A Non-Parametric Blur Measure Based on Edge Analysis for Image Processing Applications

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Abstract— A non-parametric blur measure is presented. The measure is based on edge analysis and is suitable for various image processing applications. The proposed measure for any edge point is obtained by combining the standard deviation of the edge gradient magnitude profile and the value of the edge gradient magnitude using a weighted average. The standard deviation describes the width of the edge, and its edge gradient magnitude is also included to make the blur measure more reliable. Moreover, the weight of the value is related to image contrast and can be calculated directly from the image. Experiments on natural scenes indicate that the proposed technique can effectively describe the blurriness of images in image processing applications.

Keywords—blur measure; edge analysis; image contrast calculation

I. INTRODUCTION

A measure of the sharpness or blurriness of edges in an image can be useful for a number of applications in image processing, such as checking the focus of a camera lens, helping to identify shadows (whose edges are often less sharp than object edges), the separation of variations in illumination from the reflectance of the objects in an image (known as intrinsic image extraction), and in-focus areas (or foreground) vs. out-of-focus (or background) areas in an image.

In this paper we propose a method to determine the blurriness of edges in a color image. The method needs no user-supplied parameters like shapes and positions of objects or information about light sources. Nor is information about camera geometry needed.

Marziliano et al. [5] have proposed a no-reference perceptual blur metric (we prefer the term measure rather than metric), which they define in the spatial domain as the spread of the edges. (We briefly discuss their method in section II.)

Rooms et al. [6] have proposed a technique for measuring blur using wavelets. They calculate the sharpness of the sharpest edges in the image by computing the Lipschitz exponent for edges as a smoothness measure. The Lipschitz exponent (also known as the Hölder exponent) is a smoothness measure for a certain point. It is actually the result of how many times the image can be differentiable at a point. This measure is suitable for focus estimation without spatial domain processing to avoid noise effects. However, the estimated blur measure for a whole image may not be suitable for other applications.

Our proposed blur measure for an edge point is obtained by combining the standard deviation of the edge gradient magnitude profile and the value of the edge gradient magnitude using a weighted average. The standard deviation describes the width of the edge, and the edge magnitude helps make the blur measure more reliable. The weight is calculated from the contrast of the input image and needs no manual inputs.

Experimental results covering intrinsic image extraction, image focusing, and in-focus vs. out-of-focus areas of an image are discussed in this paper. More applications of the proposed blur measure could also be investigated, such as shadow detection and removal, and benchmarking of the quality of image compression algorithms.

Our proposed approach is described in section 2. Experimental results are presented in section 3, and concluding remarks are in section 4.

II. THE PROPOSED NON-PARAMETRIC BLUR MEASURE

Fig. 1 presents a flowchart for the proposed blur measure. Given an input image $I(x, y)$, where $x$ and $y$ are the row and column coordinates, respectively, the gradient at any pixel location $p = (x, y)$ is calculated by applying the two-dimensional directional derivative

$$\nabla I(x, y) = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial}{\partial x} I(x, y) \\ \frac{\partial}{\partial y} I(x, y) \end{bmatrix}. \tag{1}$$

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The gradient magnitude (and two fast, decreasing accuracy approximations) at \( p \) can be obtained from \( G_x \) and \( G_y \) by

\[
|\nabla I(x,y)| = \sqrt{G_x^2 + G_y^2} \\
\approx \frac{1}{2}\left[ \max(G_x, G_y) + |G_x| + |G_y| \right] \approx |G_x| + |G_y|.
\]

Consider an edge point at \( p = (x, y) \) defined as a local maximum of the edge gradient magnitude, and with the \( \zeta \)-axis in the direction of the gradient. The origin of the \( \zeta \)-axis is at the point of local maximum. See Fig. 2. The edge width \( w \) is defined as the distance between the nearest local minima (\( \zeta = m_i \) and \( \zeta = m_r \)) on each side of the maximum, i.e., \( w = | m_i - m_r | \).

For comparison, Marziliano et al. [5] calculated and averaged all the width values from the output of a vertical edge filter to define their blur metric for the whole image. Their method is quick, but, in some cases, can be significantly affected by noise, as the example in Fig. 3 shows. The correct edge width is \( w \), while the calculated width is \( w' \), the difference being caused by noise around the edge pixel.

