Deblurring in fundus images

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Abstract

New method for blur detection in retinal images has been suggested. The procedure includes original algorithm of edge width estimation. A method of image deblurring with ringing control is proposed.

Keywords: *Retinal images, blur detection, edge width, ringing control.*

1. INTRODUCTION

Automatic quality analysis of medical images has become an important research direction. However, the automatic blur detection in fundus images has not received enough attention. Fundus images are acquired at different sites, using different cameras operated by people with varying levels of experience. This results in a variety of images with different quality, and in some of them pathologies cannot be clearly detected or are artificially introduced. These low quality images should be specially examined by an ophthalmologist and reacquired if needed.

Current approaches for retinal image quality determination are based on global image intensity histogram analysis [1] or on the analysis of the global edge histogram combined with localized image intensity histograms [2]. In both these approaches a small set of excellent quality images was used to construct a mean histogram. The difference between the mean histogram and a histogram of a given image then indicated the image quality. Nevertheless these methods cannot be used as general fundus image quality classifiers because images of poor quality that match the method's characteristics of acceptable quality can be easily presented.

In [3] a correlation between image blurring and visibility of the vessels was pointed out. By running a vessel segmentation algorithm and measuring the area of detected vessels over the entire image, the authors estimate if the image is good enough to be used for screening. The main drawback is that the classification between good and poor quality needs a thresholding.

In [4] a quality class classification of the images is proposed. Vasculature is analyzed in a circular area around the macula. The presence of small vessels in this area is used as an indicator of image quality. The presented results are good, but the method requires a good quality segmentation of the vasculature and other major anatomical structures to find the region of interest around the fovea.

This paper presents a novel approach for blur detection in fundus images based on estimation of blur level of automatically segmented vasculature. The method does not require the segmentation of optic disk or macula, and only a rough segmentation of blood vessels is necessary. This allows us to perform the procedure of vasculature segmentation using downsampled images and significantly decrease computational time. The method can be also applied to noisy images or images with non-uniform luminosity.

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2. EDGE WIDTH ESTIMATION

2.1 Edge model

We consider general edge model as a result of convolution of the ideal step edge of unit height and a Gaussian kernel with some dispersion σ. Such assumption gives us a unique correspondence between the edge and a numeric value, i.e. the dispersion σ of the Gaussian kernel, which we take as the value of the edge width.

We define the ideal step edge function of unit height as:

$$H(x) = \begin{cases} 1, & x \geq 0, \\ 0, & x < 0. \end{cases} \tag{1}$$

The edge $E_\sigma(x)$ (see fig. 1) is defined as

$$E_\sigma(x) = [H * G_\sigma](x). \tag{2}$$

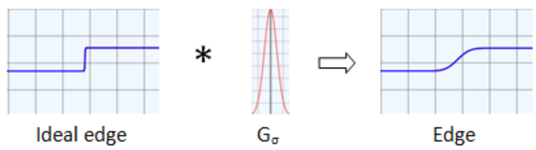


Figure 1: Edge model

Note that the function $E_\sigma(x)$ holds

$$E_\sigma(x) = E_{\sigma'}(\frac{\sigma'}{\sigma}x). \tag{3}$$

2.2 Edge width

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

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

$$\begin{aligned} &U_{\sigma,\alpha}[E_{\sigma_0}](x) = \\ &\quad = (1+\alpha)E_{\sigma_0}(x) - \alpha E_{\sigma_0} * G_\sigma = \\ &\quad = (1+\alpha)E_{\sigma_0}(x) - \alpha E_{\sqrt{\sigma_0^2+\sigma^2}}(x). \end{aligned} \tag{4}$$

Using (3) and supposing $\sigma = \sigma_0 = \sigma_1$, (4) holds

$$\begin{aligned} &U_{\sigma_1,\alpha}[E_{\sigma_1}](x) = \\ &\quad = (1+\alpha)E_{\sigma_1}(x) - \alpha E_{\sqrt{2}\sigma_1}(x) = \\ &\quad = (1+\alpha)E_{\sigma_1}(x) - \alpha E_{\sqrt{2}\sigma_2}(\frac{\sqrt{2}\sigma_2}{\sqrt{2}\sigma_1}x) = \\ &\quad = U_{\sigma_2,\alpha}[E_{\sigma_2}](\frac{\sigma_2}{\sigma_1}x). \end{aligned} \tag{5}$$

