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Retinal vessel segmentation using multiwavelet kernels and multiscale hierarchical decomposition

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A B S T R A C T

We propose a comprehensive method for segmenting the retinal vasculature in fundus camera images. Our method does not require preprocessing and training and can therefore be used directly on different images sets. We enhance the vessels using matched filtering with multiwavelet kernels (MFMK), separating vessels from clutter and bright, localized features. Noise removal and vessel localization are achieved by a multiscale hierarchical decomposition of the normalized enhanced image. We show a necessary condition to achieve the optimal decomposition and derive the associated value of the scale parameter controlling the amount of details captured. Finally, we obtain a binary map of the vasculature by locally adaptive thresholding, generating a threshold surface based on the vessel edge information extracted by the previous processes. We report experimental results on two public retinal data sets, DRIVE and STARE, demonstrating an excellent performance in comparison with retinal vessel segmentation methods reported recently.

1. Introduction

We propose a novel, general method for segmenting the retinal vasculature in fundus camera images.

Locating the retinal vasculature, assessing its morphological properties and detecting abnormalities play an important role for various purposes. These include, among others, diabetic screening [1] and the detection of lesions associated with diabetes, e.g., diabetic retinopathy [2,3], retinopathy of prematurity [4,5], and cerebrovascular diseases [6]. For such diagnostic purposes, automatic or semi-automatic image analysis holds important promises. First, rich, quantitative sets of measurements providing clinicians with extensive information extracted from images and supporting accurate diagnosis. Second, repeatable measurements which could contribute to reduce the variability of medical diagnosis [7]. Third, identifying and summarizing key information in the large quantities of data present in retinal exams. For instance, fundus cameras acquire nowadays high-resolution images [8].

On the non-diagnostic side, much work has been reported on the discovery of biomarkers associated with the retinal vasculature and a variety of conditions, e.g., stroke [9] and hypertension [10]. Typical candidate biomarkers are related to vessel calibre, branching angles and branching coefficients, vessel tortuosity and, less frequently, the fractal dimension of the vasculature network [2,9]. In cognitive psychology, retinal biomarkers have recently been correlated with cognitive decline [11].

For image analysis, detecting the retinal vasculature means, in essence, generating a binary mask in which pixels are labeled as vessel or background. The target is to capture as much detail (small vessels) as possible, simultaneously avoiding false positives and, ideally, preserving vessel connectivity. However, it should be noted that many clinical investigations do *not* use fine vessels, taking measurements only on major ones in a limited region around the optic disc [12,6,11]. This may of course depend on the current absence of reliable detectors of fine vessels. The relevant literature is discussed in Section 2.

This paper brings the following contributions:

1. We introduce a novel vessel enhancement technique based on the matched filters with multiwavelet kernels (MFMK). We identify kernels separating vessels from clutter edges and bright, localized features (e.g., lesions).
2. For noise attenuation and vessel localization, we apply a multiscale hierarchical decomposition [13,40], which is particularly effective for the normalized enhanced image. This process performs an iterative segmentation at increasing image resolutions, locating smaller and smaller vessels. A single scale

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parameter controls the level of detail included in the vessel map. We show a necessary condition to achieve the optimal decomposition, deriving a rule to identify the optimal number of the hierarchical decomposition.

3. Our method does not require preprocessing and training it can therefore be used directly on images with different characteristics. In addition, it relies on adaptive thresholding so that no numerical parameter is tuned manually to obtain a binary mask.

The image segmentation we obtain from the iterative multiresolution analysis is a gray-scale image. To achieve a binary map, we adopt the spatially adaptive thresholding method [15], which computes a threshold surface over the image. The main idea is to use zero-crossings points as interpolation constraints for the target threshold surface. The interpolating problem is solved by minimizing an energy functional. In this way no threshold value must be tuned by hand.

We report experimental results on two standard retinal data sets, DRIVE and STARE, demonstrating excellent performance in comparison with retinal vessel segmentation methods reported recently.

The remainder of this paper is organized as follows. Section 2 summarizes the state-of-the-art automatic retinal vasculature detection. Section 3 presents our algorithm. Section 4 reports and discusses our experimental results. Section 5 summarizes the paper and offers some conclusive remarks.

2. Related work

Retinal vessel detection systems can be discussed along several dimensions. Here, we consider briefly filters, tracking, supervised learning, and cross-sectional intensity models. This section builds on our discussion of the literature in [16].

