A NOVEL INTEGRATED TECHNIQUE FOR AUTOMATIC DIABETIC RETINOPATHY DETECTION

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Abstract

Many diseases can come through the retina blood vessels. Diabetic retinopathy is one of the diseases which will damage the retina vessels which will leads to blindness. In this paper the segmentation of vessels can be done by using the method called Gabor filter with local entropy thresholding. By using this method we can get the high accuracy and easy extraction of vessels. Green channel is extracted from RGB because the frequency and orientation of Gabor filters are tuned to match. Local entropy thresholding is used for segmentation of blood vessel pixels.

Keywords: ***Retinal image, Blood vessels, Diabetic retinopathy, Optimized Gabor filter, Local entropy thresholding.***

1. Introduction

Diabetic retinopathy is a disorder of the retinal vasculature that eventually develops to some degree in nearly all patients with long-standing diabetes mellitus [1]. It is estimated that by the year 2010 the world diabetic population will be doubled, reaching an estimated 221 million [2]. The timely diagnosis and referral for management of diabetic retinopathy can prevent 98% of severe visual loss. Color retinal images are widely used for detection and diagnosis of Diabetic retinopathy. In computer assisted diagnosis the automatic segmentation of the vasculature in retinal images helps in characterizing the detected lesions and in identifying false positives [3]. The performance of automatic detection of pathologies like micro aneurysms and hemorrhages may be improved if regions containing vasculature can be excluded from the analysis. Another important application of automatic retinal vessel segmentation is in the registration of retinal images of the same patient taken at different times [4]. The registered images are useful in monitoring the progression of certain diseases. In the literature [5] it is reported that many retinal vascular segmentation techniques utilize the information such as contrast that exists between the retinal blood vessel and surrounding background and all vessels are connected and originates from the same point that is the optic disc. Four techniques used for vessel detection are classified as filter based methods, tracking of vessels; classifiers based methods and morphological methods. In filter based methods the cross-sectional gray-level profile of a typical retinal vessel matches the Gaussian shape and the vasculature is piecewise linear and may be represented by a series of connected line segments [6]. These methods employ a two-dimensional linear structural element that has a Gaussian cross-profile section, rotated into different angles to identify the cross-profile of the blood vessel. Tracking methods [7] [8] use a model to track the vessels starting at given points and individual segments are identified using a search procedure which keeps track of the center of the vessel and makes some decisions about the future path of the vessel based on certain vessel properties. Classifier-based methods use a two-step approach [9].

They start with a segmentation step often by employing one of the mentioned matched filter-based methods and next the regions are classified according to many features. In the next step neural networks classifier is constructed using selected features by the sequential forward selection method with the training data to detect vessel pixels. Morphological image processing exploits features of the vasculature shape that are known a priori, such as it being piecewise linear and connected. The use of mathematical morphology for segmentation of blood vessels is explained in [10] [11]. These approaches works well on normal retinal images with uniform contrast but suffers in the presence of noise due to pathologies within the retina of eye.

In our work the vessel segmentation is performed using Gabor filter. Gabor filters have been widely applied to image processing and computer vision application problems such as face recognition and texture segmentation, strokes in character recognition and roads in satellite image analysis [12][13]. A few papers have already reported work on segmentation of vessels using Gabor filters [14] [15].

This paper has been proposed a much robust and fast method of retinal blood vessels extraction using optimized Gabor filter with local entropy thresholding.

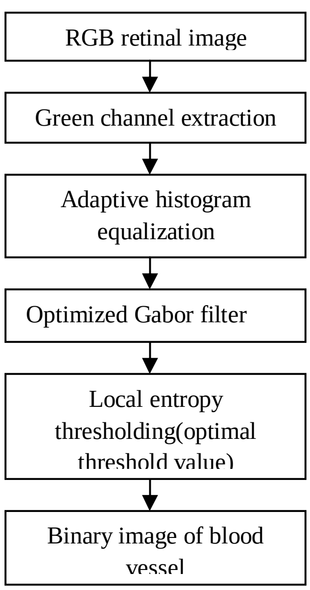

Fig 1: Flow chart of the proposed methodology for blood vessel segmentation in retinal image

