International Journal of Scientific & Engineering Research, Volume 6, Issue 9, September-2015 1277
ISSN 2229-5518

# Retinal Vessel Segmentation Using Crest Lines and Morphological Operations

J. C. Rodrigues, F. N. Bezerra
Programa de Pós-Graduação em Ciência da Computação (PPGCC)
Insituto Federal de Educação, Ciência e Tecnologia do Ceará (IFCE)

**Abstract**— Retinal vessel segmentation algorithms play an important role for the detection of numerous diseases, such as diabetic retinopathy, glaucoma and many others. The aim of this paper is report an automated method for segmentation of retinal blood vessels using the crest lines and morphological operations. Initially, each image is preprocessed and the green channel is obtained. Then, we extract the vessels crest lines using a parallel thinning algorithm for grayscale images, simultaneously we perform the sum of top-hats transforms using a linear structuring element in eight directions. Both of these two techniques are performed in the green channel of the input image. The final steps consist in intersecting the two resulting images, smoothing the borders and removing spurious objects remaining. The proposed method is simple and presented robustness and high performance on the DRIVE retinal database.

**Index Terms**— Medical imaging, Mathematical Morphology, Fundus images, Retinal blood vessels, Thinning algorithm, Retinal vessel segmentation.

---

## 1 Introduction

RETINAL blood vessels analysis allows earlier detection of many eye diseases, such as diabetic retinopathy, glaucoma, retinopathy of prematurity, arteriosclerosis and choroidal neovascularization [1]. It allows the patients to treat themselves before the disease can advance and avoid more serious complications, like tunnel vision or even total blindness, in case of diabetic retinopathy, for example [2]. Furthermore, the retinal vascular tree can be used for biometric identification [3]. The blood vessels originate from the center of optic disk, spread over the region of the retina, and are responsible for supplying the blood throughout the entire region.

Various methods are found in the literature and they can be divided in two categories: supervised methods and unsupervised methods [4]. The supervised methods exploit some prior labeling information to decide wheter a pixel belongs to a vessel or not, and their performance is usually better than the supervised ones. Various approaches can be found in this category and use artificial neural networks (ANNs) and back-propagation algorithms, support vector machines (SVMs), principal component analysis (PCA) and Gaussian mixture model (GMM). The unsupervised methods work without prior knowledge of labels. They can utilize many techniques, such as matched filtering, multi-scale techniques, mathematical morphology, fuzzy c-means clustering and vessel tracing/tracking. Our proposed method is categorized in unsupervisioned ones, i.e. do not utilize any information from manual labeling and it comprises five main steps.

This paper is organized as follows: Section 2 briefly reviews the researched works in recent years. Section 3 discuss about the proposed method. Section 4 exhibits the results and comparison with other methods. Finally, the conclusions and future works are presented in Section 5.

## 2 Segmentation Methods

The manual segmentation of retinal blood vessels is a long and hard task, mainly when the databases contain a large number of fundus images, and requires a specialist. Several methods for detecting retinal blood vessels are reported in the literature; so far, retinal blood vessels segmentation has remained an intricate problem. The authors often classify these tecnhiques in supervised and unsupervised methods [4]. This section presents a briefly review, categorization and analysis of retinal blood vessels segmentation techniques.

### 2.1 Supervised Methods

The segmentation of the blood vessels in retinal fundus images has been heavily researched in recent years. A detailed survey of retinal blood vessels segmentation techniques can be found in [5]. The computerized understanding of the ocular fundus dates back to 1982 and the first paper on retinal vessel segmentation appears in 1989 by Chaudhuri et al. [6].

Marin et al. [7] presented a supervised methodology based on neural network for the segmentation of retinal vessels. The methodology uses a 7-D feature vector composed of moment invariant-based and gray level features. A multilayer feed forward neural network is utilized for training and classification. The first layer consists of seven neurons, the three hidden layers consist of fifteen neurons each and output layer consists of one single neuron.

A semi-supervised methodology based on the radial projection is proposed by You et al. [8]. The radial projection is used to detect the low-contrast and narrow vessels. It is developed to locate vessel centerlines. When the vessels are very thin, the centerlines are the thin vessels themselves, because the width of these vessels is small. So the vessel centerlines contain the thin vessels and the centerlines of the major vessels, which are used as guidelines for the subsequent union of vessels. Further, a modified steerable complex wavelet is applied to adaptively enhance the retinal image, and vector feature is constructed to train a classifier, yielding the segmentation of major structures of vessels. The union of the vessel centerlines and the major structures of vessels obtain the final segmentation.