In our proposed method, local maximum points, \( p' = (x', y') \), of the gradient magnitude of edges are used to denote the edge locations. The gradient orientation (direction of the \( \zeta \)-axis) indicates the direction of the normal to the edge at \( p' \) with respect to the \( x \)-axis and is defined as \( \alpha(x', y') = \text{atan2}(G_y, G_x) \), where we have used the atan2 function found in most programming languages since the result is in the interval \(-\pi \) to \(+\pi\). We treat the edge gradient magnitude (across the edge) between \( \zeta = m_l \) and \( \zeta = m_r \) as a discrete probability distribution, with the mean at point \( p' \) corresponding to \( \zeta = 0 \). Let \( m_r \) be on the positive \( \zeta \)-axis, and \( m_l \) be on negative \( \zeta \)-axis, i.e., \( m_r > 0 \) and \( m_l < 0 \). Refer to Fig. 4. For this distribution, we calculate the (spatial) variance as...
Figure 4. Illustration of the blur measure for an edge point \( p(x, y) \), (a) the edge point location, (b) fitting \( em(\zeta) \) by normal distribution \( \Phi(\zeta) \).

\[
\sigma^2(p^i) = \frac{1}{|m_r - m_l|} \sum_{\zeta = m_l}^{m_r} |\nabla I(\zeta)| \zeta^2. \tag{3}
\]

(While this may a scaled version of the variance, it does not matter, since in the next equation, we divide by a normalizing term.) The blur measure \( A(p^i) \) for an edge point \( p^i \) is obtained by computing the weighted average of the standard deviation \( \sigma \) and the edge magnitude \( |\nabla I(p^i)| \)

\[
\beta(p^i) = \eta_\beta \frac{\sigma(p^i)}{\sigma_{\max}} + (1 - \eta_\beta) \frac{|\nabla I(p^i)|}{|\nabla I(p^i)|_{\max}}, \tag{4}
\]

where \( \sigma_{\max} \) and \( |\nabla I(p^i)|_{\max} \) are normalization terms denoting the maximum values for all standard deviations and for all edge gradient magnitudes.

The weight \( \eta_\beta \) is related to image contrast and is given by

\[
\eta_\beta = \frac{1}{BC} \sum_{i} \sum_{(x,y)} \frac{R_{MSR}(x,y)}{\log I_i(x,y)}, \tag{5}
\]

where \( B \) is the number of pixels in image \( I(x,y) \) and \( C \) is the number of color bands. Since we are processing RGB images, we use \( C = 3 \), but it could be different for another color space; for example, for the CMYK color space, \( C = 4 \). \( I_i(x,y) \) is the \( i^{th} \) color band of image \( I(x,y) \), and \( R_{MSR} \) is the \( i^{th} \) color component of the output of the Multiscale Retinex (MSR) algorithm [3], which is the combined weighted sum of \( N \) Single-scale Retinex (SSR) outputs (discussed below) [4]. The MSR output indicates the amount of enhancement needed for edge contrast. The \( i^{th} \) component of the MSR is given by

\[
R_{MSR}(x,y) = \frac{1}{N} \sum_{n=1}^{N} [\log(I_i(x,y)) - \log(F_n(x,y)^i I_i(x,y))]. \tag{6}
\]

where the symbol \( \ast \) indicates convolution. \( F_n(x,y) \) is a Gaussian smoothing filter and is calculated as \( F_n(x,y) = Ke^{-(x^2+y^2)/c_n^2} \). Parameter \( c_n \) is the scale constant for the \( n^{th} \) scale, and \( K \) is a normalizing constant such that \( F_n(x,y) \) sums to 1. (Values of \( c_n \) are given in the next section.)

III. EXPERIMENTAL RESULTS

Sobel operators are commonly used as the filter to detect horizontal and vertical edges in digital images. Due to the discrete coordinate system used, the gradient directions \( \alpha \) calculated from Sobel filters require a subpixel level correction to decrease the error in the calculated angles [1]. To correct \( \alpha \), it is first reduced to the octant \([0, \pi/4]\). When \( \alpha \) is in the range \( \tan^{-1}(1/3) \) to \( \pi/4 \), the correction is [1]

\[
\alpha'(x,y) = \begin{cases} 
\alpha(x,y) & \text{if } 0 \leq \alpha \leq \tan^{-1}(1/3) \\
\tan^{-1}(7\tan^2\alpha + 6\tan\alpha - 1) & \text{if } \tan^{-1}(1/3) < \alpha < (\pi/4).
\end{cases} \tag{7}
\]

Then the angle is restored to its proper octant. The difference between \( \alpha \) and \( \alpha' \) and the percent difference are shown in Fig. 5. The maximum error without correction is about 4.3%.

