Blood Vessel Enhancement and Segmentation for Screening of Diabetic Retinopathy

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Abstrak

Diabetic retinopathy adalah penyakit mata yang disebabkan kenaikan kadar insulin dalam arah dan penyakit ini merupakan salah satu penyebab utama kebutaan di negara industri. Penyakit ini merupakan penyakit progresif dan membutuhkan deteksi dan penanganan awal. Pola vaskular dari retina manusia membantu opthamologis dalam skrining otomatis dan diagnosa diabetic retinopathy. Pada makalah ini, disajikan sebuah metode untuk segmentasi dan peningkatan pola vaskular. Sistem terotomisasi yang menggunakan wavelets disajikan untuk menaikkan pola vaskular dan kemudian diterapkan pada probing ambang sesepenggal dan pengambangan adaptif untuk kegunaan lokalisasi pembuluh darah dan segmentasi berkaitan. Metode dievaluasi dan diuji menggunakan database retina yang tersedia umum dan lebih jauh metode yang diusulkan dibandingkan dengan teknik yang sudah ada.

***Kata kunci**, diabetic retinopathy, blood vessels, : probing ambang, wavelets*

Abstract

Diabetic retinopathy is an eye disease caused by the increase of insulin in blood and it is one of the main cuases of blindness in idusterlized countries. It is a progressive disease and needs an early detection and treatment. Vascular pattern of human retina helps the ophthalmologists in automated screening and diagnosis of diabetic retinopathy. In this article, we present a method for vascular pattern ehnacement and segmentation. We present an automated system which uses wavelets to enhance the vascular pattern and then it applies a piecewise threshold probing and adaptive thresholding for vessel localization and segmentation respectively. The method is evaluated and tested using publicly available retinal databases and we further compare our method with already proposed techniques.

***Keywords**: Diabetic retinopathy, blood vessels, wavelets, threshold probong.*

1. Introduction

Diabetic retinopathy is the result of microvascular changes in retina [1]. In some patient with diabetic retinopathy, blood vessels may swell and leak fluid [2]. In other, new abnormal blood vessels grow on the surface of the retina [3] that is why blood vessel segmentation is an important part of automated diabetic retinopathy screening system. A tool which can be used to assist in the diagnosis of diabetic retinopathy should automatically detect all retinal image features such as optic disk, fovea and blood vessel [3], [5], [6] and all abnormalities in retinal image such as microaneurysms [2], [7], [8], hard exudates and soft exudates [9], [10], hemorrhages, and edema [2]. Illumination equalization is needed to enhance the image quality as the acquired color retinal images are normally of different qualities.

Retinal vascular pattern facilitates the physicians for the purposes of diagnosing eye diseases, patient screening, and clinical study [4]. Inspection of blood vessels provides the information regarding pathological changes caused by ocular diseases including diabetes, hypertension, stroke and arteriosclerosis [11]. Patients with diabetes are more likely to have eye diseases [35]. The hand mapping of retinal vasculature is a time consuming process that entails training and skill. Automated segmentation provides consistency and reduces the time required by a physician or a skilled technician for manual labeling [1].

Retinal vessel segmentation may be used for automatic generation of retinal maps for the treatment of age-related macular degeneration [12], extraction of characteristic points of the retinal vasculature for temporal or multimodal image registration [13], retinal image mosaic

synthesis, identification of the optic disc position [5], and localization of the fovea [14]. The challenges faced in automated vessel detection include wide range of vessel widths, low contrast with respect with background and appearance of variety of structures in the image including the optic disc, the retinal boundary and other pathologies [15].

Different approaches for automated vessel segmentation have been proposed. Methods based on vessel tracking to obtain the vasculature structure, along with vessel diameters and branching points have been proposed by [16]-[21]. Tracking consists of following vessel center lines guided by local information. In [27], ridge detection was used to form line elements and partition the image into patches belonging to each line element. Pixel features were then generated based on this representation. Many features were presented and a feature selection scheme is used to select those which provide the best class separability. Papers [22]-[25] used deformable models for vessels segmentation. Chuadhuri et al. [26] proposed a technique using matched filters to emphasize blood vessels. An improved region based threshold probing of the matched filter response technique was used by Hoover et al. [28].