The methodology proposed by Ricci and Perfetti [9] is based on line operators as feature vector and a SVM classifier is responsible for pixel classification. The green channel of an RGB image is extracted and a line detector, which is based on the evaluation of the average gray level along lines of fixed length passing through the target pixel at different orientations, is applied on it. The response is thresholded to obtain the pixel classification.

### 2.2 Unsupervised Methods

Sindhu and Jeeva [10] proposed a method that uses morphological operations and threshold. The green channel is extracted from RGB fundus image, because it provides the maximum contrast between the vessels and the background. The retinal vessel segmentation is done using morphological close operation. The output image is the retinal blood vessel extracted from the background. After applying a threshold, the background is eliminated and the properly segmented binary image of the retinal vessel is obtained.

Aramesh and Faez [11] introduced a new methodology for the detection of retinal blood vessels in fundus images. A preprocessing technique is applied to reduce the noise and then, the image is divided into 16 smaller blocks. Afterward, a threshold is obtained for each block using maximum and minimum points of image histogram. Line detector filters and mathematical morphology were applied to the image and the best results were obtained.

Mendonça and Campilho [12] proposed vessel segmentation algorithm using vessel centerlines followed by the vessel filtering process. Multiscale morphological enhancement technique is used to improve the contrast of the blood vessels. The outputs of four directional differential operators are processed in order to select connected sets of candidate points to be further classified as centerline pixels using vessel derived features. The final segmentation is obtained using an iterative region growing method that integrates the contents of several binary images resulting from vessel width dependent morphological filters.

## 3 THE PROPOSED METHOD

Our method comprises five main steps. Firstly, the green channel of RGB image is extracted, in order to get maximum contrast between vessels and background. Then, we perform simultaneously the sum of top-hats transform with a linear structuring element varying in several angles, in order to get the initial structure of the vessels, and crest lines extraction, to get a skeleton that will provide a preliminary tree made by vessels, which is dilated. Finally, these two images are superimposed and the intersection of them is obtained, resulting in an image wich the borders are smoothed and spurious objects remaining from previous stages are removed.

The Fig. 1 presents a schematic overview of the proposed method.

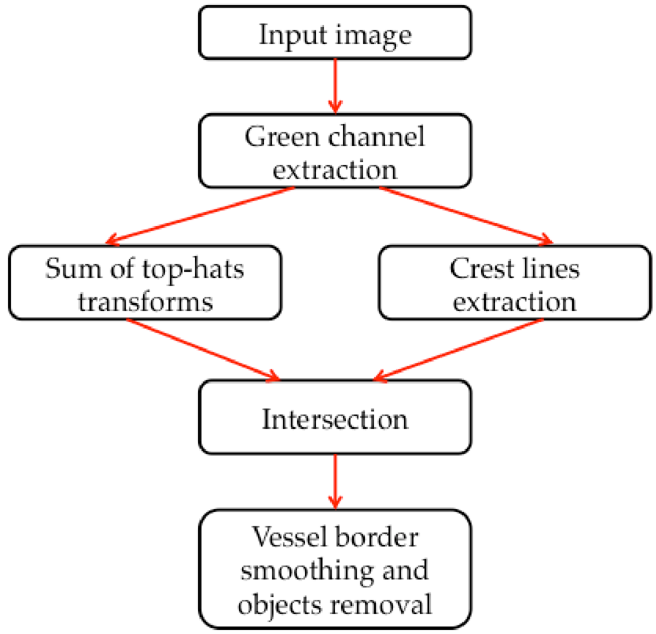


Fig. 1. Schematic overview of proposed method

### 3.1 Conversion to green channel

The preprocessing consists of separating red, green and blue channels from the input fundus image. In order to get maximum contrast between the vessels and background, we use only the green channel [10], [11]. Afterward, the fundus mask for each image is used to remove background noise by multiplying it by the original image and the image complement is obtained. The mask is a binary image with the same fundus image resolution where positive pixels correspond to the foreground area. It is important to separate the fundus from its background so that the further processing is only performed for the fundus and does not affect the background. In a fundus mask, pixels belonging to the fundus are marked with ones and the background of the fundus with zeros [13].

