An Image Quality Assessment Technique using Defocused Blur as Evaluation Metric

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Abstract: In this paper, an image quality assessment technique based on defocus blur identification is proposed. Some representative image regions containing edge features are first extracted automatically. A histogram analysis based on the comparison of real and synthesized defocused regions is then carried out to estimate the blur extent. By iteratively changing the convolution parameters, the best blur extent is identified from histogram matching. The image quality is finally evaluated based on the overall blur extent of the selected regions. We have performed the experiments using real scene images. It is shown that accurate image quality assessment results can be achieved using the proposed technique.

1 INTRODUCTION

Image quality assessment is an important issue for many image processing systems and multimedia applications. It aims to evaluate the image quality based on some possible measures, such as contrast, brightness, and sharpness, to reflect the human visual perception. Since the idea of image quality is perceptual and sometimes subjective, deriving a universal approach based on a specific standard is either infeasible or very difficult. Thus, the current objective quality metrics are commonly categorized according to the availability of a reference image, namely *full-reference*, *no-reference*, and *reduced-reference* methods (Furht and Marques, 2003).

Among the existing techniques, the full-reference and reduced-reference approaches are mostly designed for image compression and transmission purposes, rather for the assessment of originally acquired images. For those images directly captured by a camera, there is no ground truth reference for quality evaluation. Thus, the particular interest is the no-reference image quality assessment techniques (Gabarda and Cristóbal, 2007; Ciancio et al., 2011; Ye and Doermann, 2011). Since the low noise images can be easily produced by the modern sensing technologies, the image quality is mainly affected by the improper image formation during the acquisition process. In general, the most prominent issue is the image blur introduced by optical defocus or the relative motion between the camera and the scene (Bondzulic and Petrovic, 2011). Consequently, the evaluation of image blur lies on the core of most image quality assessment techniques.

In this work, we present a defocus blur identification technique based on histogram analysis for image quality assessment. The defocus process of a camera system is formulated by the spatial convolution of the image with a pillbox point spread function. For a given image for quality assessment, the regions containing edge features are selected for blur extent estimation. The histogram of a defocused region is compared with the ones derived from the image regions generated with synthetic pillbox blur. By iteratively changing the point spread function parameters, the best blur extent can be identified from image histogram matching. The image quality is then evaluated based on the overall blur extent of the selected edge regions.

The proposed blur parameter identification approach does not rely on the system calibration or camera parameters. Since no prior knowledge is required other than the captured image itself, the histogram matching algorithm can be carried out on the selected image regions for blur estimation. To demonstrate the effectiveness of our image quality assessment technique, we have conducted several experiments using the images captured with known ground truth quality rankings and some test images in the LIVE image database (Sheikh et al., 2006). The experimental re-

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sults have shown that our approach is able to achieve high accurate image quality rankings using an objective evaluation metric.

2 QUALITY ASSESSMENT

Given an ideal black and white image with intensity values μ_1 and μ_2, the histogram consists of only two sharp peaks at these two intensity values. For a real scene image captured by a camera, the intensities are spread out due to the optical system and noise, and the histogram usually contains two bell-shape distributions located at μ_1 and μ_2. If the image contains defocus blur, the mixture of high and low intensity values introduced by the point spread function generates a smooth transition between μ_1 and μ_2 in the histogram.

According to the defocused image formation, the histogram changes with the blur extent (Lin et al., 2012). When the defocus blur becomes severe, the two main lobes corresponding to the high and low intensity regions diminish, and the transition area between the two main lobes increases. Thus, the blur extent of a defocused image can be characterized by the distribution of its histogram. By comparing the histogram of the unknown defocused image with the histogram of a calibrated image, the blur extent of the unknown image can be identified. More specifically, the blur parameter of the point-spread function can be derived by this *histogram matching* technique and used to represent the amount of defocus blur associated with the given image (Lin and Chou, 2012).

To apply our blur identification technique for image sharpness evaluation, we need to select several regions of interest (ROI) for histogram matching. This is accomplished automatically by performing the following steps. First, an edge image obtained from Canny edge detection is used to derive suitable edge segments for blur extent estimation. Since the blur identification is carried out locally along the horizontal direction, the edge segments are constrained by three criteria to ensure the robustness of histogram matching: (a) the vertical 8-neighbor connectivity, (b) a minimum edge length threshold (typically about 1% of the original image height), and (c) no other edges present in the neighborhood.

Second, an initial ROI with a fixed width (typically about 2% of the original image width) is assigned for each edge segment. The intensity distribution of each ROI is analyzed, and only those ROIs with low intensity variation on both sides of the edge segment are preserved. Finally, each ROI is enlarged in the horizontal direction if the local intensity distributions on both sides of the edge still remain uniform when including an extra column of pixels from the left and right of the ROI respectively. This process is carried out iteratively until the local intensity variation is no longer uniform. It aims to provide larger ROIs for histogram matching and achieve better blur identification results.

