Blur Estimation for Document Images

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***Abstract*—In this paper, we propose a new measure for estimating defocus blur in document images and compare it with a good existing method proposed in [1]. This new measure is the average value of blur levels of edge points detected by the method proposed in [2]. This method uses three edge models (transition, peak and line) and analytically calculates their maxima functions. Then maxima functions of the input image are calculated at possible edge locations. By comparing maxima function with the models, the type of the edge and then the blur level can be estimated. We apply this measure to some document images and compare it with the measure of [1].**

I. Introduction

In many image processing applications, we encounter blurred images. Blur is caused by different reasons: defocusing, movement of the object, limited focus depth when imaging objects in 3D and so on. Most times blur is a problem and we try to remove it; sometimes we exploit it, e.g., for detecting the depth [3].

In document images, we would like to convert paper documents to digital files. To automate this work, we need to know the correct focus of the camera. One way to do that is to change the focus till reach the minimum blur level. In addition, most times the whole surface of the pages of the books are not flat (in the same distance from the camera) so in every image of the stacks some parts are blurred and some parts are sharp. So first we need to find the images with bigger sharp parts and then fuse them to reach an image with all parts sharp. To find the sharpest image from a stack a blur/focus measure is needed. Several measures are proposed in literature for blur estimation.

In [1] several measures are mentioned and a new wavelet-based one is proposed. All these measures use all information in the image including the noise while we know that in images most information are carried by edge points [4] so it is desirable to use only edge points for blur estimation.

In [2] a wavelet-based method is proposed for detection of edge points and estimation of the blur level of every edge point. Based on this method, we define a new measure. The contribution of [2] is how to find edge points and some guides to find the type of edges and estimation of the blur level. Then we calculate the average of the blur levels of the individual edge points to characterize the global blur level of the whole image. To illustrate, we show practical results for document images.

In section II we discuss several existing methods from [1]. In section III we explain the method of edge detection and blur estimation explained in [2] and introduce our new measure. In section IV we show practical results and finally conclude in section V.

II. Existing Blur Measures

The most blur measures proposed in literature use this fact that blurring acts as a lowpass filter and so the high frequencies of the blurred image are less than ones of a sharp image [5]. Most popular measures are: [1]

- Variance of Image Gray Levels
- L1 and L2 Norm of Image Gradient
- L1 Norm of Second Order Derivatives
- Ratio of High-pass and Low-pass Bands of Wavelet Transform
  This measure is proposed in [1]: when an image $f(x, y)$ is decomposed using a wavelet transform, we have a low-pass band image that we denote by $low(f)$ and several high-pass band images. We denote all of them by $highs(f)$; The proposed measure is:

$$M_1 = \frac{\|highs(f)\|}{\|low(f)\|}$$

  where $\|.\|$ denotes the discrete Euclidean norm. So the numerator of this ratio is the summation of squared values of all pixels in the low-pass image and its denominator is the summation of squared values of all pixels in high-pass band images. Therefor the resulted measure is a number that decreases when the blur increases.

A disadvantage of all these measures is that they take into account noise. In the last one the value of the numerator may be close to zero.

III. The New Measure

First we explain shortly the proposed method for detecting edge points and estimating their blur level in [2].

One way to detect the singularities in an image is using local maxima of the wavelet transform [5]. In [2] for calculating the wavelet transform, a complex wavelet is used of which the real part is the derivative of a 2 dimensional Gaussian in the x-direction and its imaginary part is its derivative in the y-direction. To understand the method used in [2], we need to know exactly what a maxima function is. So we explain it first.

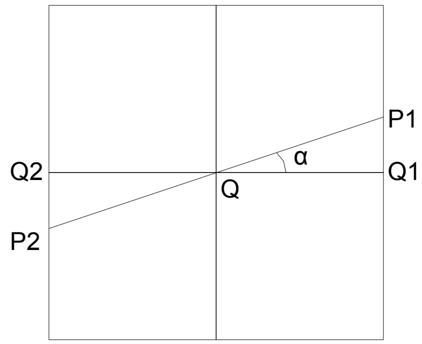

Fig. 1.