In this paper, we present an automated system for blood vessel enhancement and segmentation using digital retinal images. We use Gabor wavelet to enhance vascular pattern and piecewise probing and adaptive thresholding to localize and segment the vascular pattern respectively. We check the validity and accuracy of proposed method using three publicly available fundus image databases and also compare the results with already proposed techniques.

The paper is organized in four sections. In section 2, a schematic overview of our implementation methodology is illustrated. Section 2 also presents the step by step techniques required for automated vessel enhancement and segmentation. Experimental results of tests on different retinal images and their analysis are given in Section 3 followed by conclusion in Section 4.

2. System Overview

Automatically locating the accurate vascular pattern is very important in implementation of vessel screening system. Our proposed method segments the blood vessels from retinal images with great accuracy as compared to previous techniques. In proposed method, the monochromatic RGB retinal image is taken as an input and 2-D Gabor wavelet is used to enhance the vascular pattern especially the thin and less visible vessels are enhanced [28]. Locating of blood vessels is done using piecewise threshold probing and vessel segmentation binary mask is created by thresholding the enhanced retinal image. The blood vessels are marked by the masking procedure which assigns one to all those pixels which belong to blood vessels and zero to non vessels pixels. Figure 1 shows the complete flow diagram for designing an automated vessel screening system using proposed blood vessel enhancement and segmentation technique.
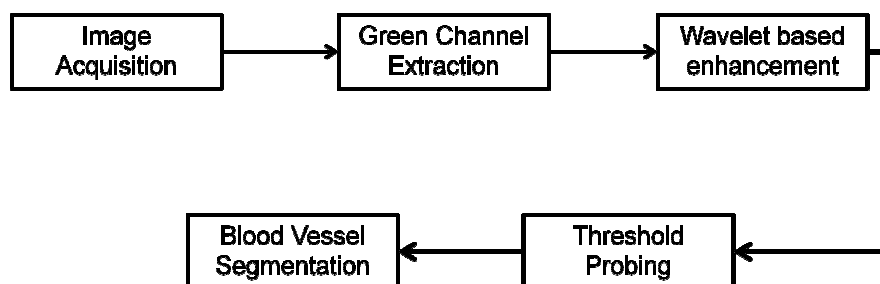
Figure 1. Flow diagram of proposed system

2.1. Blood Vessel Enhancement using Gabor Wavelets

In order to find the vascular abnormalities, it is very important to extract vascular pattern accurately. The vessels varies in terms of structure, shape and size so it is dificult to extract them. Thin blood vessels or capillaries are less visible than the normal blood vessels and

require enhancement before extraction. Mostly matched filters (MFs) [6] are used for blood vessel enhancement but the drawback is that MFs not only enhance blood vessels edges but also enhance bright lesions. On the other hand, Gabor wavelets can be tuned for specific frequencies and orientations which is useful for both thick and thin vessels. Gabor wavelet has its application in almost every field and they are mostly used to enhance the pattern at some specific orientation [36]. 2-D Gabor wavelet is used due to its directional selectiveness capability of detecting oriented features and fine tuning to specific frequencies [29], [30]. The Gabor wavelet is defined in equation 1

$$\psi_G(x) = \exp(jk_0 x)\exp(-\frac{1}{2}|Ax|^2) \tag{1}$$

where k0 is a vector that defines the frequency of the complex exponential and A = diag[ε−1/2, 1], ε>1 is a 2×2 diagonal matrix that defines the elongation of filter in any desired direction.

The algorithm for the gabor wavelet based enhancement is as below:

Step 1: Set $T_\psi(b,\theta,a) = C_\psi^{-1/2} a \int \exp(jkb)\hat{\psi}^*(ar_{-\theta}k)\hat{f}(k)d^2k \tag{2}$

where f Є L^2 is an image represented as a square integral (i.e., finite energy) function defined over R^2 and ψ Є L^2 be the analyzing wavelet. C_ψ, ψ, b, θ and a denote the normalizing constant, analyzing wavelet, the displacement vector, the rotation angle, and the dilation parameter respectively.