2. Proposed method

2.1 Preprocessing

Preprocessing is applied to eliminate the noises in the fundus image. Regarding the acquisition process, retinal images have often low contrast that cause to hardly detect the blood vessels. This method is to improve the image dynamic range to prepare images for next step, detection the blood vessels, and attain to higher accuracy and precision of segmentation. Concerning our purpose, contrast enhancement, the green channel of colored retinal images is used, because compare to other channels it has the highest contrast [4]. Combining advantages of brightness in red channel decreasing the contrast between the abnormalities and the retinal background; this helps to reduce some responses from abnormalities which do not resemble any blood vessels that would otherwise decrease the performance of blood vessels segmentation methods. Contrast-limited adaptive histogram equalization is used for this analysis that enhancing the contrast of the green channel retinal image.

2.2 Optimized Gabor Filter

Gabor filters have been widely used for multi-directional analysis in image processing. In this algorithm optimized Gabor filter is used for detecting the blood vessel in retinal image. The optimized Gabor Filters are a set of orientation and frequency sensitive band pass filters which have the optimal localization in both the frequency contents of the patterns [8]. The optimized Gabor filter kernels are sinusoids modulated.

$$\sigma_x = k \qquad (1)$$

$$\sigma_y = \frac{\sigma_x}{\gamma} \qquad (2)$$

$$x_\theta = x cos\theta + y sin\theta \qquad (3)$$

$$y_\theta = -x sin\theta + y cos\theta \qquad (4)$$

Optimized Gabor filter kernel:

$$g_\theta(x,y) = exp\left\{-\frac{1}{2}\left(\frac{x_\theta^2}{\sigma_x} + \frac{(y_\theta)^2}{\sigma_y}\right)\right\} cos\left(2\pi\frac{x_\theta}{\lambda} + \psi\right) \qquad (5)$$

Where,

σ_x: Standard deviation of Gaussian in x direction along the filter that determine the bandwidth of the filter.

σ_y: Standard deviation of Gaussian filter that control the orientation selectivity of the filter.

θ: Orientation of the filter, an angle of zero gives a filter responds to vertical feature.

λ : Wavelength of the cosine factor of the Gabor filter kernel i.e. preferred wavelength of this filter.

γ : Spatial aspect ratio, specifies the ellipticity of the support of the Gabor function

ψ : Phase offset

The optimization Gabor filter kernel (9×7 matrix) is rotated in different rotations with the optimized parameters set as follows:

$\sigma_x \in [3.91, 4], \lambda \in [5.1, 5.3], \gamma \in [1.2, 1.4]$

$\sigma_x \in 3.91$

$\lambda = 5.1$

$\gamma = 1.3$

$\psi = 2\pi$

σ_x is required so that the shapes of the filter are invariant to the scale. The width of the vessels is found to lie within a range of 2-14 pixels (40-200μm). Here, λ and γ values maintain false positive rate. ψ always (2π) rotation phase in this method. The optimized parameters are to be derived by taking into account of size of the lines structures to be detected. Only six optimized Gabor filters with different orientations (0 to 360° intervals of sixty degrees) are used to convolve with the preprocessing image. The magnitude of each response is retained and combined to generate the result image.

2.3 Local Entropy Thresholding

An image can be viewed as an information source with a probability vector described by its grey-level image histogram, the entropy of the histogram can be used to represent a certain level of information contained in the image. Pun [16] and Kapur et al. [17] had taken this concept to derive entropy thresholding methods.

a) Original image b) red channel c) green channel d) blue channel

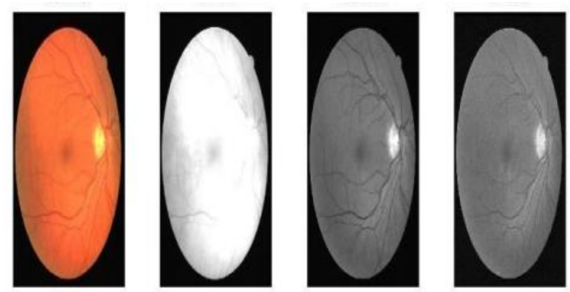

Fig 2: Original image with extraction channels

However, their approaches did not take into account the correlation among grey levels. As a result, two different images with an identical image histogram will result in the same threshold value [18]. One way to resolve this problem is to consider the grey-level co-occurrence matrix, which contains the information of greylevel transitions in an image. In the proposed method the grey-level co-occurrence matrix developed by Haralick et al [19] is used to derive the Haralick texture feature for retinal image segmentation. The Haralick texture feature chosen is the entropy of the retinal image.

