Group NO:12

MINI PROJECT

Aim:

To determine appropriate threshold value from simple image statistics, using RATS algorithm. Apply this threshold to Gabor response of retinal image and compare it with ground truth of retinal image, to determine accuracy, true positives, true negatives, false positives and false negatives.

Introduction:

Many important applications in medicine or industrial inspection, the main features of an image can be represented by as few as two grey levels. So, it becomes necessary to classify or segment each pixel of image into one of the two classes. Thresholding segmentation is also necessary because it is data reduction step and it produces a binary representation of image. Binary images are readily manipulated to produce higher level descriptions of the scenes and objects, i.e., borders, relational graphs, etc.

Till date, many thresholding methods have been proposed and here is the overview of those thresholding methods.

<u>Ridler's Method:</u>

It is an iterative method of thresholding.A switching function image which is the binary version of the picture obtained by using the threshold value of the last iteration. The initial switch function is arbitrarily chosen as a binary image with the comer points assigned as background and the rest of the picture as object. At each iteration the mean luminance values of the pixels in the object and background classes of the associated switching function image are calculated.

The average of these grey level means is used as a new threshold value to produce a new switching function. This process is iterated until a stable solution is found. The method consists of arbitrarily dividing the histogram into two parts and calculating the mean grey level of each part. The next approximation to the best threshold is the average of these two mean values. This new approximation is used to divide the histogram and the process is iterated until a stable solution is obtained. This method is simple and the process is much faster.

Variable thresholding Method

Chow and Kaneko proposed a method of variable thresholding in which an image is divided into windows. Assumes that the grey level histogram contains only two prominent modes and they are both Normally (Gaussian) distributed. Thresholds are selected for those windows that have bimodal histograms .These thresholds are interpolated to define a variable threshold for the entire image .

Thresholding using Entropy of the Histogram:

This method tries to maximize the entropy of the thresholded image while considering its relationship to the entropy of the grey level distribution of the original image. Unfortunately the entropy of a distribution is maximal for a flat distribution and the method strongly favours a trivial solution in which there are equal numbers of pixels in each class of the thresholded image histogram. Thus, this method is very poor.

Thresholding using second-order statistics:

Deravi and Pal have published a method of threshold selection based on a grey level transition matrix . This is a n * n matrix, where n is the number of possible grey levels. The matrix is constructed by horizontally and then vertically scanning the image and incrementing the (i, i) entry of the matrix by one if a transition from an i grey level to a i grey level is encountered. A trial threshold at TO will partition this matrix into four parts. The sum of two of these parts suitably normalised yields a measure of the number of times a pixel is followed by a pixel of the opposite class. For good thresholding this measure should be a minimum. Deravi and Pal claim that this method is useful in segmenting even unimodal distributions. An obvious disadvantage is the large storage space which is required for its implementation.

All the above methods are involve the analysis of the histogram of grey level values which involves several iterations through the image data. They are neither simple to implement, nor free from artifacts. In this paper, the correct threshold is determined on the basis of simple statistics defined directly in terms of pixel grey level values and possibly their functions, without the need to rely on histogram analyses or some criterion optimization involving multiple data passes. This method is called as robust automatic threshold selector(RATS).

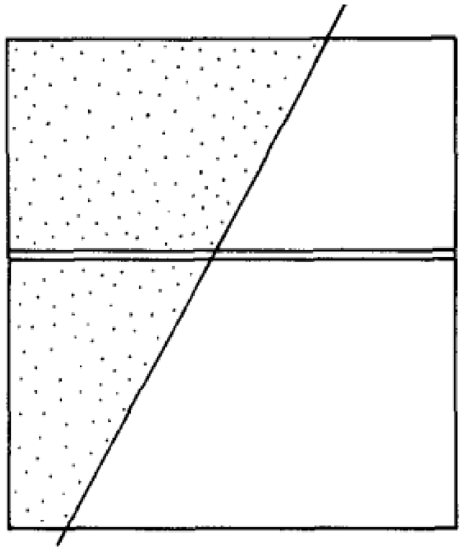
Basic principle of RATS :

The search for a simple statistic which could provide a basis for a thresholding method is based on Absorption edge detection. This detector has the desirable property of yielding the edge magnitude proportional to the contrast between the background and the object independent of the actual edge position and orientation.

