Edge width estimation for defocus map from a single image

Andrey Nasonov, Alexandra Nasonova, Andrey Krylov

Laboratory of Mathematical Methods of Image Processing,
Faculty of Computational Mathematics and Cybernetics,
Lomonosov Moscow State University
kryl@cs.msu.ru

Abstract. The paper presents a new edge width estimation method based on Gaussian edge model and unsharp mask analysis. The proposed method is accurate and robust to noise. Its effectiveness is demonstrated by its application for the problem of defocus map estimation from a single image. Sparse defocus map is constructed using edge detection algorithm followed by the proposed edge width estimation algorithm. Then full defocus map is obtained by propagating the blur amount at edge locations to the entire image. Experimental results show the effectiveness of the proposed method in providing a reliable estimation of the defocus map.

Keywords: edge width, image blur, defocus map, edge model

1 Introduction

There are two general approaches for defocus estimation: methods that require multiple images [6, 16] and methods that use only one image [4, 1]. The former use a set of images captured with multiple camera focus settings. This approach has limited application due to the occlusion problem and requirements of a scene to be static. The latter split the problem into two steps: construction of a sparse defocus map via blur level estimation at edge locations and obtaining the full defocus map using a propagation method.

Elder and Zucker [4] find the locations and the blur amount of edges according to the first- and second-order derivatives of the input image, they only get a sparse defocus map. Bae and Durand [1] extend this work to get a full defocus map from the sparse map by a defocus interpolation method.

In [17] authors propose a blur estimation method based on the Gaussian gradient ratio, and show that it is robust to noise, inaccurate edge location and interference from neighboring edges. In [15] the image blur estimation method is based on the observation that defocusing can significantly affect the spectrum amplitude at the object edge locations in an image. Both these methods use matting Laplacian [9] for defocus map interpolation. These methods are the state-of-the-art methods. References to other methods can be found in these papers.

General purpose blur estimation methods can also be used for sparse defocus map construction problem. The method [7] is based on the assumption that the blur of the image is close to Gaussian. The image is divided into blocks, and the blur kernel is supposed to be uniform inside the block. The estimation of the blurriness of the block is based on the maximum of difference ratio between an original image and its two re-blurred versions. Block-based approach provides good blur estimation for highly textured areas but it shows inadequate results for blocks not containing edges, for example, flat areas.

There are some simple and fast methods for blur estimation at edge locations [10–12], but generally they are not adequate for noisy images. A lot of methods use Gaussian filter as blurring approximation. In [2, 5] authors propose methods of multi-scale edge detection, where the scale of detection for each edge can roughly approximate blur level. In [14] neural networks are used. In [8] edge neighborhood is expanded in radial-symmetric functions with the method of principal components as a classifier of blur level.

In this work we present a novel approach for edge width estimation suggested in [13] which is accurate and is robust to noise. Then we demonstrate the effectiveness of the proposed method for the problem of obtaining the defocus map from a single image.

2 Edge width

2.1 Gaussian edge model

We propose modeling an edge as a convolution of the ideal step edge function with a Gaussian filter (see Fig. 1):

$$E_\sigma(x) = [H * G_\sigma](x),$$

where $*$ denotes convolution.

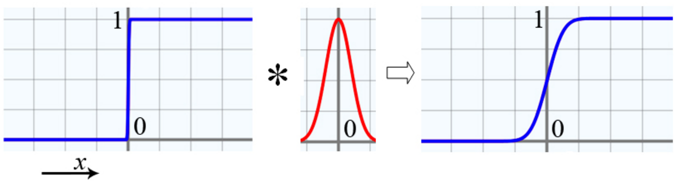


Fig. 1. Edge model

In our model we use the following definitions of the Gaussian filter and ideal step edge function

$$G_\sigma(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}}, \qquad H(x) = \begin{cases} 1, & x \geq 0, \\ 0, & x < 0. \end{cases}$$

It should be noted that $H(kx) = H(x)\ \forall k > 0$, which leads to the following property for the model edge:

$$E_\sigma(x) = E_{\sigma'}(\frac{\sigma'}{\sigma}x) \qquad \forall \sigma > 0, \sigma' > 0. \tag{1}$$

2.2 Estimation of edge width

For the estimation of edge width we use the unsharp masking approach.

