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Automatic and Improvised Method of Diabetic Retinopathy Effected Eye Detection

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Abstract

Diabetic Retinopathy (DR) is a complication of diabetes and a leading cause of vision loss. DR detection, poor quality retinal image makes more difficult the analysis for ophthalmologist. Automatic segmentation of blood vessels in retina is helpful for ophthalmologists to screen larger populations. This literature presents a new automatic analysis to extract blood vessels with high accuracy. In this algorithm comprised of Gabor filter with local entropy thresholding for vessels extraction under various normal or abnormal conditions. The frequency and orientation of Gabor filter a retuned to match that of a part of blood vessels to be enhanced in a green channel image. Extraction of blood vessels pixels are classified by local entropy thresholding technique in this method. The performance of the proposed algorithm is analysed by MATLAB software with DRIVE database.

Index Terms- ***Retinal image, Bloodvessels, Diabetic Retinopathy,Vessels extraction, Fundus images, Gaborfilter, Local entropy thresholding.***

I. Introduction

Medical Image diagnostic processing has already become an important part of clinical routine. Blood vessels damaged from diabetic retinopathy can cause vision loss. Diabetic retinopathy is a leading cause of adult blindness, and screening can reduce the incidence. Retinal images are noise and low contrast poses significant Challenges to these segegmentation of blood vessels.

Many Segmentation algorithms have been presented to provide either automated or semi automated detection of Blood vessels. Automated diagnosis may also aid decision making for optometrists. The greatest emphasis in automated diagnosis has unsurprisingly been given to the detection of diabetic retinopathy. Computer based analysis for automated extraction of blood vessels in retinal images will help ophthalmologists screen larger populations for vessel abnormalities. A wide variety of approaches have been proposed for retina blood Vessels segmentation. Many image processing methods proposed for retinal vessels extraction. In this literature is based on Gabor filter with local entropy thresholding. Gabor filter methods often produce false Positive detections when retinal image abnormal condition thresholding. Gabor filter methods often produce false positive detections when retinal image abnormal condition.

II. Literature Survey

Survey of Exudates detection:

Opticaldisc, fovea, and four red and yellow abnormalities (microaneurysms, hemorrhages, exudates, and cotton wool spots) in 38 color fundus images, which were previously graded by an ophthalmologist. The abnormalities were detected using a combination of template matching, region growing, and thresholding techniques. 87% of exudates were detected during the first stage while the

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detection rate for the cotton wool spots was up to 95% in terms of the lesion-based criterion. Following preliminary detection of the abnormalities, a Bayesian classifier was engaged to classify the yellow lesions into exudates, cotton wool spots, and noise. The classification performance for this stage was only 62% for exudates and 52% for the cotton wool spots Wang et al. addressed the same problem by using a minimum distance discriminant classifier to categorize each pixel into yellow lesion (exudates, cotton wool spots) or nonlesion (vessels and background) class. The objective was to distinguish yellow lesions from red lesions, therefore other yellowish lesions (e.g. cotton wool spots) were incorrectly classified at the same time. The image-based diagnostic accuracy of this approach was reported as 100% sensitivity and 70% specificity. 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.

III. 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, multiscale Gabor and morphological features
3. Diabetic retinopathy using Region Growing Segmentation (RRGS) algorithm
4. Global thresholding for exudates detection

III. Proposed Model

Medical Image diagnostic processing has already become an important part of clinical routine. Blood vessels damaged from diabetic retinopathy can cause vision loss. Diabetic retinopathy is a leading cause of adult blindness, and screening can reduce the incidence.

Retinal images are noise and low contrast poses significantChallenges to the segmentation of blood vessels. Many Segmentation algorithms, have been presented To provide either automated or semi-automated detection of Blood vessels. Automated diagnosis may also aid decision making For optometrists. The greatest emphasis in automated diagnosis has unsurprisingly been given to the detection of diabetic retinopathy.

Computer based analysis for automated extraction of blood vessels in retinal images will help ophthalmologists screen larger populations for vessel abnormalities. A wide variety of approaches have been proposed for retina blood vessels segmentation. Many image processing methods proposed for retinal vessels extraction. In this literature is based on Gabor filter with local entropy thresholding. Gabor filter methods often produce false. Positive detections when retinal image abnormal condition thresholding. Gabor filter methods often produce false positive detections when retinal image abnormal condition.

