Moura, J. de, Novo, J., Rouco, J., Penedo, M.G., Ortega, M. (2017). Automatic Detection of Blood Vessels in Retinal OCT Images. In: Ferrández Vicente, J., Álvarez-Sánchez, J., de la Paz López, F., Toledo Moreo, J., Adeli, H. (eds) Biomedical Applications Based on Natural and Artificial Computing. IWINAC 2017. Lecture Notes in Computer Science, vol 10338. Springer, Cham. https://doi.org/10.1007/978-3-319-59773-7_1

Link to published version: https://doi.org/10.1007/978-3-319-59773-7_1

Automatic Detection of Blood Vessels in Retinal OCT Images

Joaquim de Moura(✉), Jorge Novo, José Rouco, M.G. Penedo, and Marcos Ortega

Department of Computing, University of A Coruña, A Coruña, Spain
{joaquim.demoura,jnovo,jrouco,mgpenedo,mortega}@udc.es

Abstract. The eye is a non-invasive window where clinicians can observe and study in vivo the retinal vasculature, allowing the early detection of different relevant pathologies. In this paper, we present a complete methodology for the automatic vascular detection in retinal OCT images. To achieve this, we analyse the intensity profiles between representative layers of the retina, layers that are previously segmented. Then, we propose the use of two threshold-based strategies for vessel detection, a fixed and an adaptive approach. Both methods have been tested and validated with 128 OCT images, that include 560 vessels that were labelled by an ophthalmologist. The approaches provided satisfactory results, facilitating the doctors' work and allowing better analysis and treatment of vascular diseases.

Keywords: Computer-aided diagnosis · Retinal imaging · Optical coherence tomography · Vessel detection

1 Introduction

Retinal vascular morphology can represent an important biomarker for diseases like diabetes [1], hypertension [2] or arteriosclerosis [3], among others. In recent years, the introduction and popularization of Optical Coherence Tomography (OCT) as a non-invasive exploratory technique for the analysis of the eye fundus became a reality. This image modality allows the doctors to obtain images of the retinal tissues, including the presence and location of the retinal vascular structure [4]. These images enable the experts to make a clinical evaluation of the retinal vascular tree morphology, permitting the identification and analysis of different types of diseases.

In OCT imaging, the retinal vessels are visualized as structures that block the transmission of light and leave a shadow. In the literature, we can find many different approaches that solve this problem in classical retinographies. As reference, the method in [5] is based on the use of a Hessian multiscale enhancement filter to detect the vessels. [6] uses an approach based on Gaussian and Kalman filters. Other approach include the use of neural networks [7]. A similar aim was proposed in [8] where authors use a deformable contour model

J.M. Ferrández Vicente et al. (Eds.): IWINAC 2017, Part II, LNCS 10338, pp. 3–10, 2017.
DOI: 10.1007/978-3-319-59773-7_1

to identify the vasculature. However, few studies were proposed in OCT images, as the works in [9–11], but using as support the corresponding near-infrared reflectance retinography for the vascular detection process.

We propose a complete methodology for the automatic detection of retinal vessels using, only, the histological sections of the OCT images. The method segments the retinal layers and detects the vessel structures by the analysis of statistical features of the intensity profile obtained between these layers. Two approaches are considered for this purpose: one using a fixed threshold and a second using an adaptive threshold.

2 Methodology

The proposed methodology, represented in Fig. 1, is divided into four main steps: a first step, where the retinal layers are segmented using the input image; a second step, applying a preprocessing to enhance the characteristics of the vascular structures; a third step, where a set of statistical features is extracted; and a fourth step, where the vessels are finally detected. Each one of these steps is going to be discussed next.

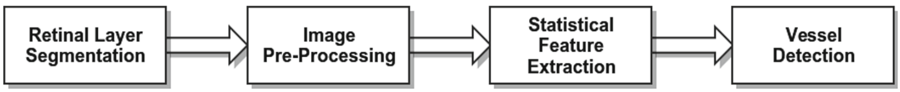

Fig. 1. Main steps of the proposed methodology.

