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Nonlinear Retinal Image Enhancement for Vessel Detection

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ABSTRACT

Retinal vessel detection is an essential part of the computer-aided diagnosis of eye diseases. Due to non-perfect imaging environment, retinal images often appear with intensity variations and artificial noises. This work proposes a two-step nonlinear retinal image enhancement to compensate for those imperfections of retinal images. The first step reduces intensity fluctuations of the image and the second step attenuates impulsive noise while preserving retinal vessels. Classification on the feature vector extracted from the enhanced retinal images is performed by using a linear SVM classifier. Experimental results demonstrate that the proposed method of two-step nonlinear image enhancement visibly improves the vessel detection performance, achieving better accuracy than that without enhancement process on the both DRIVE and STARE databases.

Keywords: Retinal vessel detection, retinal image, nonlinear image enhancement.

1. INTRODUCTION

Automatic detection of retinal vessel plays a central role in the computer-aided analysis of retinopathy [1-4], such as arteriosclerosis and diabetic retinopathy. Many methods have been proposed for the segmentation of retinal vessel, like matched filter based methods [5-7], tracking methods [8] and supervised learning methods [9-10]. Improvements of matched filter-based methods were reported, e.g. the matched filter with the derivative of Gaussian [5], multi-scale production [6], and multi-wavelet kernels [7]. Vessel tracking methods start with the selection of the seed pixels. Supervised learning methods classify each image pixel into vessels or background based on a training model. Various image features [11-12], can be used to represent the retinal image pixels. Features used in [10] were derived from the steerable complex wavelet. Neural networks [13] can be applied for classification. For example, Vega *et al.* [14] reported a lattice neural network with dendritic processing (LNNDP) to classify moment-invariant based feature vector.

Although methods mentioned above provide good retinal vessel segmentation, automatic retinal vessel detection is still a challenging step due to the variations in vessel diameter and the poor quality of retinal images caused by the non-perfect imaging environment. In order to highlight the retinal vessel structure, some enhancement techniques have been reported, like vessel enhancements via multi-dictionary and sparse coding (VE-MAC) [15] and enhanced genetic algorithm (EGA) [16]. However, EGA distorts the structure of retinal vessel tree and loses some retinal vessel details, while VE-MAC ignores the intensity variations of retinal images and amplifies noises in the background. In this paper, we propose a two-step nonlinear retinal vessel enhancement method to tackle the problems generating from imperfect imaging environment, e.g. artificial noises, low contrast, as well as intensity fluctuations of images. The first step is background normalization by median filter, aiming to reduce intensity variations in retinal images and improve contrast between vessel and background. The second step is impulsive noises removal by truncation filter, aiming to preserve images details (e.g. retinal vessel edges) and reduce impulsive noises (e.g. isolated blob regions). Detection of retinal vessel is implemented by using a linear SVM classifier to classify each candidate pixel denoted by features extracted from the enhanced retinal image. Experiments results verify that the proposed method can enhance the segmentation accuracy effectively on the both DRIVE and STARE databases.

2. PROPOSED METHOD

2.1 Retinal Image Enhancement

Colour retinal images usually appear with noises which result from non-ideal imaging environment during images acquisition process. In order to reduce these imperfections and generate more suitable images for feature extraction, one

effective way is to use image filtering technologies that not only smooth artificial noises, but also avoid retinal vessel boundary distortion. This paper proposes a two-step retinal image enhancement method that comprises the following parts: 1) Background normalization by median filter; 2) Impulsive noises removal by truncation filter. Details of each step are described in follows.