The proposed method uses the following steps shown in

(1) Green Channel Extraction
(2) Adaptive Histogram Equalization
(3) Gabor Filtering
(4) Local Entropy Thresholding
(5) Binary Image Conversion
(6) Detection and Removal of Optical Disk
(7) Application of Mask, Subtraction of Mask and Disk
(8) Display of either Normal Eye or Abnormal Eye

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Block Diagram showing different modules:

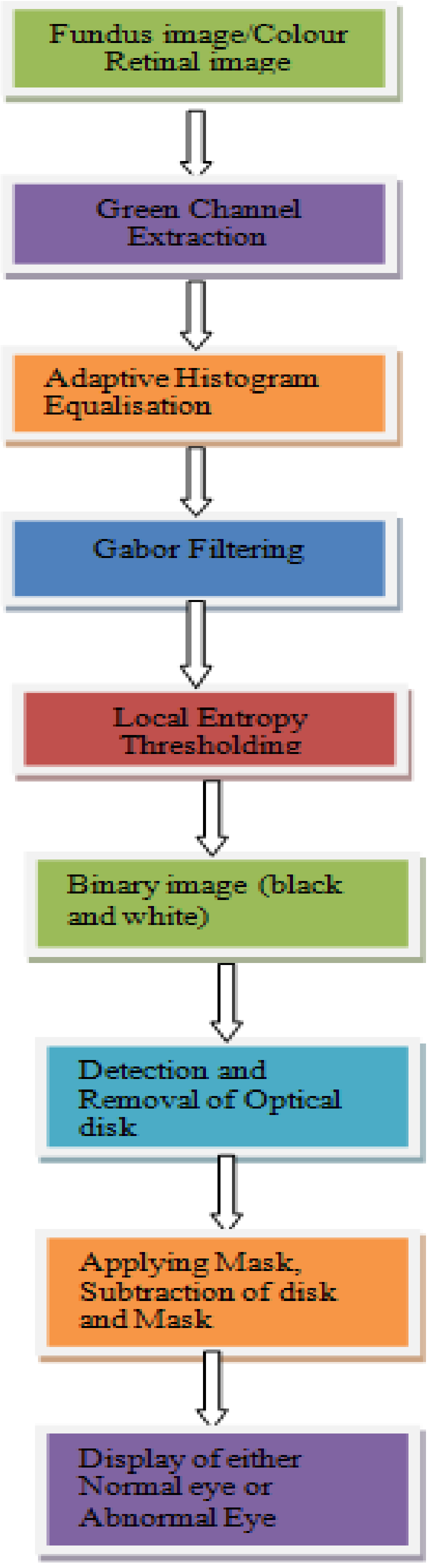

Fig.1 Block Diagram

Fig.2. Typical Retinal Image

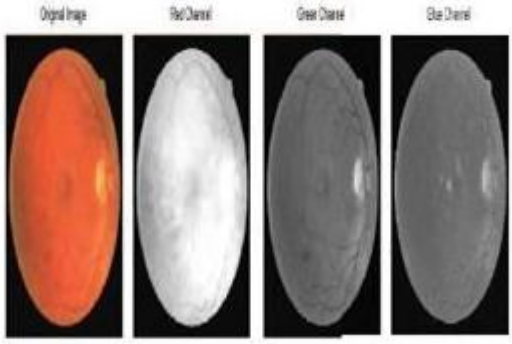

Fig.3. Extraction of channels

Pre-processing

Preprocessing is a technique of image enhancement.Iimproves the quality of an image. Preprocessing is used to enhance the contrast in fundus image. Low contrast cause very hard to extract the fundus.So that from color retinal images we are extracting green channel which is having high contrast .Then adaptive histogram is used to improve the contrast of green channel.

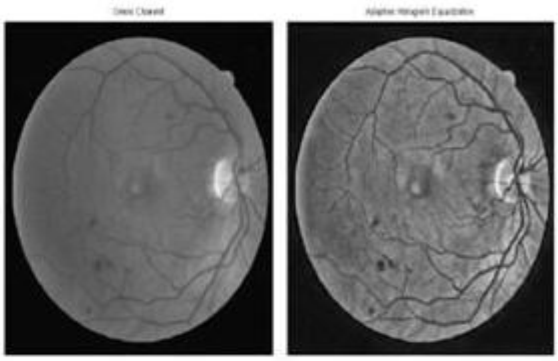

Fig.4. Green Channel of the Original Image (left) and Equalization Image (right)

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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 an 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 . 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 Gabor functions.