Absorption Principle:

It has the property that the sum of the edge magnitudes output by conventional edge operators in the vicinity of an edge and along a line intersecting the edge is constant.

Let us consider a scene segment Containing a boundary between the dark dark background and light object illustrated in Fig.1



Each horizontal scan line can be viewed as

background	D	D	a_1	a_2	a_3	.	.	a_{k-1}	a_k	B	B	object

Where B and D are the luminance of the object and the background respectively. Applying 1×3 edge gradient operator along one scan line, we get

-1	0	1

X-derivative mask

Output of X-derivative mask:

		e_0	e_1	e_2	.	.	.	e_{k-1}	e_k	e_{k+1}		
background	0	$a_1 - D$	$a_2 - D$	$a_3 - a_1$	.	.	.	$a_k - a_{k-2}$	$B - a_{k-1}$	$B - a_k$	0	object

Assumed that B and D do not vary over the image part other than edges.

RATS ALGORITHM:

For Horizontal Edge:

Let e j, j = 1... N be the outputs of the differentiation operator along a horizontal scan line intersecting one vertical edge. Then

$$\sum_{j=1}^{N} |e_j| = 2E.$$

Where E = B-D. Assumed that B and D do not vary over the image.

- Assuming that the total number of horizontal scan lines (n)is equivalent to the number of pixels in each scan line. For whole image, we obtain

$$\sum_{i=1}^{N} \sum_{j=1}^{N} |e_{ij}| = 2nE.$$

- For a complicated shape of an object or several objects may give rise to several vertical edges being intersected by one scan line. We will get

$$\sum_{i=1}^{N} \sum_{j=1}^{N} |e_{ij}| = \sum_{i=1}^{N} 2En_i$$

where ni is the no of vertical edge pixels.

For Vertical Edge:

Applying y-derivative mask we can obtain

$$\sum_{i=1}^{N} \sum_{j=1}^{N} |e_{ij}| = 2nE.$$

Irrespective of the edge directions it makes no difference to the output of the summation operator whether the summation is carried out row-wise or column-wise.

Defining New Parameter Hj:

hj is given by product of grey value multiplied by corresponding magnitudes of the x derivative.

- The sum of grey values each multiplied by corresponding magnitudes of the x derivatives is given by

$$\sum_{j=0}^{k+1} h_j = \sum_{j=0}^{k} \alpha_j(\alpha_{j+1} - \alpha_{j-1}) + \alpha_0(\alpha_1 - \alpha_0) + \alpha_{k+1}(\alpha_{k+1} - \alpha_k)$$

simplifying, we get

$$\sum_{j=1}^{k+1} \mathbf{h}_j = a_{k+1}^2 - a_0^2 = (B+D).E$$

- Let eij be the maximum of the outputs of the x and y gradient masks centered at the (i, j)th pixel.

- The sum of the absolute values of the products hij of eij and the grey level values g,, over the entire image is equal to the contrast E times the sum of the background and object intensities times the number n of edge pixels in the image.

$$\sum_{i=1}^{N} \sum_{j=1}^{N} |h_{ij}| = (B + D)E \cdot n$$

Threshold:

The threshold is given by the ratio of the sum of grey-grad values to the sum of grad values.

$$T = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} |h_{ij}|}{\sum_{i=1}^{N} \sum_{j=1}^{N} |e_{ij}|} = \frac{B + D}{2}$$

Thresholding of Retinal Image:

Vessel Segmentation can be obtained by using multiscale Gabor filters. Thresholding and binarization of the result of vessel detection is a crucial step for further analysis of the characteristics of blood vessels such as thickness and tortuosity.

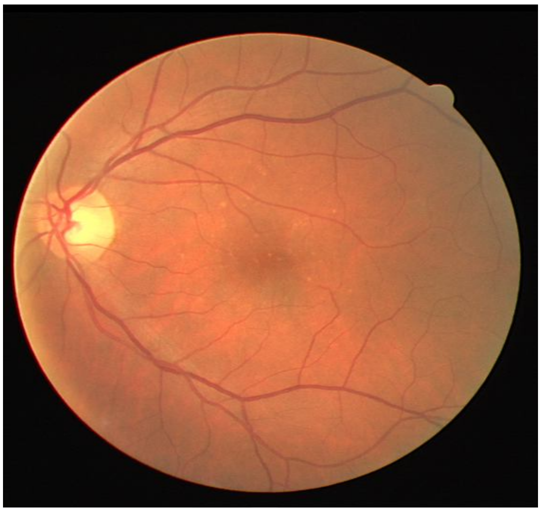
- Multiscale Gabor Filters are used for the detection of blood vessels by considering the fact that blood vessels are elongated, piecewise-linear, or curvilinear structures with a preferred orientation.
- Gabor Filters are sinusoidally modulated Gaussian functions that are suitable for the analysis of oriented structures because they provide optimal localization in both the frequency and space domains. The real Gabor Filter kernel oriented at the angle µ = ¡¼=2 can be represented as

