Automatic Diabetic Retinopathy Detection Using Entropy Thresholding

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Abstract— *A major complication arising in diabetic patients is Diabetic retinopathy, which leads to vision loss. The disease Diabetic retinopathy (DR) can be detected by observing the images of retina of the eye. Retinal images usually have low resolution and this makes it more difficult for analysis by an ophthalmologist. Detection of blood vessels in retina is helpful for ophthalmologists to diagnose larger populations in very less time. Blood vessel detection is very complicated due to the presence of bright and dark tissues in retinal images. Here, an algorithm is proposed to segment blood vessels in both normal and abnormal retinal images of diabetic patients based on their image features. In the process, the negative impact of bright tissues of retinal images is decreased by using clustering segmentation by image processing methods. Then, for ignoring dark tissues a multi-scale line operator is utilized to detect vessels while ignoring some of the dark tissues, which have intensity structures that are different from the line-shaped vessels in the retina. The algorithm involves Gabor filter enhanced with local entropy thresholding for blood vessel extraction under different normal and abnormal conditions. The main characteristic of Gabor filter is its frequency. This Gabor filter frequency and orientation are set to match that of a part of blood vessels to be enhanced in a second channel of an input image.*
The working of the below mentioned algorithm is analyzed by MATLAB software with DRIVE database.

***Keywords*— Diabetic Retinopathy, segmentation, linear structure, perceptive transform, retinal vessel segmentation, Retinal image, Blood vessels, Vessels extraction, Gabor filter, Local entropy thresholding.**

I. Introduction

Diabetic Retinopathy(DR),a complication of diabetes, occurs as a result of damage to the very small blood vessels that are located in the retina. The blood vessels which are affected from diabetic retinopathy become a cause for vision loss. Diabetic retinopathy is a leading reason for adult blindness and screening can decrease its incidence. Screening will increase the chances that an abnormal condition is not neglected, found early, or is able to be able to be cured. It is widely suggested that all persons with diabetes should regularly check for diabetic retinopathy.

Computer aided analysis for automatic segmentation of blood vessels in retinal images will help ophthalmologists to screen a larger patient database for vessel abnormalities. Many image processing methods have been proposed for retinal thresholding.

Gabor filters have been widely applied to image processing and computer vision application problems such as face recognition and texture segmentation. Optimized Gabor filter methods often give false positive detections and fail to detect vessels of different widths. Also detection process is much more complicated when retinal image is in abnormal condition. This paper has proposed a much robust and fast method of retinal blood vessels extraction using optimized Gabor filter with local entropy thresholding.

Materials and Methods:

This analysis used DRIVE database in which all images are in tagged image file format. Every image was capture with asize of 584×565 pixels, 8 bits per colour. Blood vessels normally have low local contrast compared to background.

II.PROPOSED VESSELS SEGMENTATION METHOD

The proposed algorithm uses the following steps:
(i) Green plane extraction,
(ii) Class limited Adaptive Histogram Equalization
(iii) Optimized Gabor filter
(iv) Local Entropy Thresholding
(v) Binary conversion.

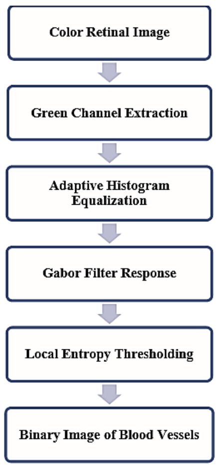

Fig: proposed methodology

The green plane is inverted before the application of the Gabor filter transform to it, so that the vessels look slightly brighter than the background.

