

Segmentation of Vessels in Retinal Images Based on Directional Height Statistics

Istvan Lazar, Andras Hajdu

Abstract— In this paper we present a fast and simple, yet accurate method for the segmentation of retinal blood vessels. Many diseases of the eye result in the distortions of the vessels. The precise location of the major optic veins may be used for the localization of other anatomical parts, such as the macula and the optic disc. Also, many microaneurysm detection methods consider an additional vessel segmentation step. The proposed method realizes the recognition of vessels through considering cross-sections of the image at different orientations. Peaks on the profiles are localized and their heights are measured. This way, a set of height values are assigned to every pixel of the image. Simple statistics are calculated for every pixel, and combined to construct a vessel score map. We apply a simple thresholding procedure and postprocessing step to obtain a binary vessel mask. The method has been tested on the publicly available DRIVE database, and it proved to be competitive with the state-of-the-art.

I. INTRODUCTION

The extraction of the retinal vasculature has a key role in the automated analysis of retinal (fundus) images. Precise vessel segmentation can be used to locate the optic disc (fovea) and the macula by using clinically established formulae. Diabetic retinopathy (DR), the complication of diabetes that affects the eye has several symptoms, including the distortions of the blood vessels in later stages of the disease. Microaneurysms (MAs) are the earliest symptoms of DR, and their detection is essential in an automated screening system. Many MA detection methods rely on a vessel segmentation step, since the crossings and bifurcations of vessels may be locally similar to MAs. In the process of exudate detection, vessel maps may be used to eliminate bright regions that appear close to the vessels, usually on youthful images, and are easily confused with real exudate regions. A sample fundus image is shown in Figure 1.

The main part of the vessel segmentation method presented in this paper is the construction of a vessel score map, where vessel points are assigned a higher score than points of the background and lesions such as MAs and haemorrhages. The method is based on the fact that if we consider the perpendicular cross-section of a vessel, i.e., the

This work was supported in part by the TECH08-2 project DRSCREEN - Developing a computer based image processing system for diabetic retinopathy screening of the National Office for Research and Technology of Hungary (contract no.: OM-00194/2008, OM-00195/2008, OM-00196/2008). This work was also supported by OTKA/NK101680 - Mathematical modeling of clinical observations for improved melanoma detection and by the TÁMOP-4.2.2/B-10/1-2010-0024 project which is cofinanced by the European Union and the European Social Fund.

Istvan Lazar and Andras Hajdu are with the University of Debrecen, Department of Informatics, Hungary (phone: +36 52 512-900/62830 fax: +36 52 512-900/62822, e-mail: lazar.istvan@inf.unideb.hu, hajdu.andras@inf.unideb.hu)

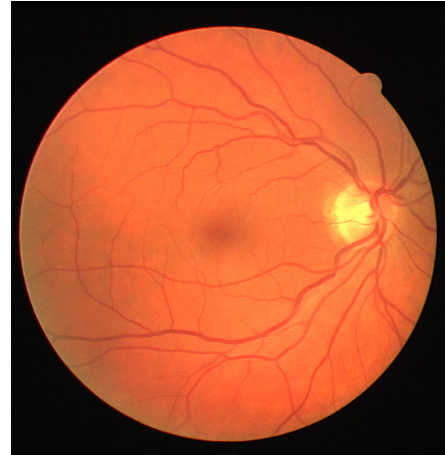


Figure 1. A sample fundus image from the DRIVE database.

intensity values along a discrete line segment, an inverted Gaussian like peak is shown on the resulting intensity profile. If the orientation of the cross-section is such that it fits the vessel, then no such obvious peak is shown. By using a suitable way to measure the height of the peaks on the individual profiles, we find that the variation as the cross-section orientation changes is larger in the height values in the case of vessels than in the case of background points and MAs.

The methods in the literature for MA detection and vessel segmentation show several similarities. One of the first methods proposed for MA detection is based on the calculation of the maximum of morphological openings with linear structuring elements of different orientations. After this, subtracting the resulting image from the original one, the remaining objects are considered to be MA candidates. The same morphological segmentation is applied in [1] for vessel extraction. However, while it is usually true that the vessels have a low curvature, especially in the case of images of a diseased retina, vessels may have a locally high tortuosity. This results that the structuring elements that are suitable to detect other vessels do not fit into these curves, and the usage of smaller structuring elements may give too much false detections.

