Retinal Blood Vessels Modeling based on Fuzzy Sobel Edge Detection and Morphological Segmentation

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Abstract: In the clinical ophthalmology, the retinal blood vessels processing represent a significant issue regarding the clinical diagnosis. A level of the blood vessels curvature may serve as a reliable indicator of the pathological process. For curvature estimation, a precise model of the retinal blood vessels is necessary. In this paper, we propose a method based on the sensitive edge detector utilizing the fuzzy rules and morphological techniques. The fuzzy edge detector is able to even detect edges while suppressing the high frequency image noise in the non-contrast environment where the image spatial characteristics are weak. Consequent morphological operations serve for adjustment of the segmentation procedure to obtain the smooth model which effectively separates the retinal blood vessels from the retinal background. In the final step, we obtain the binary mathematical model of the retinal blood vessels. We have verified the proposed method against the gold standard images. We have applied the proposed solution on the low-contrast retinal data from the RetCam 3 which is standard for Retinopathy of prematurity. Mostly, when using the RetCam 3, the retinal data has lower contrast therefore, the segmentation procedure is supposed to be robust, even in the noisy environment.

1 RETINAL IMAGE PROCESSING

Retinal image processing is one of the crucial tasks for the ophthalmologic practice. In the retinal area we can recognize several structures being clinically evaluated. The optical disc (optical nerve) is clinically perceived as a central point of the retinal structure. It is also a starting point where the beginning of the retinal blood vessels is observable. Optical disc is utilized as a reference point when the retinal lesions are present to track their dynamical progress over the time because the optical disc geometrical features should be stable over the time.

Regarding a lot of clinical reasons, the retinal blood vessels are perceived as the most important clinical structure for the retinal diagnosis. On the base of the blood vessels curvature (clinically called tortuosity) we can at least estimate whether the retina exhibits signs of the pathological process. Generally it supposed that no retinal blood vessel is narrow, but it is curved in the whole length. Nevertheless, we recognize an extreme curving which can be observed as oscillating waves is some parts of the blood vessels (Fig. 1).

Judging by a current state of the ophthalmological practice, the software tools allowing for automatic modeling and quantification of the retinal blood vessels would significantly contribute to the precise diagnosis. Currently, there is a lack of such software instruments which would generate the retinal mathematical models. It may be caused by several reasons. There are more clinical imaging alternatives for the retinal visualization, especially fundus cameras and retinal probes. These devices give images in different resolution, and other spatial features. Regarding segmentation procedure effectivity, it is supposed the worse image features images have, the worse segmentation accuracy we achieve. We primarily process the data from the retinal probes (RetCam 3) which have a worse image features, therefore the segmentation procedure should have higher sensitivity against the image noise, and simultaneously should be robust even in the low-contrast environment. When

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comparing with the Fundus camera data processing, for the RetCam 3 data the segmentation procedure is supposed to be robust even in the noisy environment. (Tan 2016; Meng 2015; Wankhede 2015)

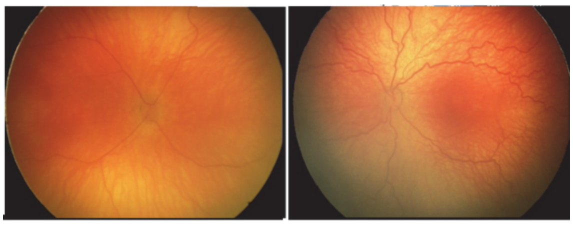

Figure 1: Comparison of a retina with the physiological blood vessels (left) – vessels are direct, and blood vessels having the pathological tortuosity signs in a form of the oscillations (right).

2 RELATED WORK

Generally, there are many segmentation techniques available in the recent literature. It is important to mention that mostly of them are intended to the fundus images processing having a great resolution and other spatial characteristics. We are focused on different type of data (RetCam 3) having significantly different image features even though imaging same retinal area. Therefore, research in this area is important.

Mostly, the segmentation techniques involve stages as the image preprocessing which is focused to improving the contrast between the blood vessels and retinal image background, and own segmentation procedure which detects the blood vessels system. The techniques can be categorized on: (a) Kernel-based techniques (Omasundaram 2017) , (b) retinal vessel tracking (Omasundaram 2017; Mapavi 2015), (c) multiscale techniques (Ben 2018; Wang 2017; Kaur 2016; Huang 2017), (d) model-based (Annunziata 2016; Lazar 2015), (e) adaptive local thresholding (Palomera-Pérez 2010; Yan 2018; Zou 2018) and (f) machine learning (Khan 2018; Mapavi 2015).