Fig: Typical Retinal Image

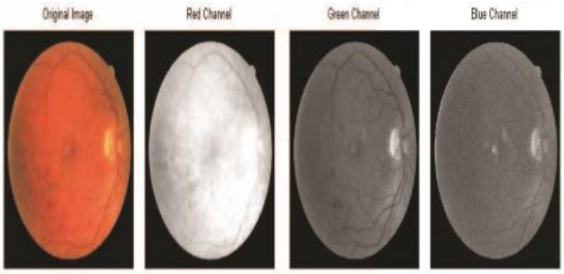

Fig: Original with Extraction Channel Images

A.Preprocessing:

Image preprocessing steps are applied to delete the noise content in the retinal image. About the acquiring process, retinal images have normally poor contrasts that are a cause of complexity in detecting the blood vessels. This algorithm is used to increase the image dynamic intensity range for preparing images for next step- detection of the blood vessels and attain to very high accuracy and precision of segmentation. Concerning our purpose, contrast increment, the second channel of colored retinal images is used, because compared to other channels of RGB image it has the highest contrast. Adding advantages of brightness in red channel decreasing the contrast between the abnormalities and the retinal background, this helps to decrease some responses from abnormalities which do not resemble any blood vessels otherwise reduce the performance of blood vessels segmentation methods. The contrast-limited adaptive histogram equalization (CLAHE)is applied for this analysis for enhancing the contrast of the second channel of retinal image.

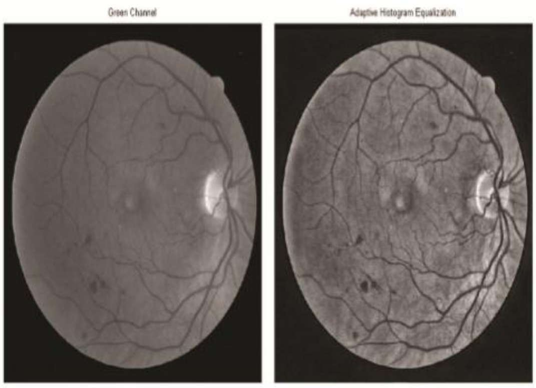

Fig.4. Green Channel of the Original Image (left) and Adaptive histogram Equalization Image (right)

B. Gabor Filter

Gabor enhancement filters have been mostly used for multi-directional analysis in digital image processing. In this algorithm Gabor filter is applied for detecting the blood vessel in retinal image. These 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. Gabor filter kernels are modulated sinusoids.

$$\sigma_x = k$$

$$\sigma_y = \frac{\sigma_x}{\gamma}$$

$$x_\theta = x\cos\theta + y\sin\theta$$

$$y_\theta = -x\sin\theta + y\cos\theta$$

Optimized Gabor filter kernel:

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

Where,

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

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

θ : Orientation of the filter, an angle of zero gives a filter which 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 which 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

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

$$\sigma_x = 3.91$$

$$\lambda = 5.1$$

$$\gamma = 1.3$$

$$\psi = 2\pi$$

σ_x is required so that the shapes of the filter are invariant to the scale.

The width of the blood vessels is found to lie within a range of 2-14 pixels (40-200µm).

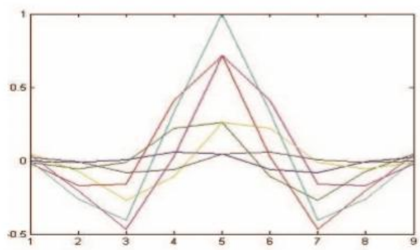

Fig: matrix(9x7)of Gabor filter

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 3600 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.

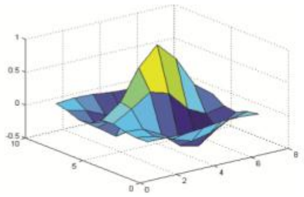

Fig: Gabor filter response in 60 degrees

Fig: Gabor filter response image

III. LOCAL ENTROPY THRESHOLDING:

Image can be expressed as an information source with a probability vector described by its grey-level image histogram; histogramentropy can be used to represent a certain level of information contained in the image. The image processing experts Pun and Kapurhad had taken this concept to derive entropy thresholding methods. Anyway, the approaches done by these people did not take into consideration the correlation among grey levels. Finally, two different images with an identical image histogram will result in the same threshold value. The way to resolve this problem is to the grey-level co-occurrence matrix, which contains the information of greylevel transitions in an image. In a previouslyproposed method the grey-level co-occurrence matrix developed by Haralick is used to obtain the Haralick texture feature for retinal image segmentation. The texture feature of Haralick chosen is the entropy of the retinal image.

