Study of Retinal Biometrics with Respect to Peripheral Degeneration with Clinically Significant Features

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ABSTRACT

Retinal biometrics has been very handy in most parts of the world with respect to diabetic retinopathy.

In diabetic retinopathy, the most complicated part comes when patients loose their eye sight. This is called as Macular Degeneration. Macular Degeneration comes in two stages. The first stage is when clinically significant features are present on the retina, the second stage is when non clinically significant features are present on the retina. Clinically significant features are present near the macula which is the center of retina. Non clinical features which are also called artifacts which are distortions on the retina are present on the periphery. In this paper the main focus has been on the clinically significant features. The clinically significant features are micro-aneurysms, hemorrhages and exudates. In this paper the main concentration has been on the degeneration of macula. The macula is the region of illumination on the retina. The extraction of micro-aneurysms has been based on the red component of the retinal image. Similarly the extraction of hemorrhages and exudates has been based on the other color components. The extraction of macula has been based on the texture of retinal images. The goal of this paper is to device a method which constricts the region of the macula depending on high or low intensity regions. Based on this goal , the two main objectives which were defined are fixing the regions of macula and then deciding on which stage of diabetes , the person is in. Lots of research has been done in the area of extracting the basic diabetic features which are based on filters like the gabor filter. The scope in the area of extracting the macula has been very limited because the intensities of the vessels and macula is same in the gray scale image. Therefore in this paper an attempt has been made to extract the macula using textures. The most serious stage of diabetes is blindness where macular degeneration is seen. Keeping in mind the real life threats from macular degeneration, efforts have been made in this paper to correlate biometrics and macular degeneration with respect to retinal images. With respect to classification of retinal images, macular degeneration gives lot of insight into the reasons for blindness of a person.

General Terms g(x,y) as image, theta for angle, x and y for coordinates, sqrt for square root, arctan for calculating inclination.

Keywords Gabor, Biometric, Color, Ridge, Macula, Segmentation.

1. INTRODUCTION

Diabetes is a disease which affects 5 million people a year. This disease has different stages mild, moderate, severe all three being non proliferative and the last one severe proliferative diabetes. In case of severe proliferative diabetes, macular degeneration results. In macular degeneration, the macula begins to degenerate. The macula is the region because of which we are able to see. The center of the macula is fovea because of which we are able to see. In this paper the main concentration is on macular degeneration. To evaluate the features for macular degeneration, first segmentation needs to be done on the retinal images. Segmentation results in the extraction of vessels. In this paper efforts have been made in the direction of peripheral degeneration of retina due to diabetes. To extract the features on the periphery work has been done in the direction of extracting the features which are exudates which doesn't affect the macula. If the exudates affect the macula, macular degeneration results. Efforts have been made to extract the exudates using the RGB color model with different components of colors. This paper is divided into four sections. Section 2 deals with extraction of different features of diabetes using color components. Section 3 deals with Analysis. Section 4 deals with Discussion. Section 5 deals with Conclusion.

2. COLOR COMPONENT EXTRACTION OF DIABETIC FETAURES:

To extract the blood vessels [1], ridge based technique is used. The ridges are areas where local maxima is found out. To find the ridges first the images are smoothened[18] and then the entropies defined and then mask[16] is found out to extract the vessels.

Algorithm ColorComponentExtraction (g(x,y))

\\ x, y are co-ordinates of pixel; g(x,y) is the image.

\\ g_x, g_y are partial differentials w.r.t x and y respectively

\\ theta(x,y) is the angle made by pixel (x,y) with the X-axis.

\\ e(x,y) is an array of pixels whose gray values are greater than or equal to 27

x=1; y=1;

While x<= 576 do

    While y<= 720 do

        g(x, y)=sqrt((g_x(x, y)^2)+(g_y(x, y)^2));

        theta(x, y)=arctan((g_x(x, y))/(g_y(x, y)));

        if g(x, y)>=27 then e(x, y)=g(x, y);

        y=y+1;

    endwhile;

x=x+1;

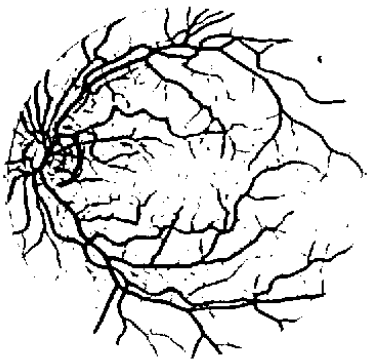endwhile;

