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No-Reference Image Quality Assessment Based on Edges

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ABSTRACT

Image quality assessment is a crucial topic in the field of image processing. In this paper, we propose an edge-based no-reference image quality assessment method. The following factor is applied to assess image quality, namely, improved blur measurement. In the improved blur measurement method, we propose an algorithm that improves the accuracy in measuring image blurs and attains effective execution speed in time complexity. Experimental results reveal that using the proposed approach helps attain satisfactory image quality assessment results.

Keywords: Image Quality; Blurring; No-reference; Image Edge.

1 Introduction

Because of the demands for and popularity of various types of imaging equipment, improving image quality analysis abilities to enable images precisely reflect the characteristics of the objects they portray has become the most crucial objective of image quality measurements. In modern image processing studies, the problem of image distortion during the capturing, transmission, and compression processes can be solved by using assessment indicators, which assess image quality and the degrees of distortion and blur. This enables higher-quality images to be obtained for use in the relevant equipment or systems.

Studies on the image quality technologies employed for computer vision have utilized objective computer digital technologies to capture and obtain image content similar to that observed by the human eye. Therefore, identifying how digital technologies can be used to capture images that are deemed authentic and clear by human observers is the ultimate goal of image quality–related studies. For example, when developing image quality technologies, image detection, identification, and analysis technologies are critical approaches to identify and address problems such as inadequate lighting, blurred images, exposure problems, and poor image quality (for photographs taken by digital cameras). The human visual system (HVS) presents an intuitive understanding of image perception. By contrast, blurring can be caused by problems with digital equipment, such as errors created by objects moving during the image capturing process, errors in the digital or analogue quantification process, changes created by object edges shifting, and edge signal blurring created by digital equipment when attempting to reduce noise. When these problems occur, digital equipment produces blurred images. Therefore, regardless of the blur type (e.g., dynamic blur or out-of-focus blur), strengthening the image information for digital equipment and designing high-quality algorithms to elevate interpretation accuracy are required for image quality measurements. [2, 3, 6]

Among the image quality analysis and measurement methods, the no-reference (NR) image quality assessment method may be used in all operating environments. However, because this method does

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not utilize original images for references and comparisons, measurements are prone to large errors. Nevertheless, the goal of the NR method is to develop a system that is comparable to the HVS. Image distortion–related studies, such as those on blur, the blocking effect, and sharpness, have produced favorable results [5, 12–13]. The blur measure (BM) method [4] is an algorithm based on the NR image quality assessment method, in which the Sobel algorithm is used to detect image edges. In the Sobel measurement method, one-dimensional analysis is first used to identify the pixel with the largest change in edge color, after which two-dimensional analysis is conducted. In this paper, an improved blur measure (IBM) was proposed in order to develop a more sophisticated algorithm for measuring the degree of blur. In the proposed algorithm, improvement strategies were implemented to increase performance and strengthen image operation speed and capabilities, thus enabling blurred images to be accurately measured and used.

The rest of this paper is structured as follows. Section 2 reviews related works. Section 3 describes our method. Section 4 describes the experimental results. Finally, Section 5 presents the conclusions.

2 Related Works

Objective image quality assessments involve classifying original and processed images into categories and determining changes in image distortion through comparison. The assessment results are influenced by factors including tone reproduction, detail and edge reproduction, noise, and color reproduction. Objective image quality assessments can be broadly divided into three categories: full-reference (FR) [7], reduced-reference (RR) [14], and NR image quality assessments [1, 8]. FR image quality assessments compare the differences in the pixels of complete images before and after image processing to identify changes in the degree of distortion between original and processed images. This type of assessment is suitable for subjective assessments of image quality with the support of objective assessment indicators that are intended to yield optimal-quality images. RR image quality assessments extract and compare the eigenvalues before and after image processing to reveal the attenuation situation. This type of assessment is a combination of FR and NR image quality assessments. NR image quality assessments do not require original images, and they determine image quality by examining the error results after image processing. Thus, the calculation and comparison costs of NR image quality assessments are substantially lower than those of FR and RR image quality assessments, rendering the NR methods frequently studied.

The blur measurement method [4] mainly involves using Sobel operators to measure image edges, and the measurement results are compared with those obtained using the just noticeable blur (JNB) method. This method yields higher difference of mean opinion scores. The blur measurement method uses the Sobel method for image edge detection. The Sobel method first performs one-dimensional analysis to identify pixels with the maximum edge color changes, and proceeds to two-dimensional analysis. The Sobel method employs a connected-component method that adopts the concept of image pixel neighbors to connect adjacent pixels.