The unsharp masking approach (4), due to (5), holds that the intensity values of corresponding extrema of $U_{\sigma,\alpha}[E_\sigma](x)$ at x_{max_σ} and x_{min_σ} are the same for all $\sigma > 0$ with fixed α. Thus, taking into account the monotonicity of $U_{\sigma,\alpha}[E_\sigma](x)$ as a function of σ due to (5) and the properties of Gaussian functions, fixing the value of α and $U_E = \max_x U_{\sigma_E,\alpha}[E_{\sigma_E}](x)$ for some σ_E

$$\begin{aligned} U_{\sigma,\alpha}[E_{\sigma_0}](x_{max_\sigma}) \geq U_E, \sigma < \sigma_0 \\ U_{\sigma,\alpha}[E_{\sigma_0}](x_{max_\sigma}) \leq U_E, \sigma > \sigma_0. \end{aligned} \quad (6)$$

2.3 The edge width estimation algorithm

The final edge width estimation algorithm looks as follows:

1. Given values: α, U_E, 1-dimensional edge profile $E_{\sigma_0}(x)$.

2. for $\sigma = \sigma_{min}$ to σ_{max} : σ_{step}

    compute $U_{\sigma,\alpha}[E_{\sigma_0}](x)$,

    find local maxima x_{max_σ} of $U_{\sigma,\alpha}[E_{\sigma_0}](x)$,

    if $U_{\sigma,\alpha}[E_{\sigma_0}](x_{max_\sigma}) \geq U_E$

        result = σ,

        stop cycle.

3. Output: result.

2.4 Automatization of the parameters of the edge width estimation algorithm

The algorithm requires the values of α, σ_{min}, σ_{max}, σ_{step} and U_E that is dependent on α. The research shows that the best value for α is 4 (see Table 1).

The value of U_E for $\alpha = 4$ is equal to 1.24.

The value for σ_{min} is fixed and is equal to 0.5. This value is the smallest possible value for the edge blur due to the digitization of the image. The value of σ_{step} is also fixed to 0.1 as this is an acceptable accuracy for the task.

The value of σ_{max} depends on the size l of the edge profile sample. In order to reach the best approximation of the edge width estimation the size of the Gaussian filter with dispersion σ is taken as 8σ. Thus the value of σ_{max} is set to $l/8$.

$\sigma \downarrow \alpha \rightarrow$	2	2.5	3	3.5	4	4.5	5
0.5	0.6	0.6	0.6	0.6	0.6	0.6	0.6
1.5	1.5	1.5	1.5	1.5	1.5	1.6	1.6
2.5	2.5	2.6	2.6	2.6	2.5	2.5	2.5
3.5	3.6	3.5	3.5	3.5	3.5	3.5	3.6
4.5	4.5	4.5	4.5	4.6	4.5	4.5	4.5
5.5	5.5	5.6	5.5	5.5	5.5	5.5	5.6
6.5	6.5	6.5	6.5	6.6	6.5	6.5	6.5
7.5	7.6	7.5	7.5	7.5	7.5	7.5	7.5
8.5	8.5	8.5	8.5	8.5	8.5	8.5	8.5
9.5	9.5	9.5	9.5	9.5	9.5	9.5	9.5
10.5	10.5	10.5	10.5	10.5	10.5	10.5	10.5
11.5	11.5	11.5	11.5	11.5	11.5	11.5	11.5
12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5
13.5	13.5	13.5	13.5	13.5	13.5	13.5	13.5
14.5	14.5	14.5	14.5	14.5	14.5	14.5	14.5
15.5	15.5	15.5	15.5	15.5	15.5	15.5	15.5
16.5	16.5	16.5	16.5	16.5	16.5	16.5	16.5
17.5	17.5	17.5	17.5	17.5	17.5	17.5	17.5
18.5	18.5	18.5	18.5	18.5	18.5	18.5	18.5
19.5	19.5	19.5	19.5	19.5	19.5	19.5	19.5

Table 1: The results of the edge width estimation algorithm for different values of parameter α

3. APPLICATION OF THE EDGE WIDTH ESTIMATION ALGORITHM TO BLUR DETECTION IN FUNDUS IMAGES

In order to compute the blur value of the image we use the following algorithm:

a) Extract vessels,

b) Preliminary blur the image in order to suppress noise,

c) Extract vessel edge profiles,

d) Compute the image blur value taking into account the edge heights.

3.1 Vessel detection

The algorithm for vessel segmentation was previously described in [5]. We perform vessel detection on downsampled fundus images in order to fusten the algorithm.