The results are shown below:
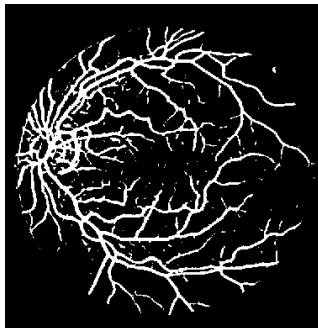

Fig 1(a) Ridge with noise
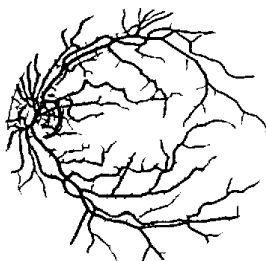

Fig 1(b) (a) in black and white background

Fig 1(c) (a) with reduced entropy
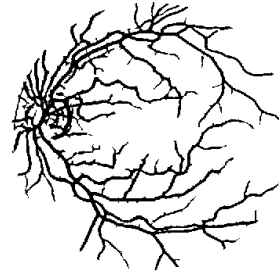
Fig 1(d) (a) with reduced noise

2.1 Extraction of Hard Exudates

The red component [4,5] of the image is used. The intensities of pixels are inverted. Borders are removed using Canny edge [8] method. The holes are filled to calculate micro-aneurysms[15]. The original image is subtracted with the edge detected image to give micro-aneurysms.
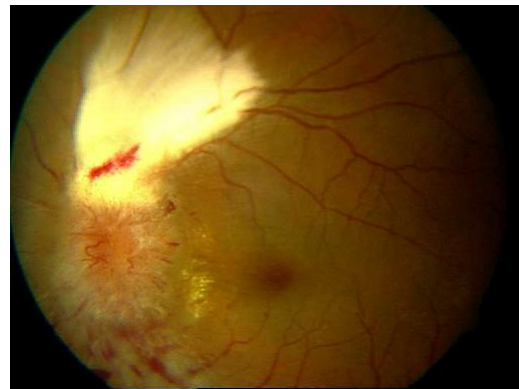
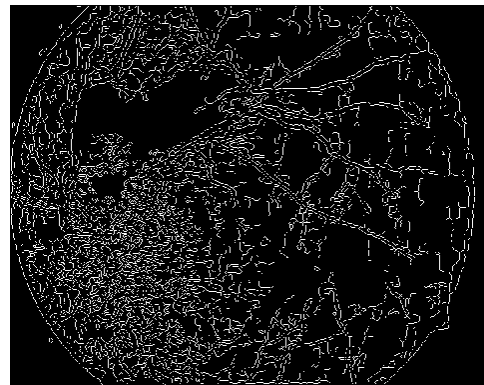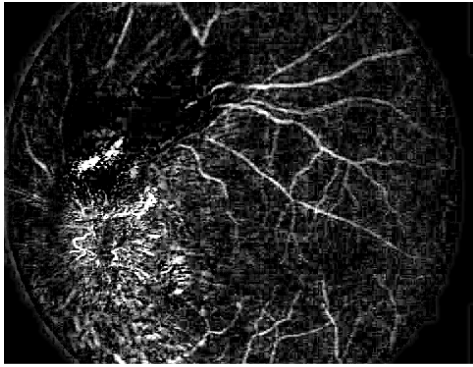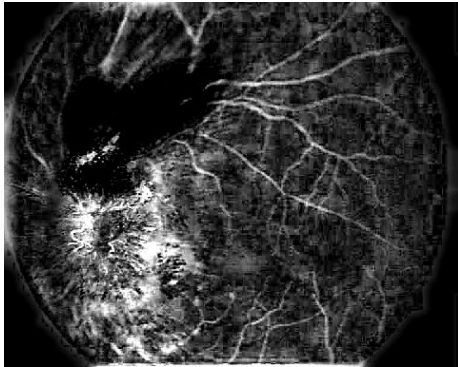

Fig 2 (a): Image showing Exudates.

Fig 2 (b): Shows the segmentation of exudates for the given image.