In order to performing the proper extraction of the enhanced segments from the Gabor filter response images, an effective thresholding method is required.

Assume that a Gabor filter response image has a size of M * N with L grey levels denoted by G = {0, 1. . . L – 1}. A co-occurrence matrix of an image is an L * L square matrix, denoted by $TT = |t_{ij}|_{L\times L}$ whose elements are specified by the numbers of transitions between all pairs of grey levels in G = {0, 1 . . . L – 1} in a particular way.

That gives an idea about the transition of intensity between adjacent pixels, indicating spatial structural information of image. Depending upon the ways in which the gray level i follows gray level j, different definition of co-occurrence matrix are possible. Here, we made the co-occurrence matrix asymmetric by considering the horizontally right and vertically lower transitions. Let t_{ij} be the (i,j)th entry of the cooccurrence matrix. Then the probability of co-occurrenceI_{ij} of gray levels i and j is Normalizing the probability within individual quadrants, such that the sum of probabilities of each quadrant equals to one, we get the following cell probability.

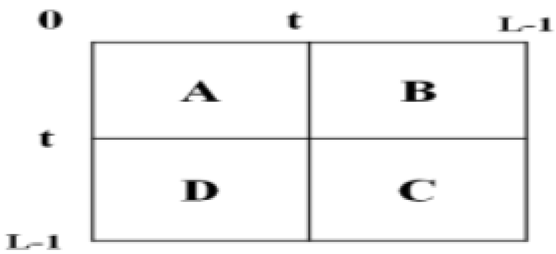

Fig 3: Quadrants of co-occurrence matrix

Let t be a value used to threshold an image. It partitions the co-occurrence matrix into four quadrants, namely, A, B, C and D. We assume that pixels with grey levels above the threshold are assigned to the foreground (corresponding to objects), and those equal to or below the threshold are assigned to the background. Then quadrants A and C correspond to local transitions within background and foreground, respectively, whereas quadrants B and D are joint quadrants which represent joint transitions across boundaries between background and foreground. The probabilities associated with each quadrant are then given by

$$p_{ij} = \frac{t_{ij}}{\sum_i \sum_j t_{ij}} \qquad (6)$$

Obviously $0 \leq p_{ij} \leq 1$

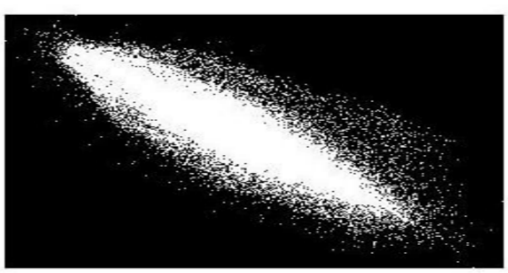

Fig 4: Scatter plot obtained by plotting the local entropy of the optimized Gabor Filter retinal response image

$$p_{ij}{}^{(1)} = \frac{t_{ij}}{\sum_{i=0}^{s} \sum_{j=0}^{s} t_{ij}} \qquad (7)$$

$$p_{ij}{}^{(2)} = \frac{t_{ij}}{\sum_{i=s+1}^{L-1} \sum_{j=s+1}^{L-1} t_{ij}} \qquad (8)$$

The second order local entropy of the object can be defined as

$$H^{(A)}(s) = -\frac{1}{2} \sum_{i=0}^{s} \sum_{j=0}^{s} p_{ij}{}^{(1)} log_2 p_{ij}{}^{(1)} \qquad (9)$$

Similarly the background written as

$$H^{(C)}(s) = -\frac{1}{2} \sum_{i=s+1}^{L-1} \sum_{j=s+1}^{L-1} p_{ij}{}^{(2)} log_2 p_{ij}{}^{(2)} \qquad (10)$$

$$H_T(s) = H^{(A)}(s) + H^{(C)}(s) \qquad (11)$$

$$t^* = arg\{max H_T(s)\} \qquad (12)$$

The entropy threshold determines the optimal threshold t* by maximum of the entropy curve. t* is used as the threshold for segmentation of the retinal image. This Threshold find it automatically form the Entropy-Threshold Curve