Step 2:   for each θ=10°,20°,30°,40°,……,170°

Calculate $M_\psi(b,a) = \max_\theta |T_\psi(b,\theta,a)| \tag{3}$

end_for

Table 1. Parameter values for gabor wavelet

Parameter	Value
Dilation	3
Elongation	4
Rotational angle	10^0
K_0	[0,3]

2.2. Blood Vessel Segmentation using Threshold Probing

We present a method for blood vessel localization that compliments local vessel attributes with region-based attributes of the network structure. A piece of the blood vessel network is hypothesized by probing an area of the wavelet based enhanced image, iteratively decreasing the threshold. Pixels from probes that are not classified as vessel are recycled for further probing. The strength of this approach is that individual pixel labels are decided using local and region-based properties and afterwards adaptive thresholding has been applied. The basic operation of our algorithm is to probe regions in a wavelet based enhanced image. During each probe, a set of criteria is tested to determine the threshold of the probe, and ultimately to decide if the area being probed (termed a piece) is blood vessel. A queue of points is initialized, each of which will be used for a probe. Upon a probe's completion, if the piece is determined to be vessel, then the endpoints of the piece are added to the queue. In this way, different probes (and thus different thresholds) can be applied throughout the image.

This gives us the enhanced vascular pattern for the retinal image. Histogram for the enhanced retinal image is calculated. Maximum values occur for the grayish background while the vessel corresponds to values a slight greater than the background values as they are of bright color. An adaptive thresholding technique is used that selects this point which separates the vessels from the rest of image. Vessel segmentation mask is created by applying this threshold value. Figure 2 shows the step by step outputs of proposed system
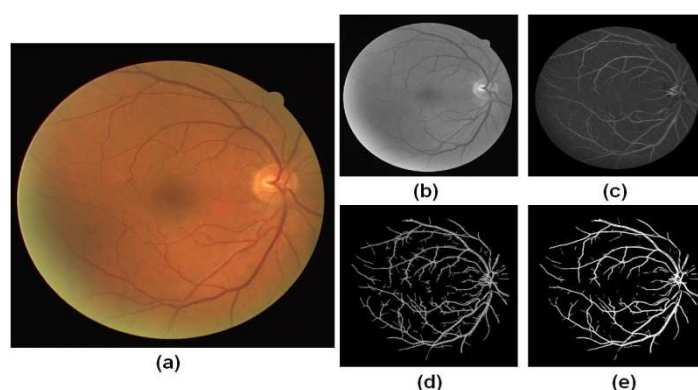
Figure 2. The step by step outputs of proposed system; a) original colored retinal image; b) extracted green channel image; c) enahnced blood vascular pattern using wavelets; d) output of threshold probing; e) segmented blood vessels

3. Results and Analysis

The tests of proposed technique are performed with respect to the vessel segmentation accuracy using three publicly available databases i.e. DRIVE [32], STARE [33] and DIARETDB1 [34]. The DRIVE database consists of 40 RGB color images of the retina. The images are of size 768x584 pixels, eight bits per color channel. The STARE database consists of 20 RGB color images of the retina. The images are of size 605x700 pixels, 24 bits per pixel (standard RGB). Both retinal image datasets (DRIVE and STARE) are divided into a test and training set and each one contains 20 images. The test set is used for measurement of performance of the vessel segmentation algorithms. There are two hand-labeling available for the 20 images of test set made by two different human observers. The manually segmented images by 1st human observer are used as ground truth and the segmentations of set B are tested against set A, serving as a human observer reference for performance comparison truth [28], [31]. Another standard diabetic retinopathy retinal image database is diaretdb1. Diaretdb1 database contains 89 retinal images with a resolution of 1500 x 1152 pixels and of different qualities in terms of noise and illumination. Diaretdb1 is a good standard database to evaluate different lesions of diabetic retinopathy as out of 89 images 84 contain at least mild NPDR signs (MA's) of the DR, and 5 are considered as normal which do not contain any signs of the DR according to all experts who participated in the evaluation. Images were captured using the same 50° FOV digital fundus camera with varying imaging settings. The performance of proposed technique is measured using receiver operating characteristic (ROC) curve which is a plot of true positive fraction versus false positive fraction. In order to find the accuracy and area under the ROC curve, following parameters are calculated.
a. TP (true positive): Pixels that are computed as vessel pixels and they also belong to vessels in ground truth.
b. FP (false positive): Pixels that are computed as vessel pixels but they are non-vessels in ground truth.
c. TN (true negative): Pixels that are computed as nonvessel pixels and they are also non-vessels in ground truth.
d. FN (false negative): Pixels that are computed as nonvessel pixels but they belong to vessels in ground truth.