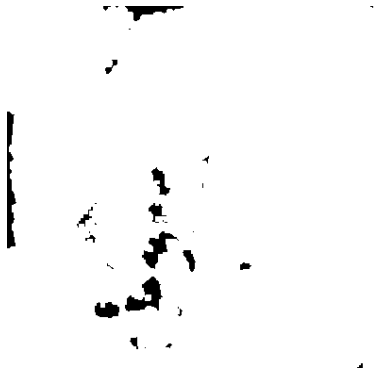## 2.2 Extraction of Hemorrhages

Consider the red component of the image. Invert in intensity. Then use structuring element [9,10] of size 10 and 25. Then fill the holes which gives the hemorrhages.
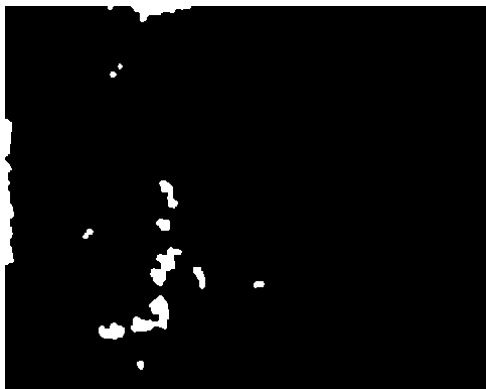
Fig 3 (a): Shows swelling of optical ball

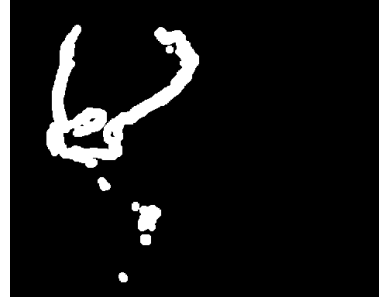**Fig 3 (b): Shows blur in swelling of optical ball**

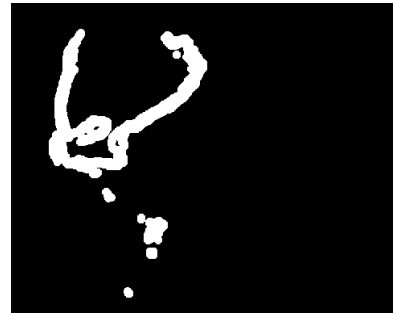**Fig 3 (c): Shows the Hemorrhages in dilated mode**

Fig 3 (d): Shows the Hemorrhages

2.3 Optical ball swelling segmentation

Consider the green component of the image. Invert it in color [12] and then find the canny edges. Then apply structuring element of size 50 to extract the exudates.
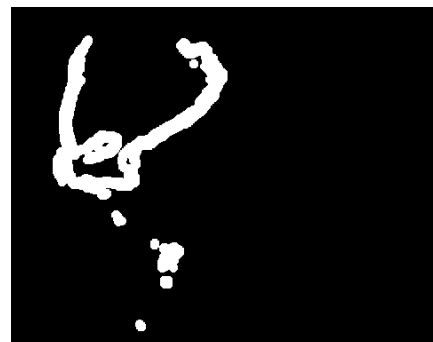

Fig 4 (a): Shows optical ball swelling in dilated mode.

Fig 4 (b): Shows optical ball swelling In erosion mode.

Fig 4 (c): Shows Noise.

Fig 4 (d): Shows disease of optical ball(swelling).

In all the above methods, ridge based method is modified from the equations given by

g_{xx}=[0 -0. 0040 -0. 0060 -0. 0040 0

0 -0. 0058 -0. 0088 -0. 0058 0

0 -0. 0066 -0. 0099 -0. 0066 0

0 -0. 0058 -0. 0088 -0. 0058 0

0 -0. 0040 -0. 0060 -0. 0040 0]

g_{xy}=[-0. 0037 -0. 0027 0 0. 0027 0. 0037

  -0. 0027 -0. 0019 0 0. 0019 0. 0027

   0   0 0 0   0

  0. 0027 0. 0019 0 -0. 0019 -0. 0027

  0. 0037 0. 0027 0 -0. 0027 -0. 0037]

g_{yy}=[0   0   0   0   0

  -0. 0040 -0. 0058 -0. 0066 -0. 0058 -0. 0040

  -0. 0060 -0. 0088 -0. 0099 -0. 0088 -0. 0060

  -0. 0040 -0. 0058 -0. 0066 -0. 0058 -0. 0040

   0   0   0   0   0]

