

STUDY OF IMAGE SEGMENTATION TECHNIQUES ON RETINAL IMAGES FOR HEALTH CARE MANAGEMENT WITH FAST COMPUTING

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Abstract

The role of segmentation in image processing is to separate foreground from background. In this process, the features become clearly visible when appropriate filters are applied on the image. In this paper emphasis has been laid on segmentation of biometric retinal images to filter out the vessels explicitly for evaluating the bifurcation points and features for diabetic retinopathy. Segmentation on images is performed by calculating ridges or morphology. Ridges are those areas in the images where there is sharp contrast in features. Morphology targets the features using structuring elements. Structuring elements are of different shapes like disk, line which is used for extracting features of those shapes. When segmentation was performed on retinal images problems were encountered during image pre-processing stage. Also edge detection techniques have been deployed to find out the contours of the retinal images. After the segmentation has been performed, it has been seen that artifacts of the retinal images have been minimal when ridge based segmentation technique was deployed. In the field of Health Care Management, image segmentation has an important role to play as it determines whether a person is normal or having any disease specially diabetes. During the process of segmentation, diseased features are classified as diseased one's or artifacts. The problem comes when artifacts are classified as diseased ones. This results in misclassification which has been discussed in the analysis Section. We have achieved fast computing with better performance, in terms of speed for non-repeating features, when compared to repeating features.

Keywords:

Pupil, Sclera, Limbus, Diabetes, Micro- Aneurysms, Exudates, Gabor, Log, Bifurcation, Sobel, Gray Level, Decision Tree, KNN

1. INTRODUCTION

The human eye is made up of sclera, limbus, pupil and retina. Sclera is the white portion of the iris. Sclera surrounds the pupil. The retina is made up of optical ball, fovea and the vessels. The vessels give lot of information like the bifurcation points, optical ball and fovea. The fovea is the illumination region of retina. The bifurcation points branch the vessels into finer pieces. In this paper an innovative method to extract the vessels has been proposed using the ridge based segmentation technique. Ridge based segmentation technique works well with biometrics where the color information is of lesser intensity. For example with faces for generating templates of the same individual, ridge based segmentation gives good results.

Over the years it has been seen that biometric information fails to capture details of people who replicate themselves using some or the other medical techniques. This biometric information is related to fingerprints, faces, handwriting. But if retina is considered, then the information gathered about any individual is unique because retinal [1] data cannot be duplicated from one person to another person. Therefore if retina is considered to be a superior biometric then segmentation of the

images have to be done, keeping in mind the artifacts of the images. Artifacts are distortions in the images. These distortions look to be features which contribute to classification but they don't contribute to the anatomy and physiology of retina.

Researches in the modern days have gone for morphology as a replacement tool for segmentation. In this paper a step by step procedure has been shown for segmentation of retinal images. Section 2 deals with Laplacian of Gaussian filter to detect the blood vessels. Section 3 deals with detection of bifurcation points using Laplacian of Gaussian filter. Section 4 deals with detection of blood vessels using morphology. Section 5 deals with detection of bifurcation points using Gabor [4], [5], [6] filter. Section 6 deals with segmentation of vessels using Ridge based segmentation technique.

2. DETECTION OF BLOOD VESSELS USING LAPLACIAN OF GAUSSIAN FILTER

The vessels are extracted using local maxima and local minima [11]. For example the local maxima for 16 16 17 is 16 17 17.

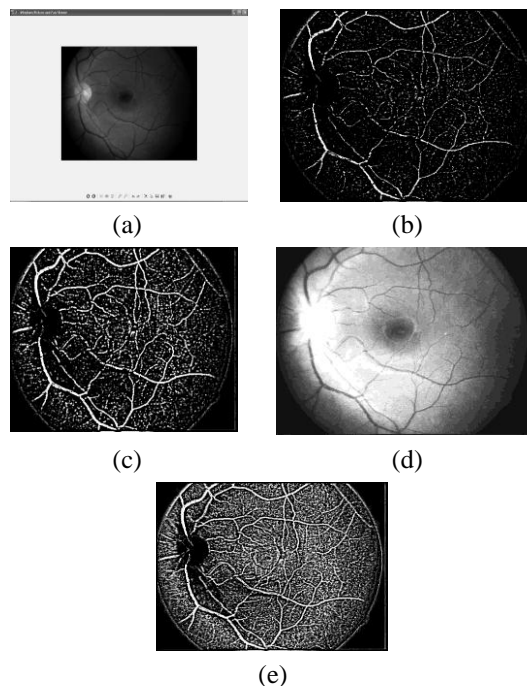


Fig.1. Effect of LOG on a retinal image

The LOG [19] function as shown in Eqs.(1), (2) and (3),

$$g(x, y, t) = \frac{1}{2\pi^2} e^{-\frac{(x^2+y^2)}{2t^2}} \quad (1)$$

$$\Rightarrow L(x, y, t) = g(x, y, t) * f(x, y) \quad (2)$$

$$\Rightarrow \text{Laplacian Operator} = \nabla^2 L = L_{xx} + L_{yy} \quad (3)$$

where, $f(x, y)$ is the image. The results are shown in Fig.1.

