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PREPROCESSING AND BLOOD VESSEL SEGMENTATION OF RETINAL IMAGES

M. Usman Akram
Computer Engineering
College of E&ME, NUST
Rawalpindi, Pakistan
usmakram@gmail.com

Ali Atzaz
Computer Engineering
College of E&ME, NUST
Rawalpindi, Pakistan
aliatzaz@gmail.com

M. Younus Javed
Computer Engineering
College of E&ME, NUST
Rawalpindi, Pakistan
myjaved@ceme.edu.pk

Umair Ali Khan Niazi
Computer Engineering
College of E&ME, NUST
Rawalpindi, Pakistan
umairali15@gmail.com

ABSTRACT

Automated diagnosis of Diabetic Retinopathy is done by taking retinal images into account. Before detecting the features and abnormalities in the retinal image, preprocessing is required. Retinal image vessel segmentation and their branching pattern are used for automated screening and diagnosis of diabetic retinopathy. We propose a method for color retinal image preprocessing i.e. creating a binary mask to remove the noisy area and background from retinal image. We present a method that uses 2-D Gabor wavelet and sharpening filter to enhance and sharpen the vascular pattern respectively. Our technique extracts the vessels from sharpened retinal image using edge detection algorithm and applies morphological operation for their refinement. The proposed method is tested on publicly available DRIVE database of manually labeled retinal images. The validation of our retinal image preprocessing technique and vessel segmentation is supported by experimental results.

KEY WORDS

Retinal image preprocessing, wavelet, vessel segmentation.

1 Introduction

Diabetes affects almost every one out of ten persons, and has associated complications such as vision loss, heart failure and stroke. Complication of diabetes, causing abnormalities in the retina and in the worst case blindness, is called diabetic retinopathy [1]. There are no such symptoms in the early stages of diabetes, but the complications' increases in the advanced stages. Small changes in the retinal capillary indicate the beginning of diabetic retinopathy . Therefore to assist in the diagnosis of diabetic retinopathy, retinal images can be used as developing tools [2].

Diabetic retinopathy is the result of microvascular changes in retina. In some patient with diabetic retinopathy, blood vessels may swell and leak fluid. In other, new abnormal blood vessels grow on the surface of the retina [3]. The retina is the light-sensitive tissue at the back of the eye and a healthy retina is necessary for good vision [4].

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]. 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].

The first step in the automatic diagnosis of diabetic retinopathy is the preprocessing of retinal image leading to detection of retinal image features and abnormalities. The noisy area and unwanted regions from retinal image are removed as a result of segmentation. It is especially significant for the reliable extraction of features and abnormalities. Feature extraction and abnormality detection algorithms give poor results in the presence of noisy background area.

Standard contrast stretching techniques have been applied by [2], [12] for preprocessing segmentation and noise reduction. In [13], [14] and [15] the local contrast enhancement method is used for equalizing uneven illumination in the intensity channel of retinal images. A large mean filter, large median filter and sometimes collectively are used for retinal image background estimation by [16]. Wang et al. in [17] have used intensity channel values to detect the dark regions from retinal image. Background noise and variable grey levels across the image introduce artifacts.

Retinal vessel segmentation may be used for automatic generation of retinal maps for the treatment of age-related macular degeneration [18], extraction of characteristic points of the retinal vasculature for temporal or multimodal image registration [19], retinal image mosaic synthesis, identification of the optic disc position [5], and localization of the fovea [20]. 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 [21].

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 [22]-[27]. Tracking consists of following vessel center lines guided by local information. In [33], 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 [28]-[31] used deformable models for vessels segmentation. Chuadhuri et al. [32] 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. [34].

In this paper, we present the retinal image preprocessing technique that detects the dark background using local mean and variance and removes noise using hue and intensity channel values. We also present the colored retinal image vessel segmentation technique that enhances and sharpens the vascular pattern using 2-D Gabor wavelet and sharpening filters respectively. Our techniques creates a binary mask for vessel segmentation applying edge detection algorithm on sharpened retinal image and a fine segmentation masks is obtained by applying morphological dilation operation.