The evaluation of the image cross-sections is also a widely used approach. Such an early technique is the usage of rotating two-dimensional matched filters [2]. The calculation of the absolute largest eigenvalue of the matrix of second order derivatives of the image intensities is a popular technique, e.g., it is used in methods based on ridge detection [3], and region-growing [4].

The method proposed in this paper overcomes the problem of most morphological methods, i.e., finding a structuring element of suitable size, which is realized by

using a criteria morphology operator. This also eliminates the issue of finding an appropriate filter, which occurs in the matched filter based methods. While in most similar methods the responses for the different directions are used to find the maximal one, which will represent the given pixel, we also calculate the most common statistical descriptors, the mean and the standard deviation, and the combination of these values result in a score map in which the vessels are well distinguished from the background and the diagnostically most important MAs.

II. THE PROPOSED METHOD

The way the image cross-sections are obtained, and the peak heights are measures are the same as in a previous method of ours, which we proposed for MA detection. For a more detailed description of these steps refer to [5].

A. Preprocessing and cross-sectional scanning

As a first step, the green channel of the input color retinal images is extracted, since this is where the vessels and other anatomical parts have the largest contrast. If necessary, the images are resized, so that the diameter of their region of interest (ROI) is equal to 540 pixels. After this, convolution with a Gaussian mask with a deviation of 0.5 is applied to suppress noise. We note that the green channel is inverted, so that the vessels which are otherwise darker than the background, i.e., negative Gaussian shapes in cross-sections become positive ones.

The basis of the scanning is that we consider scan lines, discrete lines with different slopes that pass through the entire image. The lines are shifted in a way that every pixel of the image is accessed from every direction. The directions cover 180° , with equidistant sampling. Empirically we found that 6° steps are adequate, depending on image spatial resolution. The recordings of the intensity values along these scan-lines result in the intensity or cross-section profiles.

B. Pixelwise directional heights

In this step, we assign a vector to every pixel inside the ROI. Each element of this vector represents the height of the pixel at a given direction. The height is calculated from the corresponding cross-section profiles using a peak detection method.

Since the perpendicular cross-section profile of a vessel shows a Gaussian like peak, we apply a method called diameter opening [6] to construct a height profile to each image cross-section profile. The only parameter of this operation is the maximal diameter, which we chose to be 9, based on our experiments. The procedure itself is based on extending the maximum regions on the profile, i.e., locally lowering the threshold level, until the size of the region becomes larger than the predefined maximum diameter parameter. When this criterion is satisfied, the values in the resulting profile are set to the latest threshold level, i.e., the one before the size became too large. The difference of this profile with the original one is called the top-hat, and its values give a good measure of the height of the peaks. An example for this operation is shown in Figure 2.

When this procedure is performed for every cross-section profile of the image, and the height values are recorded for the corresponding pixels, a vector whose elements represent the measured height for a given direction is assigned to every

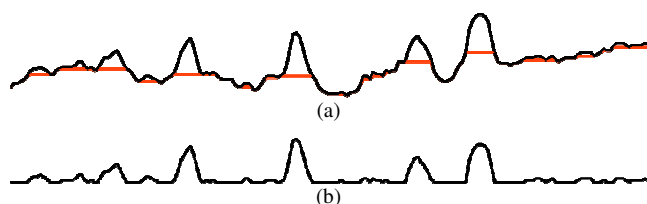


Figure 2. An example cross-section profile segment with the result of the diameter opening (a), and the tophat (b).

pixel. These vectors are called the directional height vector (DHVs). We calculate statistical measures for every pixel using these height vectors, in order to construct the score map in which vessels become well recognizable.

C. Vessel score calculation

We calculate the following statistical measures for each pixel from its directional height values: the mean (μ), the standard deviation (σ), and the maximum (max). The mean of the height values gives a good measure of the local contrast of the pixel, and this way it is a good basis to calculate a score. However, the mean may also be high in the case of MA points. The standard deviation on the other hand is high in the case of vessel points and relatively low for MAs, since these are circular structures and have nearly equal height values for all directions. The most common way in statistics to obtain a normalized measure of the dispersion is to consider the ratio of the standard deviation to mean, i.e., the coefficient of variation ($cv = \sigma / \mu$). Another issue that arises in the case of vessel detection is the regions between exudates. Exudates are bright structures, thus the region between close exudates have a locally high contrast, which results in a high cv value. We found that by considering the ratio of the standard deviation to the maximal value (σ / MAX) we keep the ability to numerically separate MAs from vessel points without over-representing the regions between close exudates. Finally, the score is calculated as the product of this value and the mean. That is,