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

Let us 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

$$T = \left| t_{ij} \right|_{L \times L}$$

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 co-occurrence matrix. Normalizing the probability within individual quadrants, such that the sum of probabilities of each quadrant equals to one, we get the following cell probability.

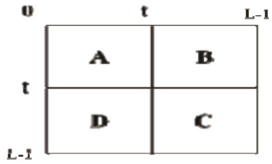

Fig.8. GLCM Quadrants

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

$$P_{ij} = \frac{t_{ij}}{\sum_i \sum_j t_{ij}}$$

Obviously 0<=Pij<=1

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

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

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

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

The local entropy of background

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

Total Entropy:

$$H_T(s) = H^{(1)}(s) + H^{(2)}(s)$$

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

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 is found automatically form the Entropy-Threshold Curve.

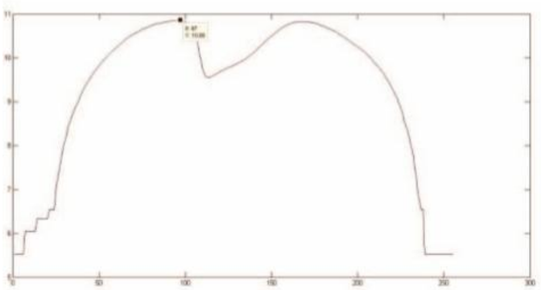

Fig: Entropy threshold curve

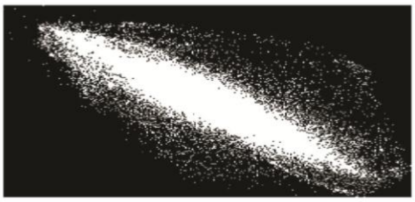

Fig: Scatter plot obtained by plotting the GLCM of the Gabor filter response retinal image.

IV. RESULTS:

For this analysis, MATLAB 2013a is used. MATLAB GUI is created for this analysis. Input images are taken from DRIVE Database. Accuracy is calculated with reference to ground truth image.

Fig: Original input image

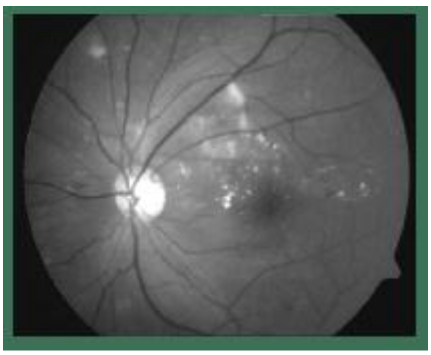

Fig: Green Channel Image

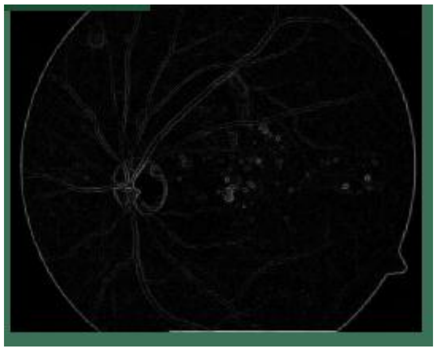

Fig: Vessel Segmented image

V. CONCLUSION:

This segmentation method is a very useful application that can be used as an automatic tool for early Diabetic Retinopathy (DR) detection. This paper, first introduces Gabor filter with local entropy thresholding for vessels extraction automatically. This analysis manifests maximum true positive rate and reduces false vessels detection in the fundus. The execution of the proposed method is assessed by comparing DRIVE database images. This method's average accuracy and sensitivity (*Se*) are calculated. This method can be applied for image registration purpose to track the change in fundus for monitoring Diabetic Retinopathy.

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