Proc. 3^{rd} IEEE Benelux Signal Processing Symposium (SPS-2002), Leuven, Belgium, March 21–22, 2002

PSF ESTIMATION WITH APPLICATIONS IN AUTOFOCUS AND IMAGE RESTORATION

F. Rooms[1], *M. Ronsse*[2], *A. Pizurica*[1], *W. Philips*[1]

Ghent University
[1] Dept. of Telecommunications and Information Processing (TELIN)
[2] Dept. of Elektronics and Information Systems (ELIS)
Sint-Pietersnieuwstraat 41, 9000 Gent, Belgium
Filip.Rooms@telin.rug.ac.be

ABSTRACT

In this paper, a wavelet based method is proposed to estimate the blur in an image using information contained in the image itself. We look at the sharpness of the sharpest edges in the blurred image, which contain information about the blurring. Specifically, a smoothness measure, the Lipschitz exponent, is computed for these sharpest edges. When one assumes that the blur can be described by one parameter (e.g., blur from a gaussian PSF can be described by the variance of the gaussian, defocus blur can be described by the radius of the circular PSF, ...). A relation between this parameter and the magnitude of the Lipschitz exponent is shown, which is only dependent on the blur in the image and not on the image contents. This allows us to estimate the blur parameter directly from the image itself.

1. INTRODUCTION

Blurring of edges in an image occurs in many different fields. Image blur is modelled as:

$$g(x, y) = (h * f)(x, y) \tag{1}$$

with $g(x, y)$ the blurred image, $f(x, y)$ the unknown sharp image and $h(x, y)$ the point spread function (PSF). The symbol $*$ represents the convolution operator, which models the image blur. It is in fact the response of the imaging system to an ideal point source. This blur is often unwanted and has to be compensated for (this is image restoration, and is applied in astronomy, medical imaging, microscopy, ...). For this purpose, the blur must be estimated to restore the ideal image $f(x, y)$ from degraded data $g(x, y)$.

Sometimes, the blur contains extra information. For example, it can provide information about the settings of the camera. When dealing with autofocus cameras, one expects to find a sharp image, because ideally all natural images contain sharp objects in front of a background. When the camera is out of focus, the sharpness of the sharpest edges that are still present in the image gives us information about how much an out-of-focus camera needs to be adjusted.

Blurred edges can also provide information about the 3D nature of the scene itself. In those applications, depth is estimated from focus/defocus [1, 2]. Again, we assume that all objects in front of a background have sharp edges. However, only objects in the focal plane are imaged with sharp edges. For objects not in the focal plane, these sharp edges are blurred in proportion to their distance from the focal plane, thus providing some depth information about the image.

In this paper, a method is proposed to estimate the PSF in an image by estimating how sharp the sharpest edges still present in a blurred image still are, in order to find information about the PSF. In particular, our method estimates the variance σ_{bl} of a gaussian PSF from information contained in the image itself:

$$\mathrm{PSF}(x, y) = \frac{1}{\sqrt{2\pi}\sigma_{bl}}\, e^{-(x^2+y^2)/(2\sigma_{bl}^2)}. \tag{2}$$

Our method can estimate the image blur σ_{bl} with an accuracy of about 10%. Other techniques for blur estimation using Gaussian PSF's [3, 4] use derivatives of the Gaussian PSF to determine the variance of the Gaussian blur. We present an alternative method, which doesn't use derivatives, but a measure of the smoothness of the image at a certain position. This method can also be extended to gaussian PSF's that are not axially symmetrical and even to PSF's that aren't even gaussian. For out-of-focus blur, a uniform circular PSF is used [5, 6]. Our method requires only minor modifications to adapt to this kind of PSF, as will be shown in the paper.

2. PRINCIPLE

2.1. Some theory

Our method for blur estimation is based on estimating the sharpness of the sharpest edges in the image. To analyse edges in the image, we calculate the Lipschitz exponent in all points where a change in intensity is found either in the horizontal or vertical direction. The Lipschitz exponent (sometimes referred to as Hölder exponent) is a measure of how smooth the image is in a certain point. In fact, it is an extension of how many times the image is differentiable in a certain point. For example, a signal that is differentiable once, has Lipschitz exponent 1, a step function has Lipschitz 0 and a dirac impulse Lipschitz -1. In the wavelet domain, it is possible to calculate the Lipschitz exponent in a certain point in the image from the evolution of the modulus maxima of the wavelet coefficients corresponding to that point through successive scales. This is illustrated in figure 1: for a sharp variation in amplitude, the wavelet coefficients decrease in magnitude, and for a smooth variation, the wavelet coefficients increase in magnitude. From this rate of increase or decrease through the successive scales, the lipschitz exponent can be calculated, as Mallat has shown in [7, 8, 9].