3. DETECTION OF BIFURCATION POINTS USING LAPLACIAN OF GAUSSIAN FILTER

Here first the R,G, B [2,3] components are extracted from the image. After performing the histogram equalization, Laplacian of Gaussian filter is applied on the image. A structuring element disk of size 1 is applied and subsequently the image is eroded and dilated. The structuring element is so chosen that ‘Y’ [7] shapes are got from the retinal images. The maximum and minimum of pixel intensities are evaluated and these values are subtracted to get the subsequent edges. Noise is removed using two straight lines as structuring elements. Using the Painter’s algorithm wherein we take the binary format of the image, and where ever we have higher values of pixels for the binary image(white),we replace them with low values of pixels (black).Thus superimposition of bifurcation points is obtained over the original image. The steps for evaluating the bifurcation points are given as follows:

- a) Get R, G, B component of the images.
- b) Perform Histogram Equalization [11] of the image.
- c) Apply Laplacian [9], [10] of Gaussian [8] on the preprocessed image.
- d) Take a structuring element disk of size 1 and erode and dilate the image.
- e) Find difference of Maximum and Minimum [11] of each pixel.
- f) Find edges using Sobel Filter [11].
- g) Use Structuring elements which are two lines to remove the noise.
- h) Find negation of the image.

The results are shown in Fig.2.

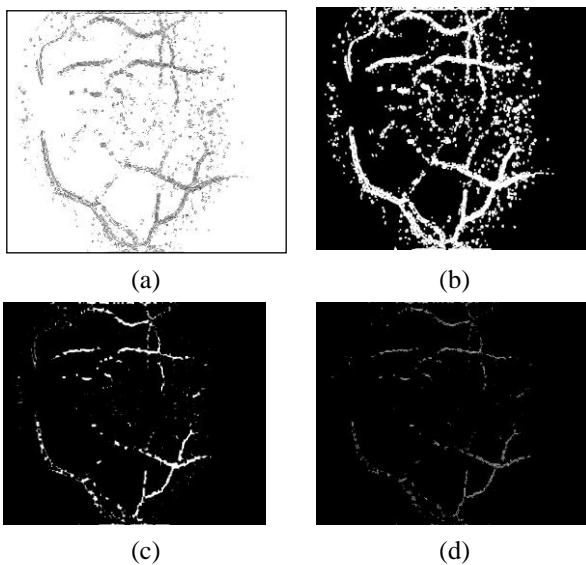


Fig.2. Extraction of Bifurcation points using LOG filter

4. DETECTION OF BLOOD VESSELS USING MORPHOLOGY

Here we first apply a structuring element disk of size 6 to avoid artifacts and then subsequently dilation and erosion of the image is performed.

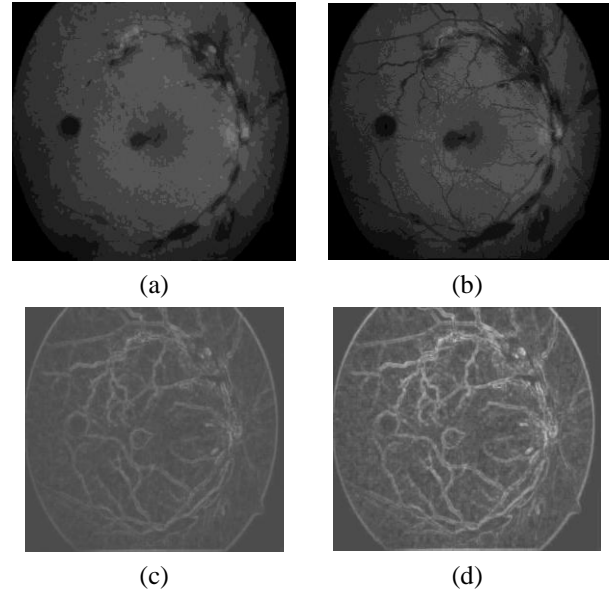


Fig.3. Residue image after Morphology

The residue [12] is calculated as the subtraction of dilated [14] minus the eroded image. The areas where the residue is less than five, we display the image.

