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Detection of Retinal Blood Vessels in Diabetic Retinopathy Using Gabor Filter

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ABSTRACT:

Diabetes mellitus, a metabolic disorder, has become one of the rapidly increasing health threats both in India and worldwide. The complication of the diabetes associated to retina of the eye is diabetic retinopathy. A patient with the disease has to undergo periodic screening of eye. For the diagnosis, ophthalmologists use color retinal images of a patient acquired from digital fundus camera [1]. The present study is aimed at developing an automatic system for the extraction of normal and abnormal features in color retinal images. Prolonged diabetes causes micro-vascular leakage and micro-vascular blockage within the retinal blood vessels. Filter based approach with a bank of Gabor filters is used to segment the vessels. The frequency and orientation of Gabor filter are tuned to match that of a part of vessel to be extracted in a green channel image [2]. To classify the pixels into vessels and non vessels entropic thresholding based on gray level co-occurrence matrix is applied. The performance of the method is evaluated on publicly available retinal databases with hand labeled ground truths. The system could assist the ophthalmologists, to detect the signs of diabetic retinopathy in the early stage, for a better treatment plan and to improve the vision related quality of life[2].

INDEX TERMS:

Retinal image, Blood vessels, Diabetic retinopathy, Vessels extraction, Gabor filter, Local entropy thresholding.

INTRODUCTION:

One of the most important diseases that cause blood vessels structure to change is diabetic retinopathy that leads to adult's blindness. Diabetic affects almost 31.7 million Indian, and has associated complications such as vision loss, heart failure and stroke. Diabetic disease which occurs when the pancreas does not secrete enough insulin or the body is unable to process it properly. This disease affects slowly the circulatory system including that of the retina. As diabetes progresses, the vision of a patient may start to deteriorate and lead to diabetic retinopathy. Diabetic retinopathy (DR) is a common cause of blindness among the diabetic population. Despite various advances in diabetes care over the years, loss of vision is still a potentially devastating complication in people with diabetes. The risk of severe vision loss can be reduced significantly by timely diagnosis and treatment of DR. [3] Manual diagnosis is usually performed by analyzing the images from a patient, as not all images show signs of diabetic retinopathy; it increases the time and decreases the efficiency of ophthalmologists. Therefore, an automatic segmentation of the vasculature could save workload of the ophthalmologists and may assist in characterizing the detected lesions and to identify false positives [4]. Different techniques of segmentation of retinal images have been investigated so far. They are filter based methods, vessel tracking methods, classifier based methods and morphological methods.

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These methods suffer from problems associated with detecting smaller and tortuous vessels that are prone to changes in background intensity [5]. The proposed retinal vessel detection method is comprised of two steps that is the retinal vessel enhancement followed by entropic thresholding. A set of Gabor filters tuned to particular frequency and used to filter vessels. Entropy based thresholding based on gray level co-occurrence matrix is employed to convert filtered image to binary image [6].

LITERATURE SURVEY:

Survey of Exudates detection:

Ege et al. located the optic disc, fovea, and four red and yellow abnormalities (micro aneurysms, hemorrhages, exudates, and cotton wool spots) in 38 color fundus images, which were previously graded by an ophthalmologist. Gardner et al. broke down the retinal images into small squares and then presented them to a back propagation neural network. After median smoothing, the photographed red-free images with a field-of-view of 60_ were fed directly into a large neural network (using 20_20 patches, with 400 inputs). This technique recognized the blood vessels, exudates, and hemorrhages. The neural network was trained for 5 days and the lesion-based sensitivity of the exudate detection method was 93.1%. Walter et al. identified exudates from the green channel of retinal images, according to their gray-level variation. After initial localization, the exudate contours were subsequently determined by mathematical morphology techniques. This approach had three parameters, the size of the local window, which was used for calculation of the pixel local variation, and two other threshold values [7].

Survey of optic disc detection:

The optic disc is the entrance and exit region of blood vessels and optic nerves to the retina, and its localization and segmentation is an important task in an automated retinal image analysis system. Indeed, optic disc localization is required as a prerequisite for the subsequent stages in most algorithms applied for identification of the anatomical structures and pathologies in retinal images Optic disc. One method is edge detection is followed by a circular Hough transform to locate the optic disc. The algorithm commenced with locating the optic disc candidate area. The, the Sobel operator is used to detect the edge points of the located candidate area. The contours were then detected by means of the circular Hough transform, and the best fitting circle was then determined. Moreover, edge detection algorithms often fail to provide an acceptable solution due to the fuzzy boundaries, inconsistent image contrast, or missing edge features. Li and Chutatape proposed a method for locating the optic disc using a combination of pixel clustering and principal component analysis techniques. They first determined the optic disc candidate regions by clustering the brightest pixels in graylevel retinal images. Sinthanayothin used an 80_80 sub-image to evaluate the intensity variance of adjacent pixels, and marking the point with the largest variance as the optic disc location. This technique has been shown to work well with 99.1% sensitivity and specificity when there are no or only few small exudate pathologies that also appear very bright and are also well contrasted. Lalonde et al. localized the optic disc using a combination of two procedures including a Hausdorff-based template matching technique on the edge map, guided by a pyramidal decomposition technique. A priori information of the image characteristics, e.g., right/left eye image and whether the input image is centered on the macula or an optic disc have to be provided [9].

