Pattern Recognition Letters 72 (2016) 72–81

Contents lists available at ScienceDirect

Pattern Recognition Letters

journal homepage: www.elsevier.com/locate/patrec

A fully automatic method for segmenting retinal artery walls in adaptive optics images☆

Nicolas Lermé[a,b,*], Florence Rossant[a], Isabelle Bloch[b], Michel Paques[c], Edouard Koch[d], Jonathan Benesty[c]

[a] Institut Supérieur d'Électronique de Paris, Paris, France
[b] Institut Mines-Télécom, Télécom ParisTech, CNRS LTCI, Paris, France
[c] CIC 503, Centre Hospitalier National d'Ophtalmologie des Quinze-Vingts, Paris, France
[d] Centre Hospitalier de Versailles, Versailles, France

ARTICLE INFO

Article history:
Available online 2 November 2015

Keywords:
Active contour model
Mathematical morphology
Adaptive optics
Retina imaging

ABSTRACT

Adaptive optics imaging of the retina has recently proven its capability to image micrometric structures such as blood vessels, involved in common ocular diseases. In this paper, we propose an approach for automatically segmenting the walls of retinal arteries in the images acquired with this technology. The walls are modeled as four curves approximately parallel to a previously detected reference line located near the vessel center (axial reflection). These curves are first initialized using a tracking procedure and then more accurately positioned using an active contour model embedding a parallelism constraint. We consider both healthy and pathological subjects in the same framework and show that the proposed method applies in all cases. Extensive experiments are also proposed, by analyzing the robustness of the axial reflections detection, the influence of the tracking parameters as well as the performance of the tracking and the active contour model. Noticeably, the results show a good robustness for detecting axial reflections and a moderate influence of the tracking parameters. Compared to a naive initialization, the active contour model coupled with the tracking also offers faster convergence and better accuracy while keeping an overall error smaller or very near the inter-physicians error.

1. Introduction

This paper deals with the segmentation and the quantification of retinal blood vessels in Adaptive Optics (AO) images. This recent and non-invasive technique provides a new insight on retinal vessels and their diseases. In comparison to classical eye fundus images, AO images have a better lateral resolution [1] and allow us to visualize microstructures such as photoreceptors [2], capillaries [3,4] and vascular walls [5]. This technique offers a new diagnosis and prognosis investigation tool to study the diseases affecting the retinal blood vessels of small diameter ($\leq$150 μm), which are major causes of morbidity and mortality, such as Hypertensive Retinopathy (HR) and Diabetic Retinopathy (DR). Early treatment of these diseases is crucial to avoid visual loss. This requires objective and accurate quantification of vessel features, such as wall morphometry, which can be derived from an automated segmentation of AO images. The measure of wall thickness appears to be of great importance for physicians. The automatic segmentation of AO images is the topic of this paper.

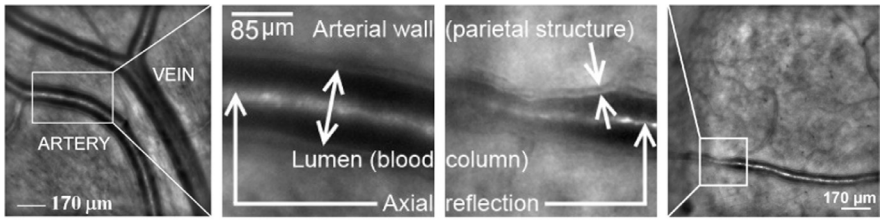
Data and challenges. The images used in this study were acquired with a rtx1 camera [6] with flood illumination at 10 Hz using a 850 nm LED light source with a pixel resolution of 1.33 μm. Flood-illumination systems usually produce noisy images making walls hardly visible. A common solution is to geometrically align a stack of images acquired in a short time (4.2 s, 9.5 frames/s) and average them to increase the signal-to-noise ratio [7]. In these images, blood vessels appear as dark elongated structures with a bright linear axial reflection, over a textured background. These characteristics will be exploited in the proposed method. Parietal structures (arterial walls) appear as gray lines along both sides of the lumen (blood column), with a typical thickness of about 15% of the latter [8] (see Fig. 1).

Segmenting arterial walls in these images is however very challenging for multiple reasons: (i) the background is highly textured, (ii) the lumens are globally dark but with significant intensity variation along them, (iii) the axial reflections may locally show discontinuities or poor contrast, (iv) the outer borders of walls are poorly

☆ This paper has been recommended for acceptance by Anders Heyden.

* Corresponding author at: Institut Supérieur d'Électronique de Paris, Paris, France. Tel.: +33 164694800.
E-mail address: nicolas.lerme@mines-paristech.fr, nicolas.lerme@free.fr (N. Lermé).

http://dx.doi.org/10.1016/j.patrec.2015.10.011
0167-8655/



(a) 924 × 947 pixels (b) 218 × 218 pixels (c) 218 × 218 pixels (d) 900 × 900 pixels

Fig. 1. Examples of images acquired by the rtx1 camera and a detailed view of them for an healthy subject (a,b) and a pathological one (c,d) [9].