From the Lipschitz exponents thus found along the significant edges in the image, a histogram is made. For this histogram, we divided the range of Lipschitz exponents in intervals with a width of 0.1.

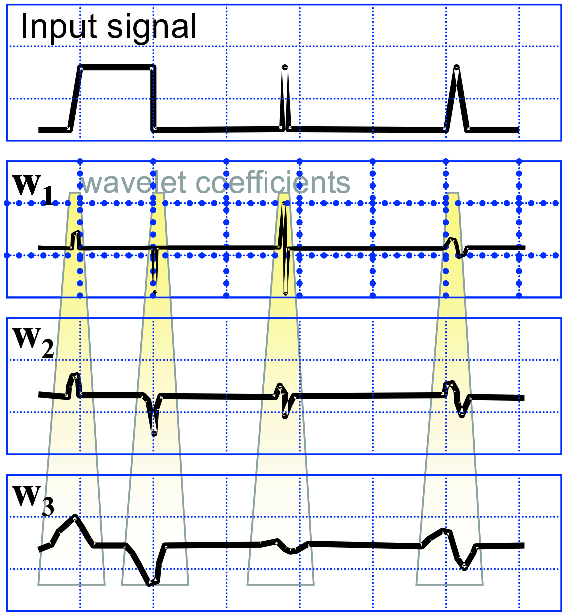


Figure 1: Estimation of lipschitz regularity for a onedimensional signal.

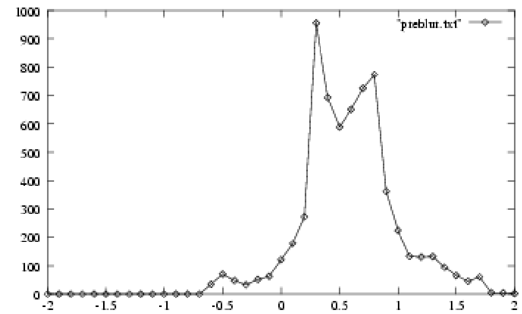
Because we restricted the lipschitz exponents to those corresponding with transitions with large amplitude, we already filtered out the sharpest transitions with a large amplitude in the image. From this histogram, we want to estimate the blur. The center of gravity (CG) of the histogram showed to be related to the blur in the image. We calculated the Lipschitz exponent that corresponds to CG of the histogram, and determined the average $\mathrm{CG}_{\sigma_{bl}}$ over the whole set of test images blurred with the same σ_{bl}. To these data $(\sigma_{bl}, \mathrm{CG}_{\sigma_{bl}})$, an exponential curve was fitted experimentally. The fitting was

$$\sigma_{bl} = a \; \exp(b \; \mathrm{CG}_{\sigma_{bl}}) \qquad (3)$$

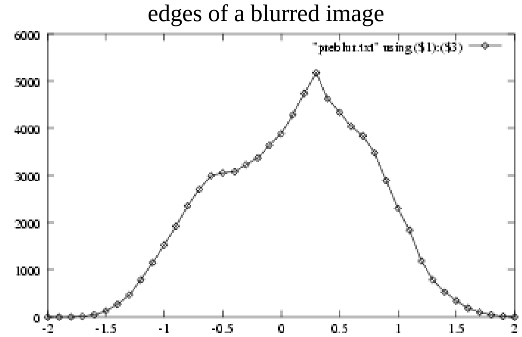
2.2. Robustness to noise

The technique described above is noise sensitive, as could have been expected for any technique based on finding local maxima. In applications like confocal microscopy or digital cameras, our initial experiments show that applying a median filter is a sufficient preprocessing step for reliable blur estimation because the noise is impulse like. In general cases however, when no precautions are taken, noise will disturb the blur estimation. There are two reasons for this. The first reason is because edges aren't detected accurately in the presence of noise. The second reason is that the lipschitz exponents on detected edges are disturbed.

