Blind Image Quality Assessment for Measuring Image Blur

Xin Wang, *Baofeng Tian, Chao Liang, Dongcheng Shi
*College of Computer Science and Engineering, Changchun University of Technology,Changchun,CHINA 130012; * College of instrumentation & electrical engineering, JILIN Univ./Changchun, Changchun, CHINA 130061*
E-mail: wx31515@yahoo.com.cn

Abstract

Blind image quality assessment refers to the problem of evaluating the visual quality of an image without any reference. In this paper, we present a no-reference blur metric for images and video using information contained in the image itself. We look at the sharpness of the sharpest edges in the blurred image, which contains information about the blurring, and is not on the image contents. The experimental results are used to justify the validity of our approach.

1. Introduction

Measurement of visual quality is of fundamental importance to numerous image and video processing applications. Most previous works on image quality assessment [1]-[3]assume the knowledge of a reference image. Their goal is to evaluate the visual difference between a target image and the reference. Although this is useful in applications such as compression, there are other applications where a reference image is not available, but quality metric is desirable. For example, in image interpolation, the original high-resolution image is often not available as the ground truth, so blind assessment of the quality of the interpolated image becomes necessary; In digital photography, a no-reference assessment algorithm will be of use to inform the user that a low-or high-quality photo have been taken; In printing, to encourage (or discourage) the printing of better (or poorer) pictures. It is easy for human vision system to determine the visual quality of an image without any reference, but it is far more difficult to design an algorithm that does the same.

For the existing no-reference image quality metrics that existed in the literature, most of these are developed for measuring image blockiness[4]. In this paper, we are mainly concerned with impairment "blur". Few research works have been reported in the literature about no-reference blur metrics. Nill and Bouzas[5]designed a metric based on power spectra incorporating human vision system(HVS); Andre Jalobeanu,[6]et al proposed a algorithm using a parametric MTF. But their methods are mainly intended for reconnaissance satellite photos. Chen and Meng[7] used statistics of block region activity scores being a function to measure image blur; Pina Marziliano[8]et al presented a blur metric based on the analysis of the spread of the edges in an image ,which demands for vertical or horizontal edges existing in images.

In this paper, we propose to blindly measure the blur of images by looking how sharp the sharpest edges in a blurred image. This paper is organized as follows. Section 2 describes the no-reference blur metric in detail. Section 3 presents experimental results and Section 4 provides conclusions and future research directions.

2. No-reference blur metric

Blur is introduced in images and video through various processes such as acquisition, transmission and compression. Different types of blurs exist. For example, motion blur due to the relative motion between the camera and the scene, and out of focus blur due to a defocused camera and lens aberrations. In this paper, we assume no knowledge of the original image, and do not make any assumptions on the type of content or the blurring process.

To measure image definition regardless of the specific contents of the scenes, starting with edge is a good choice. Edges are presumably the most important features in the image source. Our technique is based on the smoothing effect of blur on edges. For a more clear image(less blur), sharp edges are acquired, while for the image with more blur, the sharpness of edges will drop, whatever the image specific content is. Our method for blur estimation is based on estimating the sharpness of the sharpest edges in the image.

978-0-7695-3119-9/08 $25.00 © 2008 IEEE
DOI 10.1109/CISP.2008.371

2.1. Principle

We start with the sharpness of step edges that presumably capture the global structure of the image. Uniform black-and -white image block forms the step edge image, as shown in Fig.1 (a)and(b).(a)is a clear edge image, while (b) is a blur edge image. If edge image is scanned along the line direction denoted by A—B, a grey variance curve is got as shown in Fig.1(c) and Fig.1 (d). It shows that grey curve variance of figure (a) is more acute than the variance of figure (b)'s. The degree of grey curve change can be represented by the angle α from the horizontal direction as shown in Fig.1(c).The bigger α is, the steeper edge is. That is to say, the sharpness of the edge is better. Seen from Fig.1(c) and (d), it's obvious that $\alpha > \beta$.