1) Background normalization by median filter:

Different retinal images often contain intensity fluctuations caused by non-uniform illumination that can lead to a considerable bias to retinal vessel segmentation. With the purpose of reducing the effect of illumination variations, an iterative truncated arithmetic mean filter [17] or a simple median filter can be applied to estimate the background intensity distribution. For a pixel (x, y) with grey value $I(x, y)$, the median filter is defined as:

$$B(x, y) = \text{medain } I(x - m, y - n), \quad \text{for } -W \leq m, n \leq W, \quad (1)$$

where parameter W determines the window size of the median filter. Here, we set parameter W to be 15, which is based on the statistic estimate of the widths of retinal vessels, i.e. approximately the width of the widest retinal vessel. Obviously, retinal vessels whose width smaller than the half size of the median filter, W , are removed, as shown in Fig. 1(b). To recover vessel from the smoothed retinal image, a division between input image $I(x, y)$ and background intensity image $B(x, y)$ is conducted:

$$\bar{I}(x, y) = I(x, y) / B(x, y). \quad (2)$$

Equation (2) also enhances the given retinal image I by stretching its contrast between retinal vessels and background. Fig. 1(c) shows the result of background normalization, where background intensity variations are decreased and contrast between retinal vessel and background is enhanced.

Figure 1. Background normalization by median filter. (a) Green channel of a sample colour retinal image. (b) Background intensity image of (a) computed by (1). (c) Background normalized result of (a) computed by (1) and (2).

2) Impulsive noises removal by truncation filter:

Smoothing unwanted noise while preserving object details is an important part of image processing. Before automatic detection of retinal vessel, impulsive noises and some non-vessel structures should be removed firstly. Traditional enhancement methods usually distort the structure of retinal vessel tree and remove thin vessel curves. In this paper, we use a recursive truncation filter [18] that preserves image details up to the single pixel width line to attenuate the isolated impulsive noise while preserving retinal vessel details. Given u_k and v_k who denote the maximal and minimal grey values of the pixels in the surrounding band S_k respectively, i.e.

$$u_k = \max_{x, y} (\bar{I}(x, y) | (x, y) \in S_k), \quad (3)$$

$$v_k = \min_{x, y} (\bar{I}(x, y) | (x, y) \in S_k), \quad (4)$$

the recursive truncation filter can be expressed as [18]:

$$\bar{I}(x, y) \leftarrow \begin{cases} u_{\min}, & \text{iff } \bar{I}(x, y) > u_{\min} \\ v_{\max}, & \text{iff } \bar{I}(x, y) < v_{\min} \\ \bar{I}(x, y), & \text{otherwise} \end{cases} \quad (5)$$

where $u_{\min} = \min_k(u_k \mid k = 1, 2, \dots, N)$ and $v_{\max} = \max_k(v_k \mid k = 1, 2, \dots, N)$. Pixels in the N surrounding bands together with central pixel $\bar{I}(x, y)$ construct the truncation filter window. Filter process is implemented by truncating the grey values of pixels enclosed by a surrounding band to the maximal or minimal grey value of the surrounding band. Hence, impulsive noises inside the surround bands are reduced while image details are preserved if they stretch to or beyond the surrounding band. In this paper, parameter N is set to be 13×13 , which removes impulsive noise whose size are not larger than N . Fig. 2(c) shows the result of truncation filter, where isolated impulsive noise (in red circles) are removed from the background and edges of thin retinal vessel tree are preserved.

Figure 2. Impulsive noises removal by truncation filter. (a) A fragment of green channel. (b) Result of the background normalization by median filter. (c) Result of truncation filter.

2.2 Vessel detection

The feature vector represents quantifiable measures that can be used for classifier to recognize each pixel as retinal vessel or background. In this paper, the feature vector for classification is computed from the enhanced retinal images on the basis of the shape information of retinal vessels. Considering that the cross-section of retinal vessels can be modeled by a Gaussian shaped curve [6], we design a set of 2D Gaussian-based filters to match retinal vessels which stretch along different orientations. For a specific orientation (e.g. vertically along y), Gaussian-based filter is expressed as:

$$K(x, y) = -\frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{x^2}{2\sigma^2}\right), \quad \text{for } |x| \leq t \cdot \sigma, \quad |y| \leq L/2, \quad (6)$$

