessment score is determined using two main quality factor such as local entropy factor and disparity variation factor. In order to generate the disparity variation map of stereo pair image, the corresponding points between two views (left and right) are detected. The entropy value reflects the dependency relation between images pixels, thus any distortion occurs in the image content caused different results of entropy

values from the original image. The workflow of the proposed image quality assessment method ED-QA is described in Fig. 2, which applied over two given images; tested (distorted) image and reference (non-distorted) image. Let we denote the testing image and reference images by Img_T and Img_R respectively, then Img_T and Img_R are subjected to the following processes to predict the final quality score of Img_T:

- **Detect the corresponding points between stereo pair image in order to generate the disparity map matrix as shown in Fig. 3. For each stereo pair image, the corresponding points are detected using speeded up robust features (SURF) [12], which are represented by one-dimension raw vector. We have referred to the corresponding points between both views of stereo pair image as P_{LR} data set points, which have same properties (position and intensity).**
- **Generate disparity map matrix between left and right views of stereo pair image based on P_{LR} data set points for estimating the first quality score D_f of DE-QA model.**
- **Estimate the second quality factor of DE-QA model through computing local entropy quality factor E_f of stereo pair image according to the following steps:**
  - **Divide the left and right views of 3D stereoscopic image; IL, IR respectively; into blocks of pixels with size $(n \times n)$.**

- **Generate entropy map for each view by computing entropy for each block to produce left and right entropy matrices.**

- **The Final objective quality score is determined by pooling the two quality scores into linear quality formula as illustrated in Eq. (1).**

$$Final\text{-}Score\,(E_f, D_f) = w1 * E_f + w2 * D_f \qquad (1)$$

Where $w1$, $w2$ are the weighted values obtained by build in MATLAB function (rangflit) in the training mode.

- **Performing correlation process between two final quality scores of Img_T and Img_R via computing the similarity measure between their scores. The similarity measure is determined using PLCC benchmarks.**

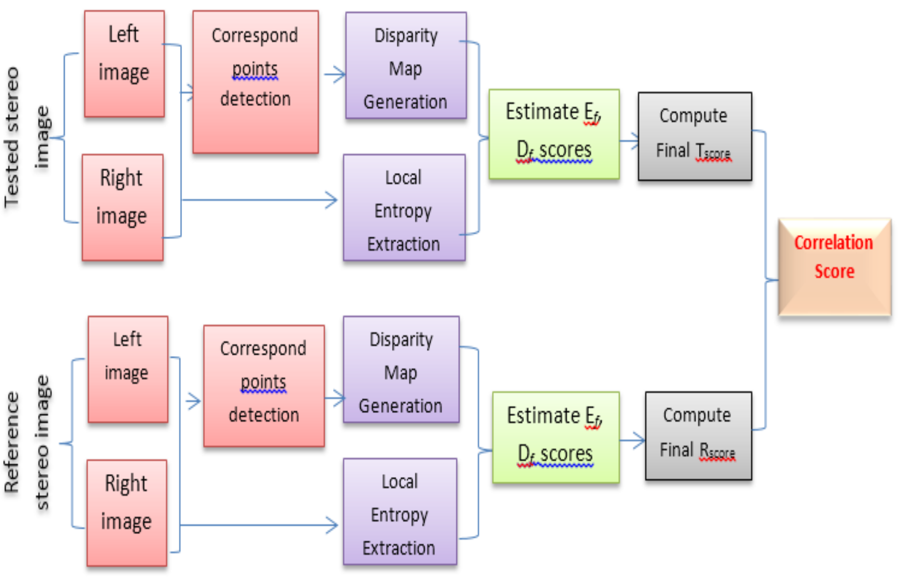

Figure 2: The framework of ED-QA objective quality model

2.1 Disparity Map Generation

The basic concept of 3D stereoscopic display systems that used to display stereo images is significantly similar to the human visual system to get the perception of depth. The visualization and analysis of stereoscopic images must regards to the depth information that estimates from both views of stereoscopic image. The disparity information of stereoscopic image could be expressed as the difference between two matching pixels coordinates in both views of stereoscopic image (left and right) [13]. In this article, the disparity map of stereo pair image was generated based on corresponding point's detection between stereo pair image.

Consequently, after detecting the corresponding points between left and right views of stereoscopic image, the disparity map function was implemented using sum of absolute differences method (SAD) [14]. Basically, the workflow of (SAD) method is based on pixel location. It applied over P_{LR} data set points and specified through calculating the absolute differences between the corresponding pixels in the stereo image pair. Furthermore, these differences are summed to originate a common measure to quantify the similarity of any two images. The disparity value between any two corresponding pixels is gained through minimizing SAD differences between these pixels.