After the ROIs are selected for a given image, histogram matching is performed on each ROI individually. The average of the identified blur extents from all ROIs is used to represent the image sharpness. For a given set of images, the quality ranking is then derived based on the amount of their blur extents. To evaluate the performance of our image quality assessment technique, the ground truth image quality ranking is used for comparison. Suppose a set of n images is indexed by $1, 2, \cdots, n$, according to their ground truth quality, and the evaluated quality ranking is given by a permutation function $p(\cdot)$. Then the quality assessment score for the image set is defined by

$$S = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} c(i, j)}{C_2^n} \tag{1}$$

where

$$c(i, j) = \begin{cases} 1 & \text{if } i < j \text{ implies } p(i) < p(j) \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

It is seen that the quality assessment score $S \in [0, 1]$. The special cases $S = 1$ and $S = 0$ correspond to the correct and completely reverse quality rankings, respectively.

3 EXPERIMENTAL RESULTS

The proposed image quality assessment technique has been tested using the images with synthetic and real defocus blur. For the experiments with synthetic blur, we choose 8 sets of images with Gaussian blur from the LIVE image database (Sheikh et al., 2006; Wang et al., 2004). A series of 10 blurred images are generated from each reference image using the circular-symmetric 2-D Gaussian kernels on with standard deviation ranging from 0.5 to 5 pixels with mask size: 5,9,13,17,21,25,31,35,39,43.

In the experiments, the number of ROIs extracted from each test image and used for image quality assessment ranges from 21 to 107. The blur identification results of the LIVE database images are tabulated in Table 1. The quality evaluation of the image datasets is illustrated in Figure 1. Index number 0 indicates the reference or focused image, and the images generated with more severe blur are those with

Table 1: The blur extents of the LIVE database images and our captured defocused images. Index number 0 indicates the reference or focused image, and the images generated or captured with more severe blur are those with higher index numbers.

#	bikes	buildings	caps	house	lighthouse	monarch	paintedhouse	parrots	plane	womanhat
0	2.33	0.00	0.59	1.00	0.50	1.00	5.50	1.86	0.78	2.75
1	2.33	0.00	0.76	1.67	0.50	1.50	5.25	2.14	1.44	3.13
2	2.33	0.33	1.41	2.00	2.50	3.00	6.75	2.43	1.33	4.63
3	3.00	0.67	2.76	2.00	2.50	3.00	7.00	3.57	2.33	4.75
4	3.67	1.33	5.29	3.00	4.50	4.00	7.25	4.86	6.11	5.75
5	7.67	4.00	7.88	4.33	11.00	3.50	12.50	9.00	6.56	7.00

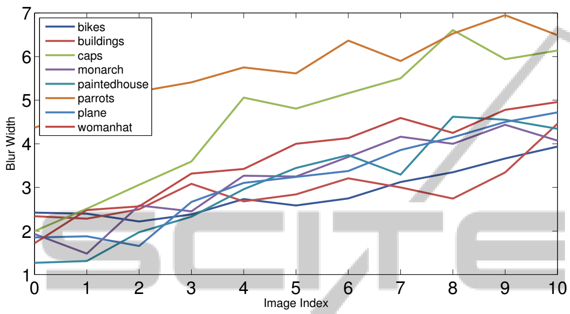

Figure 1: The quality evaluation of 8 image datasets (buildings, monarch, parrots, plane, bikes, caps, paintedhouse, womanhat) from the LIVE image database.

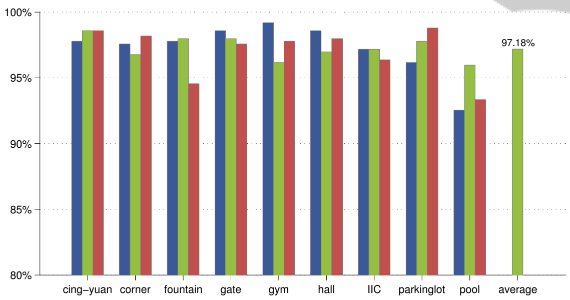

Figure 2: The accuracy of our image quality assessment evaluated using the images captured with different amount of blur.

higher index numbers. The plots reveal the consistency between the identified blur extent and the image quality in most cases.

For the experiments with real blur test, we choose 9 locations and capture 3 sets of images from different viewpoints for each location. Each of the above 27 image datasets contains a sequence of 32 images captured with different defocus settings, so there are totally 864 images in our evaluation database. Since the image sequences are captured by changing the lens focus position from the well-focused setting gradually to the most defocused setting, the ground truth image quality ranking can be obtained accordingly and used for performance evaluation.

