EVALUATION OF IMAGE QUALITY OF EXPERIENCE IN CONSIDERATION OF VIEWING DISTANCE
(INVITED PAPER)

Ruigang Fang, Dapeng Wu

University of Florida
ruigangfang@ufl.edu, wu@ece.ufl.edu

Liquan Shen

Shanghai University
jsslq@163.com

ABSTRACT

Image viewing distance plays an important role in the assessment of image Quality of Experience (QoE). In this work, we present a subjective image QoE study in which a total of 494 images evaluated by more than 30 human subjects at 7 different viewing distance. Through the study, we observed that different images have different regularities between viewing distance and their QoE. A No-Reference QoE assessment model is proposed to objectively measure image QoE considering viewing distance. The experiments conducted on our database show that the proposed model achieves high correlation between its predicted QoE score and human perception. Moreover, we have made the image database freely available to the research community.

***Index Terms*—** Image QoE Assessment, Viewing Distance, Image Database

1. INTRODUCTION

In the past few years, there have been many image and video applications appeared with the tremendous increase of personal digital assistants, smart phones, and tablets. For any multimedia application, it is important to guarantee the users' Quality of Experience (QoE). Lots of research works on image/video quality assessment have been done to ensure the Quality of Service (QoS). But higher QoS doesn't mean higher QoE, because there could be other factors affecting human perception except of multimedia quality itself, such as viewing distance, lighting, monitor.

Considerable attention has been attracted to the research on image quality assessment, such as Full Reference Image Quality Assessment (FRIQA) [1] [2] [3], Reduced Reference Image Quality Assessment (RRIQA) [4] [5] [6], and No Reference Image Quality Assessment [7] [8] [9]. All these above methods only consider image itself, and they assume that the images are viewed under the same condition for all users. However, different users have different viewing condition, so the viewing condition should be taken into consideration to understand image QoE well. For image viewing condition, viewing distance plays an important role, because it determines the visual resolution (pixels/degree of visual angle). With the increase of viewing distance, the signal visibility will decrease. However, for images with artifact, the visibility of artifact will also decrease with the increase of viewing distance. The viewing distance is an impact factor for the tradeoff between signal visibility and artifact visibility.

Although viewing distance is critical to image QoE, there is no much related research work, especially when it comes to distorted images. In [10] [11] [12], the best viewing distance for images displayed on TV is stated. [13] models subjective image quality as a function of viewing distance, resolution, and picture size, where it only explores the relationship between perfect images and viewing conditions. [14] discusses how viewing distance influences contrast sensitivity. [15] explores the effects of viewing distance and contrast masking on basis function visibility.

To explore the tradeoff between resolution/viewing conditions and visibility of compression artifacts, a subjective evaluation experiment is conducted in [16], where 4 images are compressed using JPEG and JPEG2000 at different bit rates. Another subjective study conducted in [17] tries to measure the quality of distorted image with a lower resolution compared to the reference image. In this study, 24 images are employed and distorted with JPEG, JPEG 2000, blurriness, or noisiness, and viewers are asked to choose preference for displayed image pair.

To better understand how viewing distance affect image QoE, we first constructed one image database, of which each image is distorted by different level of blurriness, blockiness, or noisiness. The QoE of these images are assessed by more than 30 testers at 7 different viewing distance. Second, for different types of images, we conducted experiments to discover the regularity between QoE and viewing distance. Finally, we proposed a model to predict the image QoE given viewing distance.

The rest of this paper is organized as follows. Section 2 gives the details of the subjective assessment on image QoE.

Section 3 describes the regularity between QoE and viewing distance. In Section 4, we propose a model to assess users' image QoE objectively given viewing distance, and show the experimental results related. Finally, Section 5 concludes this paper.

2. DETAILS OF THE EXPERIMENT

2.1. Image Database

All the images come from LIVE image database [18], which are carefully chosen and could reflect adequate diversity in image content. Most images are 768×512 in size. There are a total of 494 images, of which 29 are good images and 465 are distorted images. There are three kinds of distortion that often occur in real-world applications. The level of distortion are varied to generate images at a broad range of quality, from imperceptible levels to high levels of impairment. The distortion types are as follows.

- JPEG compression: The distorted images are generated by compressing 29 good images using JPEG at different bit rates.
- White Noise: The R, G, and B components of good color image are distorted with white Gaussian noise with same standard deviation. Different distorted images have different standard deviation of Gaussian noise.
- Gaussian Blur: A circular symmetric 2-D Gaussian filter is applied to R, G and B components of good color image to get Gaussian blur image. Different distorted images have different deviations of Gaussian filter.

2.2. Test Methodology

In this test, both good images and distorted images are evaluated by viewers. For each image, the QoE scores are evaluated at 7 different viewing distance through our test.

