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Retinal vessels segmentation based on level set and region growing

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ABSTRACT

Retinal vessels play an important role in the diagnostic procedure of retinopathy. Accurate segmentation of retinal vessels is crucial for pathological analysis. In this paper, we propose a new retinal vessel segmentation method based on level set and region growing. Firstly, a retinal vessel image is preprocessed by the contrast-limited adaptive histogram equalization and a 2D Gabor wavelet to enhance the vessels. Then, an anisotropic diffusion filter is used to smooth the image and preserve vessel boundaries. Finally, the region growing method and a region-based active contour model with level set implementation are applied to extract retinal vessels, and their results are combined to achieve the final segmentation. Comparisons are conducted on the publicly available DRIVE and STARE databases using three different measurements. Experimental results show that the proposed method reaches an average accuracy of 94.77% on the DRIVE database and 95.09% on the STARE database.

1. Introduction

The structure of retinal vessels provides important information for eye care specialists. Changes in retinal vessels may indicate diseases such as arteriosclerosis, hypertension, diabetes, cardiovascular disease, and stroke [1–5]. For example, Diabetic retinopathy is one of the main causes of blindness, and its first manifestation is tiny capillary dilations as microaneurysms [5]. Periodic screening with early recognition of retinal vessel changes can prevent major vision loss in most cases [5]. Therefore, accurate retinal vessel segmentation is a prerequisite for the subsequent retinal diseases diagnosis. However, there are several challenges in retinal vessels segmentation: firstly, besides the retinal vessels, some other structures (e. g. the optic disc, fovea) also exist in the retinal image, which makes automatic vessels segmentation difficult. Secondly, the retinal vessels have a wide range of widths, and thin vessels have a lower contrast compared with the background, which makes object detection harder.

Various methods have been proposed to segment retinal vessels automatically. Previous studies in [6–8] adopted *matched filters* (MF) to enhance retinal vessels, and then used adaptive thresholding to extract retinal vessel pixels. Considering that the cross-section of vessels can be approximately modeled as a Gaussian function, Chaudhuri et al. [6] used a set of Gaussian kernels to convolve with the retinal images, and then detected the maximum response along different orientations. An improvement of MF was presented by Hoover et al. [7], who exploited region-based threshold probes and local vessel properties to classify pixels as vessels or non-vessels. Recently, Zhang et al. [8] proposed a MF-FDOG method composed of a zero-mean Gaussian function and the *first-order derivative of Gaussian* (FDOG). In this method, the retinal vessels were extracted simply by thresholding the image's response to the MF, but the thresholds must be judged by the image's response to the FDOG.

Vessel tracking is another class of methods for retinal vessel segmentation. In these methods a group of seed points were selected, and the retinal vessels were tracked by following vessel centerlines based on local information. Grisan et al. [9] located the vessel seed points on a grid and tracked the vessel pixels using a fuzzy C-means classifier. This method can extract local vessel geometry accurately. For details of tracking strategies, refer to [10–12].

Mathematical morphology approach was used in [2,13,14]. In [2], the authors used the detected retinal vessel centerlines to grow vessel structure obtained from the morphological operations. Zana et al. [13] combined morphological filters with cross-curvature evaluation to segment vessel-like patterns, and tested their method on retinal photographs. Rossant et al. [14] proposed an algorithm based on morphological and topological analysis to extract the vascular tree from eye fundus images. Other methods such as the topology adaptive snakes in [15], the ribbon of twins in [16], have also been introduced for vessel segmentation.

Supervised learning methods for retinal pixel classification were presented in [17–20]. Niemeijer et al. [17] extracted a simple feature vector for each pixel, and used the *K-nearest neighbor* (KNN) classifier to estimate the probability of each pixel belonging to a vessel. Staal et al. [18] presented a supervised learning method based on the detection of image ridges, which were used as line elements. In this method, a set of features were generated by assigning each pixel to the nearest line element to form image

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patches, and then a feature selection scheme was applied to classify the pixels. Soares et al. [19] proposed a method based on the pixel's feature vectors, which were composed of the pixel's intensity and 2D Gabor wavelet transformation responses, and then a Bayesian classifier was used to obtain the final retinal vessels. Ricci et al. [20] applied two orthogonal line detectors along with the target pixels to construct a feature vector for vessel pixel classification by a *support vector machine* (SVM).

Although these methods have shown their good performance for retinal vessel segmentation, there are some limitations needed to be improved, including the false extraction for thin vessels, which is caused by low contrast between the retinal vessels and the background, and the connectivity loss for the retinal vessel tree, whose topological structure is relatively complex. In this paper, we propose a new retinal vessel segmentation method based on level set and region growing. Firstly, *contrast-limited adaptive histogram equalization* (CLAHE) is used to compensate for the effects of a non-uniform lighting, followed by a 2D Gabor wavelet to enhance the contrast of the retinal image. Then the retinal vessel segmentation is conducted in two parallel ways. The first way is using the anisotropic diffusion filter to smooth the retinal image and extract wide retinal vessels by the active contour model. The second way is detecting the thin vessels by region growing directly. In the end, both the segmentation results are combined to obtain the final extracted retinal vessels. The flowchart of the proposed method is shown in Fig. 1.