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

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

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

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

Gabor filter kernel:

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

Where

Bandwidth of the Gabor filter, $\sigma_x = 19.9$

Wavelength of this filter, $\lambda = 9.8$

Spatial aspect ratio, $\gamma = 6.08$

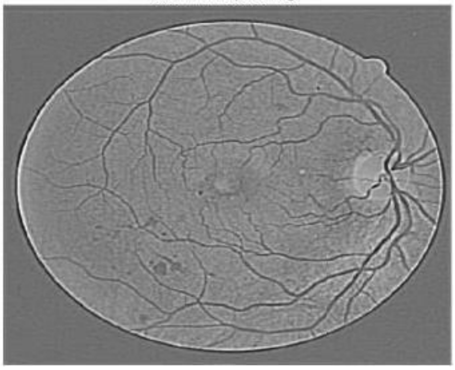

Fig.5. GaborFilterResponseImage

Local Entropy Thresholding

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. Given image F is a P×Q dimensional matrix, [tij]P×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.

Graylevel 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. (The texture filter functions, described in Texture Analysis cannot provide information about shape, i.e., the spatial relationships of pixels in an image.)It provides the information about contrast, correlation and energy.The gray-level co-occurrence matrix can reveal certain properties about the spatial distribution of the gray levels in the texture image. For example, if most of the entries in the GLCM are concentrated along the diagonal, the texture is coarse with respect to the specified offset. You can also derive several statistical measures from the GLCM. See Derive Statistics from GLCM and Plot Correlation for more information.To illustrate, the following figure shows how

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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 and3.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.

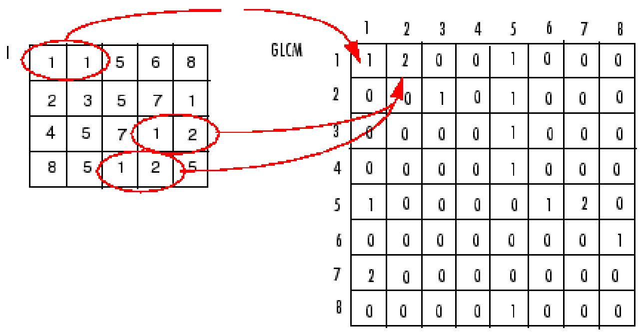
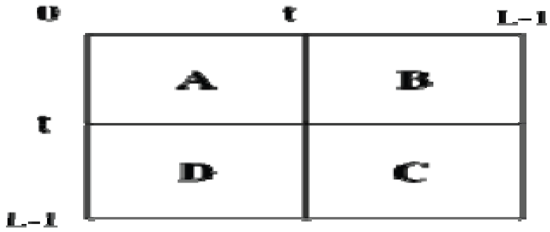


Fig.6.Process Usedto CreatetheGLCM

Gray level co-occurrence matrix consists of information of the gray level transisitions 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-ocuurence tij 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.The sum of probabilities of each quadrant equals to one, get the cell probability.



GLCM Quadrants

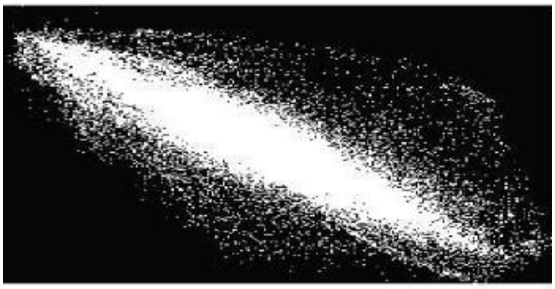


Fig.7.GLCM oftheGaborfilterresponsed image

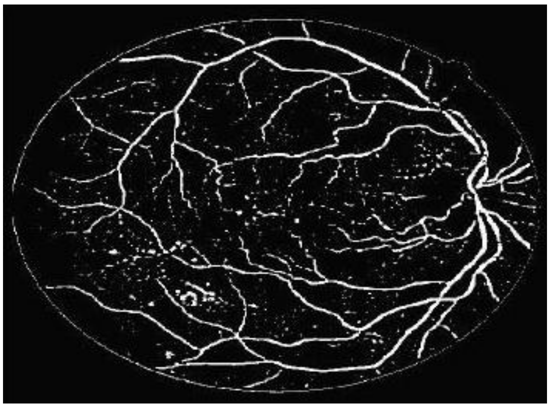


Fig.8. Proposed segmented image

$$\text{When } \sigma=1 \text{ if} \begin{cases} f(l,k) = i \text{ and } f(l,k+1) = j \\ \quad OR \\ f(l,k) = i \text{ and } f(l+1,k) = j \end{cases}$$

σ=1 otherwise.

