Quality Assessment for Out-of-Focus Blurred Images

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***Abstract*—During the process of image acquisition, images are often subject to out-of-focus or defocus blur because of the improper adjustment of the camera's focal length, this image blur will degrade the image quality. However, in the literature, image quality assessment (IQA) methods dedicated to evaluating the quality of images with out-of-focus blur remain few. Therefore, in this paper, we focus our attention on the quality assessment of images that suffer from out-of-focus blur and propose an objective quality assessment method accordingly. Concretely, we construct a dedicated out-of-focus blurred image dataset, which is composed of 150 images subjected to different degrees of out-of-focus blur and the mean opinion scores (MOSs). Then, we propose a specific objective quality metric for the blurred images, which combines image sharpness assessment and saliency-guided pooling strategy. Experimental results demonstrate the proposed metric highly correlates with human judgements of image quality.**

***Index Terms*—Image quality assessment, out-of-focus blur, subjective experiment, image sharpness, visual saliency**

I. Introduction

In our daily life, we often take photos for something we want to record using a digital camera. However, due to the improper camera parameter settings, the images we acquired often suffer from a variety of distortions, e.g. blur, noise, contrast change, which deteriorates the images' visual quality and affects their further usages. Among the factors that degrade the images' quality, out-of-focus blur occupies a large proportion. Nevertheless, there were few studies involved with specifically evaluating the quality of images with out-of-focus blur.

Generally speaking, the more blurred, the worse visual quality of the image. Under this consideration, the image quality with out-of-focus blur can be assessed through image blurriness or sharpness assessment. In the past years, influential researches of image blurriness or sharpness assessment have been done. Early attempts of image blurriness/sharpness estimation mainly concentrated on image edges. In [1], a perceptual model was proposed based on the pair edge detectors in vertical and horizontal directions. In addition, the authors presented a no-reference objective image sharpness metric [2] through the measure of just noticeable blur (JNB) around the image edges. From another point of view, image blurriness can also be assessed by analyzing its spectral behaviors. A fast wavelet-based global and local image sharpness estimation method (FISH) [3] was developed by measuring the Log-Energy in the image's DWT domain. Additionally, Hassen et al. identified image sharpness as strong local phase coherence evaluated in the complex wavelet transform domain and proposed an image sharpness index [4]. In [5], a spectral and spatial combined metric for images perceived sharpness was presented. Specifically, the spectral measure follows from the argument that the slope factor of the magnitude spectrum of an image region can reflect the sharpness degree. The spatial sharpness measure was conducted by calculating the total variation of each image block. At last, spectral and spatial measurements were fused to obtain the overall sharpness degree for the image. Certainly, the general-purpose IQA approaches [6]–[12] also possess the ability to assess the quality of out-of-focus blurred images.

Despite the successfulness of the methods for image blurriness assessment, applying these methods directly for assessing the quality of images with out-of-focus blur is insufficient for that the blur caused by out of focus usually exhibits irregularly or casually over the images and the intensity of the blur also varies in different places of the image, which might lead to large variances in subjective quality evaluation. To tackle this, in this paper, we propose an quality assessment metric dedicated to the out-of-focus blurred images. Firstly, we introduce an image dataset which contain images with out-of-focus blur in different levels and the corresponding mean opinion scores (MOSs). Then we propose an objective quality assessment method by combining image sharpness estimation and visual saliency pooling strategy. By testing our method on the constructed image dataset, we verify it correlates well with subjective opinions.

The remainder of this paper is organized as follows: Section II details the process of subjective experiment for constructing the image dataset. Section III gives the proposed quality metric for the out-of-focus blurred images. Experimental results and analyses are presented in Section IV. At last, we conclude this paper in Section V.