2.1 Retinal Layer Segmentation

The proposed method receives, as input, an OCT image. This image corresponds to a histological section representing the morphology of the retinal layers. Using these images, the retinal layers are identified and segmented, delimiting the region where the vessels are placed. For this purpose, we follow the methodology proposed in [12], where the retinal layers are segmented using an active contour-based technique. In particular, two layers are considered in this work: the Pigment Epithelium Bruch's Complex with the Choroid (RPE/C) and top boundaries of the Ellipsoid (M/E). Between these layers, a higher contrast is perceived in the areas where vascular shadows are present (Fig. 2).

2.2 Image Pre-processing

Speckle noise is a common distortion that is frequently present in OCT images. For that reason we applied a pre-processing step, removing the noise and increasing the contrast of the vascular shadows in the region between the previously detected layers. Firstly, we apply a Gaussian Blur Filter to reduce noise in the image. Then, a top-hat transform is used vertically to increase the contrast of vascular shadows. Figure 3 illustrates the results obtained in this stage.

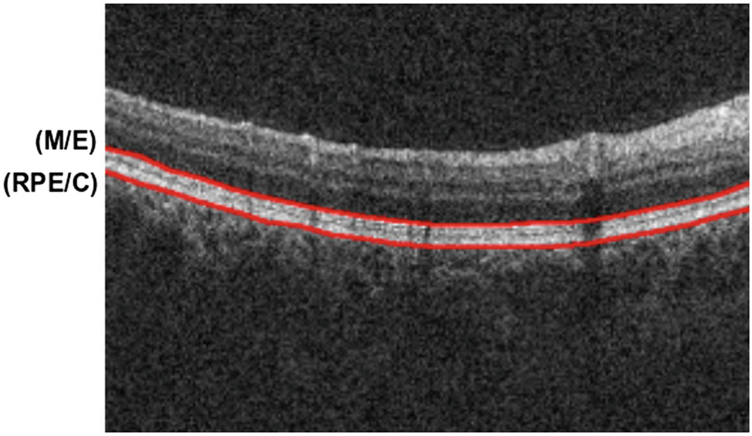

Fig. 2. Input OCT image marked with the retinal layers considered in this work: (RPE/C) and (M/E).

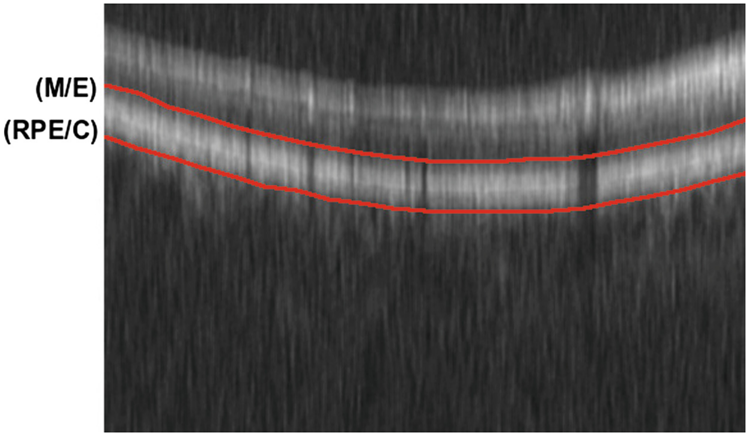

Fig. 3. Pre-processed image after noise removal and contrast enhancement.

2.3 Statistical Feature Extraction

In this phase, we detect the vessel structures by the analysis of the intensity profiles between the layers of the retina. To achieve this, we calculate a signal where each point represents the mean μ_i of the intensity I_j in each column c_i within the region of interest (ROI), as indicated in the Eq. 1, where n represents the number of elements in the column c_i.

$$\mu_i = \frac{\sum_{j=0}^{n} I_j}{n} \tag{1}$$

We calculate these values on the pre-processed image and within the ROI that is delimited by the layers (RPE/C) and (M/E). Figure 4 shows the graphic representing the mean intensity profile from the OCT images. Global mean μ and standard deviation σ are also calculated using all the column means μ_i.