A. Maxima Function

Suppose that we calculate the wavelet transform of an image $f(x, y)$ in different scales (s) and denote it by $Wf(s, x, y)$. Consider a point (Q) in scale s_0 and at position of (x_0, y_0). We know that its value is complex. We denote the modulus of Q by $|Q|$ and its argument by α. We consider two points $P1$ and $P2$ in two sides of the point Q in the direction of α on the rectangular grid of the image (see fig. 1).
The point Q is a local maximum if [2], [6]:

$$|Q| \geq |P1| \text{ and } |Q| > |P2|$$

The values of $|P1|$ and $|P2|$ should be interpolated for example using two nearest neighbors. Of course in our work to reduce the computational cost, we estimate them using only the nearest neighbor. For example if in figure 1, α be less than $\pi/8$ we estimate $|P1|$ and $|P2|$ by values of $|Q1|$ and $|Q2|$ respectively.
When the maxima in every scale are found, we construct maxima functions. A maxima function for a maximum in the first scale is created by connecting it to its corresponding maximum in the next scale till the coarsest scale is reached. By considering step scale at most 0.5, the location of the every maxima will not move more than one pixel. So for finding the corresponding maximum, we look at its 8 neighbors in the next scale. We start this procedure from the fine scales and continue till either coarsest scale or till there is not any corresponding any more. We should insist that it is possible that we can not find a corresponding maximum in the next scale; if so, constructing that maxima function is stopped. Also it is possible that some maxima are not used at all. We only use those maxima functions that have at least 3 values (For more details refer to [2]).

B. Edge Models

In [2] three edge models are defined: the transition, the peak and the line. The edge models are characterized by edge type, blur level and an amplitude.

1) Transition edge Model (Fig. 2a): The transition edge model denotes by $T_\sigma(x, y)$ is defined as:

$$T_\sigma(x, y) = AH(x, y) * G_\sigma(x, y) = \frac{A}{2}\left(1 + \text{erf}\left(\frac{x}{\sigma\sqrt{2}}\right)\right)$$

where $G_\sigma(x, y)$ is a Gaussian with variance σ^2 and H is the Heaviside function and A is the edge amplitude.

2) Peak edge Model: (Fig. 1b) This is the convolution of a Dirac point function with a Gaussian function of amplitude A and variance σ^2. The result is the Gaussian function itself:

$$P_\sigma(x, y) = 2\pi\sigma^2 A G_\sigma(x, y)$$

3) Line edge Model: (Fig. 2c) It is the convolution of a Dirac line function and a Gaussian function of amplitude A and variance σ^2. The result is a 1-D Gaussian function:

$$L_\sigma(x, y) = 2\pi\sigma^2 A G_\sigma(x, 0)$$

We emphasise that these models are just valid locally, along small sections of edges.

C. Wavelet Maxima Functions of the Edge Models

In the following subsections we calculate maxima functions of edge models **analytically** and then use them for fitting the extracted maxima functions from the input image and estimate the blur levels.

1) Transition: The real component of the wavelet transform of $T_\sigma(x, y)$ is:

$$[WT_\sigma(s, x, y)]_{re} = \frac{A}{\sqrt{2\pi}} \frac{s}{\sqrt{s^2 + \sigma^2}} \exp\left(-\frac{x^2}{2(s^2 + \sigma^2)}\right)$$