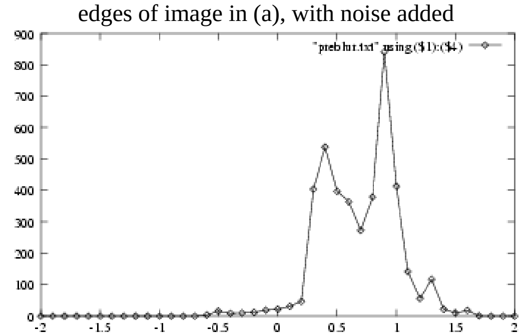
In [**?**], the problem of edge detection in the presence of noise was handled by gaussian smoothing. In [3], this technique is incorporated in a probabilistic framework, and an expression is given how much an edge must be smoothed to obtain reliable detection. This degree of smoothing depends on the contrast of the edge, the original edge smoothness and the noise level. The minimal degree of extra smoothing required is called the minimum reliable scale for that position in the image. To actually compute this value, one needs the edge characteristics and the noise level, which are



(a) Histogram of lipschitz exponents along edges of a blurred image



(b) Histogram of lipschitz exponents along edges of image in (a), with noise added



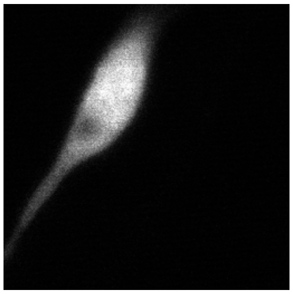
(c) Histogram of lipschitz exponents along edges of image in (b) with extra smoothing applied as preprocessing

Figure 2: Blur estimation used in restoration of a real image.

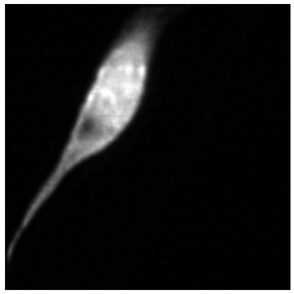
often unknown. In practice, the parameters are determined iteratively until a reliability criterium is satisfied. This is quite a time-consuming procedure.

We've performed some experiments with the technique described in [**?**] on our set of test images. We wanted to know how much smoothing was required in order to obtain a reliable blur estimation in the presence of noise. This additional smoothing was applied as a preprocessing step in our own blur estimation technique as described before. The additional blur value was later subtracted from the blur estimated in the smoothed image $\hat{\sigma}$ to obtain the original blur in the image:

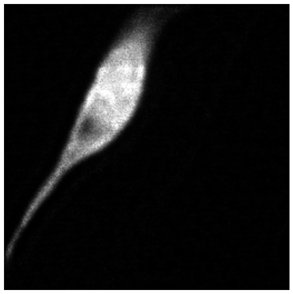
$$\sigma_{bl} = \sqrt{\hat{\sigma}^2 - \sigma^2_{postblur}} \qquad (4)$$



(a) Original microscope image.



(b) Image restored using our estimation.



(c) Image manually restored

Figure 3: Blur estimation used in restoration of a real image.

3. APPLICATIONS

3.1. Image restoration

In this section, we will show how the blur estimation can be combined with classical (non-blind) image restoration techniques, in order to adapt them to unknown blur. In figure 3, a confocal microscope image of a cell nucleus of *Arabidopsis Thaliana* is shown. The left image shows the raw microscope image, the right image shows the image, restored with the well known Richardson-Lucy restoration algorithm [10], using the raw image and our estimation of the PSF as inputs. As a comparison, we also determined σ_{bl} manually by restoring the image with different values of σ_{bl} and selecting the image with the best visual quality. The value of σ_{bl} that corresponds with this image, was the same as the one estimated with our method.

3.2. Autofocus

We also tried to estimate the PSF in case of out-of-focus blur. This kind of blur is encountered in autofocus applications, and is modelled by a uniform circular PSF [5, 6].

$$\mathrm{PSF}(x,y) = \begin{cases} K & \text{if } \sqrt{x^2+y^2} < r \\ 0 & \text{elsewhere} \end{cases} \tag{5}$$

with r the radius of the focal spot and K a factor, chosen such that the norm of the PSF is 1.0.

To estimate r_{focal} from a captured image, we repeated the same experiment as before, but this time with synthetic out-of-focus blur. In this case, relation 3 is not valid anymore. For out-of-focus blur, a polynomial provided a good fit to the data:

$$r_{focal} = 19.7\ \mathrm{CG}^3 \ - \ 19.1\ \mathrm{CG}^2 \ + \ 17.3\ \mathrm{CG} \ - \ 2.3.$$

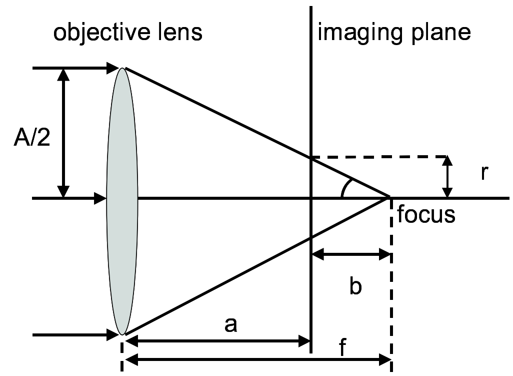


Figure 4: Autofocus application of blur estimation.