3.2 Preliminary blurring

Due to the way of acquisition the target images have some noise. In the case of sharp images the noise almost does not affect the results of the edge width estimation algorithm, but in the general case some denoising is necessary for the correct use of the algorithm.

The algorithm for determination of the Gaussian kernel dispersion for preliminary blurring is as follows:

1. Find a homogenous area $A(x, y)$ on the image that is considered constant without noise.

2. Compute the mean M on the found area.

3. Compute the percentage P of maximum absolute deviation D from mean in the area:

$$P = D/(\max A(x, y) - \min A(x, y))$$

4. Set the dispersion σ_B to value

$$\sigma_B = (P + 1) * P * 100.$$

3.3 Extraction of the vessel profiles

We analyze the profiles of the boundaries of the widest vessels. In order to obtain these vessels' segments, we use the following algorithm:

1. Skeletonize the vessel mask,

2. Take only segments with the length greater than double maximum vessel width,

3. Sort the segments list in the descending order of the segment width,

4. Take 50 of the widest segments,

5. For every segment find its center and direction. The edge profile is taken as the cross-section of the segment.

3.4 Blur value estimation

In order to obtain an adequate result of two fundus images comparison we should take into account not only the average edge widths, but also amplitudes of the edges. The median of the weighted edge widths is taken as the blur value of the image. The weights are taken as inverse amplitude of the edge $10/A$.

So the algorithm for computing the blur value of the image is as follows:

1. Compute the edge amplitude A_i and normalize every edge profile so that the values belong to the interval from 0 to 1,

2. For every normalized profile compute the edge width σ according to the algorithm described in section 2.3, and then compute the value W_i, taking into account preliminary blur:

$$W_i = \sqrt{\sigma^2 \quad \sigma_B^2},$$

3. Scale the obtained values by the inverse original edges amplitudes and obtain the value $10\frac{W_i}{A_i}$ that characterizes the edge,

4. Compute the median value of the weighted edge widths of the image.

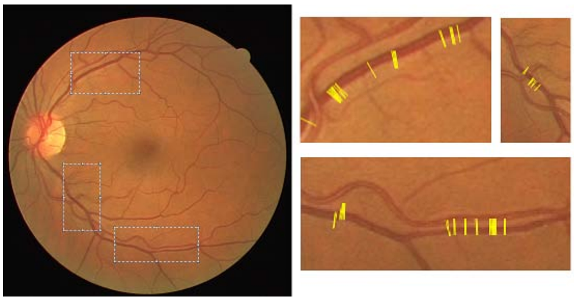
3.5 Results

Most of the publicly available databases contain images only of a good quality. As an example the proposed algorithm was tested on retinal images from the DRIVE database [6]. The average blur value for the images from this database was found as 0.29.

The method was also tested on real images from ophthalmological practice of different quality.

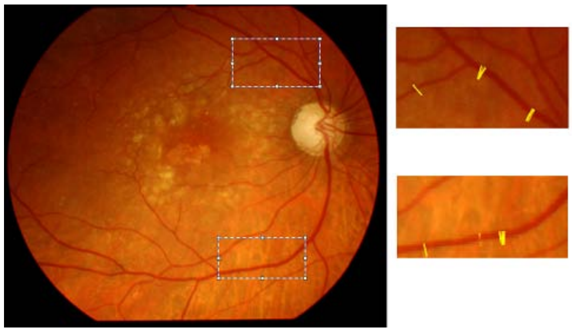
The results for images of different quality are shown in fig. 2, 3.

The results show that the images with blur value less than 1 are good enough for pathology analysis.

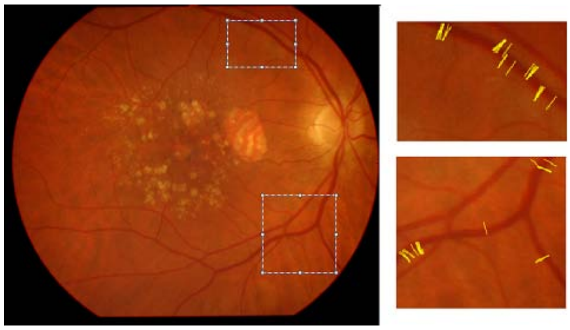


Blur value estimated 0.28

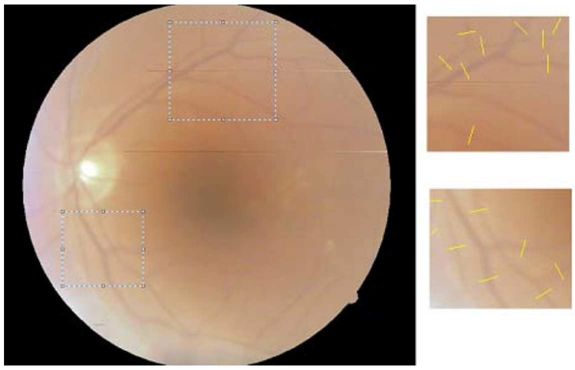
Figure 2: Blur value estimation for DRIVE image 01_test.