Repeat the below equations for the aspect ratio of image.

alpha(x, y)=sqrt(((I_{xx}(x, y)-I_{yy}(x, y))^2)+(4*(I_{xy}(x, y)^2)));

N(x, y)=sqrt(((I_{yy}(x, y))-(I_{xx}(x, y))+(alph(x, y)))^2+4*(I_{xy}(x, y)^2)); Eq-1

lamplus(x, y)=((I_{xx}(x, y)+I_{yy}(x, y)+alpha(x, y))/2); Eq- 2.

lamminus(x, y)=((I_{xx}(x, y)+I_{yy}(x, y)-alpha(x, y))/2) Eq- 3.

thetplus(x, y)=arctan((I_{yy}(x, y)-I_{xx}(x, y)+alpha(x, y))/(2*I_{xy}(x, y))); Eq -4.

thetminus(x,y)=arctan(((-2)*I_{xy}(x,   y))/(I_{yy}(x,   y)-I_{xx}(x, y)+alpha(x, y))); Eq -5.

Where g_{xx} , g_{xy} , g_{yy} are the gaussian matrices, alpha(x,y), lamplus(x,y), lamminus(x,y), thetplus(x,y) and thetminus(x,y) are normalization and dominant angles respectively.

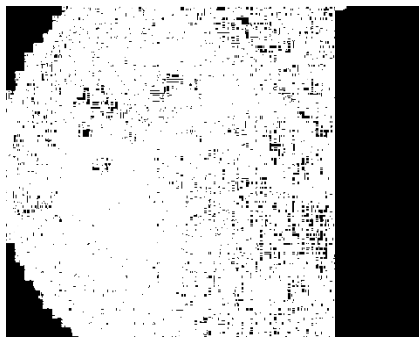In this segmentation technique, salt and pepper noise is introduced into the image.
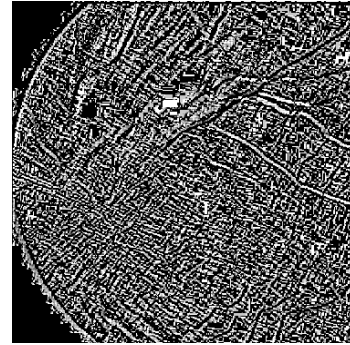

Fig 5 (a): Shows salt and pepper noise

Fig 5 (b): Shows salt and pepper noise with ridges.
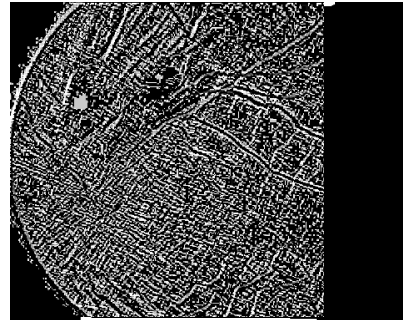
Fig 5 (c)): Shows partially segmented image.
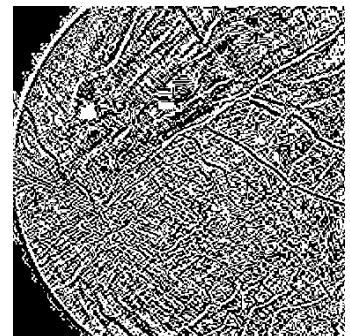
Fig 5 (d): Shows salt and pepper noise with blur ridges.

In the above images we see that salt and pepper noise is introduced uniformly which is not present in the clearlly found vessels.

3. Analysis

From the above methodologies the significant point to be gathered is that segmentation of vessels plays an important role in classification of retinal images. After segmentation is performed, features which correspond to the diabetic ones are gathered. To evaluate the bifurcation points [7], gabor filter [9] is applied in such a way that only the correct points are identified and the points where there are breaks are nullified. The form of gabor filter is as follows:

$$G\left(S_x, S_y, U, V\right) = \left(\frac{1}{2\pi S_x S_y}\right) * e^{-\frac{1}{2}\left[\left(\frac{x}{S_x}\right)^2 + \left(\frac{y}{S_y}\right)^2\right] + 2\pi i(Ux+Vy)}$$

Eq- 6.

where $U = 0.25 + 2^i \dfrac{N_c}{4}$, $V = 0.25 - 2^i \dfrac{N_c}{4}$

and i = 1, 2, ..., $\log N_c/8$, N_c is width of the image.

and Sx, Sy are standard deviations in x and y directions and U and V are frequencies among x and y dirctions. Results are shown in Fig 5(A, B, C). And x=x1cosA+y1sinA and y=x2cosA+y2sinA. Here A and the frequencies are the chosen parameters.