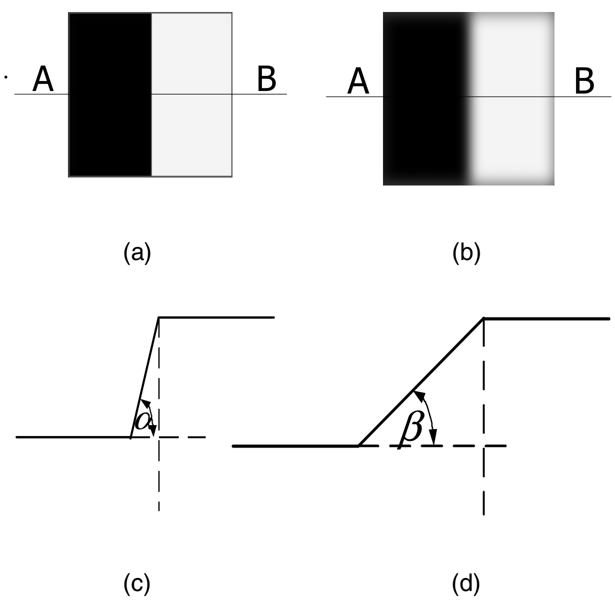

Fig.1. **Clear and blur edge images and their corresponding edge profiles**

We can also measure the image sharpness by the slope of the grey curve (seen in Fig.2).

$$tg\alpha = \frac{G}{w} \tag{1}$$

In equation (1), w is the width of edge-spread at edge pixel Q, G is the grey difference between the two pixel points (denoted by a and b respectively) corresponding to the limit pixels of edge-spread width.

Equation 1 turns to the following expression:

$$tg\alpha = \frac{I(a) - I(b)}{w} \tag{2}$$

After the slope of grey variance curve at all edge pixels have been worked out, we choose the maximum as a no-reference quality metric for measuring image blur.

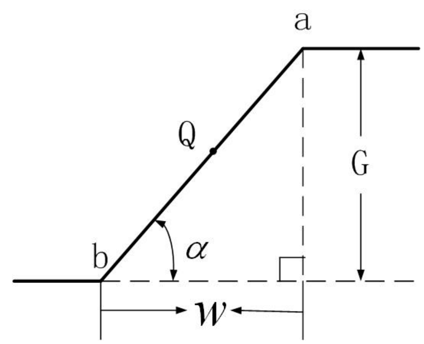

Fig.2. **Diagram of calculating α**

2.2. Implementation steps of the blur metric

The proposed algorithm for blind image quality assessment involves the following steps:

(1) Edge detection

Canny edge detector is being used here for it is the best step-edge detector and the effect of noise suppression is the best among the traditional edge detectors [9].

(2)Gradients' direction detection

To calculate the edge gradient at each edge pixel, we should compute the gradients in all directions across the edge pixel and choose the largest one, whose direction is the detected gradient's direction.

(3)Measure the edge-spread

For each pixel corresponding to an edge location, we search in both the gradients' direction of the edge pixel and also the opposing direction for the grey local extreme locations closest to this edge pixel. The number of pixels between the two local extreme locations (i.e. the locations of pixel "a" and pixel "b", seen in Fig.2) will be counted as the edge-spread.

(4)Compute the image blur metric

Bring the variable w、a、and b in to the equation(2) to get the result and repeat all the steps described above for each edge pixel. Then choose the largest one among the results to get the final value of the blur metric.

3. Simulations

The experimental results for the proposed blind blur metric are shown in this section. We examine two types of blur. The first set of blurred images are the versions blurred by circular averaging filter (pillbox), which simulates out of focus blur of autofocus cameras. The second set of blurred images are the versions blurred by uniform linear motion. The test is conducted on gray level images with 256*256 pixels. For color images, blur is measured on the luminance component Y. The experiment considers still images. It is straightforward to extend the technique to digital video by measuring blur in every frame.