### 3.2 Top-hat transform

In this step, we use the mathematical morphology to initially identify the retinal blood vessels. Using a top-hat transform, given by equation (1), the blood vessels can be extracted. It occurs because the erosion followed by dilation (opening operation) using a linear structuring element $Se^{\theta}$ will remove the vessels in the direction $\theta$. Then, the top-hat transform given by the difference between the original image $\mathbf{Im}$ and the opening operation, denoted by $(\mathrm{Im} \circ Se^{\theta})$,

$$T(\mathrm{Im})_{th}^{\theta} = \mathrm{Im} - (\mathrm{Im} \circ Se^{\theta}), \quad (1)$$

produce the images composed by vessel segments in the direction $\theta$, denoted by $T(\mathbf{Im})_{th}^{\theta}$. We sum the images, obtained by top-hat application, using linear structuring elements with length of 21 pixels and rotated at every 22.5 degrees:

ISSN 2229-5518

$$SumT(\mathrm{Im}) = \sum_{\theta \in A} T(\mathrm{Im})_{th}^{\theta} . (2)$$

The result of this sum is represented by $SumT(\mathrm{Im})$. This technique was inspired from Fraz et al. [14]. The sum of top-hats with differents angles highlight the vessels, including small and tortuous ones, since a vessel is a bright pattern on the dark background, and is piecewise connected and locally linear. After this, the image is binarized using a threshold value of 16. At the end, the binary image will present the approximated blood vessel shapes.

### 3.3 Crest Lines extraction

Several methods that use the vessel skeletons can be found at literature at [5], [11] and [12]. The thinning method apresented at [15] is an alternative to traditional skeletonization following a binarization. It allows reducing the blood vessels to thin lines in gray level space. This is important because retinal images are noisy, what makes finding a global thresholding for binarization a difficult task. In this approach the gray levels of pixels are lowered, keeping those in the brightest crest lines. The mask patterns used to lower the gray level values ensure topological robustness, keeping the connection of the brightest image objects that, in fact, are the blood vessels. After this thinning process, the thin crests are extracted, resulting in a binary skeleton. It is important to note that there is no binarization by thresholding involved. The skeleton pixels are determined based on topological connectivity features in the gray level thinned image. A further contrast criterion is used to eliminate some spurious skeleton branches. At the end, the crest image is dilated with a disc shaped structuring element of radius 3.

### 3.4 Segmentation

With the aim of getting the blood vessels segmentation, the dilated image composed by the crest lines of the vessels and the image obtained by the sum of top-hats are superimposed. The resulting intersection of these two images compounds our preliminary vessel tree. This operation is responsible to removing part of noise, given by (3).

$$Int(\mathrm{Im}) = SumT(\mathrm{Im}) \cap CDilated(\mathrm{Im}), (3)$$

where $CDilated(\mathrm{Im})$ represents the crest image dilated and $Int(\mathrm{Im})$ represents the result of intersection. The top-hat process will provide the objects with linear forms that attend a size criterion. Althought the image is oversegmented because of the binarization by a low threshold value, some noise that appears in this image will not appears in the crest image dilated. Futhermore, the thinning algorithm preserves the topology. Both of these procedures are robust to uneven illumination and the intersection will modelate the real appearance of the vessel tree, eliminanting the noise that appears in a process that does not appears in the other one, and vice versa.

### 3.5 Smoothing and objects removal

The final step of our method consists of smoothing the vessel borders and eliminating spurious artifacts. For smoothing, we use a morphological opening operation with disc shaped structuring element of radius 1. Finally, we eliminate small components using an area opening operation [16]. The Fig. 2 shows the resulting image of each step.