Blur value estimated 0.63



Blur value estimated 0.82



Blur value estimated 1.09

Figure 3: Blur value estimation for real fundus images.

4. DEBLURRING OF RETINAL IMAGES

After blur value estimation, we perform deblurring of retinal images. Unsharp masking is used for image sharpening. One of the problems of the image sharpening is introducing a ringing effect when the sharpening level is too high. We choose the parameterw of the unsharp masking in accordance to estimated edge width and image ringing level.

4.1 Ringing level estimation

We use the integral approach from [7] based on Total Variation analysis to estimate the ringing effect after applying the unsharp mask.

Ringing oscillations are located tangential to the edge producing them. The ratio between the average modulus of directional partial derivatives with normal and tangential directions nV/tV to the nearest edge is a good indicator of the presence of the ringing effect.

The ringing effect is the best noticeable near basic edges — sharp edges distant from other edges [8]. An example of basic edges detection is shown in Fig. 4.

We calculate nV and tV in the subset of basic edge area with the distance to the nearest basic edge between d and ad where a controls the size of ringing effect. For unsharp mask deblurring, we use $d = \sigma$ and $a = 2$. Then we calculate the ratio $R_V = nV/tV$. We use this value as the indicator of presence of ringing effect. If the ratio is close to 1, we assume that there is no ringing effect. If this value is significantly greater than 1, we assume that there is ringing effect. To reduce the influence of noise, we prefilter the image by Gauss filter with the radius $\sigma/2$.

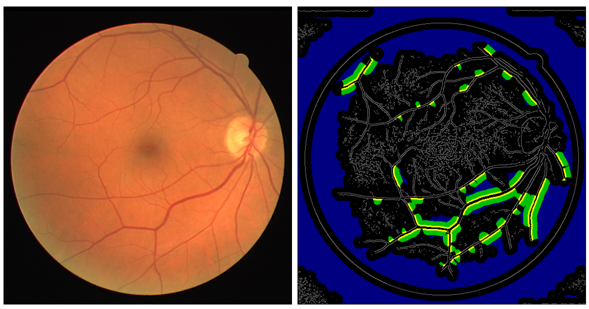


Figure 4: The results of basic edges detection. Left image: the original image. Right image: the result of basic edges detection. Green area is the area where we analyze the ringing effect.

4.2 Unsharp masking

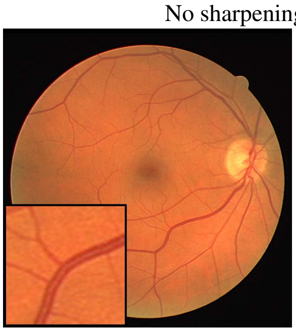
We use unsharp mask filter

$$I_\alpha = I * G_\sigma + \alpha(I \quad I * G_\sigma)$$

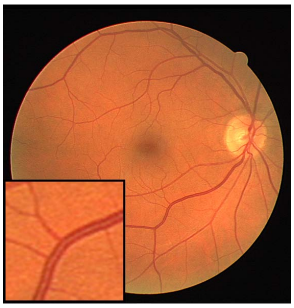
with the value σ equals to estimated edge width.

We use the maximum parameter α, which results in ringing value R_V less than 1.5. Example results are shown in Fig. 5.

No sharpening, $R_V = 1.33$



$\alpha = 1.5, R_V = 1.46$



$\alpha = 2.0, R_V = 1.55$

Figure 5: The results of retinal images sharpening using unsharp mask with ringing control, estimated $\sigma = 1.23$.

5. CONCLUSION

The paper presents a solution to the problem of the detection of blur in retinal images.

The application of the proposed algorithm to the classification of real retinal images showed good results. The algorithm can be used during the acquisition of fundus images and for the preliminary control of input data for retinal image CAD systems.

6. REFERENCES

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