Calculation models defined using the Sobel method yield more accurate results than those obtained using the JNB method. Thus, compared with the JNB method, the aforementioned computer vision calculation models produce blurred image identification results closer to those obtained using the HVS. For results obtained using the blur measurement method, a higher Gaussian blur standard deviation indicates a lower blur value, signifying a higher degree of blur. By contrast, a lower Gaussian blur standard deviation indicates a higher blur value, signifying a smaller degree of blur and a clearer image.

3 The Proposed Approach

This paper introduced an improved blur measurement calculation model called the IBM. Because humans are more sensitive to edge intensity changes when images are clear, changes in pixel intensity between neighboring areas are higher in high-quality images (e.g., clear images) than in low-quality images (e.g., blurred images). The IBM was developed on the basis of this principle. In IBM calculations, a lower value indicates a higher degree of blur and poorer object visibility in the image, whereas a higher value indicates a lower degree of blur and more favorable visibility.

The IBM was developed on the basis of pixel intensity changes around image edges. High-quality clear images contain less blur and high pixel intensity changes around image edges, whereas blurred and distorted images contain low pixel intensity changes around the edges. Horizontal and vertical detections were performed to calculate the number of edge pixels in the original. In addition, the formula was further modified to generate normalized numbers to observe changes in blurred images more clearly. The revised formula is shown as follows:

$$IBM = \frac{\sum_{I(x,y)\in HE} \sqrt{\sum_{I(x',y')\in VN_{xy}} \{I(x,y) - I(x',y')\}^2 / |VN_{xy}|}}{\sqrt{\sum_{I(x,y)\in HE} I(x,y)}} + \frac{\sum_{I(x,y)\in VE} \sqrt{\sum_{I(x',y')\in HN_{xy}} \{I(x,y) - I(x',y')\}^2 / |HN_{xy}|}}{\sqrt{\sum_{I(x,y)\in VE} I(x,y)}} \quad (1)$$

where HE and VE are defined as the horizontal and vertical edge pixels, respectively. HNxy and VNxy are defined as the neighboring horizontal and vertical pixels of pixel I(x,y), respectively, where I(x,y) ϵ HE and VE, and |HNxy| and |VNxy| are the numbers of pixels of HNxy and VNxy, respectively.

In (1), a higher value denotes higher image definition and more changes in edge pixel intensity, whereas a lower value denotes a higher degree of blur and fewer changes in edge pixel intensity. The formula introduced was developed according to the concept of blur measurement in order to clarify the differences between clear and blurred images. The original blur measurement method was revised to generate larger values that represented greater differences. Thus, high-quality clear images contained less blur and more pixel intensity changes around image edges. By contrast, blurred images contained fewer pixel intensity changes around image edges.

Distorted images were created through blurring, after which NR image quality assessments were performed; the differences between the original images and the distorted images were subsequently assessed. To create distorted images, the Gaussian blur processing method was adopted. Gaussian blur, also known as Gaussian smoothing, is a type of low-pass filter and a function that is widely used in image processing software. Gaussian blur is commonly used to remove noise and diminish detail level to facilitate image recognition. In this paper, original images were processed using the Gaussian blur method with various standard deviations to create blurred images, which then formed the image database used in the experiment. Gaussian blur uses normal distribution to obtain pixel values and calculate the value changes of all pixels in an image. Therefore, the smaller the distance between a pixel and the blur center, the higher the weight value becomes. Compared with the mean filter method, the Gaussian blur method features more effective smoothing and better edge effect retention.

4 Results

In the experiments, Windows 10 64-bit was used as the operating system and programs were written using MATLAB 2014. An Intel(R) Core(TM) i7 CPU 930 @ 2.80GHz with a memory of 12 GB was used as the CPU. The TID2013 image quality assessment database [9–11] was downloaded from the Internet to test the proposed method. The 125 blurred images in the TID2013 database were created by blurring 25 high-definition RGB images (Figure. 1) using Gaussian blurring with various standard deviations. A mean opinion score was assigned to each image in the database. Fig. 2 shows the images created using varying degrees of Gaussian blurring, where Images 1 and 5 were the clearest and most blurred images, respectively.

Figure. 1. Images used in the experiment

Original image

Image 1

Image 2

Image 3

Image 4 **Image 5**

Figure. 2. Degrees of Gaussian blurring shown in image database images

4.1 Image Quality Measurements

Three images from the image database were used to test the IBM, as shown in Figs. 3–5. The y-axis represents values obtained using the IBM, and the x-axis represents the image number; a larger image number represents a greater degree of Gaussian blurring. The results revealed that values obtained using the IBM were correlated with image quality. Higher and lower IBM values signified clearer and more blurred images, respectively.