Fig. 2. Green channel of input image

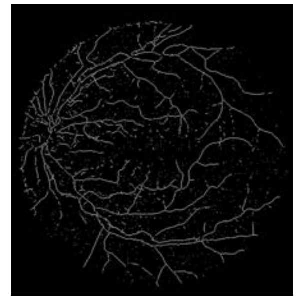

Fig. 3. Vessel skeleton formed by crest lines

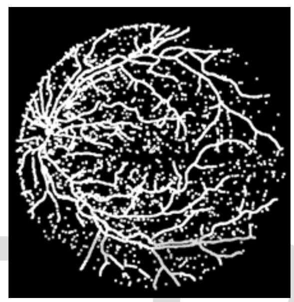

Fig. 4. Crest lines dilated

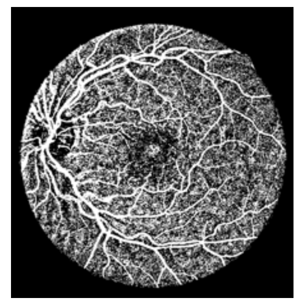

Fig. 5. Binarized sum of top-hats

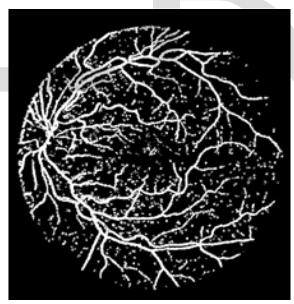

Fig. 6. Result of intersection

Fig. 7. Borders smoothing and objects removal

## 4 Results and Discussions

Our method was evaluated on 40 images from DRIVE [17] database. This database is divided in test set and training set, each one with 20 images. The Table 1 shows the measurements of the supervised techniques found at literature. The Table 2 shows the measurements of the proposed methodology in comparison with some unsupervised methods. The manually segmented images by 2nd. human observer are used as ground truth and their segmentations are tested against the segmentations of 1st. human observer, serving as a human reference for performance comparison truth [5], [11].

TABLE 1
RESULTS FOR THE DRIVE DATABASE FOR SUPERVISED METHODS

| Method | Accuracy | Sensitivity | Specificity |
|---|---|---|---|
| 2nd. human observer | 0.9473 | **0.7761** | 0.9725 |
| Marin et al. [7] | 0.9452 | 0.7067 | **0.9801** |
| You et al. [8] | 0.9434 | 0.7410 | 0.9751 |
| Ricci and Perfetti [9] | **0.9563** | - | - |

TABLE 2
RESULTS FOR THE DRIVE DATABASE FOR UNSUPERVISED METHODS

| Method | Accuracy | Sensitivity | Specificity |
|---|---|---|---|
| 2nd. human observer | 0.9473 | 0.7761 | 0.9725 |
| Sindhu and Jeeva [10] | 0.93 | **0.96** | 0.89 |
| Aramesh and Faez [11] | 0.9480 | 0.7840 | **0.9826** |
| Mendonça and Campilho [12] | 0.9452 | 0.7344 | - |
| Proposed method | **0.9523** | 0.7107 | 0.9757 |

The method proposed in this paper has proved to be a valuable tool for the segmentation of the vessel tree in retinal fundus images. We used three different measurements. They are the accuracy, sensitivity and specificity. The accuracy is defined as the number of true positive vessel pixels plus the number of true positive background pixels divided by the total number of pixels in the FOV. Sensitivity reflects the ability of the algorithm to detect vessels pixels and it also can be referred as true positive rate. Specificity reflects the ability of the algorithm to detect non-vessels pixels and it also can be referred as true negative rate. These measurements are given by:

$$\text{Accuracy} = (TP) / (\text{Total number of pixels}) \quad (4)$$
$$\text{Sensitivity} = (TP) / (TP + FN) \quad (5)$$
$$\text{Specificity } (TN) / (TN + FP), \quad (6)$$

where TP (True Positive) refers the number of vessel pixels detected correctly, TN (True Negative) refers the number of non-vessel pixels detected correctly and FP (False Positive) the number of vessel pixels detected incorrectly.
The proposed method achieves high accuracy on DRIVE database when compared to others methods and provide better results than 2nd. human observer, Marin et. al., You et. al., Sindhu and Jeeva, Aramesh and Faez, and Mendonça and Campilho (0.0050, 0.0071, 0.0089, 0.0223, 0.0043, 0.0071, respectively). Ricci and Perfetti achieved the best accuracy rate, but the sensitivity and specificity measurements are not showed. Sindhu and Jeeva applied their method on a subset of 30 images of the DRIVE database, while Mendonça and Campilho used only 20 images of test set.

## 5 CONCLUSIONS AND FUTURE WORKS

The experimental results presented the effectiveness and robustness of our methodology. An overview of the segmentation results on DRIVE images shows that our method achieves better accuracy than the most of the other methods. Moreover, the ease of adjust the parameters also makes the proposed method viable to any databases. Although Ricci and Perfetti's approach shows higher accuracy, the accuracy significantly worsens when the method is trained and tested on a different database, achieving 0.9266 when trained on STARE and tested on DRIVE and achieving 0.9452 when trained on DRIVE and tested on STARE [9]. A drawback of our approach is the difficulty to segment thin vessels. In future works, we intend to develop new techniques to overcome this fact and improve the method, also we intend to make experiments on databases to better evaluate its effectiveness.