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)\right]\cos(2\pi f_o x)$$

- The value of σx is defined based on τ as $\sigma x = \tau/(2\sqrt{2}\ln 2)$ and $\sigma y = l\sigma x$, where l represents the elongation ofblood vessels. A bank of K Gabor filters may be obtained by rotating the main Gabor filter kernel given in Equation 9 over the range $[-\pi/2, \pi/2]$. For a given pixel, the maximum output value over all K filters is saved as the Gabor magnitude response at that particular pixel; the corresponding angle is saved as the Gabor angle response.

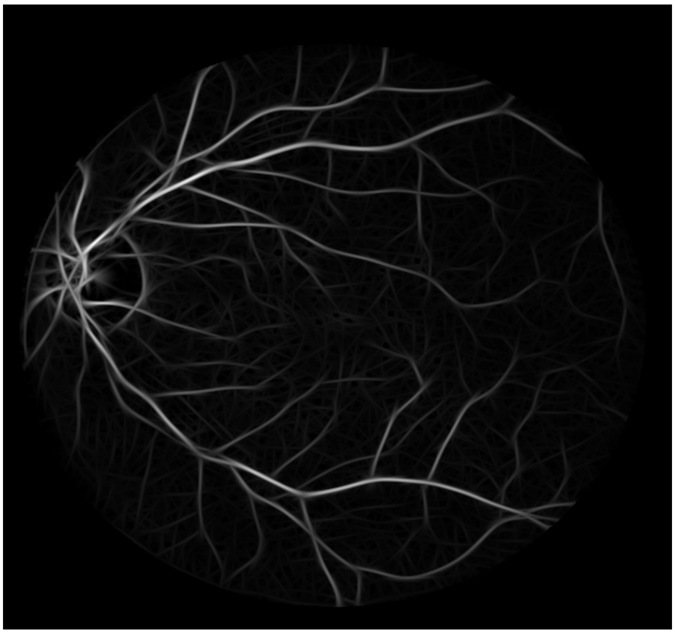
Image 21 of the DRIVE database and its corresponding Gabor response:

For Values of τ = 8 pixels, l= 2.9, and K = 180

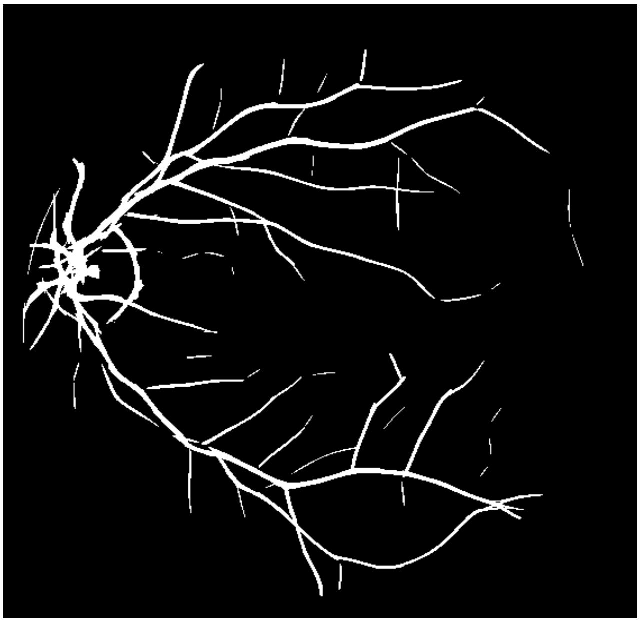


Output Results:

Applying Threshold using RATS Algorithm for the gabor respose image 21 of DRIVE database. We obtained following results

