AUTOMATIC DIABETIC RETINOPATHY DETECTION USING GABOR FILTER WITH LOCAL ENTROPY THRESHOLDING

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Abstract:

The major complication of diabetic patients is Diabetic retinopathy, which leads to vision loss. The disease Diabetic retinopathy (DR) detection, low resolution retinal image makes more difficult to analysis for ophthalmologist. Identification and detection of blood vessels in retina is helpful for ophthalmologists to diagnosis larger populations in very less time. Blood vessels detection is a complex task in retinal image analysis. Blood vessels detection is very complicated with 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 issues a multi-scale line operator is utilized to detect vessels while ignoring some of the dark tissues, which have intensity structures, differs from the line-shaped vessels in the retina. The algorithm involves Gabor enhancing filter with local entropy thresholding for blood vessels extraction under different normal or abnormal conditions. The Gabor filter has main parts as 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. Analysis of blood vessels pixels are classified by local entropy thresholding technique in this method. The working of the below mentioned algorithm is analyzed by MATLAB software with DRIVE database.

Keywords: *K-means segmentation, linear structure, perceptive transform, retina image, retinal vessel segmentation, Retinal image, Blood vessels, Diabetic retinopathy, Vessels extraction, Gabor filter, Local entropy thresholding.*

Introduction:

Diabetic retinopathy (DR) is the result of damage due to diabetes to the very small blood vessels which are located in the retina. The blood vessels which are affected from diabetic retinopathy leads to vision loss. Diabetic retinopathy is a leading reason of adult blindness, and screening can decrease the incidence. Screening just increases the chances that a condition will be neglected, found early, or are 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 larger patient database for vessel abnormalities. So many varieties of paths have been suggested for retina blood vessels segmentation. Many image processing methods proposed for retinal vessels extraction. This work is based on proposed Gabor filter with local entropy 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 vessel of different widths. And also detection process is much more complicated when retinal image abnormal condition. This paper has been proposed a much robust and fast method of retinal blood vessels extraction using optimized Gabor filter with local entropy thresholding.

Material

This analysis used DRIVE database in which all images are in tagged image file format. Every image was capture at 584×565 pixels, 8 bits per colour.

Proposed Vessels Segmentation Method

The proposed algorithm involves the following steps shown in Fig1: (1) Green Channel (second plane of RGB image) Extraction, (2) Class limited Adaptive Histogram Equalization (3) Application of Gabor Filter (4) Local Entropy Thresholding (5) Binary Conversion.

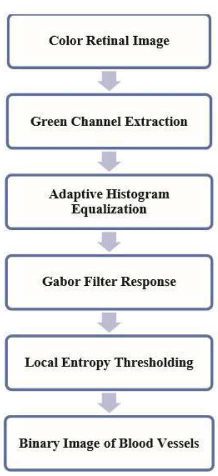

Fig: proposed methodology

Materials and Methods:

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

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

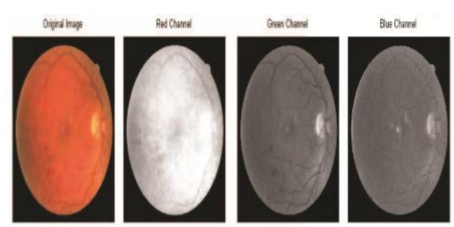

Fig: Original with Extraction Channel Images

Preprocessing:

Image preprocessing steps are applied to delete the noise content in the retinal image. About the acquiring process, retinal images have normally poor contrast that cause to complexity in detecting the blood vessels. This algorithm is to increase the image dynamic intensity range to prepare 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 compare 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 that enhancing the contrast of the second channel of retinal image.

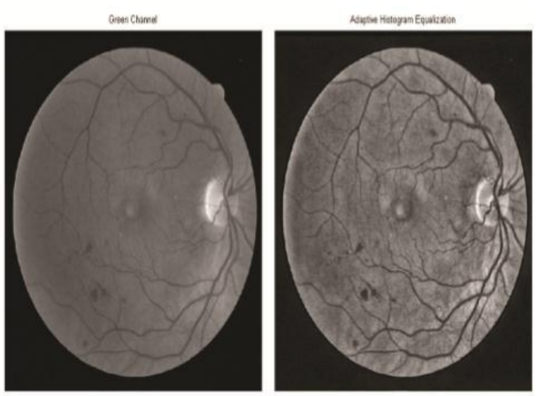

Fig.4. Green Channel of the Original Image (left) and Adaptive histogram Equalization Image (right)

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 sinusoids modulated.

$$\sigma_x = k$$

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

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

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

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 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

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

$$\sigma_x = 3.91$$

$$\lambda = 5.1$$

$$\gamma = 1.3$$

$$\psi = 2\pi$$

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).

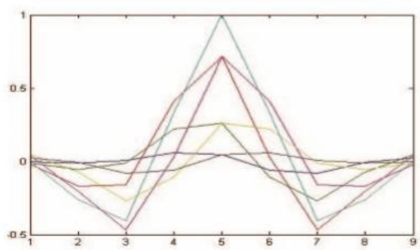

Fig: matrix (9x7) of Gabor filter

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.