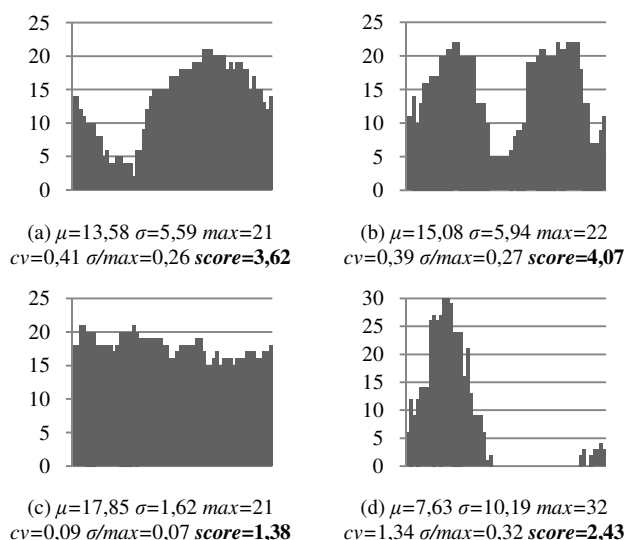


Figure 3. The DHV and statistical measures of a vessel point (a), a vessel crossing (b), an MA (c), and a region between exudates (d). Horizontal axes in the plots represent the direction, and the vertical the height, respectively.

$score = \mu \frac{\sigma}{\sigma_{max}}$. Example DHVs and statistical measures in the case of a vessel point, a vessel crossing, an MA, and a region between exudates are shown in Figure 3.

The vessel score map may be considered as a soft-classification of the pixels, i.e., the higher the score value is, the more probable that the corresponding pixel belongs to a vessel. We do not use the term probability map, since the score values are not normalized. Images of the calculated statistical measures and the final score map for the fundus image in Figure 1 are shown in Figure 4.

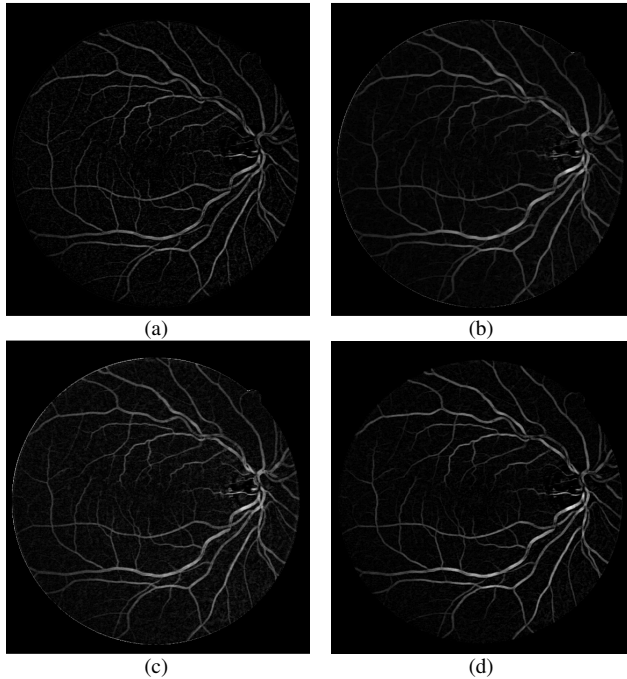


Figure 4. Normalized images of the calculated directional height mean (a), standard deviation (b), and maximum (c), in the case of the retinal image in Figure 1. The final score map (d) is also shown.

D. Score map thresholding and postprocessing.

To obtain a final binary vessel mask, we decided to use a simple thresholding technique called double, or hysteresis thresholding. The basis of this procedure is that two thresholds are considered, a high and a low, and only those pixels are considered to be foreground whose score value is larger than the low threshold (th_{low}) and are connected to a pixel with a score larger than the high threshold (th_{high}) through a path. In our experiments the main threshold was the high, and the low threshold was calculated as

$$th_{low} = 0.5 * th_{high}.$$

Finally a simple post-processing step is considered. We perform a component labeling on the binary vessel masks, and eliminate all connected components whose diameter is less than the diameter parameter used in the peak detection step as the parameter of the diameter opening method, i.e., the vessel diameter. This step filters out small regions that are probably due to noise or are other artifacts.