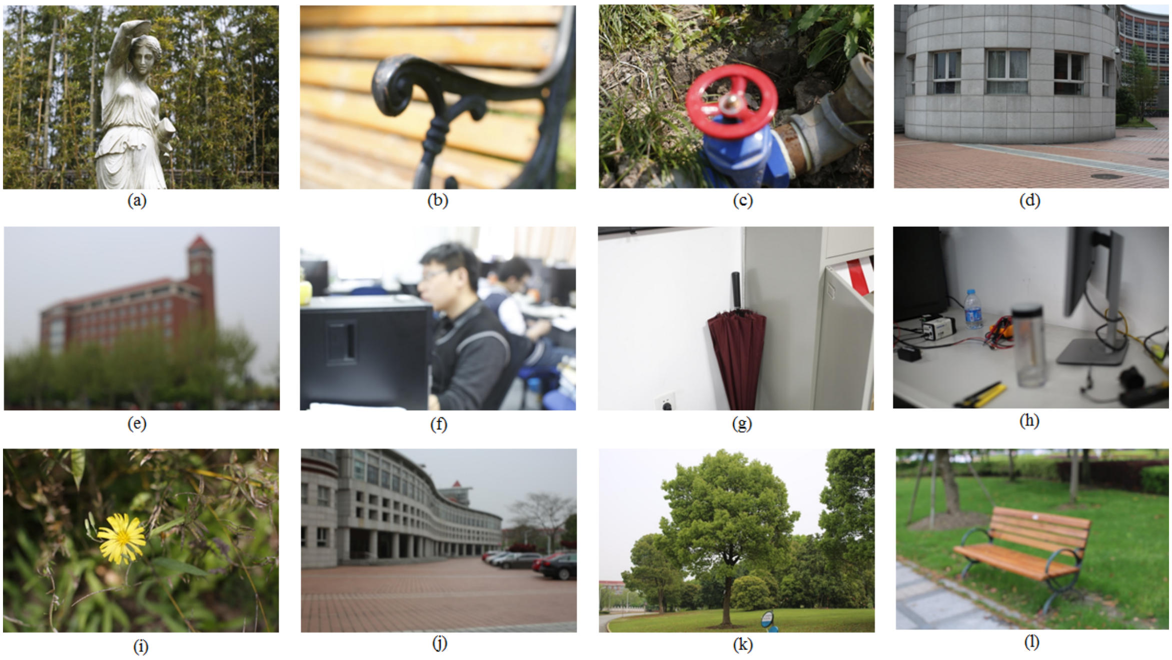

Fig. 1. Some example images in the dataset.

II. Subjective Quality Assessment

To facilitate our research on the quality assessment of out-of-focus blurred images, we established a special image dataset[1] which contains images with out-of-focus blur in different degrees and the subjective quality evaluations in the form of MOS.

A. Image Materials

Image materials of our dataset includes 150 images which can be divided into 30 categories, each category represents one scenario and contains out-of-focus blur in five different degrees ranging from the lightest (or almost none) to the worst. Fig. 1 gives some example images in the dataset. As can be clearly seen, the blur caused by out of focus distributes irregularly or unequally in the images, e.g. Fig. 1(c)(f)(h). All the images are acquired by a digital single-lens reflex (DSLR) camera (Canon EOS 5D). To avoid disturbances from other irrelevant factors, we took the photos using a tripod and all the camera parameters were set the same. We only tuned the cameras focal length manually to generate the out-of-focus blurred images. It should be pointed out that the image resolution is 720×480.

B. Subjective Experiment

Next, we performed subjective experiment on our image materials to gather subjective quality evaluations. Single-stimulus (SS) method was applied in our experiment. Twenty-six inexperienced subjects were invited for the assessment task. For easy operation, we developed an interactive interface by MATLAB to display the images and collect subjective ratings, as illustrated in Fig. 2. The subjective experiment includes two stages, which are the training stage and the rating stage. In the training stage, subjects previewed some example blurred images. The training stage would prevent subjects from rating arbitrarily. Besides, training images won't appear in the rating procedure. The experimental environment was arranged according to the recommendations specified by ITU-R BT.500-12 [13]. To be illustrate, the illuminance of the testing room keeps low. The viewing distance is fixed at three times the image height. For clearly seen, we list the main subjective experiment configurations in Table I. The subjects were asked to provide their overall perception of quality on a continuous scale from 0 to 5, as can be observed in Fig. 2. The presentation order of the images was randomized for each subject. After subjective experiment, we collected the opinion scores from all the subjects and excluded those unreliable scores in the light of the guidelines in ITU-R BT.500-12 [13]. One of the twenty-six subjects was removed and the remaining scores were averaged to obtain the final mean opinion scores (MOSs).