Let $U_{\sigma,\alpha}[E_{\sigma_0}](x)$ be the result of unsharp masking applied to the edge $E_{\sigma_0}(x)$:

$$\begin{aligned} U_{\sigma,\alpha}[E_{\sigma_0}](x) &= (1+\alpha)E_{\sigma_0}(x) - \alpha E_{\sigma_0} * G_\sigma = \\ &= (1+\alpha)E_{\sigma_0}(x) - \alpha E_{\sqrt{\sigma_0^2+\sigma^2}}(x). \end{aligned} \tag{2}$$

Using (1) and supposing $\sigma = \sigma_0 = \sigma_1$, (2) holds

$$\begin{aligned} U_{\sigma_1,\alpha}[E_{\sigma_1}](x) &= (1+\alpha)E_{\sigma_1}(x) - \alpha E_{\sqrt{2}\sigma_1}(x) = \\ &= (1+\alpha)E_{\sigma_1}(x) - \alpha E_{\sqrt{2}\sigma_2}(\frac{\sqrt{2}\sigma_2}{\sqrt{2}\sigma_1}x) = U_{\sigma_2,\alpha}[E_{\sigma_2}](\frac{\sigma_2}{\sigma_1}x). \end{aligned} \tag{3}$$

The unsharp masking approach (2), due to (3), holds that for a fixed value of parameter α the intensity values of corresponding extrema of $U_{\sigma,\alpha}[E_\sigma](x)$ are the same for all $\sigma > 0$ (note that here unsharp masking uses the same σ as the model edge):

$$U^*(\alpha) = \max_x U_{\sigma,\alpha}[E_\sigma](x),$$
$$U_*(\alpha) = \min_x U_{\sigma,\alpha}[E_\sigma](x) = 1 - U^*(\alpha)$$

Thus, taking into account the monotonicity of $U_{\sigma,\alpha}[E_\sigma](x)$ as a function of σ due to (3) and the properties of Gaussian functions:

$$\begin{aligned} \sigma < \sigma_0 : &\max_x U_{\sigma,\alpha}[E_{\sigma_0}](x) < U^*(\alpha), \\ &\min_x U_{\sigma,\alpha}[E_{\sigma_0}](x) > U_*(\alpha), \\ \sigma > \sigma_0 : &\max_x U_{\sigma,\alpha}[E_{\sigma_0}](x) > U^*(\alpha), \\ &\min_x U_{\sigma,\alpha}[E_{\sigma_0}](x) < U_*(\alpha). \end{aligned} \tag{4}$$

2.3 The edge width estimation algorithm

The edge width estimation algorithm takes the following form:

1. Given values: α, $U^*(\alpha)$, 1-dimensional edge profile $E_{\sigma_0}(x)$.
2. for $\sigma = \sigma_{min}$ to $\sigma_{max} : \sigma_{step}$

compute $U_{\sigma,\alpha}[E_{\sigma_0}](x)$,
find local maxima x_{max} of $U_{\sigma,\alpha}[E_{\sigma_0}](x)$,
if $U_{\sigma,\alpha}[E_{\sigma_0}](x_{max}) \geq U^*(\alpha)$
result $= \sigma$,
stop cycle.

3. Output: result.

We use $\alpha = 4$, $U^*(4) \approx 1.24$, $\sigma_{min} = 0.5$ (the smallest possible value for the edge blur due to the digitization of the image), $\sigma_{max} = 10$, the value of σ_{step} is fixed to 0.1 as this is an acceptable accuracy for the task.

3 Defocus blur estimation

3.1 Sparse defocus map

The previous section deals with isolated edge profiles with values from 0 to 1. In practice real image edge profiles are rarely isolated, and all of them have different amplitude.

For sparse blur map, we have to obtain edge map using an edge detector (we use Canny edge detector [3]). For each edge pixel we construct an edge profile along the gradient direction at this pixel using an interpolation method (we use bilinear interpolation). Then the values of edge profile are scaled into interval from 0 to 1 and the algorithm from section 2.3 is used.

Also, for non-isolated edge profiles we isolate the central edge: we find the nearest local maximum to the right from the center and the nearest local minimum to the left, and duplicate those values (see Fig. 2).

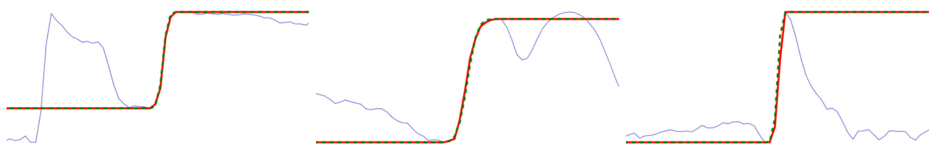


Fig. 2. Edge profile examples and the result of the proposed edge width estimation method. The blue thin line is the original profile, the red thick line is an isolated edge, the green puncture line is a model edge with found edge width.

3.2 Full defocus map

Using sparse defocus map at edge locations, the full defocus map is recovered by an edge-aware interpolation method [9]. We use the MatLab software provided by Zhuo and Sim [17] and substitute their sparse defocus map with ours.

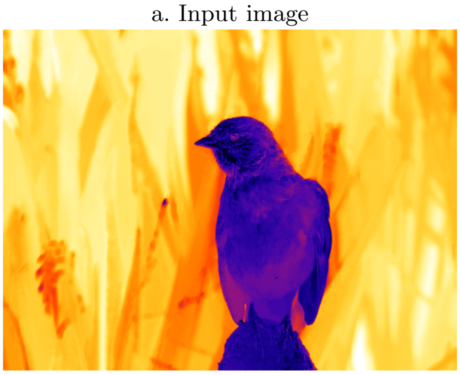
4 Results and discussion

We demonstrate the effectiveness of the proposed method by comparing our full defocus maps with results provided by [15] and [17]. The proposed edge width estimation method works well on images with a relatively low amount of noise, which is usually the case with defocused images. For noisy images some preliminary blurring can be applied.