Survey on vascular detection:

Fredric et al. proposed the morphological operations based vessel segmentation technique. This technique also incorporated the advantages of differential operators. Subhasis et al. have used the matched filters to detect the vascular network. The properties of optical and spatial properties of the retinal images are used in this work. But the requirement for huge convergence time period is the major drawback of this technique. Riccardo et al. have used the Gaussian kernels based filtering approach for retinal vessel segmentation.

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Hysteresis combined with thresholding is used in this approach after the filtering technique. The convergence rate of the proposed approach is very high but the accuracy reported in the paper is very low. Chutatape et al. have proposed a hybrid approach for vascular network detection. The advantages of tracking and filters are combined in this technique. Selection of seed pixel for the tracking algorithm is the major drawback of this method. Edge thinning combined with Sobel operators are used for vessel detection by Yiming et al. The proposed method also incorporated the concept of local thresholding. Experimental results revealed the high convergence rate of the proposed approach. The application of vessel detection for image registration is explored by Zana et al. The Hough transform with Bayesian approach is used for vessel segmentation in this approach. Ali et al. have used the tracing method to detect the vascular network of the retinal images. This approach is based on the recursive procedure to determine even the finest blood vessel [7]. This technique is also applicable for images with discontinued blood vessels. But the selection of seed pixel for the tracing procedure is the practical difficulty of this approach. Cristian et al. have used the watershed technique for blood vessel segmentation[9].

Previous Methods:

1. Blood Vessel Segmentation From Color Retinal Images Using Unsupervised Texture Classification.
2. A supervised method for retinal blood vessel segmentation using line strength, multi scale Gabor and morphological features.
3. Diabetic retinopathy using Region Growing Segmentation (RRGS) algorithm.
4. Global thresholding for exudates detection.

MATERIALS:

DRIVE database is used for this analysis. Every image was capture at 584×565 pixels, 8 bits per color in TIFF format.

METHODS:

Blood vessels usually have poor local contrast compare to background. The proposed method uses the following steps:

(1) Green channel (second plane of RGB image) extraction.

(2) Adaptive Histogram Equalization.

(3) Optimized Gabor filter.

(4) Local Entropy Thersholding.

(5) Binary conversion.

Figure1. shows the block diagram of the proposed method. It gives the overall proposed method to detect retina blood vessels in diabetic retinopathy.

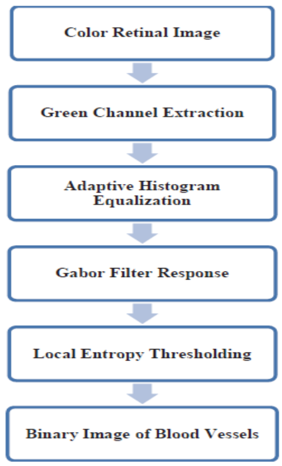

Figure 1: Proposed methodology

1. Green channel extraction:

In the color retinal images, blood vessels appear darker than the background similar to the color of lesions like micro aneurysms and hemorrhages. So it becomes essential to exempt the vessel area during the detection of lesions to avoid false positives. So we convert color image into Red, Green and Blue channel images. It can be seen in the Figure 2 that the blood vessels appear most contrasted in the green channel compared to red and blue channels in RGB image. Only the green channel image is used for further processing suppressing the other two color components. Here figure 2 shows the Original image with Extraction Channel Images [5].

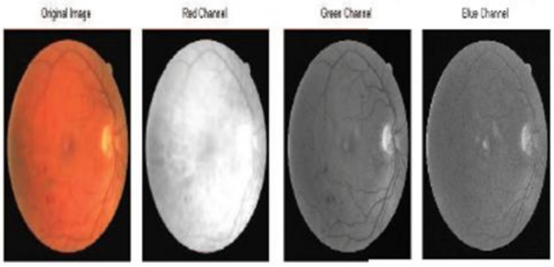

Figure 2: Original image with Extraction Channel Images.