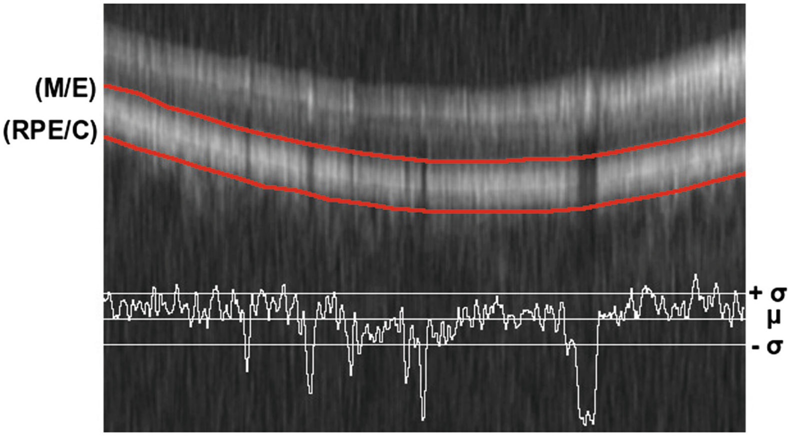

Fig. 4. Graphic representing the statistical features: μ_i, μ and σ.

2.4 Vessel Detection

In this phase, we detect the vascular structures in the slices using the information of the column means μ_i. For that purpose, we use two strategies, fixed and adaptive threshold approaches, that will be detailed below.

Fixed Threshold. In this first approach, we consider that the values obtained for the means μ_i of each column c_i approximate a Normal distribution. Therefore, we can consider that the atypical values (outlayers) of the left tail of the distribution identify the vascular shadows. Consequently, we elaborate a model that uses a fixed threshold th_{fix}, as shown in Eq. 2, where Q_1 represent the 1^{st} quartile and Q_3 and the represent the 3^{rd} quartile. This value allows us to detect the outlayers that represent the vascular structures.

$$th_{fix} = \frac{3}{2}(Q_3 - Q_1) + Q_3 \tag{2}$$

The results of this approach can be observed in Fig. 6(a), (c), where the values that are below the fixed threshold th_{fix} represent the vascular detections in the OCT image.

Adaptive Threshold. The fixed threshold approach presents, as main limitation, that the column means μ_i do not always oscillate around the global mean μ. Instead of that, many times the column means tendency is deviated to bright and dark values due to local intensity alterations. These deformations can make that a global fixed threshold miss-detects vessels (when the tendency moves brighter) or produce many false positives (when the tendency moves darker). This motivated the second approach. Based on the principle that the vessel presence produces a significant intensity depression, this second approach uses the mathematical concepts of local maxima (peak) and minima (valley) to determine the presence of vascular structures in the graphic of means μ_i. Generally, between two consecutive peaks multiples valleys can appear. In this work, we select a unique valley v between two consecutive peaks to represent a unique candidate for a vessel. Then, we obtain the set V_{cand} with all valleys v_i. Finally, we process the set V_{cand} by selecting the candidates that represent the vascular structures. For this, we will use as selection criterion the force of fall f of the valley v_i with respect to its two nearest peaks (see Fig. 5). The results of this approach can be observed in Fig. 6(b), (d).

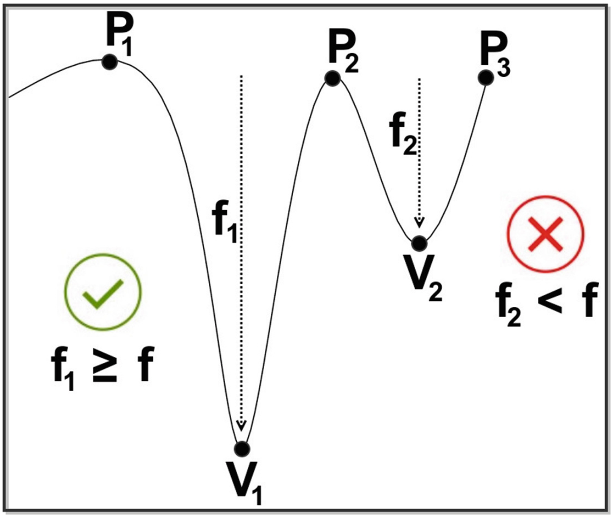

Fig. 5. Adaptive threshold approach, where v_i represents an valley and p_i represents an peak. The valleys with force $f_i \geq f$ are marked as vessels.