The paper is organized in five sections. Section 2 and 3 present the step by step techniques required for colored retinal image preprocessing and vessels segmentation respectively. Experimental results of the tests on the images of the DRIVE database and their analysis are given in Section 4 followed by conclusion in Section 5.

2 Preprocessing Technique

Preprocessing is done to extract the region of interest (ROI). In automatic diagnosis of diabetic retinopathy, the processing of the surrounding background and noisy areas in retinal image is not necessary and consumes more processing time at all stages. Cutting or cropping out the region that contains the retinal image feature minimizes the number of operations on the retinal image [41].

2.1 Background Extraction and Noise Removal Mask

We have used local mean and variance based method for background preprocessing. It creates a binary background mask. Steps for background preprocessing are summarized as follows:

1. Divide the input retinal image $I(i, j)$ into non-overlapping blocks with size $w \times w$. In our case $w = 8$.
2. Compute the local mean value $M(I)$ for each block using equation 1 [36].

$$M(I) = \frac{1}{w^2} \sum_{i=-w/2}^{w/2} \sum_{j=-w/2}^{w/2} I(i, j) \tag{1}$$

3. Use the local mean value computed in step 2 to compute the local standard deviation value $std(I)$ from equation 2 [36].

$$std(I) = \sqrt{\frac{1}{w^2} \sum_{i=-w/2}^{w/2} \sum_{j=-w/2}^{w/2} (I(i, j) - M(I))^2} \tag{2}$$

4. Select a threshold value empirically by working on different retinal images. If the $std(I)$ is greater than threshold value, the block is considered as original retinal image area otherwise it belongs to background.

Noise in colored retinal image is normally due to noise pixels and pixels whose color is distorted. In our technique, we create a binary noise removal mask which includes the noisy area and it is applied on retinal image to ensure not to process the noisy area in upcoming steps i.e feature extraction and abnormality detection [42]. Steps for noise preprocessing are summarized as follows:

1. Divide the input retinal image $I(i, j)$ into non-overlapping blocks with size $w \times w$. In our case $w = 8$.
2. Use histogram equalization to enhance the contrast between background and foreground.
3. Use a 3x3 median filter to reduce the noise in background of the image [36].
4. Convert the equalized and filtered RGB retinal image into HSI color space using equations 3, 5 and 6 [36].

$$H = \begin{cases} \theta & if B \leq G \\ 360 - \theta & if B > G \end{cases} \tag{3}$$

where

$$\theta = cos^{-1}\left\{ \frac{\frac{1}{2}[(R-G)+(R-B)]}{[(R-G)^2+(R-B)(G-B)]^{\frac{1}{2}}} \right\} \tag{4}$$

here R, G and B represent RED, GREEN and BLUE components of RGB retinal image

$$S = 1 - \frac{3}{(R+G+B)}[min(R, G, B)] \tag{5}$$

$$I_n = \frac{1}{3}(R+G+B) \tag{6}$$

5. Calculate N (noise factor) due to inadequate illumination using equation 7.

$$N(I) = \frac{H}{I_n} \tag{7}$$

6. Select a threshold value empirically working on different retinal images. If the $N(I)$ is less than threshold value, the block is considered as normal retinal image area otherwise it belongs to noisy area.

2.2 Preprocessing Mask

Preprocessing mask is prepaid by combining background mask and noise mask. Before applying preprocessing mask to retinal image, morphological operations i.e. morphological erosion and morphological dilation are applied to final mask.

Mask that is formed by the combination of background mask and noise mask contains single pixel noise and edge pixels. We have used square structuring element for erosion that removes all white single pixel noise from final mask but it increases the black single pixel noise. In order to remove the black pixel noise, same square structuring element is used for dilation. Background and noise free preprocessing mask is then applied on retinal image for its preprocessing segmentation.

Figure 1 shows the original retinal images of poor quality and their preprocessing masks for background extraction and noise removal.