3. Experimental Results

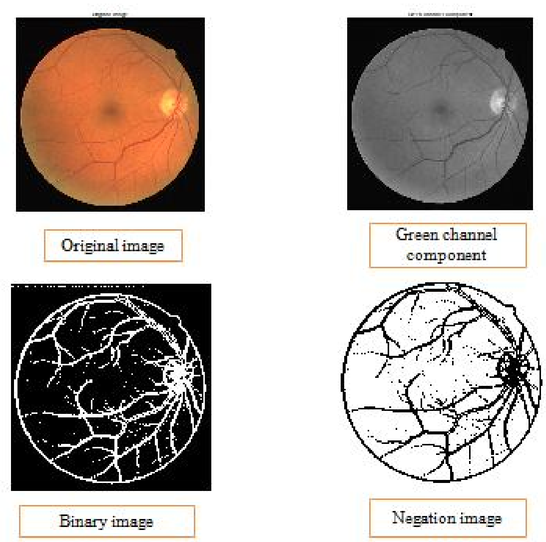

Fig.5. (a) Original Image, (b) green channel component, (c) Binary Image, (d) Negation Image

Fig.6. Median filter image

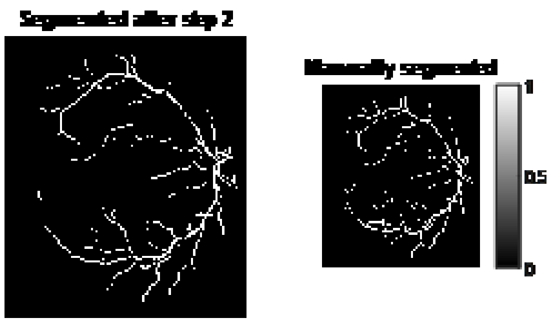

Fig.7. Segmentation of median filter image

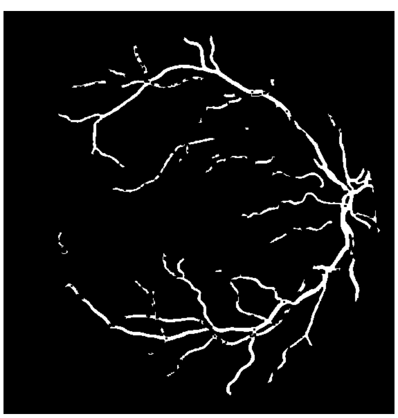

Fig.8. Enhancement of segmented image

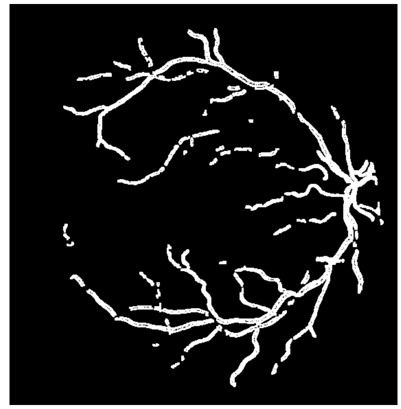

Fig.9. Dilation of an image

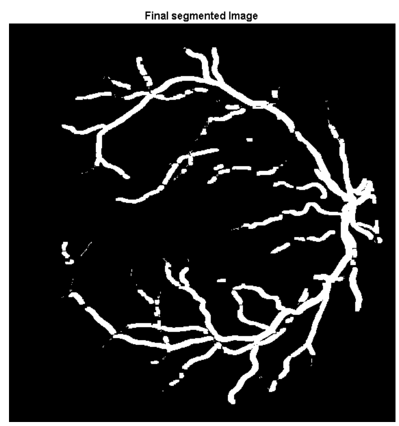

Fig.10.Final segmented image

4. Conclusion

In this paper, for extracting the vessels optimized gabor filter with local entropy thresholding is applied. From the gray level co-occurance matrix the threshold value is obtained and based on that segmentation completed.the final decision is taken based on the true possitive rate and false detection. The averge accuracey (ACC) of this method is 97.94% and average sensitivity (Se) is 98.5%. To get the more efficient accuracy the noise reduction techniques can be used. Mainly this method can be used for opthamalogists to screen large population for blood vessel abnormalities in ratinal image.

5. References

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