III. EXPERIMENTAL RESULTS AND DISCUSSION

The performance of a vessel segmentation method which results in a soft classification is usually measured through

the receiver operating characteristic (ROC) curve. A ROC curve plots sensitivity (the proportion of true positive detections) against 1 - specificity (the proportion of true negative detections) as the discrimination threshold of the system varies. The area under the ROC curve (AUC) gives a good measure to compare the performance of such methods under the same circumstances.

The proposed method has been tested on the DRIVE database [3], which consists of 40 retinal images, along with their ROI masks. The images are equally divided into a training and a test set, and the manual segmentation is available for both sets. The spatial resolution of the images is 768 by 584 pixels, and the diameter of the ROI is approximately 540 pixels on each image. Since the proposed method does not require training, we were able to test both on the test and the training set. The AUC of the proposed method was 0.9254 on the DRIVE test images, and 0.9194 on the training images. The ROC curve of the proposed method is shown in Figure 5, and the performance comparison to other methods in Table 1. Six images from the DRIVE test set, the manual gold standard segmentation, and the result of the final segmentation are shown in Figure 6. The specificity and sensitivity at this threshold was 96.7% and 76.5%, respectively.

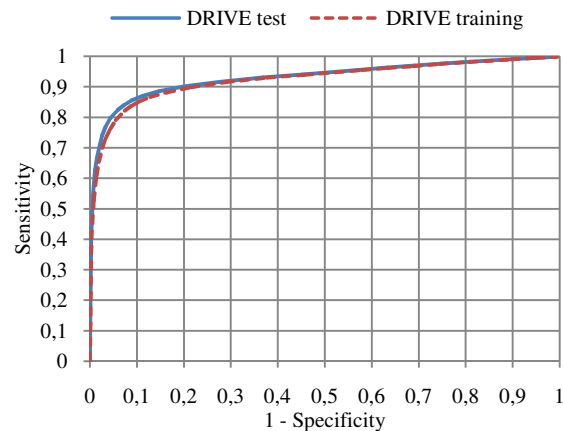


Figure 5. The ROC curve of the proposed method on the DRIVE database.

	AUC
The proposed method	0.9254
Zana et al. [1]	0.8984
Chaudhuri et al. [2]	0.7878
Staal et al. [3]	0.952
Marín et al. [7]	0.9588
Jiang et al. [8]	0.9114

Table 1. Performance of the proposed method compared to others on the test images of the DRIVE database.

As the performance results show, the proposed method is competitive in the field, however, some more sophisticated methods that apply additional classification steps provide better results. Considering that the decision making was based on a simple thresholding, it is likely that this performance can be enhanced by utilizing the constructed score maps in a supervised training based method. One advantage of the proposed method, besides that it depends only on a few parameters, is its processing time. The average