Since T_σ is constant along the y-axis, the imaginary component of the wavelet transform is null and so the maxima function for the transition edge is [2] (Fig. 3):

$$MT_\sigma(s) = \frac{A}{\sqrt{2\pi}} \frac{s}{\sqrt{s^2 + \sigma^2}}$$

This function is strictly increasing and if s tends to infinity MT_σ tends to $A/\sqrt{2\pi}$. We denote this limit by v_{inf}. On the other hand, the slope of the $MT_\sigma(s)$ at the origin can be obtained using the first derivative with respect to s:

$$(MT_\sigma(s))' = \frac{A}{\sqrt{2\pi}} \frac{\sigma^2}{\sqrt{(s^2 + \sigma^2)^3}}$$

$$\Rightarrow (MT_\sigma(0))' = \frac{A}{\sigma\sqrt{2\pi}}$$

so

$$\sigma = \frac{v_{inf}}{(MT_\sigma(0))'}$$

2) Peak: The real and imaginary components of the wavelet transform for peak edge model are:

$$[WP_\sigma(s, x, y)]_{re} =$$

$$-A\frac{s\sigma^2}{(s^2 + \sigma^2)^{3/2}} \frac{x}{\sqrt{(s^2 + \sigma^2)}} \exp\left(-\frac{x^2 + y^2}{2(s^2 + \sigma^2)}\right)$$

$$[WP_\sigma(s, x, y)]_{im} =$$

$$-A\frac{s\sigma^2}{(s^2 + \sigma^2)^{3/2}} \frac{y}{\sqrt{(s^2 + \sigma^2)}} \exp\left(-\frac{x^2 + y^2}{2(s^2 + \sigma^2)}\right)$$

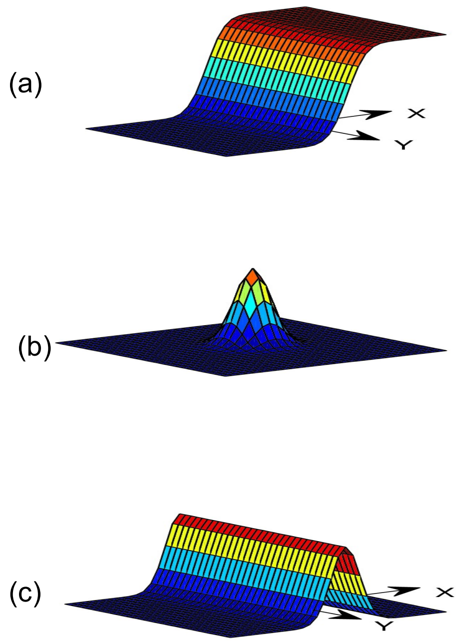

Fig. 2. Edge models [2].

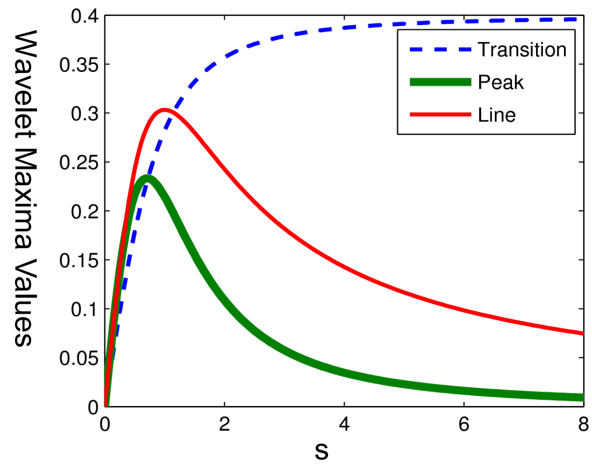

Fig. 3. Maxima functions of edge models by $\sigma = 1$ and $A = 1$ [2].