The true positive fraction is the fraction of number of true positive and total number of vessel pixels in the retinal image. False positive fraction is calculated by dividing false by total number of non vessel pixels in the retinal image. We compared the accuracy of proposed technique with the accuracies of the methods of Staal et al. [27] and Soares et al. [31]. Figure 3 shows the ROC curves for STARE and DRIVE databases using proposed method.

Figure 4, 5 and 6 illustrates the blood vessel segmentation results for proposed method for DRIVE, STARE and DIARETDB1 databases respectively. Figure 7 shows a comparison for blood vessel segmentation between Hoover et al. [28] technique and the proposed method. It is clear from this section that proposed system has outperformed already published methods.
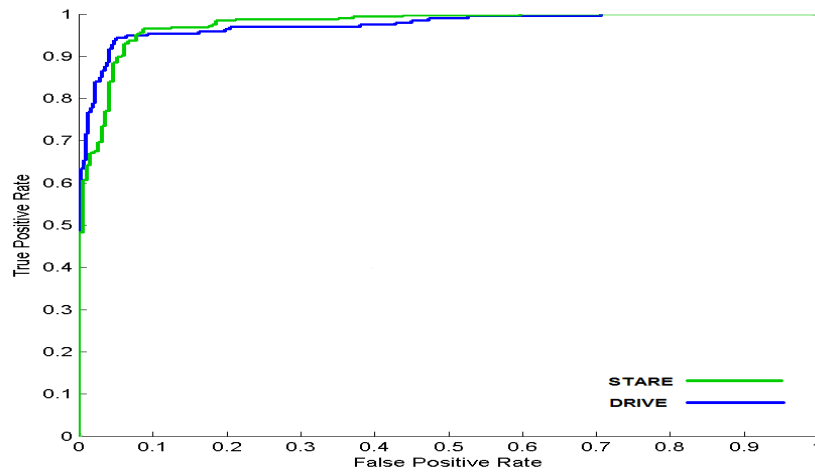
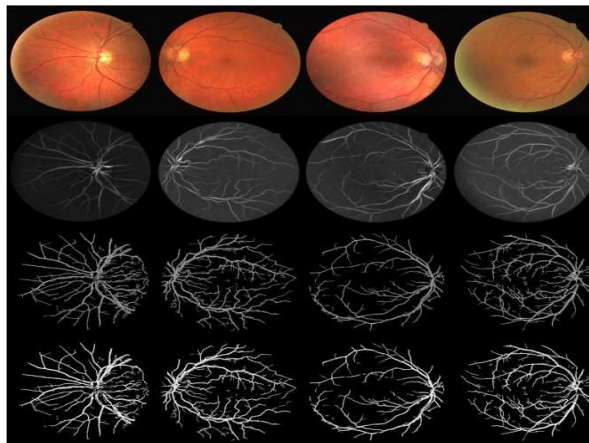Figure 3. ROC curves for STARE and DRIVE databases for proposed method

Figure 4. Proposed technique results for four images from the DRIVE database. Row 1: original retinal images from dataset; row 2: enhanced retinal images using Gabor wavelet; row 3: inverted threshold probing results; row 4: segmentation results for proposed technique
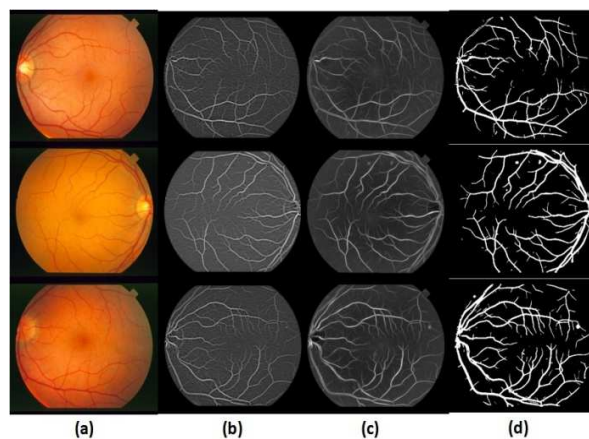