TABLE I
Experimental configurations

Configuration	**Values**
Method	Single-stimulus (SS)
Evaluation scales	0-5
Image number	150
Color depth	24-bits/pixel
Image resolution	720×480
Viewing distance	Three times the image height
Room illuminance	low

[1]The image dataset can be downloaded at *multimedia.sjtu.edu.cn*.

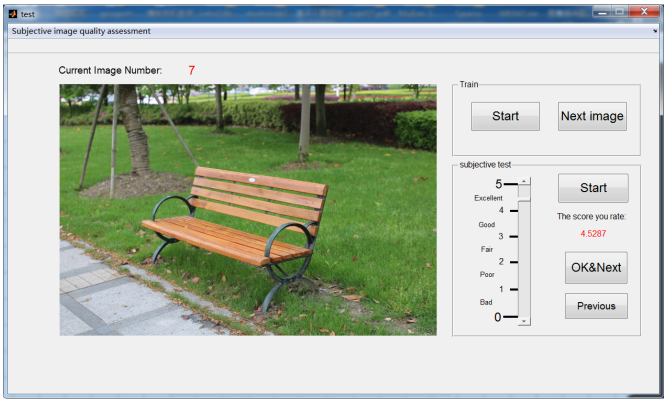

Fig. 2. The subjective experimental interface.

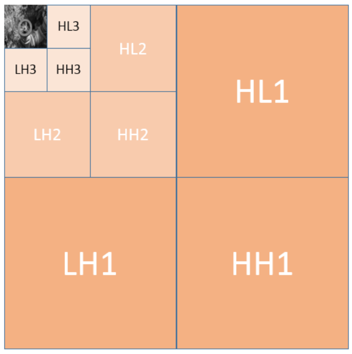

Fig. 3. DWT illustration of an image.

III. Objective Quality Assessment

In this section, we will describe the proposed objective method that evaluates the visual quality of the out-of-focus blurred images in detail. As we stated, the image blurriness / sharpness assessment can be executed in its frequency domain. Based on this, FISH [3] works in three steps: First, the image is decomposed into three-level wavelet subbands, as illustrated in Fig. 3. HH represents the decomposition coefficients in diagonal direction, HL represents the decomposition coefficients in vertical direction and LH represents the decomposition coefficients in horizontal direction. Second, the Log-energy at each DWT level was computed as:

$$E_{XY_n} = \log_{10}\left(1 + \frac{1}{N_n}\sum_{i,j} S^2_{XY_n}(i,j)\right) \tag{1}$$

where XY is either LH, HL or HH, N_n is the number of DWT coefficients of subband XY. Next, the total Log-energy at each decomposition level was measured via:

$$E_n = (1-\alpha)\frac{E_{LH_n} + E_{HL_n}}{2} + \alpha E_{HH_n} \tag{2}$$

where α was set 0.8 empirically to emphasize the high frequency content. At last, all the Log-energy of three levels was combined together to determine a scalar sharpness index by a weighted mean as:

$$FISH = \sum_{n=1}^{3} 2^{3-n} E_n \tag{3}$$

By performing the sharpness estimation block by block, a local sharpness map of the image can be obtained eventually. However, to the out-of-focus blurred images, this sharpness map can't be intermediately pooled to represent the final image quality. That is to say, the sharpness level of the image is not equal to its quality level. Because the blur caused by out of focus likely distributes irregularly or unequally in the images and this might cause large variance in subjective evaluations. Since we are not sure what the out-of-focus blur behaves in the image, instead we find other way to solve this problem. Visual saliency tells us that human visual system (HVS) mainly focuses on the salient regions of the image. Inspired by this, we at first detected the visual saliency of the blurred images and emphasized the sharpness degree of the salient areas. This can be done by visual saliency detection approaches, e.g. itti [14], FES [15], CovSal [16] etc. For implementation, we employed CovSal in this work and got a matching saliency map of the blurred image. It's known that other saliency prediction models can also be applied. Then we multiplied the saliency map with the obtained image sharpness map leading to a saliency-guided sharpness map, which can be denoted as:

$$SS = S_1 \times S_2 \tag{4}$$

where SS represents the saliency-guided sharpness map of the image, S_1 is the saliency map, S_2 is the sharpness map, "$\times$" means multiplying each element in S_1 and S_2, respectively. At last, we pooled the saliency-guided sharpness map by taking the root mean square of the 1% largest values of SS to estimate the whole image quality as:

$$Q = \sqrt{\frac{1}{N}\sum_{(i,j)\in\Omega} SS^2(i,j)} \tag{5}$$

where Q means the image quality, Ω contains the positions of the 1% largest values in SS.

IV. Experimental Results

Firstly, we mapped the results of the objective quality metric to subjective ratings through nonlinear regression of a five-parameter logistic function as suggested by VQEG [17]:

$$q(z) = \beta_1\left(\frac{1}{2} - \frac{1}{1+\exp(\beta_2\cdot(z-\beta_3))}\right) + \beta_4\cdot z + \beta_5 \tag{6}$$

with z and $q(z)$ being the input objective score and the mapped score, respectively. β_j (j=1,2,3,4,5) are free parameters to be determined during the curve fitting process. To evaluate the performance of the proposed quality assessment method, we employed three commonly used metrics which are Pearson Linear Correlation Coefficient (PLCC), Spearman

Rank-Order Correlation Coefficient (SROCC) and Root Mean-Squared Error (RMSE) respectively. Among them, PLCC evaluates IQA method's prediction accuracy, SROCC evaluates the prediction monotonicity and RMSE points out the prediction consistency. A good quality measure is expected to achieve high values in PLCC and SROCC, while low values in RMSE. We list the performance results of objective quality metrics in Table II. All the quality metrics are tested on our out-of-focus blur dataset. For clear comparison, we divided the metrics into two types, the first type belongs to the state-of-the-art general-purpose IQA methods, which are BIQI [6], BRISQUE [7], DESIQUE [8], DIIVINE [9], NFERM [10], NIQE [11] and SISBLIM [12]. The other type contains the state-of-the-art methods specific to image sharpness assessment, which are CPBD [18], ARISMC [19], FISH [3], JNB [2], LPC [4] and S3 [5] respectively. Besides, the compared methods are all blind quality metrics, which can assess the image quality without referring to its pristine version. By observing Table II, we can get that the general-purpose IQA methods can assess the quality of the out-of-focus blurred images due to their general QA ability for distorted images. While most image sharpness assessment methods perform better than the general-purpose IQA methods to the out-of-focus blurred images. However, image sharpness assessment is not enough for quality assessment. By properly combining image sharpness assessment and visual saliency pooling, our method earns superior results to all of the competing methods.

TABLE II
EXPERIMENTAL RESULTS

Methods	PLCC	SROCC	RMSE
BIQI [6]	0.2241	0.2580	1.2830
BRISQUE [7]	0.7263	0.7361	0.9049
DESIQUE [8]	0.6811	0.6899	0.9639
DIIVINE [9]	0.6475	0.5865	1.0033
NFERM [10]	0.7529	0.7756	0.8665
NIQE [11]	0.4693	0.0906	1.1625
SISBLIM [12]	0.8155	0.8554	0.7620
CPBD [18]	0.7902	0.7880	0.8068
ARISMC [19]	0.6932	0.5356	0.9489
FISH [3]	0.8257	0.8545	0.7426
JNB [2]	0.7306	0.7369	0.8989
LPC [4]	0.8447	0.8568	0.7047
S3 [5]	0.8431	0.8641	0.7079
Proposed	**0.9012**	**0.8897**	**0.5704**

V. Conclusion

In this paper, we have focused on the quality assessment of blurred images caused by out of focus. Firstly, we introduced a dedicated out-of-focus blurred image dataset to facilitate this research. The image dataset was constructed through subjective experiment. Afterwards, we designed a corresponding objective assessment method by properly combining sharpness assessment and visual saliency pooling. Experimental results demonstrated that our method outperformed the state-of-the-art blind IQA methods and image sharpness assessment methods for the out-of-focus blurred images and correlated well with subjective evaluations.

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