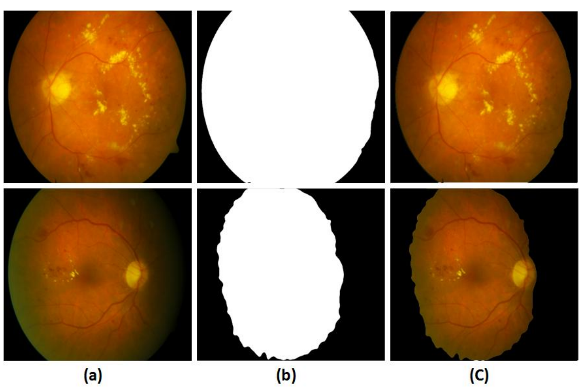

Figure 1. (a) Retinal images; (b) Preprocessing masks; (c) Preprocessed retinal images

3 Blood Vessel Segmentation

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 using Gabor wavelet [35]. Before extracting vessels from enhanced retinal image, the blood vessels are sharpened using sharpening filter [36]. Vessels segmentation binary mask is created by detecting vessels edges from sharpened image. The blood vessels are marked by the masking procedure which assign one to all those pixels which belong to blood vessels and zero to non vessels pixels. Final refined vessel segmentation mask is created by applying morphological dilation operator [36].

3.1 Vascular Pattern Enhancement and Sharpening

We have used 2-D Gabor wavelet to enhance the vascular pattern and thin vessels [35]. 2-D Gabor wavelet is used due to its directional selectiveness capability of detecting oriented features and fine tuning to specific frequencies [35], [37].

1. The continuous wavelet transform $T_\psi(\mathbf{b}, \theta, a)$ is defined in terms of the scalar product of f with the transformed wavelet $\psi_\mathbf{b}, \theta, a$ using equation 8 [38]

$$T_\psi(\mathbf{b}, \theta, a) = C_\psi^{-1/2} \langle \psi_\mathbf{b}, \theta, a | f \rangle$$
$$= C_\psi^{-1/2} a^{-1} \int \psi^*(a^{-1} r_{-\theta}(\mathbf{x} - \mathbf{b})) f(x) d^2\mathbf{x} \quad (8)$$

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

2. It is easy to implemented wavelet transform using the fast Fourier transform algorithm. Fourier wavelet transform is defined using equation 9 [37].

$$T_\psi(\mathbf{b}, \theta, a) = C_\psi^{-1/2} a \int \exp{(j\mathbf{kb})} \hat{\psi}^*(a r_{-\theta}\mathbf{k}) \hat{f}(\mathbf{k}) d^2\mathbf{k} \quad (9)$$

   where $j = \sqrt{-1}$, and the hat ($\hat{\psi}^*$ and $\hat{f}$) denotes a Fourier transform.

3. The 2-D Gabor wavelet is defined as [38]

$$\psi_G(\mathbf{x}) = \exp(j\mathbf{k}_0\mathbf{x}) \exp(-\frac{1}{2}|\mathbf{A}\mathbf{x}|^2) \quad (10)$$

   where k_0 is a vector that defines the frequency of the complex exponential and $\mathbf{A} = diag[\epsilon^{-1/2}, 1], \epsilon \geq 1$ is a 2×2 diagonal matrix that defines the elongation of filter in any desired direction.

4. For each pixel position and considered scale value, the Gabor wavelet transform $M_\psi(\mathbf{b}, a)$ is computed using equation 11 [37], for θ spanning from 0^o up to 170^o at steps of 10^o and the maximum is taken.

$$M_\psi(\mathbf{b}, a) = max_\theta |T_\psi(\mathbf{b}, \theta, a)| \quad (11)$$

We have used unsharp masking [36] on enhanced vessel retinal image to sharpen the vascular pattern. The application of Gabor wavelet on colored retinal image enhances the vascular pattern but the resulting image is a little blurred so we have used unsharp filter to sharpen the vascular edges. This helps in reliable extraction of vessels from the colored retinal image.