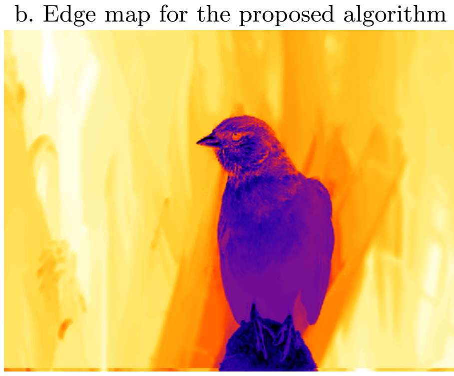
In Fig. 3 it can be seen that the proposed method makes the background more homogenous than [17]. In Fig. 4 the proposed method correctly processes the grass area and results in more gradual depth change. In Fig. 5, the proposed method and methods [17, 15] show results with almost the same quality.

a. Input image

b. Edge map for the proposed algorithm



b. Edge width estimation
by Zhuo and Sim [17]



c. Proposed edge width estimation

Fig. 3. Full defocus map for bird image. Blue and purple areas are sharp regions, yellow are white areas are blurry regions.

a. Input image b. Zhuo and Sim [17] c. Proposed edge width

Fig. 4. Full defocus map for pumpkin image

4.1 Possible improvement

Fig. 6 is the challenging problem for existing defocus map estimation algorithms because they construct sparse defocus map only using edge pixels. We suggest adding ridges and textures to the sparse defocus map as a possible improvement.

Ridges are linear image structures that also contain important information about image blur. Edge detection algorithms usually detect borders of only some ridges. Ignoring ridges results in missing thin lines from a defocus map. For example, the method [15] does not include stems into the foreground in Fig. 6.

Textured areas contain multiple edges that are hard to analyze with edge detection algorithms. Special algorithms for blur estimation in textured areas may improve the accuracy of blur estimation in these areas. Both the proposed method and the method [17] falsely include the image bottom into the foreground due to lack of edges provided by the edge detection algorithm in Fig. 6.

5 Conclusion

In this paper, we have presented new edge width estimation method and its application for the problem of obtaining full defocus map from a single image. The proposed edge width estimation is accurate, robust to noise and edge interference, and it can be used to generate accurate sparse defocus map. Possible ways to improve the defocus map are discussed.

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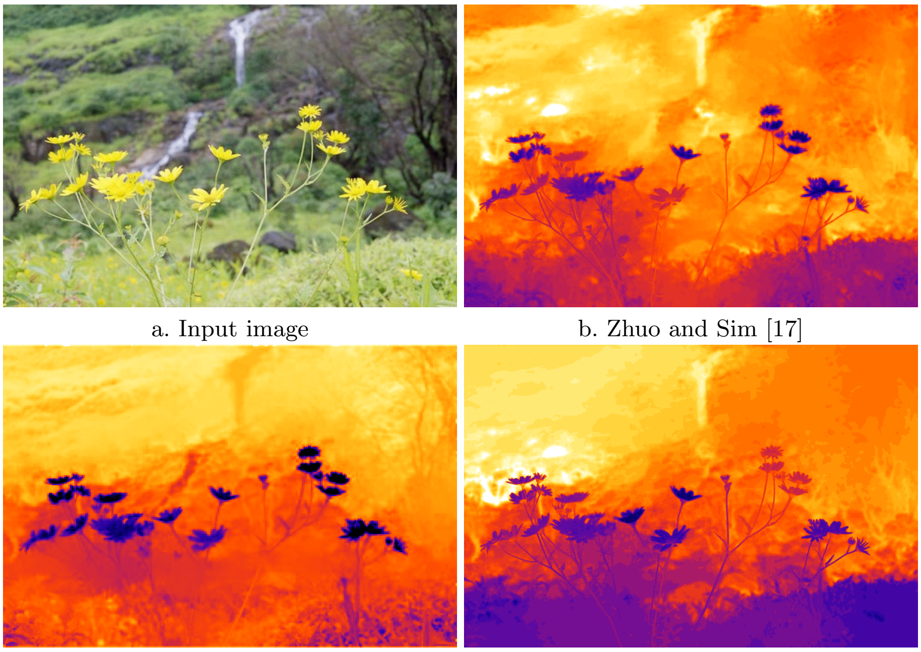
a. Input image

b. Zhuo and Sim [17]

c. Tang et al. [15]

d. Proposed edge width

Fig. 5. Full defocus map for flower image



a. Input image
b. Zhuo and Sim [17]
c. Tang et al. [15]
d. Proposed method

Fig. 6. Full defocus map for second flower image

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