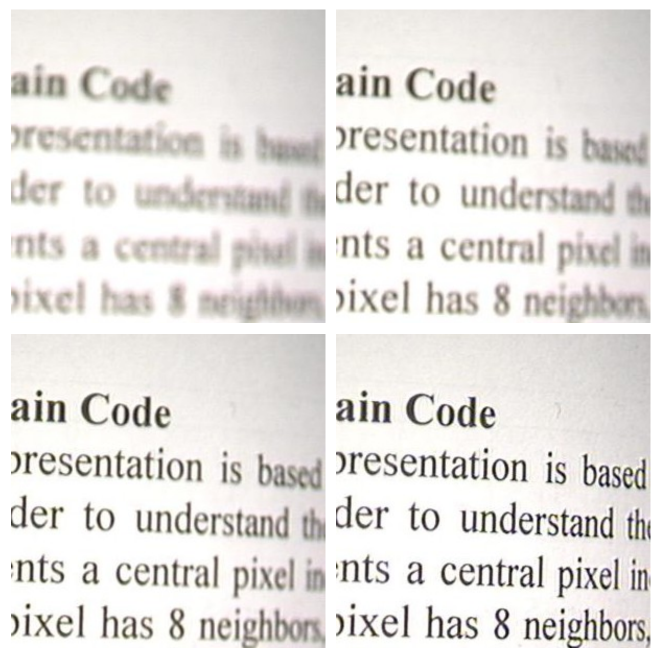

Fig. 4. input images.

Then the wavelet maxima function for the peak edge is [2] (Fig. 3):

$$MP_\sigma(s) = \frac{A}{\sqrt{e}} \frac{s\sigma^2}{(s^2+\sigma^2)^{3/2}}$$

This function has a maximum at $s = \sigma/\sqrt{2}$.

3) Line: The real component of the wavelet transform of the $L_\sigma(x, y)$ is:

$$[WL_\sigma(s,x,y)]_{re} = -A\frac{s\sigma}{s^2+\sigma^2}\frac{x}{\sqrt{s^2+\sigma^2}}\exp\left(-\frac{x^2}{2(s^2+\sigma^2)}\right)$$

and the imaginary one is null. So the wavelet maxima function for the line edge is [2] (Fig. 3):

$$ML_\sigma(s) = \frac{A}{\sqrt{e}} \frac{s\sigma}{s^2+\sigma^2}$$

This function has a maximum at $s = \sigma$.

D. Fitting and Blur Estimation

After constructing wavelet maxima functions of the input image, we compare them with maxima functions of edge models and the best fit provides the type of every edge point. From this, the blur level for their maxima functions is estimated as follows:

1) Transition: If the type of extracted maxima function is classified as transition, from III-C1 we know that its limit at infinity is $A/\sqrt{2\pi}$. We estimate this limit by the value of extracted maxima function in the largest scale. If it is v_{end} then $A = v_{end}\sqrt{2\pi}$. Its slope at the origin is estimated using the value of the extracted maxima function at the finest scale (that here is $s = 1$). We denote it by v_1. So

$$\sigma = \frac{v_{inf}}{(MT_\sigma(0))'} \approx \frac{v_{end}}{v_1}$$

2) Peak: If the type of extracted maxima function is classified as peak, from III-C2 we know that it has a maximum at $s = \sigma/\sqrt{2}$. So for estimating the σ, we locate the maximum of the extracted maxima function. Suppose it is located at $s = s_{max}$:

$$s_{max} \approx \frac{\sigma}{\sqrt{2}} \Rightarrow \sigma \approx \sqrt{2}s_{max}$$

3) Line: If the type of the extracted maxima function is classified as line, from III-C3 we know that it has a maximum

TABLE I

M_1 values	M_2 values
0.0000	2.2018
0.0000	2.0590
0.0031	1.8740
0.0212	1.7462
0.0330	1.6638
0.0387	1.6141

at $s = \sigma$. If the maximum is located at $s = s_{max}$ then

$$\sigma \approx s_{max}$$

E. Proposed measure

Now we define the new measure as follows:

M_2 = average of blur levels of detected edge points.

In the method explained in section III, the edge points are found and their blur levels are estimated. We can put a threshold to remove weak edges. Then we sum all blur values and divide the result by the number of edge pixels. It is clear that this measure is less sensitive to noise because it is only based on edge pixels, while the measures introduced in section II (specially the M_1 measure) also depend on noise of the image because they take into account all information in the image. Another big advantage of our new measure is that it estimates blurriness for every edge pixel, so it is a candidate for image fusion too.