3.1. Images blurred by circular averaging filtering

The out-of-focus operator may be defined as:

$$h(x,y)=\begin{cases}0; & \sqrt{\mathrm{x}^2+y^2}>R\\ 1/(\pi R^2) & \sqrt{\mathrm{x}^2+y^2}\le R\end{cases}\qquad(3)$$

in which R is defocus radius. The larger R is, the heavier image blur degree.Fig.3.shows the original images in descending order (form R=1 to R=9, that is form the more clear quality to the more blurred quality) according to their values of the proposed blind blur metric. It shows that the blur measurement results are consistent with the actual blur degree.

Fig.3. **Objective blur measurement versus different defocus blur R of the circular averaging filter employed to blur the image**

3.2. Images blurred by uniform linear motion

The linear motion blur operator over d pixels under an angle of θ is defined as follows:

$$h(x,y)=\begin{cases}0; & y\neq x\tan\theta, -\infty\le x\le\infty\\ 1/(2d); & y=x\tan\theta, -d\cos\theta\le x\le d\cos\theta\end{cases}\qquad(4)$$

when θ is zero, the above equation turns to be:

$$h(x,y)=\begin{cases}0; & y\neq 0, -\infty\le x\le\infty\\ 1/(2d); & y=0, -d\le x\le d\end{cases}\qquad(5)$$

which corresponds to uniform horizontal motion. The larger d is, the heavier image blur degree.

Fig.4 shows the original images (from d=3 to d=27) according to their blur metric values.Fig.4.illustrates the behavior of the no-reference edge-based blur metric at each distortion level.

Fig.4. **Objective blur measurement versus different horizontal motion pixels d of the linear motion operator employed to blur the image**

4. Conclusions

In this paper, we present a new method for no-reference image blur assessment based on the sharpness of the sharpest edges in the image. The effectiveness of such method is validated on both circular averaging filter-blurred images and also uniform linear motion-blurred images. Experimental results show that the proposed method can measure no-reference image blur correctly. Besides, the algorithm is near real-time and has low computational complexity. Compared with the algorithm proposed in ref.[7], the runtime of the algorithm proposed in this paper is nearly half that of the method presented in ref.[7].

Noise has bad effect on the accuracy of the blur metric. Due to image edges and noise all correspond to the high-frequency components in frequency domain, they are of similarity that they are all discontinuity points. If the SNR of images is low, false edges will be detected because of the existence of noise. For edge detection is one of the key steps of the algorithm, low edge detection precision will directly affect the algorithm precision. The future work should focus on finding a better edge detector which has better suppression effect for noise and higher edge detection accuracy.

5. References

[1] N. Damera-Venkata et al., “Image quality assessment based on a degradation model”, *IEEE Trans. on Image Process,* vol.9, no.4, 2000, pp. 636-650.

[2] Oh J, Wooley S I, Arvanitis T N, et al., “A multistage perceptual quality assessment for compressed digital angiogram images”, *IEEE Transactions on Medical Imaging,* vol.20, no.12, 2001, pp.1352-1361.

[3] P.Teo and D.Heeger,“A model of perceptual image fidelity”,*Proc.of ICIP,*vol.2,1995,pp.343-345.

[4]Zhou Wang, Alan C.Bovik, and Brian L.Evans,“Blind measurement of blocking artifacts in images”,*IEEE Proc.ICIP,* Vol.3,2000, pp.981-984.

[5]N.B.Nill and B.H.Bouzas,“Objective image quality measure derived from digital image power spectra”, *Optical Engineering,*vol.31, 1992, pp.813-825.

[6]Jalobeanu.A, BlancFeraud, LandZerub,“Estimation of blur and noise parameters in remote sensing”,*IEEE Proc.ICASSP,* vol.4, 2002,pp.3580-3583.

[7]Y.Chen and F.Meng,“Image quality measurement based on statistics of activity region”, *J.of Chinese Insititute Eng.,*vol.24,2001,pp.379-388.

[8]P.Marziliano,F.Dufaux,S.Winkler,etal,“A no-reference perpetual blur metric”,*Proceedings ICOIP.*2002,vol.3.pp57-60.

[9] Milan Sonka ,Vaclave Hlavac and Roger Boyle, *Image Processing Analysis and Machine Vision,* Thomson Learning and PT Press, New York,2003.