Image Segmentation

Exudate detection

The exudate detection is performed by assigning a score for each exudate candidate. The exudate candidates are selected by running a 8-neighbour connected component analysis on Icand. We have

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implemented two ways to assign this score, one based on Kirsch's Edges and the other based on Stationary Wavelets. Both methods seek to take advantage of the higher inner and outer edge values of exudates in comparison to non-exudate structures.

Kirsch's Edges

Kirsch's edges try to capture the external edges of the lesion candidate. This edge detector is based on the kernel k (shown below) evaluated at 8 different directions on Ig• The kernel outputs are combined together by selecting the maximum value found on each pixel output. The result is stored in the final Ikirsch image.

$$k = \begin{bmatrix} \frac{5}{15} & -\frac{3}{15} & -\frac{3}{15} \\ \frac{5}{15} & 0 & -\frac{3}{15} \\ \frac{5}{15} & -\frac{3}{15} & -\frac{3}{15} \end{bmatrix} \qquad (1)$$

The average edge outputs of Ikirsch under each lesion cluster are calculated and assigned to the lesion in its entirety. The thresholds used to evaluate the final output are

$$th_{fin} \in \{0 : 0.5 : 30\}.$$

Image segmentation is a process partitioning image pixels based on image feature/s. This is to separate pixels that have different colours into different regions, group the pixels hat are spatially connected and have similar colour into different region. The selection criterion is referred as the threshold value and 'im2bw' function used this value to convert the image pixels.

Figure shows the image segmentation.

Figure 2.2 Image segmentation

DETECTION OF OPTIC DISC

The optic disc is the exist point of retinal nerve fibers from the eye and the entrance and exist point for the retinal blood vessels. It appears with similar intensity, colour and contrast to other features on the retinal image. While blood vessels also appear with high contrast as the optic disc, the green channel of the image with morphological closing operator on the intensity channel will help to eliminate the vessels which may remain in the optic disc region. A flat, octagonal structuring element with a fixed radius of fifteen (SE - morphological structuring element) was used. Figure shows the result after closing operator was applied.

A columnwise neighborhood operations was applied to set each output pixel of the image to the variance value of the input pixel's 8-by-8 sliding neighborhood, as shown in Figure. The resulting image was binarized by thresholding of 0.95, shown in Figure.The location of the maximum of the image was taken as the centre of the optic disc. Figure shows the detection of the optic disc. A circular mask is then created with a radius to cover the optic disc region, shown in Figure.

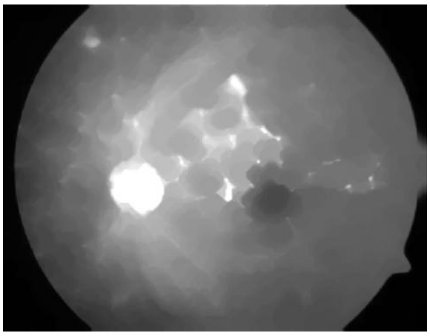
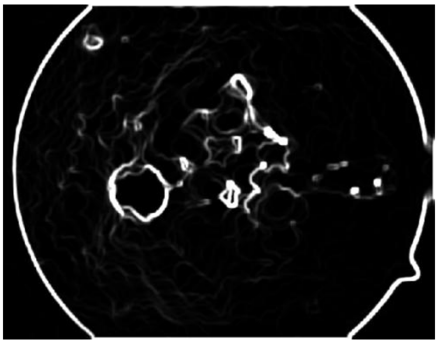