The steps for morphology are given below:

- a) Use a structuring element [15] square of size 6.
- b) Dilate and Erode [17] the image using the structuring element.
- c) Calculate Residue as (Dilated – Eroded) image.
- d) For all the pixels which have residue less than five, display the image.

The results are shown in Fig.3.

5. DETECTION OF BIFURCATION POINTS USING GABOR FILTER

After reading the image, it is converted into gray scale. Then the maximum minus the minimum of pixels is calculated to find the edges. Then we use a line structuring element to dilate the image. Finally convolve the image with a 3*3 matrix such that the Gabor matrix matches [7, 16] the frequencies of the image. If a bigger size matrix is used, diabetic features can be found out. The equation for Gabor filter are given as follows,

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

where, $U = 0.25 + 2i^{N_c/4}$, $V = 0.25 - 2i^{N_c/4}$, $i = 1, 2, \dots, N_c/8$, N_c is width of the image, and S_x, S_y are standard

deviations in x and y directions and U and V are frequencies among x and y directions. Results are shown in Fig 4. And $x=x_1\cos A+y_1\sin A$ and $y=x_2\cos A+y_2\sin A$. Here A is the angle for chosen frequencies. The steps for Gabor filter are as follows:

- a) Read the image.
- b) Convert the image to black and white.
- c) Find Maximum – Minimum [7] for each pixel.
- d) Find edge of the image using Sobel operator [7].
- e) Using structuring element as line, dilate the image.
- f) Convolve the image with a three by three matrix which is of shape ‘Y’.
- g) Mark those points.

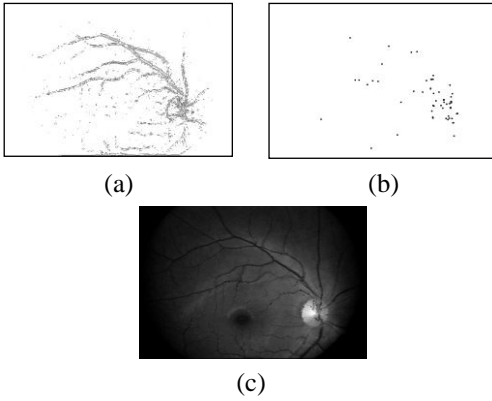


Fig.4. Extraction of Bifurcation points using Gabor filter

6. DETECTION OF BLOOD VESSELS USING RIDGE BASED SEGMENTATION

The ridge based segmentation technique uses the scaling factor and then the normalization factor [7] is defined using the scaling factor. The dominant angles are calculated to project the segmented image. The equations for scaling factor and normalization are as follows, as shown in Eq.(4) and Eq.(5) [13], [18]:

for $x < -1$ to 565 do

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

for $y < -1$ to 565 do

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

(Eq-4)(Calculates Scaling Factor)

$$N(x, y) = \sqrt{((I_{yy}(x, y) - I_{xx}(x, y)) + (\alpha(x, y)))^2 + 4(I_{xy}(x, y))^2}$$

(Eq-5)(Performs Normalisation)

end

end

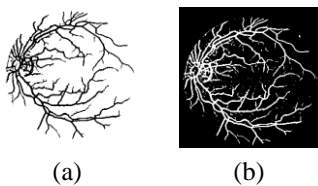


Fig.5. A fully segmented retinal image (Original image from Fig.1)

7. ANALYSIS

In this paper decision tree and k -nearest neighbor methods have been used to classify the images into normal or abnormal retinal patterns based on artifacts and diseased features like the diabetic features.

In both the methods, levels in the tree are reduced, to make the computations fast, in the sense that, entropy is reduced to zero at the earliest level. In the method of decision trees, the entropy is considered and when the features are non-repeating in a group where the contribution of white pixels is same, misclassification happens.

In case of k -nearest neighbor, statistical significance is calculated, Euclidean distances amongst features is calculated, new statistical significance is calculated to prove, to which set the element belongs to. The percentage accuracies are given below in the table.

Table.1. Non-repeating features classification accuracies

Non Diseased	Diseased
86%(Decision tree), 84%(KNN)	74%(Decision tree), 71%(KNN)

Table.1 is for non-repeating features, i.e. the features are distinct. The percentage accuracies will reduce for repeating features, which implies that the number of levels in the tree will increase, and the complexity of the algorithm for repeating features is $O(n^2)$ for repeating features, as shown in Table.2.