## Acknowledgment

The authors thank the J. J. Staal and colleagues for making DRIVE database publicly available.

## REFERENCES

[1] J. J. Kanski, *Clinical Ophthalmology: A Systematic Approach.* London, U.K.: Butterworth-Heinemann, 1989

[2] B. Srilatha and V. Malleswara rao, "Extraction of Blood Vessels and Exudates from Retinal Images using Image processing Algorithms". *International Journal of Scientific & Engineering Research*, vol. 6, issue 5, pp. 1652-1656, May-2015

[3] C. Mariño, G. Penedo, M. Penas, J. Carreira and F. Gonzalez, "Personal authentication using digital retinal images". *Pattern Analysis and Applications 9*, pp. 21-23, 2006.

[4] Nayan A. Karale and A. S. Deshpande, "Review of Retinal Blood Vessel Segmentation Technique". *International Journal of Engineering Research and Technical Research,* vol. 3, issue 1, pp. 233-236, January-2015

[5] M. M. Fraz, P. Remagnino, A. Hoppe, B. Uyyanonvara, A. R. Rudnicka, C. G. Owen, and S. A. Barman. "Blood vessel segmentation methodologies in retinal images—a survey". C*omputer Methods and Programs in Biomedicine*, 2012.

[6] S. Chaudhauri, S. Chatterjee, N. Katz, M. Nelson, and M. Goldbaum, "Detection of blood vessels in retinal images, using two dimensional matched filters", *IEEE Transactions on Medical Imaging*, vol. 8, no. 3, pp. 263-269, September-1989

[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 Transactions on Medical Imaging*, vol. 30, no. 1, pp. 146-158, January-2011

[8] X. You, Q. Peng, Y. Yuan, Y.M. Cheung, and J. Lei. Segmentation of retinal blood vessels using radial projection and semi-supervised approach. *Pattern Recognition 44*, pp. 2314-2324, 2011. doi: 10.1016/j.cmpb.2011.01.007

[9] E. Ricci and R. Perfetti. "Retinal blood vessel segmentation using line operators and support vector classification", *IEEE Transanctions Medical Imaging,* vol. 26, no. 10, pp. 1357-1365, October-2017. doi: 10.1109/TMI.2007.898521

[10] B. Sindhu and J.B. Jeeva. "Automated Retinal Vessel Segmentation Using Morphological Operation And Threshold", *International Journal of Scientific & Engineering Research*, Volume 4, Issue 5, pp. 1614-1618. May-2013

[11] R. Aramesh and K. Faez. "A new method for segmentation of retinal

blood vessels using morphological image processing technique". *International Journal of Advamced Studies in Computer Science and Engeneering,* vol. 3, issue 1, 2014

[12] A. M. Mendonça and A. Campilho, "Segmentation of Retinal blood vessels by combining the detection of centerlines and morphological reconstruction," *IEEE Transactions on Medical Imaging*, vol. 25, no. 9, pp. 1200–1213, 2006

[13] D. Gadriye, G. Khandale, R. Nawkhare. "System for Diagnosis of Diabetic Retinopathy using Neural Network". *International Journal of Recent Technology and Engineering*, vol. 3, issue 2, pp. 81-86, Blue Eyes Intelligence Engineering & Sciences Publication (2014)

[14] M. M. Fraz, P. Remagnino, A. Hoppe, B. Uyyanonvara, A. R. Rudnicka, C. G. Owen and S. A. Barman. "Retinal Vessel Extraction Using First-Order Derivative of Gaussian and Morphological Processing". *Advances in Visual Computing, Lectures Notes in Computer Science,* vol. 6938, pp. 410-420, Springer Berlin Heidelberg (2011)

[15] M. Couprie, N. Bezerra, and G. Bertrand. "A parallel thinning algorithm for grayscale images." *Discrete Geometry for Computer Imagery.* Springer Berlin Heidelberg, 2013

[16] P. Soille. *Morphological Image Analysis: principles and applications.* Springer Science & Business Media, 2013

[17] J.J. Staal, M.D. Abramoff, M. Niemeijer, M.A. Viergever, B. van Ginneken. "Ridge based vessel segmentation in color images of the retina". *IEEE Transactions on Medical Imaging,* vol. 23, pp. 501-509, 2004