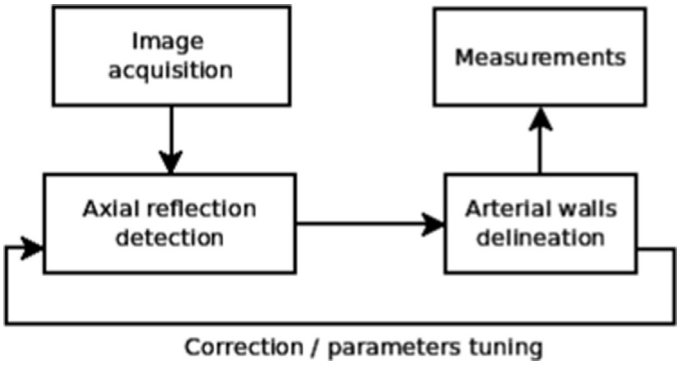


Fig. 2. Flow diagram of the proposed approach.

contrasted, (v) the vessel segments can be locally blurred due to the geometry of the retina, and (vi) morphological deformations can occur in case of pathologies.

Method overview. In this paper, we propose a fully automatic method for segmenting arterial walls in a selected region of interest[1] in the averaged images produced by [7]. Fig. 2 outlines the different steps of the proposed approach. To the best of our knowledge, this is the first method addressing this problem in such images.

To overcome the difficulties previously outlined, we propose a strategy exploiting both geometric, radiometric and topological prior information regarding vessels. More precisely, we model arterial walls as four curves approximately parallel to a common reference line located near the vessel center (axial reflection). Once this line is detected, the curves are simultaneously initialized as close as possible to the borders of walls using a tracking procedure to cope with morphological deformations along vessels (pre-segmentation). Then, these curves are more accurately positioned using a parallel active contour model where each curve evolves independently of the others towards large image gradients under a parallelism constraint [10]. This approach allows us to control the distance of the curves to their reference line, without knowing it accurately as prerequisite. This work has also permitted the physicians to establish relationships between morphometric measurements and clinical parameters [8].

This paper is an extension of our previous publication [11], considering still healthy subjects but also pathological ones in the same framework. Additionally, we provide more details on the method where some steps (such as the axial reflection detection) have been improved. The experiments and the evaluation have also been substantially expanded with the analysis of the robustness for detecting axial reflections, the influence of the tracking parameters as well as the performance of the tracking and the active contour model. This work is complementary to our previous publication [9] where curves are linked to each others to improve the robustness of the model.

[1] In particular, we do not aim at segmenting the whole vascular tree.

The rest of this paper is organized as follows. In Section 2, we detail the steps for detecting axial reflections inside vessels. Next, we introduce in Section 3 the pre-segmentation and the active contour model for segmenting arterial walls. Finally, we evaluate the performance of the method against manual segmentations in Section 4 and discuss perspectives in Section 5.

2. Axial reflection detection

All along this section, we consider 2D images as functions mapping pixels from $\Omega \subset Z^2$ into the interval [0, 1].

2.1. Pre-processing

The original image (see Fig. 3a) is first pre-processed by applying a median filter with a square structuring element of size 5 followed by a morphological closing with a circular structuring element of radius 3, in order to enhance the axial reflection. We denote the resulting image by I_{P_1} (see Fig. 3b).

The source image is also denoised by a non-linear diffusion filter [12] with the contrast parameter and the space regularization parameter respectively set to 0.2 and 2.0. We denote by I_{P_2} the resulting image (see Fig. 3c). This filter allows us smoothing the vessel lumen while preserving the contrast along its edges.

2.2. Detection of bright elongated structures

Two filters are sequentially applied on the pre-processed image I_{P_1} in order to further enhance the bright elongated structures. The first one is a white top-hat with a binary mask whose radius has a fixed size of 1/3 of the axial reflection diameter.[2] We denote by I_{T_1} the top-hat image (see Fig. 3d). The second one is a series of adapted linear filters designed to estimate the local direction of white linear structures. The mean grey-level is calculated at every pixel $(i, j) \in \Omega$ along segments of fixed length but with different orientations, centered on it. The segment length is about 55 pixels ($\simeq 73\ \mu m$) and the orientation step is equal to $\Delta\theta = 5^\circ$ ($N = 36$ filters). Let us denote by $I_{LF}^{(k)}$ the image output by the filter with orientation $k\Delta\theta$, $k \in \{0, \ldots, N-1\}$, and by I_D the image storing the estimated direction:

$$k_{opt}(i,j) = \text{argmax}_k I_{LF}^{(k)}(i,j),$$

$$I_D(i,j) = \begin{cases} k_{opt}(i,j) & \text{if } 0.75 I_{LF}^{(k_{opt}(i,j))(i,j)} > I_{LF}^{\left(\left(k_{opt}(i,j)+\frac{N}{2}\right) \bmod N\right)}(i,j) \\ -1 & \text{otherwise,} \end{cases}$$

where x *mod* y is the remainder of x divided by y. In the latter equation, the threshold 0.75 enables us to distinguish the pixels within linear bright features with well-defined local direction from all the

[2] Despite the variety of images, this parameter appears to be stable in our experiments (including those presented in Section 4).