The image quality assessment is carried out first by evaluating the quality of individual images based on the blur extent estimation, followed by deriving and comparing the quality ranking for each of the 27 image datasets. Figure 3 illustrates some results of image quality assessment for the image datasets captured from the 9 different locations. The ground truth image quality ranking and our evaluation result are shown in the x-axis and y-axis, respectively. The data points scattering around the 45° lines in the plots exhibits the high correlation between our quality evaluation and the ground truth ranking. These results are also consistent with the accuracy calculated using the quality assessment score given by Eq. (1). As shown in Figure 2, the overall accuracy on the image quality ranking is about 97% for the real scene images used in the experiment.

4 CONCLUSIONS

The image blur introduced by optical defocus is one major issue which affects the image quality. In this work, we present a histogram based defocus blur identification approach for image quality assessment. Given an input image, the edge regions are first extracted automatically, followed by a novel histogram matching technique for blur extent estimation. The image quality is then evaluated based on the overall blur extent of the selected regions. Since no prior knowledge such as camera parameters is required, the proposed non-reference method is suitable for quality assessment of archived images. The experimental results have demonstrated that our technique is able to achieve high accurate image quality rankings using an objective evaluation metric.

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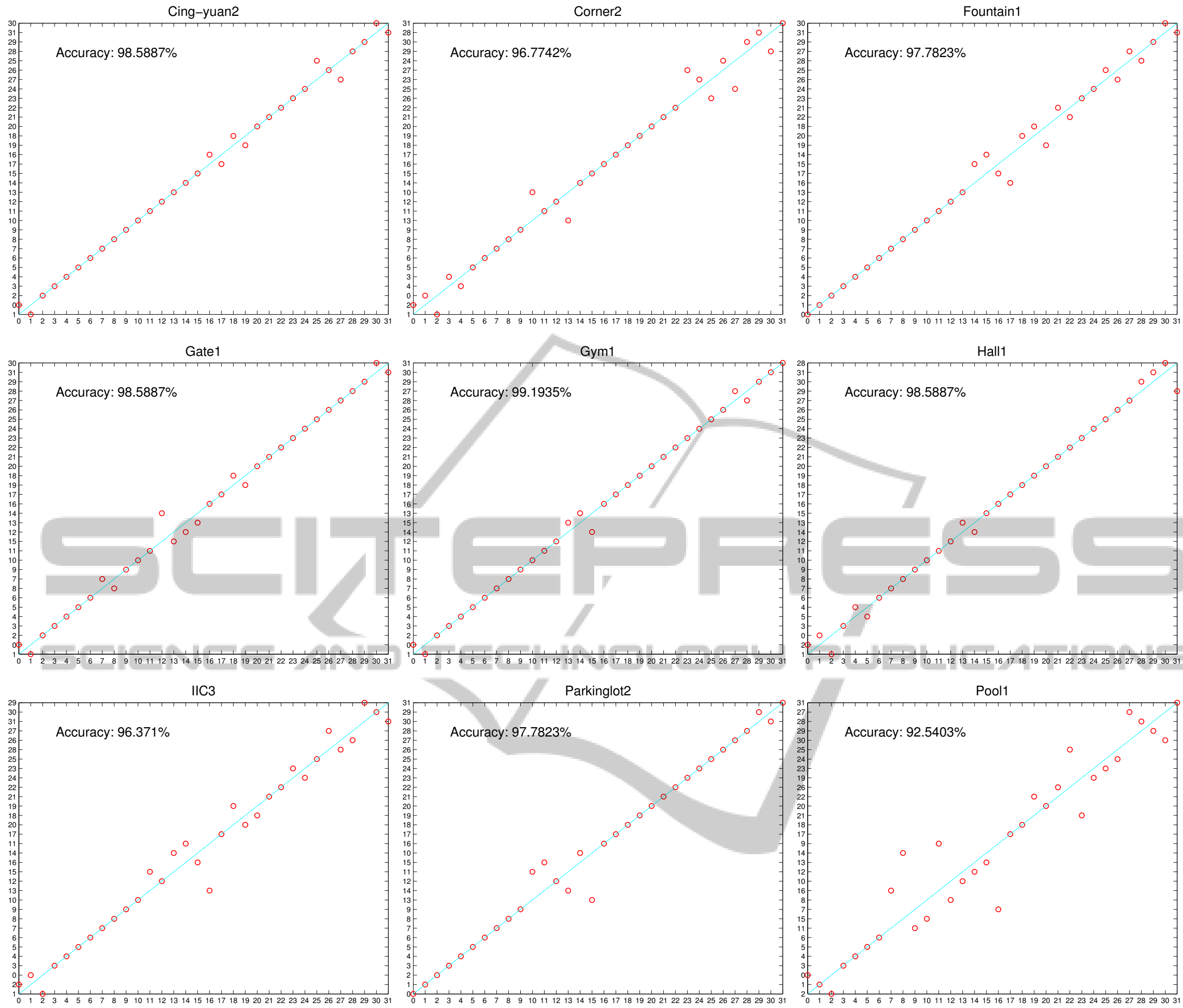

Figure 3: Image quality assessment results of the image datasets captured from the outdoor scenes.

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