Performance of each segmentation approach is evaluated by many metrics. The most common parameters are: True positive rate (TPR), average false positive rate (FPR), average sensitivity (TPR), average specificity (FPR), average accuracy and precision. From the view of the clinical practice, sensitivity and specificity represent the most frequently metrics in the medical research. The higher specificity and sensitivity we achieve, the better results we obtain. (Hatanaka 2018)

The recent literature does not contain a lot of information about the processing the low-contrast retinal images. Since the most of the presented algorithms have been primarily tested on the fundus images having a great resolution we have no information about robustness and sensitivity of the segmentation methods for the low-contrast images. Our paper just brings a significant contribution in this area. (Omasundaram 2017), (Melo, 2018)

3 DESIGN OF SEGMENTATION METHOD

In this section, we introduce a segmentation algorithm for modeling of the retinal blood vessels. In our approach, we want to avoid using the image preprocessing as one of the conventional steps of many approaches. The image preprocessing intended for an improvement of the spatial image characteristic with the goal of contrast boosting between blood vessels and adjacent retinal structures. Unfortunately, each preprocessing algorithm at least partially modifies the pixel's intensity characteristics. Thus, the original clinical information is modified. In our approach, we consciously exclude these procedures. The proposed algorithm is composed from two essential parts including the edge detection and morphological segmentation procedure.

3.1 Sobel Operator Driven by Fuzzy Logic Rules

The Sobel operator belongs to a group of the gradient edge detectors. This method computes partial derivation of the image signal in the horizontal (I_x) and vertical direction (I_y).

Image gradient representing the edges in both directions is given:

$$|I| = \sqrt{I_x^2 + I_y^2} \tag{1}$$

Generally, the main disadvantage of the gradient edge operator is an inclination to the image noise having significantly different intensity spectrum than the image background. This phenomenon is given by the hard thresholding of the horizontal and vertical gradient. Such hard thresholding is not capable classifying the image edge and noise.

We have optimized the Sobel operator by using the fuzzy rules. In the fuzzy model, each gradient direction is characterized by the Gaussian membership function (Fig. 2). The final classification of the edge pixels is driven by the triangular membership function (Fig. 3).

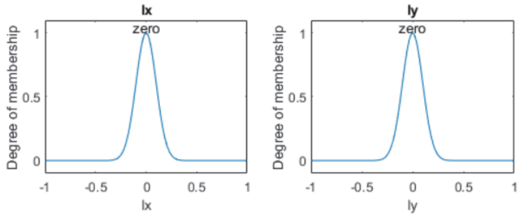

Figure 2: Gaussians membership functions for horizontal gradient (I_x) and vertical gradient (I_y).

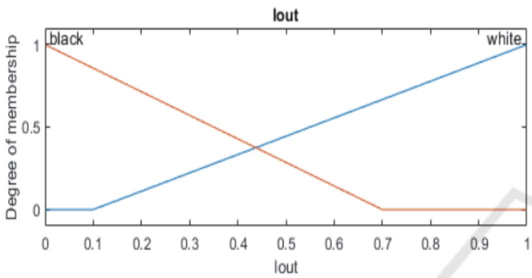

Figure 3: Triangular membership functions representing the edge classification.

On the Fig. 4, we report the fuzzy edge detection on the non-contrast retinal image. Important aspect of the detector is an elimination of the optical disc, and simultaneous boosting of the retinal blood vessels.

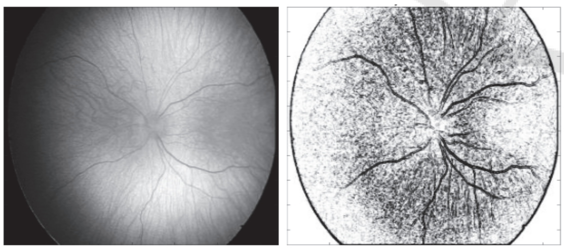

Figure 4: Native retinal image from the RetCam 3 with resolution 640x480 px (left) and result of the Sobel detector driven by the fuzzy rules (right).