The horizontal distance between arbitrary pixel P in left and right images is known as disparity d which defined in Eq. (2), where x_L and x_R are x−coordinates of the projected 3D coordinate onto the left and right image planes I_L and I_R as illustrated in Fig. 4.

$$d = x_L - x_R \tag{2}$$

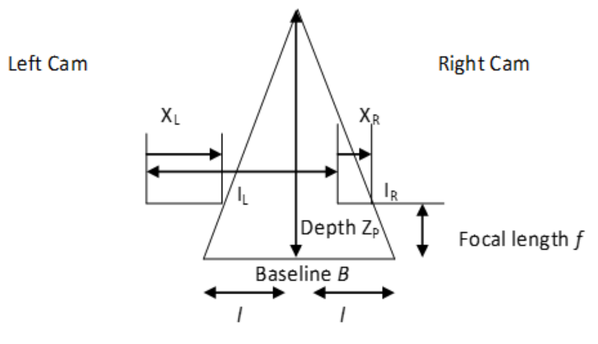

Figure 4: Demonstration of stereo image system

Obviously, the disparity is proportional to the baseline B (the distance in mm between two cameras), the larger the baseline, the higher the disparity. An example of image and its disparity map is illustrated in Fig. 5.

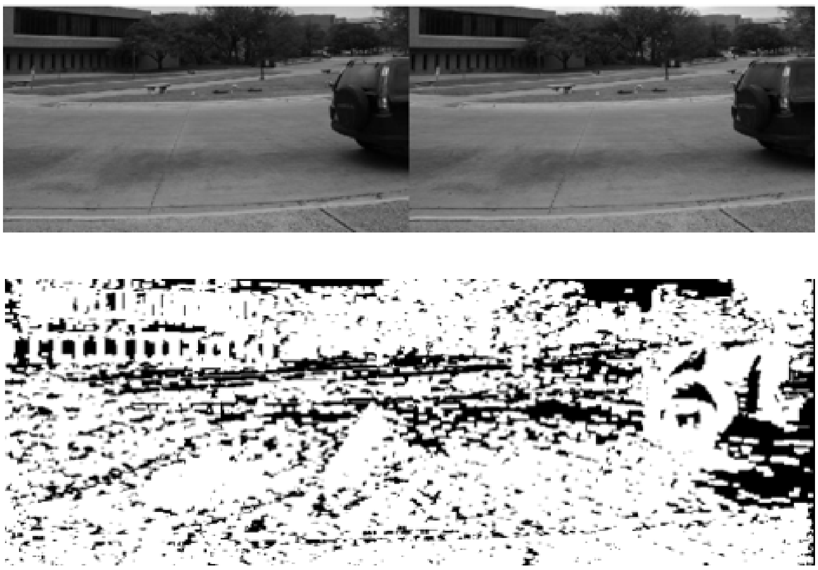

Figure 5: Sample of stereoscopic image and its disparity map image: the top image is the original stereo pair image, the bottom image is the disparity map for the original image.

2.2 Local Entropy

In general, the statistical features of an image reflect the dependency relation of its pixels adjacent. In this article, we have been employed the entropy value of stereoscopic image to detect the second quality factor of ED−QA model. The entropy value emerges the variation of information distribution contained within an image. Obviously, image local entropy is affected by different types of image distortions, therefore, it's considered as a good indicator of distortion detection as we'll going forward to clarify this point. In contrast, global entropy does not provide adequate

information about the distribution of image distortion points. Therefore, his second quality factor utilized in our proposed method is the local entropy of stereo pair image blocks. Each stereo pair image is divided into set of pixels blocks, each with size (n×n) pixel. Then, the local entropy is calculated for each block according to Eq. (3):

$$E_l = -\sum_{x} p(x)\log_2(p(x)), \tag{3}$$

Where *x* is the pixel value within a block of size (n, m) and *p(x)* is relative to histogram value.

3. Experimental Results

The validation of the proposed ED-QA model is conducted using LIVE 3D image quality database [15][16]. 3D LIVE Database includes eight reference stereoscopic images, each stereo pair image is distorted with five type of distortions such as (white Noise, JPEG, JPEG2000, Fast Fading and Gaussian Blur). Each distortion type has nine level distortion, which yields a total number of distorted images = 8*5*9 =360 image with size 640×480 pixel. Further, the subjective quality scores (mean opinion scores MOS) of the distorted images are available with this database.