where L is the length of the neighborhood and σ is the variance of the Gaussian shaped curve. To match retinal vessels at different orientations, this Gaussian kernel should be rotated correspondingly. The maximum response of convolution between retinal image and Gaussian kernel (fixed L and σ) along different orientations are extracted as one dimension of the feature vector. In this paper, we construct a 16D feature vector by Gaussian filter at four scales ($\sigma = [1, 2, 3, 4]$) and four length ($L = [5, 7, 9, 11]$), so that different widths and lengths of retinal vessels can be detected. A linear SVM classifier is utilized to classify each candidate pixel as retinal vessel or background.

3. EXPERIMENTS

The proposed method is tested on two publicly available databases: DRIVE [12] and STARE [19]. DRIVE database consists of 40 color retinal images, captured by Canon CR5 nonmydriatic 3CCD cameras. Those images are divided into training and test sets, each of which includes 20 retinal images (565×584 pixels per image). Images in training and test sets are manually segmented by three observers trained by an ophthalmologist. STARE database contains 20 color retinal images (700 × 605 per image), captured by a TopCon TRV-50 fundus camera. Images in STARE database are segmented by two experts. Fig. 3 shows a sample image and its segmentation result of the method with and without retinal vessel enhancement. It can be clearly observed that the method with the proposed retinal vessel enhancement

performs better than the method without retinal vessel enhancement. Impulsive noise and some non-vessel structures (regions in yellow circle) are removed by the proposed image enhancement method.

Figure 3. Segmentation results. (a) A sample original image. (b) Ground truth. (c) Segmentation without image enhancement. (d) Segmentation with the proposed image enhancement.

Fig. 4 shows the segmentation accuracy of each testing image in DRIVE and STARE databases. The segmentation accuracy is the ratio of the correctly classified vessel and non-vessel pixels to the total number of pixels. It shows that the proposed image enhancement method consistently improves the vessel detection accuracy for every testing image on the both database. For some testing images, the vessel detection accuracy is significantly improved, for example, from 90.5% (without enhancement) to 93.6% (with enhancement).

Figure 4. Segmentation accuracy for each image. (a) on DRIVE database. (b) on STARE database.

Table 1 lists the overall segmentation performance comparison of different methods in terms of the segmentation accuracy on DRIVE and STARE databases. Compared with those retinal segmentation methods, the proposed method performs better on retinal vessel classification, i.e. providing overall accuracy of 94.31% and 95.12% on DRIVE and STARE databases, respectively, higher than the methods used for comparison.

Table 1. Results comparison between different segmentation methods.

Methods	Accuracy	
	DRIVE	STARE
Fraz <i>et al.</i> [4]	94.30%	94.42%
Zhang <i>et al.</i> [6]	93.82%	94.84%
Li <i>et al.</i> [7]	93.43%	94.07%
Niemeijer <i>et al.</i> [11]	94.16%	-
Vega <i>et al.</i> [14]	94.12%	94.83%
Method without enhancement	93.78%	94.45%
Method with enhancement	94.31%	95.12%

4. CONCLUSION

This paper proposes a two-step nonlinear method for retinal vessel enhancement based on background normalization by median filter and impulsive noises removal by truncation filter. The first step is an effective way to reduce intensity fluctuations of retinal images, thus attenuating the effect of the non-uniform illumination. The second step of the proposed retinal vessel enhancement method performs well for impulsive noise (like some artificial blob regions) removal while preserving retinal vessel details (especially some thin vessel curves). Experimental results verify that the vessel detection method with the proposed retinal vessel enhancement segments retinal vessels more accurately on the both DRIVE and STARE databases than the segmentation method without image enhancement. The demonstrated effectiveness of the proposed retinal vessel enhancement, together with the simplicity and fast implementation of retinal vessel classification, make the proposed method a feasible tool for the computer-aided retinal images analysis.

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