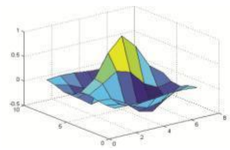

Fig: Gabor filter response in 60 degrees

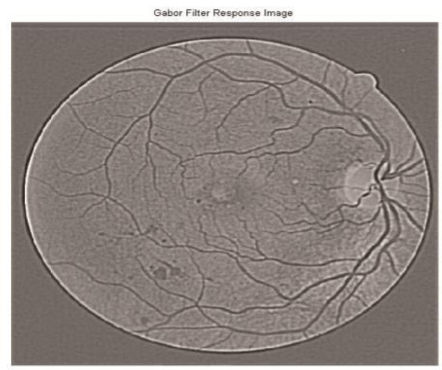

Fig: Gabor filter response image

Local Entropy Thresholding:

Image can be expressed as an information source with a probability vector described by its grey-level image histogram; histogram entropy can be used to represent a certain level of information contained in the image. The image processing experts Pun and Kapur 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 grey level transitions in an image. Previously in the proposed 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.

To 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 tij be the (i,j)th entry of the co-occurrence matrix. Then the probability of co-occurrence Iij 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.

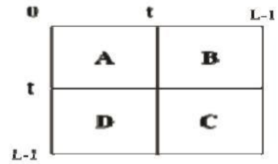

Fig.8. GLCM Quadrants

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<=P_{ij}<=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 find it automatically form the Entropy-Threshold Curve.

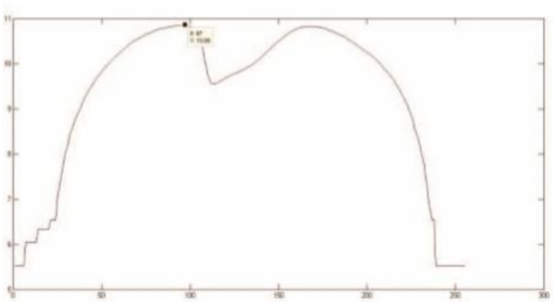

Fig: Entropy threshold curve

This Threshold * t find it automatically form the Threshold Curve.

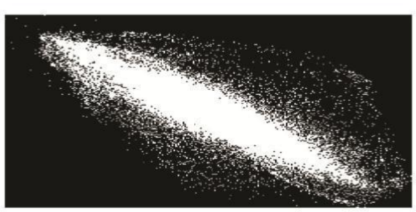

Fig: Scatter plot obtained by plotting the GLCM of the Gabor filter response retinal image.

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.

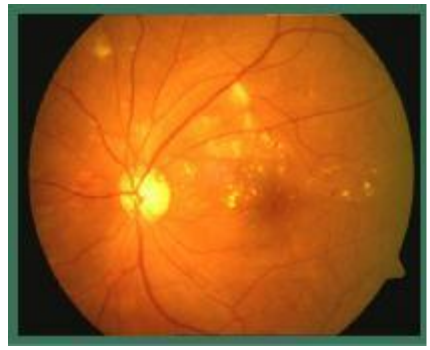

Fig: Original input image

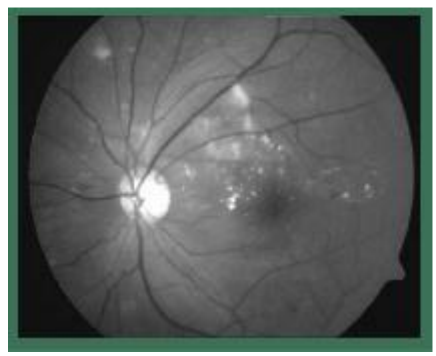

Fig: Green Channel Image

Fig: Morphological Closing Image

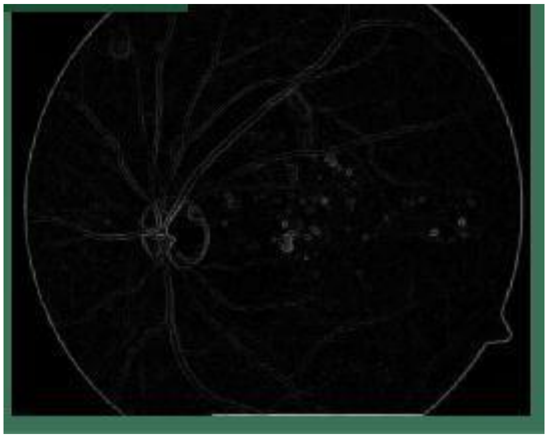

Fig: Vessel Segmented image

Conclusion:

This segmentation method is a very suitable application for automatic tool for early Diabetic Retinopathy (DR) detection. This paper, first introduce Gabor filter with local entropy thresholding for vessels extraction automatically. This analysis manifested maximum true positive rate and reduce false vessels detection in fundus. The execution of the proposed method is assessed by comparing DRIVE database images .This method 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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