2. 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 [8]. 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[9]. The resulted figure shown in figure 3.

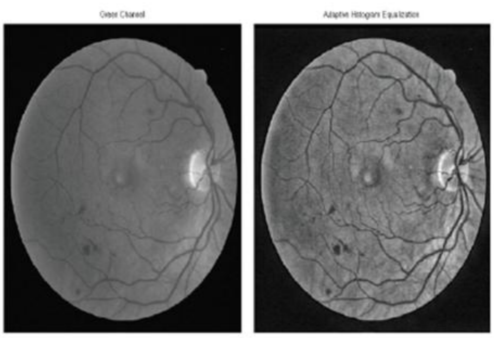

Fig.3. Green Channel of the Original Image (left) and Equalization Image (right)

3. Gabor Filter:

Gabor filters are used for texture analysis. Sinusoidal modulated gabor filter kernels are used in this analysis. Gabor filters are band pass filters which are used in image processing for feature extraction, texture analysis, and stereo disparity estimation. The impulse response of these filters is created by multiplying a Gaussian envelope function with a complex oscillation. Gabor showed that these elementary functions minimize the space (time)-uncertainty product. By extending these functions to two dimensions it is possible to create filters which are selective for orientation .Under certain conditions the phase of the response of Gabor filters is approximately linear. This property is exploited by stereo approaches which use the phase-difference of the left and right filter responses to estimate the disparity in the stereo images [3]. It was shown by several researchers that the profile of simple-cell receptive fields in the mammalian cortex can by described by oriented two-dimensional gobar filtering functions.

$$\sigma_x = k \tag{1}$$

$$\sigma_y = \frac{\sigma_x}{\gamma} \tag{2}$$

$$x_\theta = x\cos\theta + y\sin\theta \tag{3}$$

$$y_\theta = -x\sin\theta + y\cos\theta \tag{4}$$

Gabor filter kernel:

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

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 filters 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

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

$\sigma_x \in [3.91,4]$,

$\lambda \in [5.1, 5.3]$,

$\gamma \in [1.2,1.4]$

$\sigma_x = 3.15$

$\lambda=5.1$

$\gamma=1.3$

$\psi=2\Pi$

σ is required so that the shapes of the filterσ are invariant to the scale. 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 [6]. The magnitude of each response is retained and combined to generate the result image shown in figure 4.

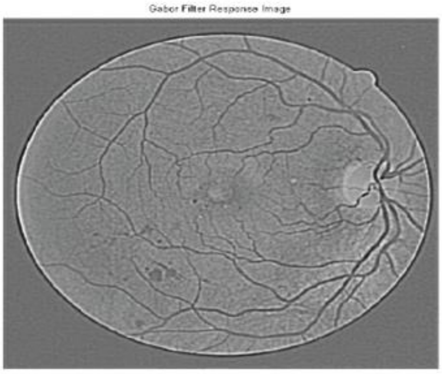

Fig.4. Gabor Filter Response Image

4. Local Entropy Threshold:

The entropy of a system was proposed by Shannon. Shannon's function is based on the concept that information gained from an event is inversely related to its probability of occurrence. Several researchers have used this concept to image processing problems. They can partition the image into object and background. An efficient entropy-based thresholding algorithm is used to retinal blood vessel detection .

This algorithm takes into account the spatial distribution of gray levels, because the image pixel intensities are not independent of each other. According to this, two images with same histograms but different spatial distribution will result in different threshold values [6]. Given image F is a P×Q dimensional matrix, $[t_{ij}]P\times Q$ is the co-occurrence matrix of the image F , this co-occurrence matrix gives an idea about the transition of intensities between adjacent pixels, indicating spatial structural information of an image.

Gray level co-occurrence matrix:

A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix [3]. To illustrate, the following figure 5 shows how graycomatrix calculates the first three values in a GLCM. In the output GLCM, element (1, 1) contains the value 1 because there is only one instance in the input image where two horizontally adjacent pixels have the values 1 and 1, respectively. Glcm (1,2) contains the value 2 because there are two instances where two horizontally adjacent pixels have the values 1 and 2. Element (1, 3) in the GLCM has the value 0 because there are no instances of two horizontally adjacent pixels with the values 1 and 3. Graycomatrix continues processing the input image, scanning the image for other pixel pairs (i,j) and recording the sums in the corresponding elements of the GLCM [2].