IV. Apply to Document Images

When we want to take pictures from a document, the camera needs to autofocus and take the picture with more sharp parts. So here finding the sharpest image from a stack of images of the same page is one of the problems. In figure 4, we show four images from a document in diffrent focuses. We calculated the M_1 measure values for them using db5 wavelet (notation as in Matlab) and depth 2 and plot them in figure 5. When the focus becomes better, this measure value increases. We calculate the M_2 measure for these images and plot them in figure 6. The wavelet transform is calculated for scales 1 to 4 by steps of 0.5. This measure decreases while the focus increases. (or we can say while blur decreases).
We have shown some more results in Table 1 for six more images. These images are sorted by increasing the focus. As we can see M_1 is zero or close to zero for several first images.

V. Conclusions and Future Work

As we can see the second measure (M_2) is more monotonic and represents a good discrimination in comparison with the first measure (M_1). Actually the first method takes into account noise too but the second method uses only edge points so is more robust to noise. The first method is faster and uses less memory but the second one is slower and uses more memory space. To solve this drawback we can compute M_2 over small parts of the input images. Another advantage of the M_2 is that it calculates blurriness for every edge point while the M_1 measure calculates the measure for whole image. So

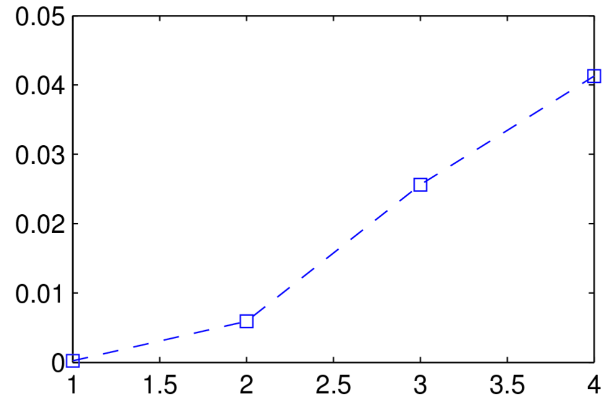

Fig. 5. Values of M_1 for input images.

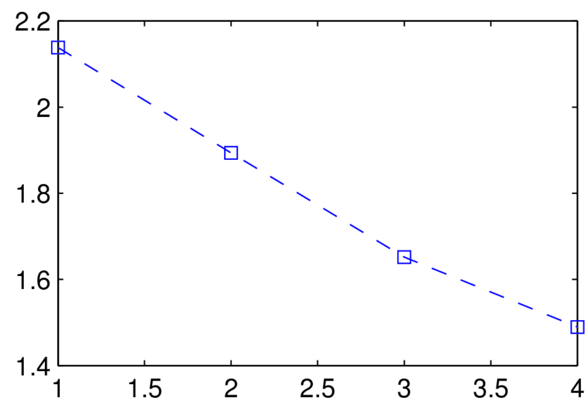

Fig. 6. Values of M_2 for input images.

M_2 is a candidate for image fusion and we will explore this later.

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References

[1] J. Kautsky, J. Flusser, B. Zitova, and S. Simberova, "A new wavelet-based measure of image focus," *Pattern Recognition Letters*, vol. 23, pp. 1785–1794, 2002.
[2] C. Ducottet, T. Fournel, and C. Barat, "Scale-adaptive detection and local characterization of edges based on wavelet transform," *Signal Processing*, vol. 84, pp. 2115–2137, 2004.
[3] N. Asada, H. Fujiwara, and T. Matsuyama, "Edge and depth from focus," *International Journal of Computer Vision*, vol. 26(2), pp. 153–163, 1998.
[4] S. Mallat and W. L. Hwang, "Singularity detection and processing with wavelets," *IEEE Transactions on Information Theory*, vol. 38, No. 2, pp. 617–643, 1992.
[5] R. Ferzli and L. Karam, "A no-reference objective image sharpness metric based on the notion of just noticeable blur(jnb)," *IEEE Transactions on Image Processing*, vol. 18, No.4, pp. 717–728, 2009.
[6] C. L. Tu and W. L. Hwang, "Analysis of singularities from modulus maxima of complex wavelets," *IEEE Transactions on Information Theory*, vol. 51, NO.3, pp. 1049–1062, 2005.