Image after morphological closing



Column wise neighborhood operations

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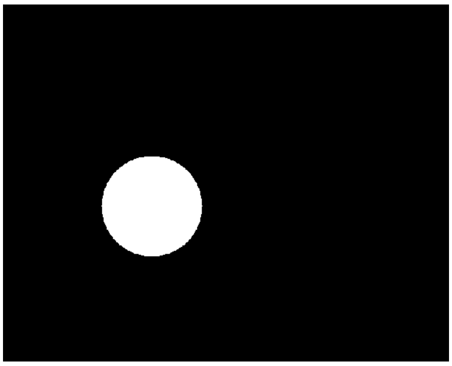
Image segmentation

Optic disc detection



Circular mask on optic disc

Exudate detection

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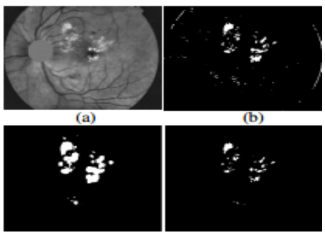
The average edge outputs of Ikirsch under each lesion cluster are calculated and assigned to the lesion in its entirety. The thresholds used to evaluate the final output are CLAHE enhances the image by transforming the intensity values of the image. It operates on small regions instead of the entire image. The contrast of each small region is enhanced with histogram equalization. After the equalizations, the neighboring small regions are combined using bilinear interpolation.

$$th_{fin} \in \{0 : 0.5 : 30\}.$$

Detection of Hard Exudates In retinal images HEs generally appear as bright regions with distinct boundaries. Two operations were carried out to detect HEs: adaptive thresholding and classification. The adaptive thresholding includes two steps: image partitioning into homogeneous regions and then segmenting candidates of HEs from the background of these regions. A classification process was carried out to classify HEs from non-HEs using a rule-based classifier.

Edge Detection

We will use the Kirsch edge detectoralgorithm to detect edges in 8-bit gray



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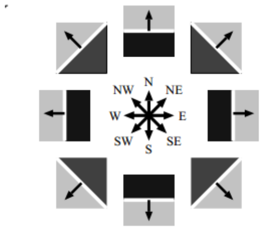
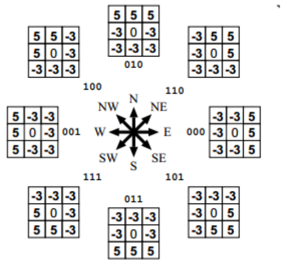
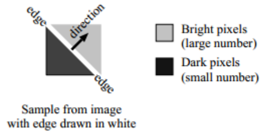






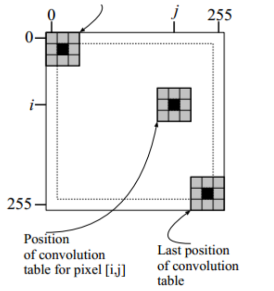


Figure 3: 256×256 image with 3×3 neighborhood of pixels

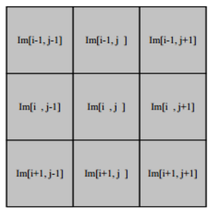
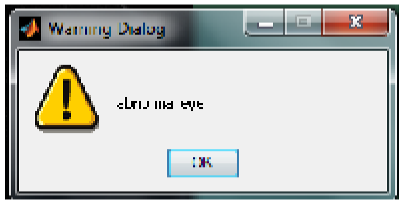


Figure 4: Contents of convolution table to detect edge at coordinate [i, j]

```
for i = 1 to 254 {
  for j = 1 to 254 {
    for m = 0 to 2 {
      for n = 0 to 2 {
        table[m,n] = image[i+m-1, j+n-1];
      }
    }
  }
```

[0,0]	[0,1]	[0,2]
[1,0]	[1,1]	[1,2]
[2,0]	[2,1]	[2,2]

The Kirsch edge detection algorithm uses a 3×3 table of pixels to store a pixel and its neighbors while calculating the derivatives. The 3×3 table of pixels is called a convolution table, because it moves across the imagein a convolution-style algorithm.whether the pixel at [1,1] is on an edge), the last position (calculating whether the pixel at [254,254] is on an edge, and at the position to calculate whether the pixel at [i, j] is on an edge.convolution table will move through 64516 (254×254) different locations. The algorithm in how to move the 3×3 convolution table over a 256×256 image. The lower and upper bounds of the loops for i and j are 1 and 254, rather than 0 and 255, because we cannot calculate the derivative for pixels on the perimeter of the image. Matlab with the GUI based system displays a window showing whether an eye is abnormal or normal.



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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