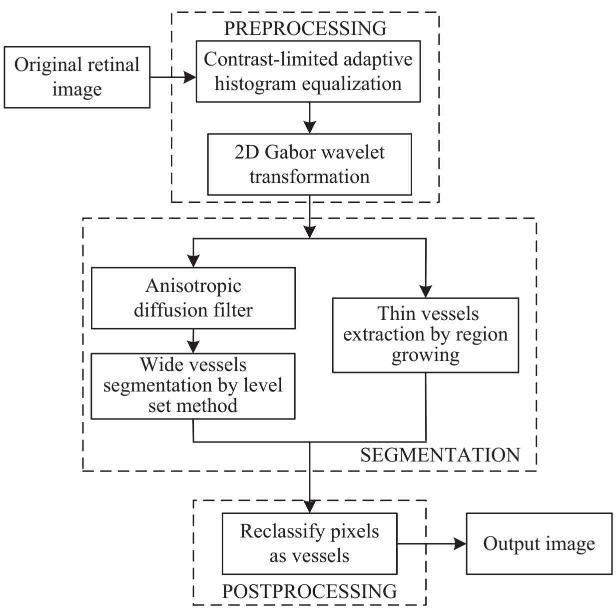

Fig. 1. Flowchart of the proposed method.

The remaining of this paper is organized as follows. The preprocessing of color retinal images is described in Section 2. Then retinal vessel segmentation method is presented in Section 3. In Section 4, experimental evaluation and comparisons are conducted. Finally, conclusions are drawn in Section 5.

2. Preprocessing

2.1. Contrast-limited adaptive histogram equalization

As red, green and blue lights entering the eye have been absorbed differently by the lens pigments, the green channel (Fig. 2(c)) of the RGB color retinal image (Fig. 2(a)) presents a higher contrast between the vessels and the background, which means that blood-containing elements (such as vessels) in the retinal layer can be best represented. The red channel (Fig. 2(b)) is the brightest color channel but with low contrast, and the blue channel (Fig. 2(d)) suffers from poor dynamic range [21]. Therefore, we work on the green channel of retinal image in this paper.

Generally, histogram equalization techniques can achieve contrast enhancement by stretching the gray level values of a low-contrast image. In this paper, we apply the CLAHE operator to obtain a local contrast enhanced retinal image. The CLAHE chooses the clipping level of the histogram flexibility by computing the local histogram mapping function, which can reduce the undesired noise amplification of the retinal image [22].

2.2. Two-dimensional Gabor wavelet transformation

The Gabor wavelet transformation is useful for image enhancement due to its capabilities of selecting directions and tuning to specific frequencies. We adopt the 2D Gabor wavelet transformation to enhance the contrast of retinal images in the frequency domain. A continuous wavelet transformation, $T_\psi(\mathbf{b},\theta,a)$, is determined by the scalar product of image I with the transformed wavelet $\psi_{\mathbf{b},\theta,a}$ as

$$T_\psi(\mathbf{b},\theta,a) = C_\psi^{-1/2}\langle \psi_{\mathbf{b},\theta,a} | I\rangle = C_\psi^{-1/2} a^{-1} \int \psi^*(a^{-1} r_{-\theta}(\mathbf{x}-\mathbf{b})) I(\mathbf{x})\, d^2\mathbf{x} \quad (1)$$

where ψ denotes the analyzing wavelet, ψ^* is the complex conjugate of ψ, and C_ψ is the normalizing constant. The parameters a, $\mathbf{b}$, and θ denote the dilation scale, displacement vector and rotation angle, respectively. r_θ is the rotation operator acting on $\mathbf{x}=(x,y)$, which is defined as

$$r_\theta(\mathbf{x}) = (x \cos\theta - y \sin\theta,\quad x \sin\theta + y \cos\theta),\quad 0 \le \theta \le 2\pi \quad (2)$$

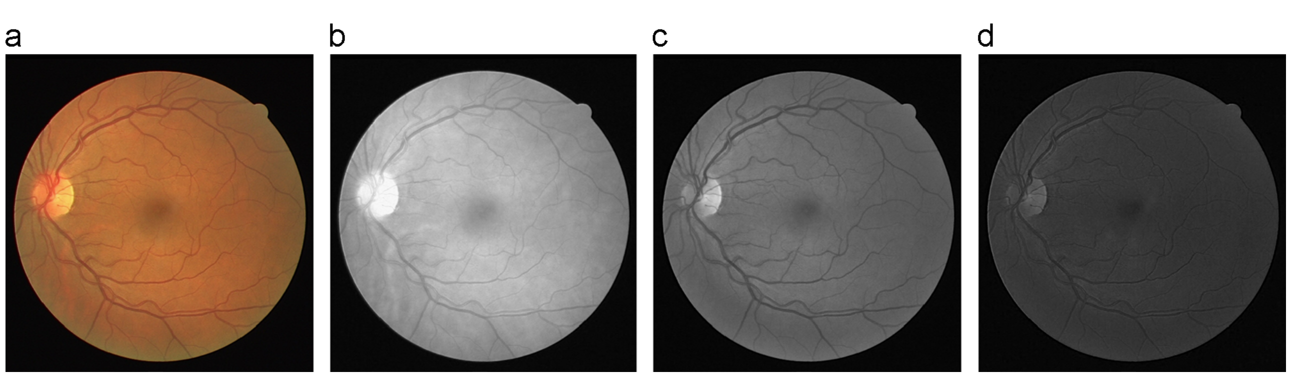

Fig. 2. Retinal vessel image and its red, green and blue channels (from left to right). (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)