1) Equipment and Display Configurations: A Matlab-based interface is applied to display images, where the function *imread* and *imshow* are employed to read images from files and display them to viewers. The Matlab version is R2012 (7.14.0.739) win32. The monitor is at resolution of 1024×768 pixels. The test is conducted in an office environment with normal indoor illumination levels. The different viewing distance are determined through our extensive sensitive experiments, which are 40cm, 112cm, 176cm, 240cm, 296cm, 376cm, 560cm from the screen. Visual resolution of the display (in pixels/degree of visual angle) is determined by display resolution (in pixels/cm) and viewing distance (in cm) [15]. In our experiment, the display resolution is fixed, and the change of viewing distance is related to the change of visual resolution of display. So the viewing distance in our test configuration could be transformed to the related viewing distance in any other applications.

2) Human Subjects, Training, and Testing: The viewers are graduate from the University of Florida or Shanghai University, and they have the similar visual acuity. There are 494 images evaluated for each viewer at each viewing distance. At the beginning of each test, there is training to help viewers regain what is the best image QoE. In the training, the viewers will watch a set of good color images from one monitor with a distance of 40cm. During the tests, the viewers watch each image for 5 seconds and record his/her QoE score on that image. The range of image QoE score is from 0 to 100, and the larger the score is, the better the QoE is.

2.3. Processing of Raw Data

For each viewing distance of each image, there could be outliers existing in QoE scores from all the viewers. To obtain better understanding of image QoE, these outliers need to be detected and rejected. We assume the collected scores for one image at one viewing distance following a Gaussian distribution, because they are from more than 30 testers. A score is considered to be an outlier if it is outside an interval of width standard deviation of Gaussian distribution about the mean score. This outliers rejection algorithm is run twice. Then, the mean of scores without outliers is taken as the QoE score of that image at that viewing distance. We didn't calculate the DMOS score as image QoE score, because there could be other factors affecting human perception, and another reason is that these good color images may not provide the best QoE.

The detailed image database is available by the following link: http://www.wu.ece.ufl.edu/SourceCode/data/image.rar.

3. THE REGULARITIES BETWEEN QOE AND VIEWING DISTANCE

In this section, we roughly separate the images into three types: good images, distorted images, and poor images. For each type of images, we conduct experiments to explore the regularities between their QoE and viewing distance. Since viewers cannot see most details of displayed images when the viewing distance is larger than 560cm, the range of viewing distance discussed later is from 40cm to 560cm.

1) For good images, the image QoE will decrease with the increase of viewing distance. The good images are the images without any distortions, of which the quality score (QoS) is from 85 to 100, just like the 29 reference images in LIVE image database. We chose 4 good images and display the relationship between their QoE and viewing distance in Figure 1, where 4 curves present 4 images, respectively. With the increase of the viewing distance, the viewers see less image details, which makes them feel uncomfortable.

2) For distorted images, the image QoE will first increase and then decrease with the increase of viewing distance. The

(a) (b) (c)

Fig. 2. Distorted images: (a) JEPG compressed image, (b) blurry image, (c) noisy image

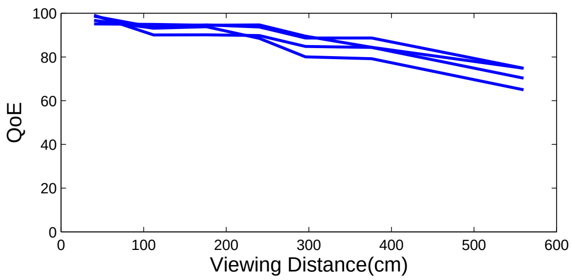

Fig. 1. Regularity between QoE and viewing distance for good images

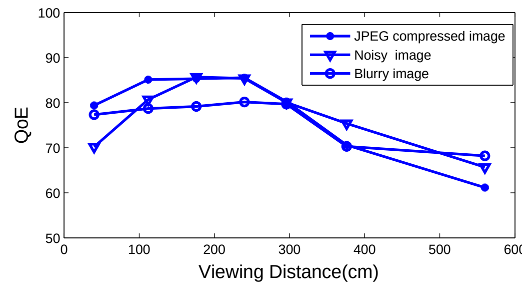

Fig. 4. Regularity between QoE and viewing distance for distorted images

distorted images are the images with low level of distortions, of which the quality score (QoS) is from 30 to 85. Figs 2(a), 2(b), 2(c) show three distorted images, where they are JPEG compressed image, blurry image and noisy image. Since the three images are displayed in smaller size than their regular ones, the distortion may not be observed in Fig 2, but they do have low level of distortion. With the increase of viewing distance, the viewers see less details, and if the image is distorted by low level of distortion, the viewers will also see less distortion. Here, the visibility of artifact has more significant effect on the change of QoE than the visibility of signal. But with continued increase of viewing distance, the visibility of signal has much more significant effect on QoE compared to visibility of artifact. This is the reason why QoE of distorted image first increase then decrease. The regularities between QoE and viewing distance for three distorted images are shown in Fig. 4, where three curves present three images in Fig. 2.