Filters. Matched filters for retinal vessel segmentation appear in early works. For instance, in [17] the gray-level profile of the cross-section of a blood vessel is approximated by a Gaussian curve. Vessel segments are searched in all possible directions using a two-dimensional matched filter. Hoover et al. [18] noticed that a single global threshold applied to the filter's output does not yield a satisfactory classification, and propose a vessel segmentation method that uses local and region-based properties at each pixel. Pixels are classified as vessel or non-vessel by thresholding the image generated by a matched filter using a probing technique. Probing allows a pixel to be tested in multiple region configurations before the final classification. Mendonca and Campilho [19] detected the retinal vascular network automatically by first extracting vessel centerlines using differential filters and then applying morphological operators for filling vessel segments. Mathematical morphology and curvature evaluation are used also by Zana and Klein [20] for the detection of vessel-like patterns. Soares et al. [21] adopt Gabor wavelets as they provide directional selectivity and fine tuning to specific frequencies, enabling noise reduction. In our system, we choose a system of wavelets providing the same properties, and additionally accounting for the different cross-sectional intensity profiles

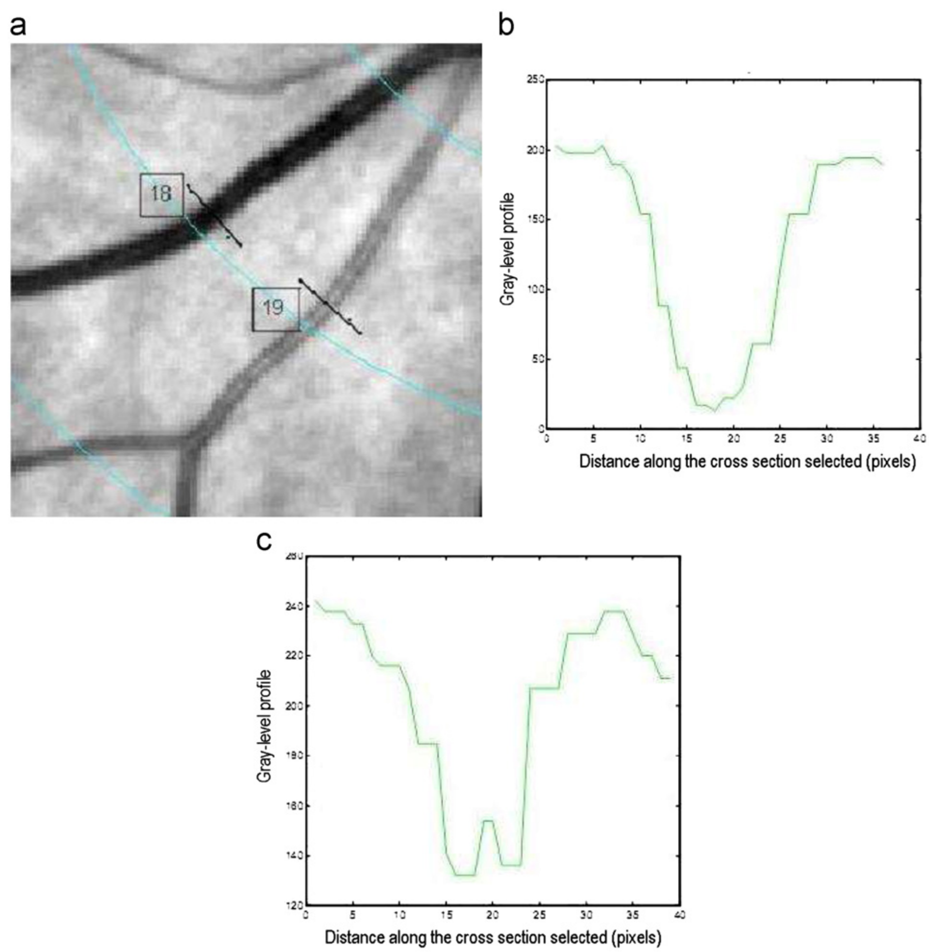

Fig. 1. Example of central reflection. (a) Excerpt from fundus image, showing vein (marked 18) and artery (marked 19). (b) Intensity profile across vein, taken along black line is shown. (c) Same for artery, showing central reflection.