Fig 6 (a): Shows Bifurcation points.

Fig 6 (b):Shows the superimposition of bifurcation points.

From the above images, the most important fact that is gathered is that diabetes comes in the way of finding the exact bifurcation points.

Decision trees and KNN [11] is used for classification of images into normal and abnormal images. When decision trees were used a classification accuracy of 84 % was achieved and with KNN a classification accuracy of 71 % was achieved. The size of training data set was 350 and testing data set was 150. It was also seen that when peripheral degeneration was seen, this paper has given better results when compared to macular degeneration. Rajendra Acharya et-al has got a classification accuracy of 92. 3% when he used Support Vector Machines. The advantage of decision trees is that those regions are spotted which has least entropy. In KNN, first we take the four classes, mild, moderate, severe

non proliferative, severe proliferative, take an element x, calculate the statistical significance of the four classes, calculate the euclidean distance of x from every point of the four classes, again calculate the statistical significance of the four classes, now with element x. The class which is most statistically significant, x belongs to that class.

4. Discussion

In this paper it has been noted that peripheral degeneration gives better results with respect to blindness as peripheral degeneration has something to do with peripheral neuropathy. Thickening of vessels, hemorrhages on sclera are the symptoms to decide on that. But still it is to be seen whether peripheral degeneration wins over macular degeneration for blindness.
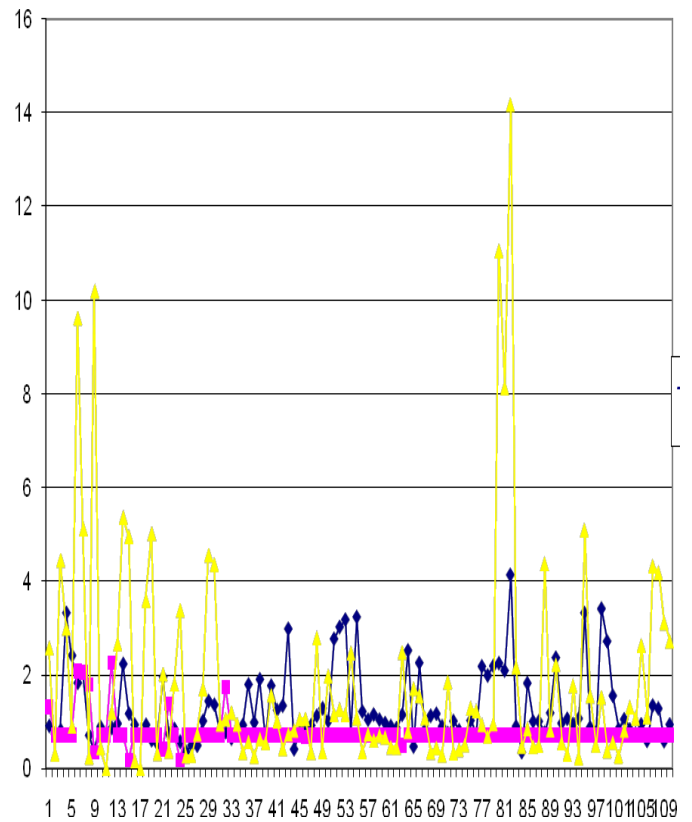

Fig 7: Graph of Image index(X-axis) vs Area (Y-axis)

5 Conclusions

From the above graph we infer that peripheral degeneration has the most effect on the body, more than macular degeneration. The yellow curve shows peripheral degeneration, blue line shows other eye diseases, pink line shows artifacts. From the paper we also infer that Diabetic Retinopathy can be a precursor for Diabetic Neuropathy. From the graph the abnormal patterns are occupying large amount of area when compared to normal ones and artifacts. This is quantified for abnormal patterns by the yellow line, for normal patterns by the pink line and artifact patterns by the blue line in the graph. Moreover greater accuracies were achieved for correct misclassification, where we got a higher

retinal disease when compared to clinical ones, while the user inputs are matched with the database.

6. References

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