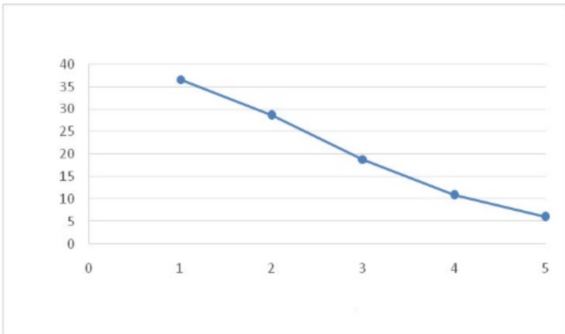

Figure. 3. IBM measurement results

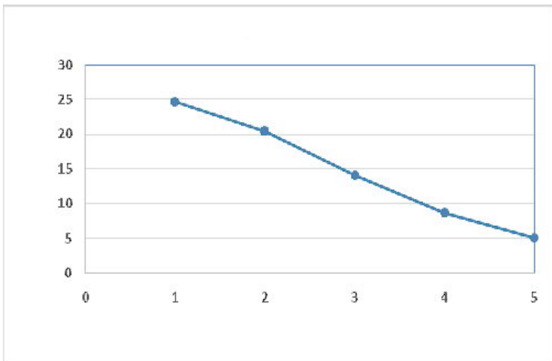

Figure 4. IBM measurement results

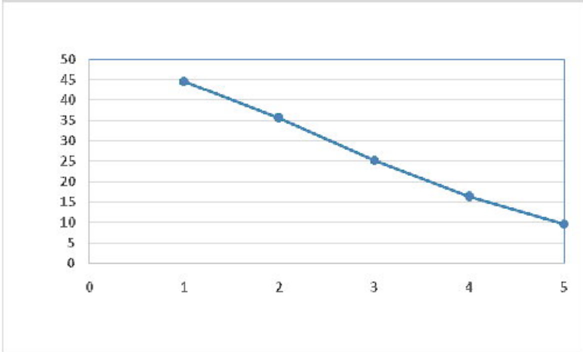

Figure. 5. IBM measurement results

4.2 Analyses of the Subjective and Objective Assessments

Correlation coefficients (CC) are commonly applied for statistical analysis. The theorem involves calculating two covariances and subtracting the standard deviations of their distributions from the two covariances. Root mean squared error (RMSE) and mean absolute error (MAE) are the most basic and widely used methods for representing random errors. However, neither RMSE nor MAE measure error values or ranges; they perform estimations on the reliability of a set of measured data.

The differences between clear and blurred images were evaluated using the proposed image quality measurement method. Subjective and objective scores were obtained and analyzed to determine whether the image quality measured was consistent with the subjective scores. Mean scores provided by the TID2013 image quality assessment database were used as the subjective scores. To verify the feasibility of the image quality assessments, three commonly used performance indicators were employed to determine the correlation between the subjective and objective scores. The CC was utilized to determine whether the image quality measurement results were consistent with the subjective scores, whereas the RMSE and MAE were used to evaluate errors and accuracies of the objective scores. Fig. 6 shows a scatter plot of the IBM results for the TID2013 database and the subjective scores, where the x-axis is the subjective score and the y-axis is the objective assessment score.

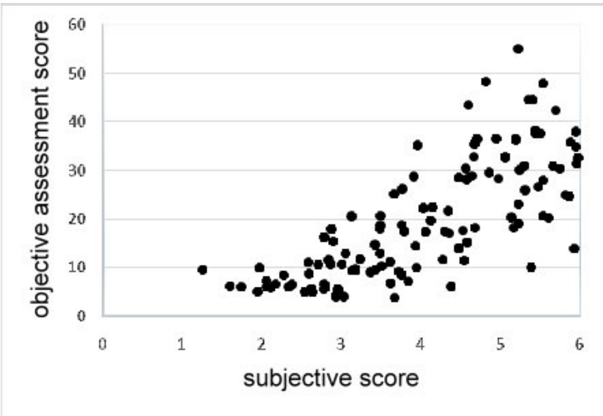

Figure. 6. Scatter plot of IBM measurements and subjective scores

The proposed image quality measurement method, subjective score scatter plot, and subjective–objective score correlation were compiled on the basis of the experimental results (Table 1). According to the image quality measurement method, the subjective and objective scores were moderately correlated.

Table 1. Correlations between objective and subjective scores

	CC	RMSE	MAE
IBM	0.7264	16.671	15.863

5 Conclusion

In this paper, an edge-based NR image quality assessment method was introduced to measure the differences between clear and blurred images. An improved algorithm was proposed to measure the degree of blur in images more accurately, promptly, and efficiently. This method also yielded favorable image quality assessment results.

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