3 Experimental Results

The proposed method was tested with 128 OCT histological sections, where 560 vascular structures have been manually labelled by an expert clinician. The images were taken with a confocal scanning laser ophthalmoscope, CIRRUS$^{\mathrm{TM}}$ HD-OCT Zeiss, with Spectral Domain Technology, at a resolution of 490×500 pixels. Regarding the adaptive threshold approach, a force of fall, f, has been empirically established to a value of 50. We evaluated the accuracy of the proposed method using two metrics: precision and recall. Table 1 summarizes the results obtained by each approach. As we can see, the adaptive threshold approach offers a better and more complete performance.

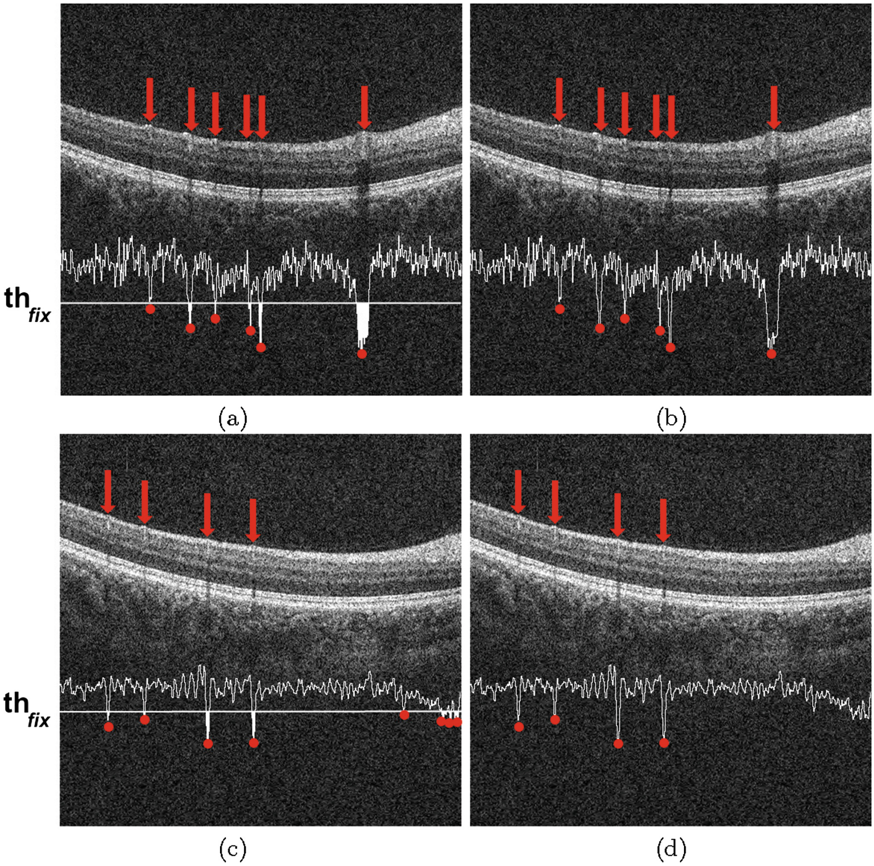

Fig. 6. Results of the approaches. Red arrows, the vascular segments annotated by the experts. Red circles, the results of the different approaches. (a), (c) Fixed threshold approach. (b), (d) Adaptive threshold approach. (Color figure online)

4 Discussion and Conclusions

In this paper, new strategies for the automatic detection of retinal blood vessels in OCT images are presented. The proposed methodology exploits two approaches, a fixed and an adaptive threshold, over the mean intensity of all the columns between the retinal layers (RPE/C) and (M/E), to detect vascular structures. We used OCT images labelled by an expert clinician to evaluate the robustness and accuracy of the proposals, obtaining promising results. Analysing the results of the experiments (see Table 1), we can conclude that the adaptive threshold approach offers a more robust and coherent behaviour than the method with the fixed threshold. This is because the adaptive method is more robust to deviations in the global tendency of the column means, as explained before. An example of this situation is illustrated in Fig. 6(c), (d), where we can observe

Table 1. Precision and recall results in the vessel detection process.