3.2 Morphological Image Segmentation

Morphological operations are commonly intended for adjustment of the binary images. In our approach, we are using a sequence of the morphological operations for adjustment of the spatial characteristic of the retinal blood vessels.

Firstly, we apply the morphological dilatation. Dilatation sums of two sets with using of the Minkowski sum. By applying this procedure, we achieve the object expansion in the binary image, and mainly filling the holes. Such procedure compensates a sensitivity of the edge detection when non-homogenous intensity distribution. The dilatation is defined by the following way:

$$X \oplus B = \{p \in \epsilon^2, p = x + b, x \in X, b \in B\} \tag{2}$$

Where X stands for the binary image and B is the structural element, characterizing a shape of the dilatation. Here, we are using the square matrix 3x3.

In the next step, we are using the morphological closing as the dilatation with erosion with the same structural element. By this procedure, we achieve smoothing curves better representing the real blood vessels connecting of tiny holes and also removing of small holes. Closing is similar in some ways to dilation in that it tends to enlarge the boundaries of foreground (bright) regions in an image (and shrink background color holes in such regions), but it is less destructive of the original boundary shape. The morphological operation closing is defined by the following expression:

$$X \circ B = (X \oplus B) \ominus B \tag{3}$$

In the last part of the segmentation model, the binary skeleton is applied. We need to represent the blood vessels by one pixel line thickness in order to mathematically describe curvature of the individual blood vessel's pixels. Output is a typological skeleton precisely describing shape of retinal blood vessel system. This process is given by the following definition:

$$X \oplus B = X(X \otimes B) \tag{4}$$

This iteration process is terminated when two gradual steps achieve same results.

$$X \oplus \{B_i\} = \left(\left(\left(X \oplus B_{(1)}\right) \oplus B_{(2)}\right) \dots \oplus B_{(n)}\right) \tag{5}$$

Individual steps of the morphological operations are depicted on the Fig. 5.

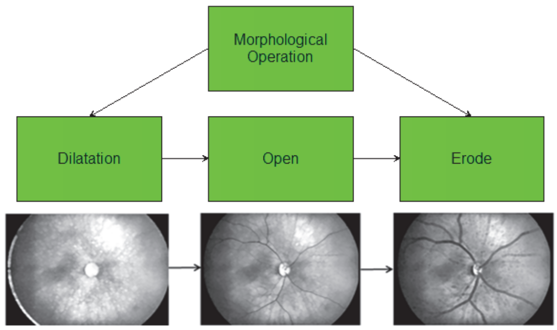

Figure 5: Process of the morphological operations: dilatation, morphological opening and erosion.

4 TESTING AND QUANTITATIVE COMPARISON

We cooperate with the Ophthalmological clinic of the University hospital of Ostrava on the task of the retinal blood vessels processing. We were given a dataset containing 120 patients. These images have been used for the testing of the segmentation algorithm. This database is structuralized into physiological and pathological blood vessels. All the data have been acquired by the retinal probe RetCam 3 having the image resolution 640x480 px.

The input data are stored in the RGB format being represented by three dimensional matrixes. Each such matrix represents one channel of the RGB model. We have experimentally found out that G channel reliably reflects area of the blood vessels while other channels nearly do not bring information about the retinal blood vessels. Therefore, we have done the RGB model decomposition with consequent extraction of the G (green) channel (Fig. 6).

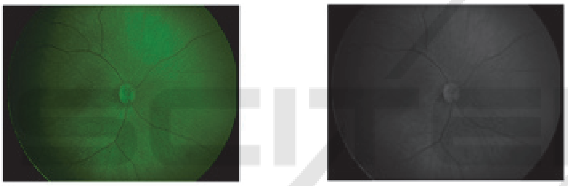

Figure 6: Extraction of green channel (left) and its monochromatic conversion (right).

For the testing, we have divided the retinal records into two groups, depending on their spatial characteristics: contrast and non-contrast data. Since it cannot be ensured that data will be always acquired in a good contrast, we are primarily focused on the non-contrast data to demonstrate segmentation function in a worse environment (Fig. 7). The segmentation results are provided in the binary mathematical model classifying the blood vessels (white) from the image background (black).