Figure 5. Proposed technique results and for three images from the STARE database.
a) original retinal images from dataset; b) enhanced blood vessels using matched filter response [6]; c) enahanced blood vessels using gabor wavelts; d) segmentation results for proposed technique
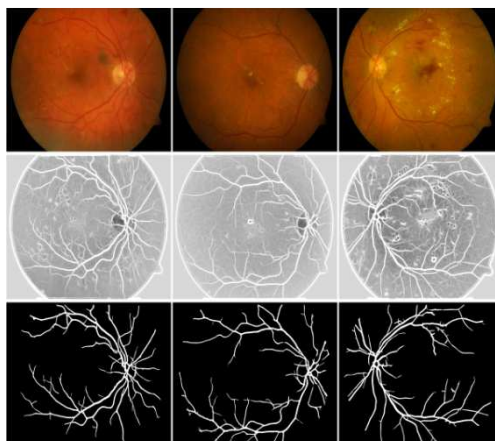
Figure 6. Blood vessel segmentation for DiaretDB: row 1: Original images; row 2: Wavelet based enhanced images; row 3: segmentred blood vessels
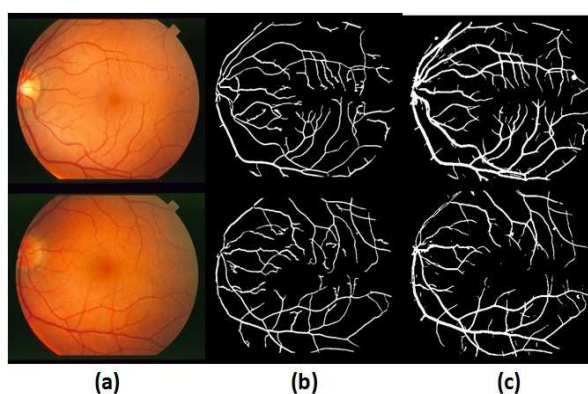

Figure 7. Comparison results for blood vessel segmentation. a) Original retinal images; b) Segmented blood vessels using Hoover et. Al. method [28]; c) Segmented blood vessels using proposed technique

Table 2 summarizes the results of vessel segmentation for DRIVE and STARE databases. It shows the results in terms of average accuracy and their standard deviation for different Segmentation methods and a second human observer. Average accuracy is the fraction of pixels correctly classified.

Table 2. Vessel Segmentation Results (DRIVE & STARE Databases)

Methods	DRIVE		STARE	
	Accuracy	Std Dev	Accuracy	Std Dev
2nd Observer	0.9473	0.0048	0.9351	0.0171
Staal et. al	0.9441	0.0079	0.9516	0.0329
Soares et. al	0.9466	0.0055	0.9480	0.0298
Bit Plane	0.9303	0.0318	0.9367	0.0311
PM	0.9469	0.0053	0.9502	0.0253

4. Conclusion
The appearance of blood vessels in retinal images plays an important role in diagnosis of many eye diseases. The proposed method segments the blood vessels from retinal images with great accuracy as compared to previous techniques. This paper presented a system for blood vessel ehnacment and segmentation which can help the ophthalmologists in screening of

diabetic retinopathy. Blood vessel enhancement is done in colored retinal images by using Gabor wavelet and then vessels are probed and segmented using piecewise threshold probing and adaptive thresholding. Three standardard retinal images databases i.e. DRIVE, STARE and DIARETDB1 are used for through evaluation of proposed system. The accuracies are measured with respect to manually labeled blood vessels which are available with the databases. Experimental results show that our method performs well in enhancing, probing and segmenting the vascular pattern. The presented method will be helpful in screening process of blood vessel for diagnosis of diabetic retinopathy as it has a high accuracy of detecting blood vessels.

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