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Retinal vessel segmentation using a multi-scale medialness function

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ABSTRACT

Recently, automated segmentation of retinal vessels in optic fundus images has been an important focus of much research. In this paper, we propose a multi-scale method to segment retinal vessels based on a weighted two-dimensional (2D) medialness function. The results of the medialness function are first multiplied by the eigenvalues of the Hessian matrix. Next, centerlines of vessels are extracted using noise reduction and reconnection procedures. Finally, vessel radii are estimated and retinal vessels are segmented. The proposed method is evaluated and compared with several recent methods using images from the DRIVE and STARE databases.

1. Introduction

Inspection of the optic fundus assists ophthalmologists in diagnosis and evaluation of general diseases, which include diabetes, hypertension, arteriosclerosis, cardiovascular diseases, stroke, and vascular/nonvascular retinal diseases like retinopathy of prematurity [1]. Initial symptoms of such diseases are revealed by morphological features of retinal veins and arteries such as diameter, length, branching angle, and tortuosity [2]. Thus, the measurement and recognition of the exact location of retinal blood vessels has diagnostic relevance for the ophthalmologists. However, because of the complex structure of vessels, manual tracking of retinal vessels is difficult. Furthermore, manual segmentation results vary a lot between inter- and intra-observers. Therefore, automated segmentation of retinal vessels in optic fundus images has been a subject of intensive research during recent years.

According to [3], automatic retinal segmentation methods generally fall into three categories: tracking, kernel-based, and classifier-based methods. In each category, several algorithms are proposed in [4–13]. In [4], a tracking method is presented, which is initialized by a generalized morphological order filter to determine approximate vessel centerlines, and uses a "Ribbon of Twins" (ROT) active contour model for segmenting and measuring retinal vessels. A novel multi-scale line tracking procedure is proposed by Vlachos and Dermatas [5]. In this method, an initial vessel network is obtained by map quantization of a multi-scale confidence matrix. The result is filtered by a median filter to restore disconnected vessels and remove noisy structures. Finally, a post-processing step is applied to correct misclassified areas.

Several classifier-based methods are introduced in [6–10]. Soares et al. [6] suggest that feature vectors can be extracted from a two-dimensional Gabor wavelet transform and the pixel's intensity. Also, a Gaussian mixture model classifier can be used for classification. A method based on multi-scale feature extraction is introduced in [7] to automatically segment the retinal blood vessels from the background. The method uses the first and second derivatives of the image intensities in a multiple pass region growing algorithm. In another approach proposed by Ricci and Perfetti [8], two line operators are used to extract the feature vectors whilst a Linear Support Vector Machine (LSVM) is used as a classifier. In [9], a feature-based AdaBoost classifier (FABC) is applied for classifying 41-dimensional feature vectors constructed by encoding information from the local intensity structure, spatial properties, and geometry at multiple scales. Improved results are obtained in [10] where a 7-dimensional vector composed of gray-level and moment invariants-based features is calculated, and a neural network (NN) scheme is used for pixel classification.

The methods introduced by Mendonça and Campilho in [11], Yan Lam and Yan in [12], and Zhang et al. in [13] can be considered as kernel-based methods. In [11], Mendonça et al. segment retinal vessels using a combination of differential filters, that is difference of offset Gaussians filters (DoOG filters), to find vessel centerlines, along with an iterative region-growing method that integrates the contents of several binary images to fill the vessel segments. Yan Lam and Yan [12] suggest a scheme based on the Laplacian operator to segment blood vessels in the pathological retinal images. For this purpose, the centerlines of vessels are first detected using a normalized gradient vector field. Due to noise in pathological regions, noisy objects should be

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eliminated from the image background. Therefore, at the next step, they are pruned based on centerline information. Zhang et al. [13] use an extension of the Matched Filter (MF) approach, named the MF-FDOG, which is a combination of the original matched filter and the first-order derivative of Gaussian (FDOG). To detect retinal vessels, the retinal image's response to the matched filter is thresholded using an adaptive threshold obtained from the image's response to the FDOG.

In this paper, we use a multi-scale technique to segment the vessels and extend our earlier conference results [14]. We introduce a medialness function (previously used to detect tubular structures in the 3D space [15]) for the 2D space and weight it with a function designed to reduce the effect of asymmetric structures. To improve the results for the vessel-like structures, the resulting image is multiplied by the smoothed eigenvalues of the Hessian matrix at every pixel of the image. Next, to eliminate noise from the image background while retaining vascular structures, we apply a noise reduction step that uses a formula based on area and elongation. A reconnection step is then applied for connecting truncated vessels based on structural characteristics of the retinal vessels. Finally, the exact boundaries of vessels are estimated using eigenvalues and the result of the medialness function. To evaluate the performance of our algorithm, we tested it on the DRIVE and STARE databases and compared our results with those reported in recent articles.