3) For poor images, the image QoE will increase with the increase of viewing distance. The poor image is the image distorted by high level of distortions, of which the quality score is from 0 to 30. There are three poor images showed in Figs. 3(a), 3(b), 3(c), and they are JPEG compressed image, blurry image and noisy image. Because the level of distortion is high, the distorted images are unacceptable for viewers at a close viewing distance. Although the viewers cannot see most image details at a long viewing distance, they also cannot see most image distortion. For images displayed in Fig. 3, their regularities between QoE and viewing distance are showed in Fig. 5.

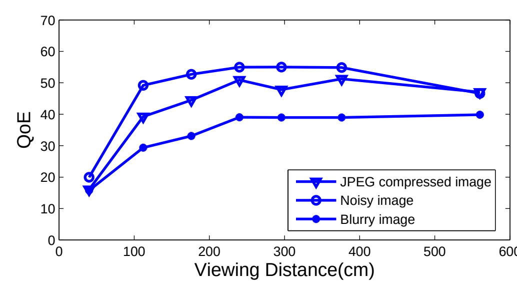

Fig. 5. Regularity between QoE and viewing distance for poor images

4. OBJECTIVE NO-REFERENCE IMAGE QOE ASSESSMENT BASED ON VIEWING DISTANCE

4.1. Image QoE Prediction

BNB metrics are proposed in our previous work [9] , which could measure image blurriness, noisiness and blockiness well. In this paper, we employ these three features and

(a) (b) (c)

Fig. 3. Poor images: (a) JEPG compressed image, (b) blurry image, (c) noisy image

combined them with viewing distance into a model, named **BNBV**, to predict image QoE score objectively. The detailed model is as follows.

(1) Codebook Construction The ith element of the codebook is a vector including five values: blurriness feature, noisiness feature, blockiness feature, viewing distance, QoE score, which are noted as $C_{i,1}$, $C_{i,2}$, $C_{i,3}$, $C_{i,4}$, $C_{i,5}$. All the images in our database are transformed into the elements of codebook.

(2) Neighborhood Construction For any test image I viewed at distance d, its blurriness feature value, noisiness feature value, and blockiness feature value could be calculated and noted as I_1, I_2, and I_3. The neighborhood distance D_i between image I and ith element could be calculated by equation (1), where α, β, γ, λ are weight for blurriness, noisiness, blockiness and viewing distance effect to image QoE.

$$D_i{}^2 = \alpha(I_1-C_{i,1})^2+\beta(I_2-C_{i,2})^2+\gamma(I_3-C_{i,3})^2+\lambda(d-C_{i,4})^2 \quad (1)$$

(3) QoE Score Prediction Based the neighborhood distance definition, the k nearest neighbors of image I could be found in the codebook. The QoE score (Q_I) of image I could be predicted using the mean of QoE scores from k nearest neighbors, as described in equation (2).

$$Q_I = \sum_{j=1}^{k} \frac{1}{k} C_{j,5} \quad (2)$$

4.2. Experiment Verification

In the codebook, there are almost 3500 elements, which is not enough to to construct a content-rich codebook. In this case, we apply the ONE-VS-ALL model to our experiment, which selects one virgin element as test data and construct a training codebook using the rest elements, then predict the QoE score of the virgin element by the training codebook. So the QoE score of whole elements could be predicted once, which is persuasive. In the experiment, the weight parameters α, β, γ, λ and k are searched using genetic method. The experimental result is showed in Table 1. In Table 1, SROCC is the Spearman rank order correlation coefficient and LCC is the Linear correlation coefficient. The **QoS** is the subjective image quality assessment without consideration viewing distance [18]. The experimental result shows that our proposed **BNBV** could predict image QoE score well in consideration of viewing distance.

Table 1. The experimental result of **BNBV** and **QoS** applied on our database

	SROCC	LCC
BNBV	0.8919	0.8633
QoS	0.4187	0.1046

5. CONCLUSION

In this paper, we conducted extensive study on how viewing distance affects image QoE, especially for distorted images. And the study resulted in one image QoE database, which includes 494 images evaluated at 7 different viewing distance by more than 30 testers. Besides that, we explored the regularities between image QoE and viewing distance for different types of images. A **BNBV** model was proposed to predict image QoE in consideration of viewing distance, which achieved acceptable result. In the future work, we will explore the relationship between viewing distance, image/video QoE, and image/video transition bit rate over internet.

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7. REFERENCES

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