The experimental results were conducted by utilizing and selecting images with three distortion types (JPEG, Gaussian Blur and Fast Fading). We have trained the proposed quality model by splitting the dataset into two sets: training set and testing set.

The training set is constitute 30% of the total number of the distortion images which is used to determine the weighting values $w1$, $w2$ related to the quality score equation. The testing set constitutes 70% of the total number of distortion images, which is used to evaluate the performance of the proposed ED-QA model.

The weighting values w1, w2 are determined in the training mode through applying (rangflit) MATLAB function over 66 training images. In the testing mode, a raw feature vector is constructed for both distorted and reference images in order to report the mean differences between reference and distorted images. The aim of our experiment is to determine the final quality score of the distorted image which is indicate the objective quality assessment of this image. The correlations between objective quality scores (obtained in this experiment) and corresponding mean opinion scores MOS provided with LIVE database are obtained using the common statistical performance benchmark such as Pearson Linear Correlation Coefficient PLCC measure. In general, a better correlation value obtained by PLCC benchmark is close to 1. Based on our experiments, we have obtained a correlation factor equal to 0.865 which indicates a well correlation with the subjective quality scores. Furthermore, in order to obtain insights into the impact of the proposed method on the performance of 3D IQA models, two objective quality methods were selected based on their performance as well as to

perform a comparative study between their performances. The reported results in Table (1) are represent the mean value of the experimental results for the applied ED-QA model over 150 images in terms of mean PLCC benchmarks. The correlation between ED-QA objective quality scores model and the corresponding subjective quality scores is illustrated in Fig. 6.

Table 1: Mean PLCC for 150 tested images

Objective Metric	JPEG	Gaussian Blur	Fast Fading
SSIM	0.74	0.78	0.76
PSNR	0.70	0.81	0.73
ED-QA	0.85	0.88	0.81

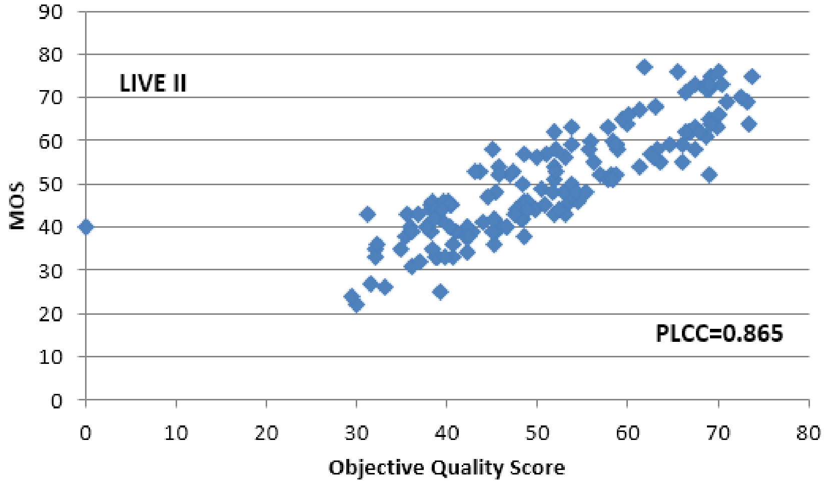

Figure 6: The correlation between ED-QA objective quality scores and MOS scores based on PLCC benchmark.

4. Discussion and Conclusions

In this article, we have proposed a full-reference objective quality metric for 3D stereoscopic image namely ED-QA based on local entropy feature combined with disparity map information. The main contributions of the proposed method was to handle the mentioned challenges confronted by quality assessment research through two main robust features extracted from stereoscopic image; local entropy variation and disparity map information. The proposed method has been applied upon two main distortion behaviors, symmetric and asymmetric distortions. Also, the proposed quality model is based on local regions (blocks of pixels) rather than pixel information to estimate the entropy variation map of stereo pair image. Based on the experiments; local entropy feature are correlated tightly with distortion detection process.

The performance evaluation of ED-QA model was compared versus full reference metrics such as SSIM and PSNR metrics. The validation of ED-QA model was achieved based on three types of image distortion such as JPEG, Gaussian Blur and Fast Fading. The ED-QA model has been achieved a competitive results compared to state-of-the-art full reference quality assessment methods. The experimental results were shown that the objective quality assessment (using local entropy and disparity features) is correlated well with the MOS subjective quality assessment as shown in Fig. 6.

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