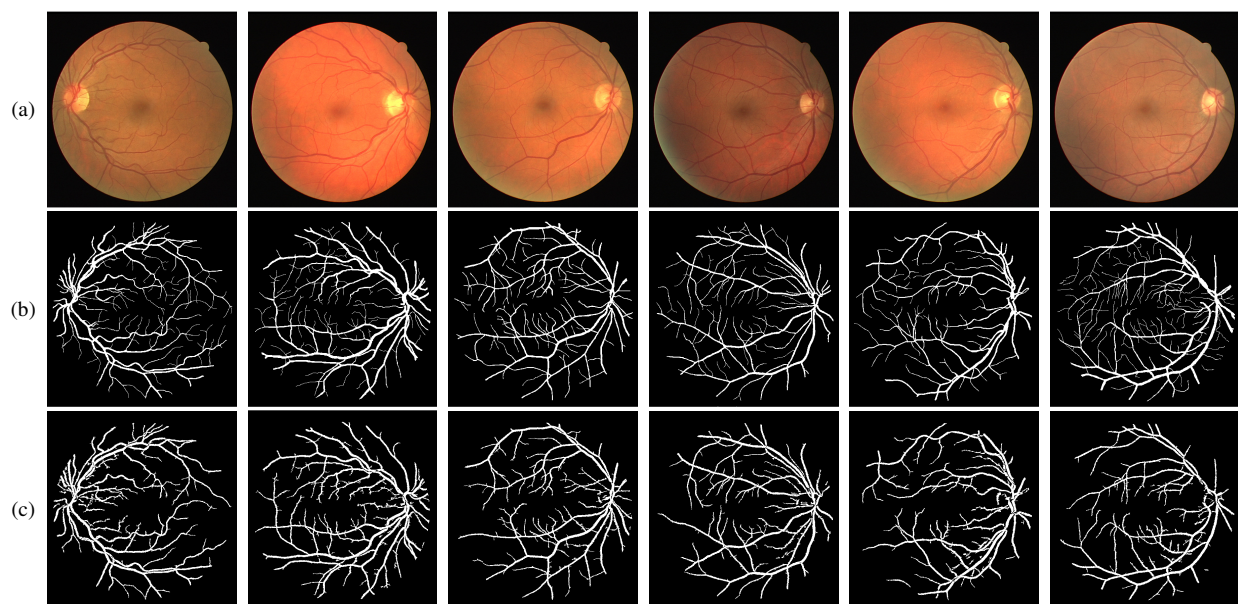


Figure 6. Six images from the DRIVE test set (a) the gold truth segmentation (b), and the results of the proposed method (c) at 96.7% specificity and 76.5% sensitivity.

time of the construction of the score map for an image from the DRIVE database was approximately 5 seconds, using an unoptimized Java implementation running on a PC with an Intel® Core™2 Quad 2.33 GHz Processor and 2 GB RAM.

IV. CONCLUSION AND FUTURE WORK

In this paper, we have presented a method for retinal vessel segmentation. Advantages of the proposed method are accuracy, speed, and that it produces a soft classification of the input image that may be the basis of other more complex detection methods. We have demonstrated the capability of vessel recognition using a simple segmentation and post-processing procedure. The results have shown that the performance is competitive with the state-of-the-art, even using this simple final segmentation.

We have discussed the issues of separating vessel crossings from MAs, and the problem of high contrast regions between exudates, which deteriorates the results of most available methods. It has been shown that the proposed directional height statistics based score has the capability to numerically express the difference between such pixels.

Though the proposed method showed good performance itself, it is likely that using it in combination with other vessel segmentation methods that output a soft classification would provide even better results. These ensemble based approaches have already been proven to outperform individual detectors, and we believe that the score maps as calculated in this paper could be well used in such environment, which is also supported by the short execution time.

REFERENCES

- [1] F. Zana and J. C. Klein, "Segmentation of vessel-like patterns using mathematical morphology and curvature evaluation," *IEEE Trans. Image Proc.*, vol. 10, pp. 1010–1019, July 2001.
- [2] S. Chaudhuri, S. Chatterjee, N. Katz, M. Nelson, and M. Goldbaum, "Detection of blood vessels in retinal images using two-dimensional matched filters," *IEEE Trans. Med. Imag.*, vol. 8, no. 3, pp. 263–269, 1989.
- [3] J. Staal, M. D. Abramoff, M. Niemeijer, M. A. Viergever, and B. van Ginneken, "Ridge based vessel segmentation in color images of the retina," *IEEE Trans. Med. Imaging*, vol. 23, pp. 501–509, April 2004.
- [4] M. E. Martinez-Prez, A. D. Hughes, A. V. Stanton, S. A. Thom, A. A. Bharath, and K. H. Parker, "Retinal blood vessel segmentation by means of scale-space analysis and region growing," *Medical Image Computing and Computer-Assisted Intervention MICCAI99*, 2003, vol. I, pp. 131–137.
- [5] I. Lazar and A. Hajdu, "Microaneurysm detection in retinal images using a rotating cross-section based model," *Biomedical Imaging: From Nano to Macro, 2011 IEEE International Symposium on*, pp. 1405–1409, 2011.
- [6] L. Vincent, "Morphological Area Openings and Closings for Greyscale Images," *Proc. NATO Shape in Picture Workshop*, Springer-Verlag, pp. 197–208, 1992.
- [7] D. Marín, A. Aquino, M.E. Gegundez-Arias, and J.M. Bravo, "A New Supervised Method for Blood Vessel Segmentation in Retinal Images by Using Gray-Level and Moment Invariants-Based Features," *IEEE Trans. Med. Imaging*, vol. 30, pp. 146–158, 2011.
- [8] X. Jiang and D. Mojon, "Adaptive local thresholding by verification-based multithreshold probing with application to vessel detection in retinal images," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 25(1), pp. 131–137, 2003.