Figure 5. The difference of \( \alpha \) (continuous line), \( \alpha' \) (dotted line) and percent error (dashed line) of Sobel operators.
Jobson et al. [3] and Starck et al. [7] recommended that the number of SSR scales of the MSR be three, and so we used \( N = 3 \). Since this value gave good results, we did not bother experimenting with other values. In addition, the Gaussian scale parameters \( c_n \), \( (n = 1, 2, 3) \) in [3] are suggested to take on the values 15, 80, and 250.

Fig. 6 shows an example image of the proposed blur measure. Applying vertical and horizontal derivative filters to the input image Fig. 6(a) produces the edge magnitude image Fig. 6(b), where blue indicates the vertical edge magnitude and green, the horizontal edge magnitude. From (5), weight \( \eta_0 \) is 0.5772. The blur measure \( \beta(x, y) \) for an edge point \( p \) is obtained by averaging the standard deviation \( \sigma \) and the edge magnitude \( |\nabla I(p')| \) from (3). The blur measure is shown in Fig. 6(c), where sharper edges correspond to higher intensities in the image. The computation of \( \beta(x, y) \) took less than one second on a Pentium based PC.

There are many potential applications of the proposed measure. One is for the extraction of intrinsic images (i.e., reflectance and illumination images) from a single image. The blur measure provides important information about the scene illumination because edges of shadows tend to be blurred compared to object edges. With the proposed blur measure, the results of our previous study of the extraction of intrinsic images [2] can be improved. Fig. 6(d) is the resulting improved reflectance image, comparing with the original reflectance image, Fig. 6(e) [2], the details of the recovered reflectance image is obviously better and this demonstrates that the proposed blur measure is effective, e.g., the utility pole in the left upper corner is better recovered in (d) than (e). Fig. 6(f) is the improved illumination image, and the original illumination image is shown in Fig. 6(g) [2].

Another example that is applicable to camera focusing is shown in Fig. 7. An in-focus image is shown in Fig. 7(a), and
its edge magnitude image in Fig. 7(b). From (5), \( \eta_6 = 0.6514 \). The blur measure image is shown in Fig. 7(c). An out-of-focus is shown in Fig. 7(d), and its edge magnitude image in Fig. 7(e). A simple way of calculating a measure of focus \( F \) is

\[
F = \frac{L \sum_{(x',y')} \beta(x',y')}{\sum_{(x',y')} |\nabla I(x',y')|},
\]

(8)

where \( L \) is a normalizing constant, \( \beta(x, y) \) is the blur measure image, \( |\nabla I(x, y)| \) is the gradient magnitude image, and \( L = 255 \) and, since \( 0 \leq \beta(x, y) \leq 1 \), we have made the measure of focus \( 0 \leq F \leq 1 \).

If the image is not correctly focused on the target, the blur measure can provide useful information to evaluate the image quality. For the images shown in Fig. 7(a) and (c) with correct focus, \( F \) is 0.564, Fig. 7(d) and (e) are out of focus, and \( F \) is 0.459. A more blurred version of the image is shown in Fig. 7(f) for which \( F \) is 0.434.

Fig. 8 presents another example, with the input image in Fig. 8(a) and the edge magnitude image in Fig. 8(b). From (5), \( \eta_6 = 0.6205 \). The blur measure of the edges is shown in Fig. 8(c). This example demonstrates that foreground (in-focus) and background (out-of-focus) can be distinguished using the blur measure. In this example, the birds in the foreground (near the camera) have sharp edges, while the background flowers and plants (farther from the camera) are blurred.

More applications of the proposed blur measure could be investigated, such as shadow detection and removal, and benchmarking of the quality of image compression algorithms, etc.

IV. CONCLUSION

A technique for a non-parametric blur measure based on edge analysis was presented. The proposed blur measure \( \beta(x, y) \) for any edge point \( p' = (x', y') \) is obtained by a weighted average of the standard deviation of the edge magnitude profile around \( p' \) and the value of the edge gradient magnitude using a weighted average. The standard deviation plays an important role in effectively describing the edge width around \( p' \), and its edge magnitude is also included to make the blur measure more reliable. Moreover, the value of the weight, which is based on image contrast information, is computed directly from the image.

The proposed blur was also tried with some applications, including the extraction of intrinsic images, camera focus, and foreground/background classification. In addition, more applications of the proposed blur measure could be investigated, such as shadow detection and removal and benchmarking the quality of image compression algorithms, etc.

REFERENCES