3.2 Vessel Segmentation Mask

Vessels segmentation mask is created by extracting vessels boundaries using edge detection algorithm and then by applying morphological dilation operator [36]. In this paper, we have used canny edge detector [39]. Canny operator simultaneously optimizes three criteria: detection criterion, localization criterion, and elimination of multiple responses and these rules also become a standard to evaluate edge detection algorithm performance [39]. The vessels extracted using edge detection algorithm are refined using standard morphological dilation operator [36]. Dilation will fill the gaps between vessel boundaries detected by edge detection algorithm.

4 Experimental Results

The tests of proposed technique are performed with respect to the vessel segmentation accuracy using publicly available DRIVE database [40] and retinal images of different qualities. The DRIVE database consists of 40 RGB color images of the retina. The images are of size 768×584 pixels, eight bits per color channel. The image set is 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. The segmentations of set B are tested against those of A, serving as a human observer reference for performance comparison [38]. We compared the accuracy of proposed technique with the accuracies of the methods of Staal et al. [33] and Soares et al. [38]. Table 1 and table 2 summarize the results of preprocessing and vessel segmentation respectively. Figure 2 illustrates the step by step blood vessel segmentation results for proposed method.

Table 1. Preprocessing Results

Masks	Accurately Processed (number)	Accurately Processed (%)	Poorly Processed (number)	Poorly Processed (%)
Background Preprocessing	217	99.08	2	0.92
Noise Preprocessing	202	92.23	17	7.77
Final Preprocessing	201	91.78	18	8.22

Table 2. Vessel Segmentation Results (DRIVE Database)

Segmentation Methods	Average Accuracy	Standard Deviation
2nd. Observer	0.9473	0.0048
Staal et al.	0.9441	0.0079
Soares et al.	0.9466	0.0055
Proposed Method	**0.9469**	**0.0053**

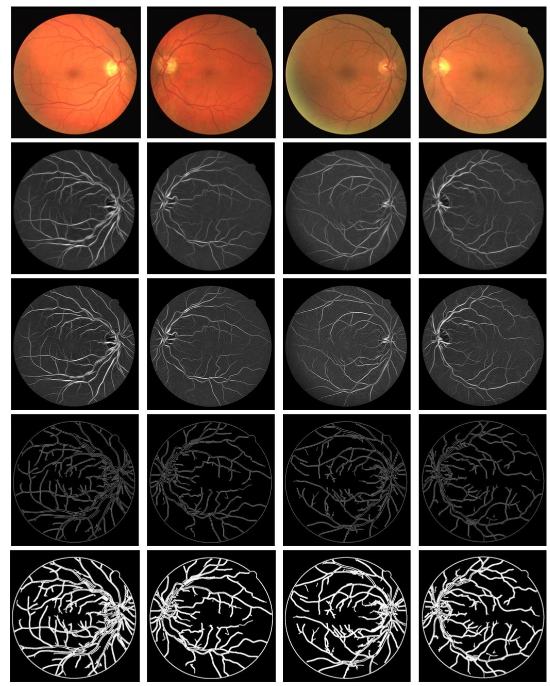

Figure 2. Row 1: Original retinal images from DRIVE database, Row 2: Enhanced Retinal Images, Row 3: Sharpened vascular pattern, Row 4: Vessels detection using canny edge detector, Row 5: Blood vessel segmentation mask for each retinal image

5 Conclusion

In this paper, preprocessing is done on the colored retinal images by extracting background and noise effect from the image and then vessel segmentation of retinal image is done by applying 2-D Gabor wavelet. The problem of the quality of acquired retinal images is resolved by combining the background mask and noise which results in final mask. After preprocessing vessel segmentation is applied. Vessels are enhanced and sharpened prior to their detection. We have tested our technique on publicly available DRIVE database of manually labeled images and other standard databases. Experimental results show that our method performs well in preprocessing, enhancing and segmenting the retinal image and vascular pattern.

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