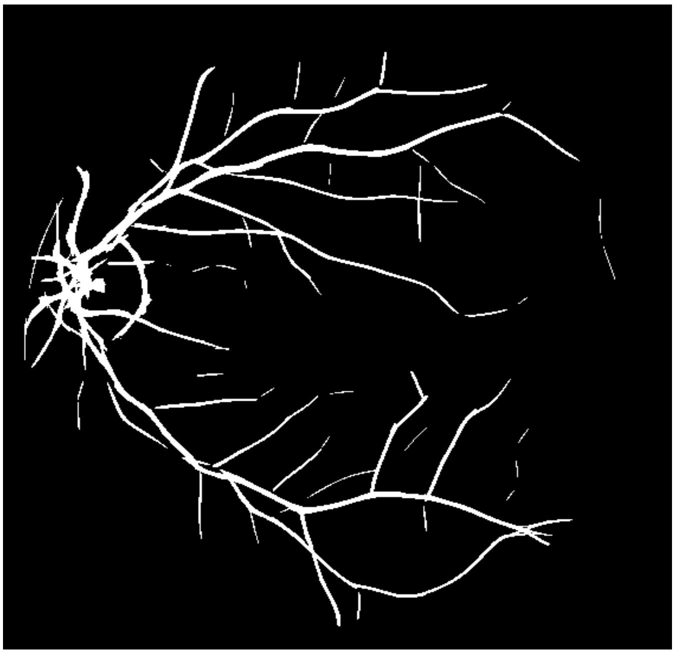


Gabor response image 21 of DRIVE Database

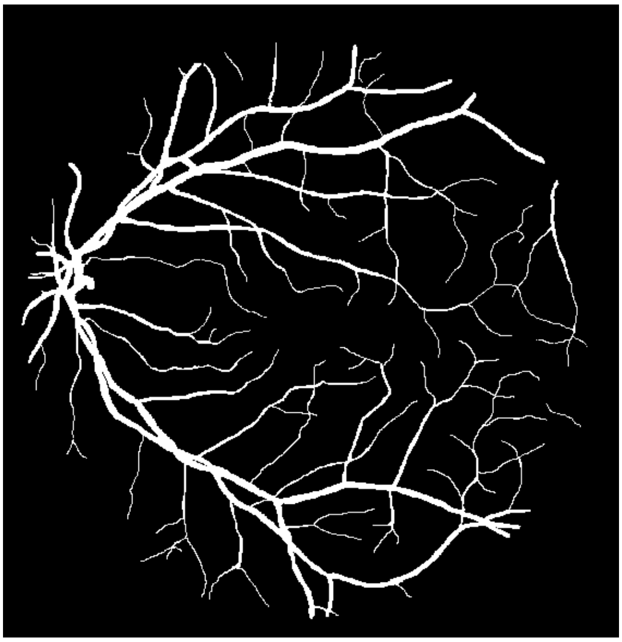


Segmented image using RATS Algorithm

Comparison results :