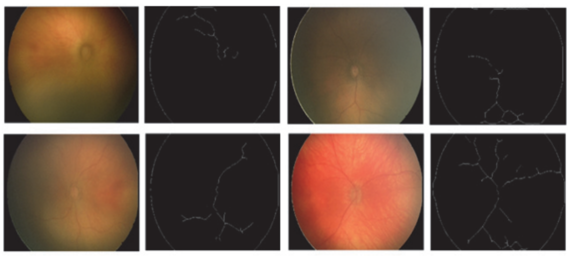

Figure 7: Testing extract of the segmentation procedure for four non-contrast native images.

In the last part of the model building, retinal blood vessel have been skeletonized and fused. Image fusion is an important procedure performing the overlaying of the binary model with the native records (Fig. 8).

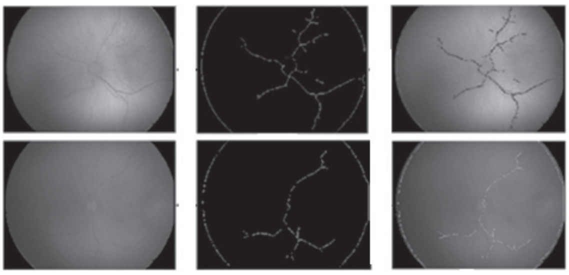

Figure 8: Native retinal data (left column), binary skeleton (middle column) and image fusion (right column).

In the last part of the analysis, we have performed a quantitative comparison to objectification of the segmentation process. We have analyzed the segmentation performance against the ground truth data representing the gold standard. This gold standard has been done by the manual segmentation performed by the clinical ophthalmologic expert. In order to proper testing of the segmentation robustness, we have done a comparison against native image data and same records corrupted by the salt and pepper noise and Gaussian noise.

The segmentation performance has been evaluated based on the four metrics. Rand index (*RI*) measures a level of the similarity between the binary model against the gold standard. Structural similarity (*SSIM*) measures a mutual structure. 2D correlation (*2D corr*) measures a level of the linear dependence. These parameters are normalized in a range [0; 1] where 0 indicates no similarity, contrarily 1 stands for completely identical results. A last parameter is the Mean Squared Error (*MSE*) which measures an average quadratic difference between the segmentation result and the gold standard. Average values of the parameters are reported in the Table 1.

Table 1: Quantitative comparison of the segmentation model against the gold standard.

	Native data	Gaussian noise (0.1, 0.05)	Gaussian noise (0.1, 0.1)	Salt and Pepper (0.05)	Salt and Pepper (0.1)	Salt and Pepper (0.3)
RI	0.91	0.84	0.77	0.83	0.78	0.71
SSIM	0.84	0.65	0.55	0.89	0.66	0.61
2D corr	0.98	0.91	0.88	0.87	0.74	0.65
MSE	33.12	36.22	41.21	35.88	51.12	55.67

Based on the quantitative comparison it is apparent that artificial noise slightly influences the segmentations results. The worst results are reported when adding the Salt and Pepper noise. This noise is strongly manifested as the binary signal which significantly visually impairs the native retinal data.

5 CONCLUSIONS

The retinal image analysis has a significant impact to practice of the clinical ophthalmology. In comparison with the subjective analysis performed by the clinical experts, the automatic segmentation and modeling has unexceptionable benefits. Mainly, it's a relevant reproducibility of the clinical results and features extraction allowing for classification of the pathological blood vessels.

In our work, we have proposed the segmentation model based on a combined approach of the Sobel edge detector driven by the fuzzy rules and the morphological operations. Conventional gradient edge detectors lack of robustness in the noisy environment, and insufficient contrast. It is also case of the processing the retinal records from the retinal probes which typically have lower resolution and worse spatial features. Soft gradient thresholding of the edge detector ensures robustness against image noise. Judging by the experimental results, the fuzzy edge detector is capable of efficiently detect contour of the low-contrast blood vessels contours.

The morphological operations serve for optimization of the edge detector with a target of suppressing image noise and inhomogeneity. Final model of the blood vessels is given by the blood vessels skeleton and image fusion. We have analyzed the blood vessels modeling against the gold standard images. We have analyzed native image records and noisy images (Gaussian and Salt and Pepper noise). Judging by the results, the segmentation model is able to reliably work even in the noisy environment. It is a good prediction for using in the clinical conditions where we cannot ensure stable conditions of measurement.

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