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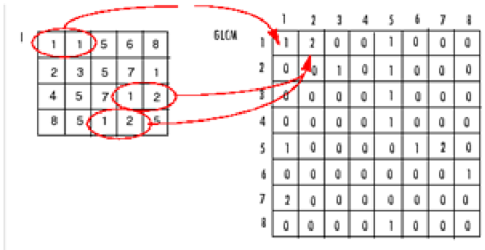

Fig.5.Process Used to Create the GLCM

Gray level co-occurrence matrix consists of information of the gray level transactions in an image. A gabor filter response image has a size of M*N with L grey levels that converted co-occurrence matrix of this image is an L*L square matrix, denoted by

$$T = | t_{ij} |_{L \times L} \; .$$

The probability co-occurrence t_{ij} of gray levels I and j is normalizing the probability within individual quadrants. A, B, C and D are four quadrants of co-occurrence matrix. Let t is threshold value of retinal image. Quadrant A and C consists of local transitions within object and background. In some respects B and D are joint quadrants which represent joint transitions across boundaries between background and object [2]. The sum of probabilities of each quadrant equals to one, get the cell probability.

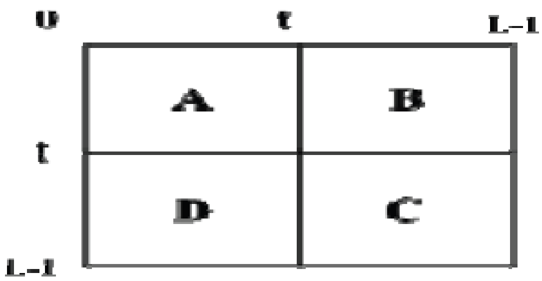

Figure: 6 GLCM quadrants

The probabilities associated with each quadrant are then given by

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

Obviously $0 <= p_{ij} <= 1$

Figure 3.8 represent the scatter plot obtained by plotting the local entropy of the optimized gobar filter retinal response image. This is obtained after filtering we perform thresholding on filtered image to differ background form our image.

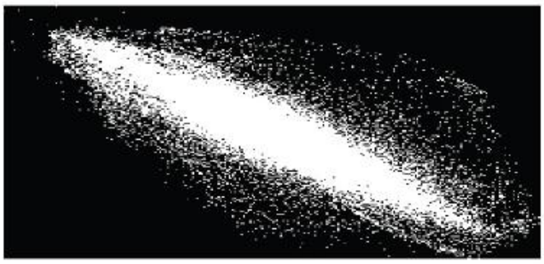

Fig 7: Scatter plot obtained by plotting the local entropy of the optimized Gabor Filter retinal response image

RESULTS:

For this analysis, Matlab 2010a is used. MATLAB GUI is created for this analysis. Input images are taken from DRIVE Database. The accuracy (Acc) is calculated by the ratio of the number of correctly classified pixels to the total number of pixels in the image. This method average accuracy is 97.94%. The sensitivity (Se) represents the fraction of pixels correctly classified as vessel pixels, where the false positive defines the fraction of pixels erroneously classified as vessel pixels. Average sensitivity is 98.5%. The computational time of whole process of our method takes approximate 2 seconds for each retinal image.

Accuracy (Acc):

$$A_{cc} = \frac{TP+TN}{TP+TN+FP+FN}$$

Sensitivity (Se):

$$S_e = \frac{TP}{TP+FN}$$

Vessels Classification:

	Vesal present	Vesal absent
Vessel detected	True Positive (TP)	False Positive (FP)
Vessel not detected	False Negative (FN)	True Negative (TN)

Figure 6.1 shows the Gabor Filter Response Image is a image that is produced after filtering the green channel image. Where we observe that noise of picture of green channel image is filtered using gobar filtering.

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So here we observe blood vesels clearly , so that we have to detect diabetic retinopathy.

Fig 8: Gabor Filter Response Image

Figure 6.2 is proposed segmented image. It is produced after performing thresholding operation on gobar filtered image. Gobar filter filters image maximum but our gobar response image not so clear. So here using thresolding we convert filtered image into binary image. So that it separate background from foreground. So the image shown above is so clear to diagnose to diabetic retinopathy.

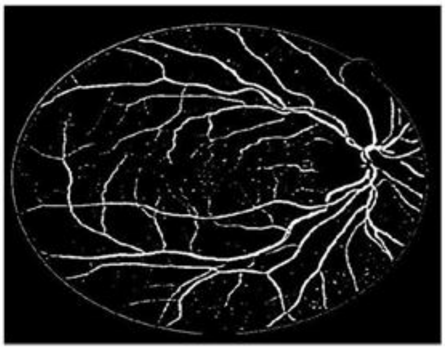

Fig 9: Proposed Segmented image

CONCLUSION:

This segmentation method is a suitable 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 (ACC) is 97.72% and sensitivity (Se) is 98.15%. This method can be applied for image registration purpose to track the change in fundus for monitoring Diabetic Retinopathy

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