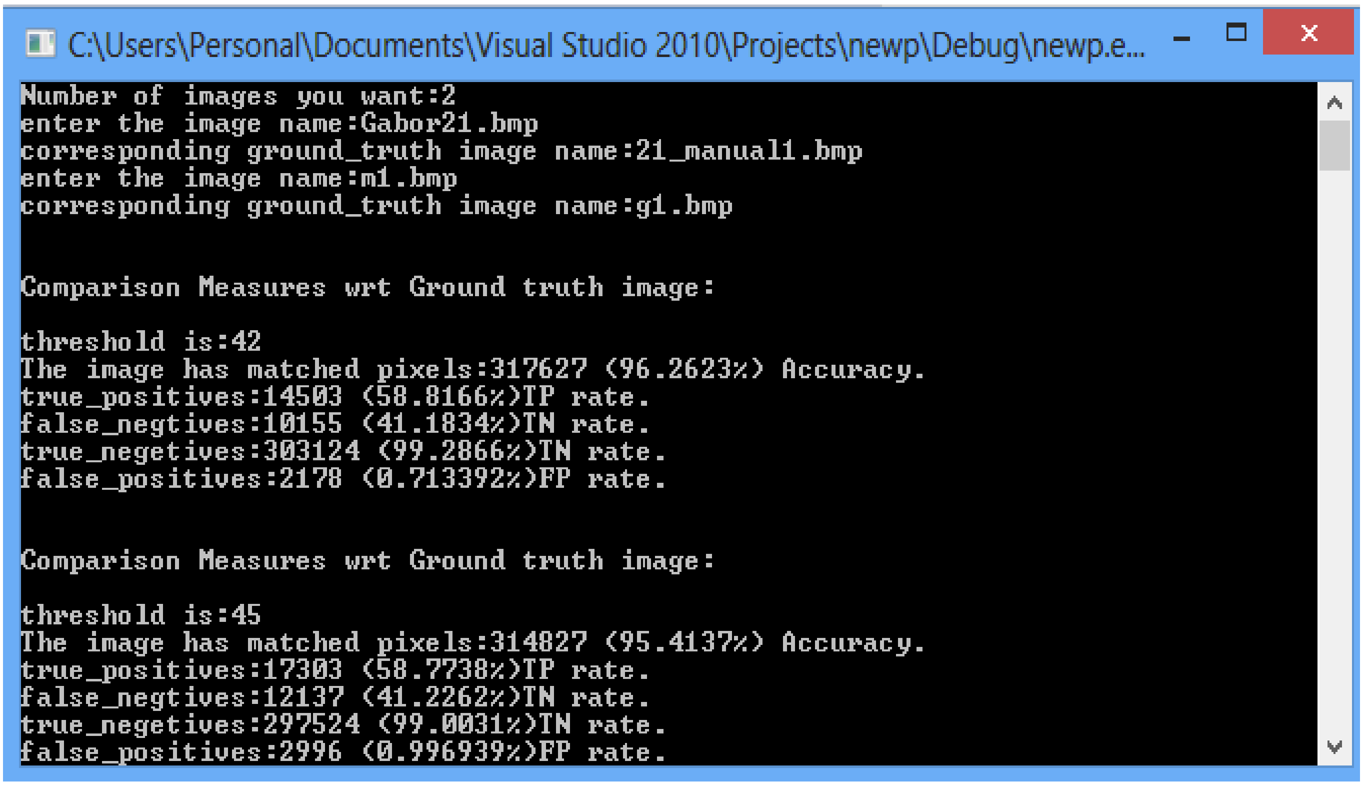
Segmented image



Ground truth

Comparison Measures:

- TP = True Positives. Are how many positive pixels from your ground truth match the segmented image.
- TN = True Negatives. Are how many negative pixels from your ground truth match the segmented image.
- FP = False Positives. Are how many negative pixels from your ground truth match positive pixels from your segmented image.
- FN = False Negatives. Are how many positive pixels from your ground truth match negative pixels from your segmented image.
- TPR = True positives rate. It is a rate that measure how many TP pixels form all positive pixel.. Closer to 100 is better.
- FPR = False Positive rate, It is a rate that measure how many FP pixels from all positive pixels. Closer to 0 is better.



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C:\Users\Personal\Documents\Visual Studio 2010\Projects\newp\Debug\newp.e...
Number of images you want:2
enter the image name:Gabor21.bmp
corresponding ground_truth image name:21_manual1.bmp
enter the image name:m1.bmp
corresponding ground_truth image name:g1.bmp


Comparison Measures wrt Ground truth image:

threshold is:42
The image has matched pixels:317627 (96.2623%) Accuracy.
true_positives:14503 (58.8166%)TP rate.
false_negtives:10155 (41.1834%)TN rate.
true_negetives:303124 (99.2866%)TN rate.
false_positives:2178 (0.713392%)FP rate.


Comparison Measures wrt Ground truth image:

threshold is:45
The image has matched pixels:314827 (95.4137%) Accuracy.
true_positives:17303 (58.7738%)TP rate.
false_negtives:12137 (41.2262%)TN rate.
true_negetives:297524 (99.0031%)TN rate.
false_positives:2996 (0.996939%)FP rate.
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Observation and Analysis:

RATS algorithm is implemented by using simple image statistics. The simple statistics includes applying horizontal and vertical gradient masks. The maximum of these masks multiplied with corresponding gray value of pixel is used for determining threshold.

It is computationally less intensive, as it doesn't include histogram calculation unlike all other thresholding techniques. This method is robust to noise. For non uniform images, this method can be used thresholding after dividing the image into windows for better segmentation.

In this paper, RATS Algorithm is used for blood vessel segmentation of retinal image. Testing this Algorithm with a set of gabor response images, average accuracy of 95% is obtained with respect to their corresponding ground truth images.