Using this relation, we can estimate r_{focal}. This is illustrated in 5. These images were used, captured from a Sony DFW-VL500 camera. The diameter of the focal spot was estimated to be zero in the first image, and 10 pixels in the second image, which proved to be correct...

In most autofocus applications one doesn't estimate the PSF of the blurring, but one only tries to determine whether an image is in focus or not. This can easily be checked by computing the total norm of the image gradient. When this norm is maximal, the image is in focus because the image is on its sharpest. However, this can be a lot of guessing before one actually find this point of maximal gradient.

In figure 5, the usage of blur estimation in autofocus applications is illustrated: a is the distance from the lens to the imaging plane, which is at a distance b from the focus of the objective lens, which has an aperture A. The focal distance is then given by $f = a + b$, and one has to move the imaging plane by b in order to obtain a sharp image.

Nevertheless, it is possible to retrieve more information about the blurring, and to use it to adjust the focus more accurately. One can calculate the size of the focal spot r_{focal} and when one knows the focal distance f and the aperture A of the objective lens, one can calculate how much the focus needs to be adjusted from the following relation:

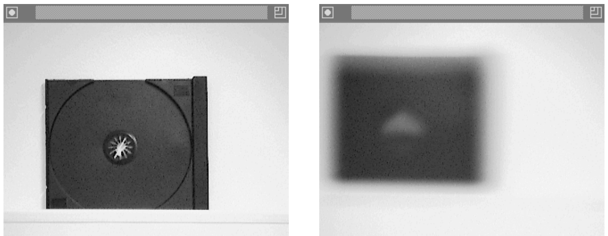
$$tg\ \alpha = \frac{A/2}{f} = \frac{r_{focal}}{b}$$

The only unknown aspect is if the imaging plane is in front of or behind the focal plane. This can be solved by one additional measurement of r_{focal} with a different focal distance, check if the situation improves or gets worse, and correct the focal distance accordingly.

and correct the focal distance accordingly if necessary.

4. CONCLUSIONS AND FUTURE WORK

In the experiments, we see that the CG of the histogram of Lipschitz exponents calculated among the edges in the image is a reliable parameter to estimate parametric modeled blur in an image. However, the standard deviation on the estimate increases as the blur increases. Applying additional blur reduces the effect of noise in our blur estimation within an acceptable range of blur and noise values.



(a) Sharp image (b) Image out of focus

Figure 5: Autofocus illustration of a real image.

5. REFERENCES

[1] Yalin Xiong and Steve Shafer, "Depth from focusing and defocusing," in *Proc. of IEEE Conf. on Computer Vision and Pattern Recognition*, 1993.

[2] Yoav Schechner and Nahum Kiryati, "Depth from defocus vs. stereo: How different really are they?," in *Proc. International Conf. on Pattern Recognition*, 1998.

[3] James Elder and Steven Zucker, "Local scale control for edge detection and blur estimation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 20, no. 7, pp. 699–716, 1998.

[4] V. Kayargadde and J.-B. Martens, "Estimation of edge parameters and image blur from local derivatives," *Journal on Communications*, pp. 33–34, 1994.

[5] Andreas Savakis and H. joel Trussell, "Blur identification by residual spectral matching," *IEEE Tans. Image Processing*, vol. 2, no. 2, pp. 141–151, 1993.

[6] Andreas Savakis and H. joel Trussell, "On the accuracy of psf representation in image restoration," *IEEE Tans. Image Processing*, vol. 2, no. 2, pp. 141–151, 1993.

[7] Stephane Mallat and Sifen Zhong, "Characterization of signals from multiscale edges," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 14, no. 7, pp. 710–732, 1992.

[8] Stephane Mallat and Wen Liang Hwang, "Singularity detection and processing with wavelets," *IEEE Trans. Information Theory*, vol. 38, no. 8, pp. 617–643, 1992.

[9] Stephane Mallat, *A wavelet tour of signal processing (2nd ed.)*, Academic Press, Oval Road, London, 1998,1999.

[10] H.T.M. van der Voort and K.C. Strasters, "A quantitative comparison of image restoration methods for confocal microscopy," *Journal of Microscopy*, vol. 185, no. 3, pp. 354–365, 1997.