Method	Precision	Recall
Fixed threshold	68.42%	90.37%
Adaptive threshold	96.55%	80.02%

that the mean tendency moves darker at the right columns of the image, making that the fixed threshold approach produce several false positives in this region. However, the adaptive threshold approach, as there is no significant dropping profiles with respect to their surroundings, is capable to overcome this situation. Both proposals offer an automatic vessel identification, facilitating the work of the ophthalmologists in diagnostic processes of many vascular pathologies that are present in the retina facilitating, therefore, therapeutic processes.

Acknowledgments. This work is supported by the Instituto de Salud Carlos III of the Spanish Government and FEDER funds of the European Union through the PI14/02161 and the DTS15/00153 research projects.

References

1. Nguyen, T., Wong, T.Y.: Retinal vascular changes and diabetic retinopathy. Curr. Diab. Rep. **113**(9), 277–283 (2009)
2. Won, T.Y., Mitchell, P.: Retinal vascular changes and diabetic retinopathy. N. Engl. J. Med. **351**, 2310–2317 (2004)
3. Klein, R., Sharrett, A.R., Klein, B.E., Chambless, L.E., Cooper, L.S., Hubbard, L.D., Evans, G.: Are retinal arteriolar abnormalities related to atherosclerosis? The atherosclerosis risk in communities study. Arterioscler. Thromb. Vasc. Biol. **20**, 1644–1650 (2000)
4. Huang, D., Swanson, E., Lin, C., Schuman, J., Stinson, W., Chang, W., Hee, M., Flotte, T., Gregory, K., Puliafito, C.: Optical coherence tomography. Science **254**, 1178 (1991)
5. Elbalaoui, A., Fakir, M., Taifi, K., Merbouha, A.: Automatic detection of blood vessel in retinal images. In: 13th International Conference on Computer Graphics, pp. 324–332 (2016)
6. Chutatape, O., Zheng, L., Krishnan, S.: Retinal blood vessel detection and tracking by matched Gaussian and Kalman filters. In: Engineering in Medicine and Biology Society, pp. 3144–3149 (1998)
7. Nekovei, R., Sun, Y.: Back-propagation network and its configuration for blood vessel detection in angiograms. IEEE Trans. Neural Netw. **6**, 64–72 (1995)
8. Espona, L., Carreira, M., Penedo, M., Ortega, M.: Retinal vessel tree segmentation using a deformable contour model. IEEE Trans. Neural Netw. 1–4 (2008)
9. Niemeijer, M., Garvin, M., Ginneken, B., Sonka, M., Abramoff, M.: Vessel segmentation in 3D spectral OCT scans of the retina. In: Medical Imaging, p. 69141 (2008)
10. Guimarães, P., Rodrigues, P., Lobo, C., Leal, S., Figueira, J., Serranho, P., Bernardes, R.: Ocular fundus reference images from optical coherence tomography. Comput. Med. Imaging Graph. **38**, 381–389 (2014)

11. Moura, J., Novo, J., Ortega, M., Barreira, N., Penedo, M.G.: Vessel tree extraction and depth estimation with OCT images. In: Luaces, O., Gámez, J.A., Barrenechea, E., Troncoso, A., Galar, M., Quintián, H., Corchado, E. (eds.) CAEPIA 2016. LNCS, vol. 9868, pp. 23–33. Springer, Cham (2016). doi:10.1007/978-3-319-44636-3_3
12. Ortega, M., López, A.G., Penedo, M.G., Cardeñoso, P.C.: Implementation and optimization of a method for retinal layer extraction and reconstruction in optical coherence tomography images. Med. Appl. Artif. Intell. **12**, 175–191 (2013)