The rest of the paper is organized as follows. In Section 2, we detail the methods used for vessel segmentation. Experimental results are presented and compared with other methods in Section 3. Finally, we discuss our results and conclude in Section 4.

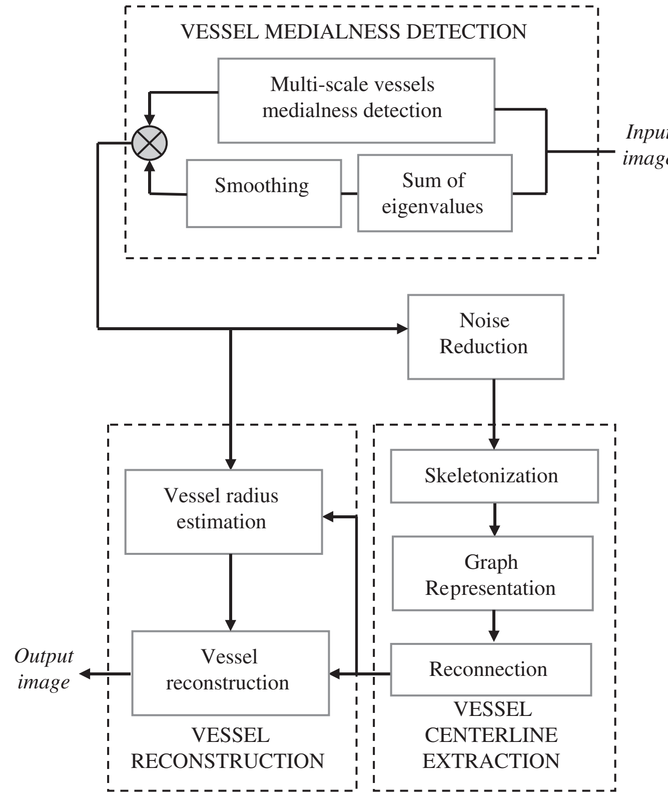

Fig. 2. A block diagram of the proposed method of vessel segmentation.

2. Proposed methods

Since the green channel of color retinal images provides the highest contrast between vessels and background in retinal image analysis [16], the green channel of these images is used as input to our vessel segmentation algorithm (Fig. 1). Fig. 2 shows a block diagram of our proposed scheme. The method has three major phases: vessel medialness detection; vessel centerline extraction; and vessel reconstruction. Each phase is subdivided into several steps as follows:

Vessel medialness detection: (1) *Multi-scale vessel medialness detection* is applied at several scales using a weighted medialness function to extract the medial line of vessels. (2) *The sum of eigenvalues* is used to strengthen the vessel medial response, which has been attenuated due to an adaptive threshold in a previous step.

Fig. 1. Green channel of image 16 from DRIVE dataset.

Vessel centerline extraction: (1) *Skeletonization* is applied to extract the skeleton of vessels. (2) *Graph representation* is obtained by labeling the pixels as an end-, curve-, or branch-point and finding the edge of the graph. (3) *Reconnection* is connecting disconnections in vessels tree based on the vessel's structural characteristics.

Vessel reconstruction: (1) *Vessel radius estimation* based on the information obtained from each step of phase 1, using eigenvalues and the result of the medialness function. (2) *Vessel reconstruction* using the estimated radius and the vessels' graph.

In addition, a noise-reduction step is used to suppress background noise and reduce the complexity of the other steps, especially the reconnection step. The details of these steps are explained in the next subsections.

2.1. The vessel medialness detection filter

Because of robustness of the medialness function in extracting tubular structures, this function has been previously applied for segmenting these structures in 3D space. The initial medialness function is defined in [17] as follows:

$$m_0(y,\sigma) = \int_{R^n} b(x,\sigma)\delta(y-x-r\hat{\mathbf{n}}(x,\sigma))d^n x \quad (1)$$

where δ is the delta function. For each point x in the boundaryness space, the initial contribution $b(x,\sigma) = |\mathbf{B}(x,\sigma)|$ is made at $y = x + r\hat{\mathbf{n}}(x,\sigma)$ where $\hat{\mathbf{n}}$ is a unit vector determined by $\hat{\mathbf{n}}(x,\sigma) = \mathbf{B}(x,\sigma)/|\mathbf{B}(x,\sigma)|$, r is a variable that changes according to scale σ as $r = k\sigma$ (where k is constant), $B(x,\sigma)$ is the boundaryness function and is equivalent to the image gradient at the point x in the image convolved with a Gaussian with standard deviation σ. The relationship of the medialness function to boundaryness is illustrated in Fig. 3.