Table.2. Repeating features classification accuracies

Non Diseased	Diseased
49%(Decision tree), 45.5%(KNN)	43%(Decision tree), 41%(KNN)

From the table it is clear that when an artifact is found we get better results for classification using decision tree and KNN. When diseased features are present, chances for misclassification are more as artifacts and diseased features have the same shapes but not color parameters. So it is very apparent that when diseased features have to be classified, better methods have to be incorporated so that misclassification rates reduce. It has also been seen in this paper that the features selected are statistically significant.

The method of segmentation does not take into account the color information of the images, where as if the red, green and blue components are taken into consideration, better results are obtained as the color information helps in extracting features like vessels or exudates in the case of diabetes. There are some interesting observations seen in this paper.

Section 2 shows extraction of features like vessels using LOG filter. Section 3 shows extraction of features like the bifurcation points using LOG filter. But LOG filter leaves a lot of blur in the images, so the resulting output is not clear. Section 4 shows extraction of vessels using morphology and we see the diseased features in the resulting output. Section 5 shows the extraction of bifurcation points using Gabor filter. Section 6 shows the fully segmented image. In all these sections, a logical conclusion is made that the distance parameter using Gabor filter has no effect to determine whether a feature is artifact or diseased.

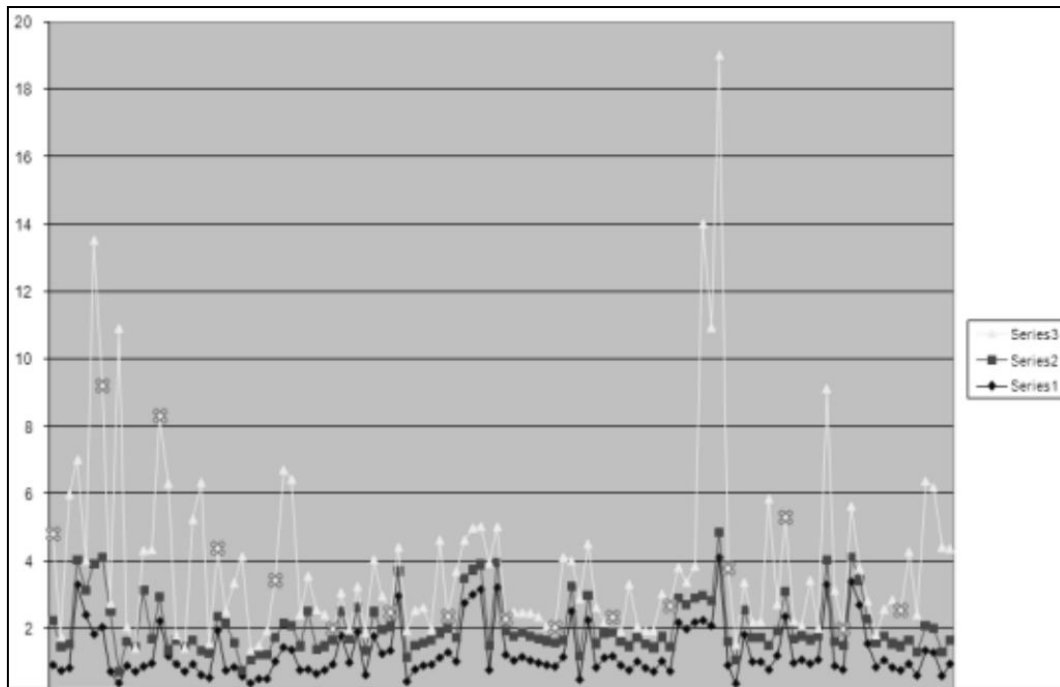


Fig.6. Graph for artifacts (gray and black) and diseased features (white)

So if retinal patterns are considered as biometrics, only the artifacts or diseased feature can determine whether a retinal pattern is normal or abnormal. The graph in Fig.6 the white curve shows the images as diseased with, gray curve shows artifacts and black curve shows the normal retinal patterns. On the x -axis are the images and on the y -axis is the contribution in terms of number of white pixels in the artifacts and the diseased patterns. In this paper, Chernoff bound has been used and the probability of error is less than or equal to 0.10719, that is chance of a misclassification is 10%.

8. CONCLUSION

In this paper segmentation of retinal images gives lot of insight into the extraction of artifacts and diseased features of retina specially the diabetic features and it has been seen through the classification methods that images with artifacts only gives good classification accuracy when compared with those with diseased features because artifacts and diseased features have different styles of extraction.

Nevertheless using better image processing techniques we can classify different diseases like hypertension, glaucoma and many other retinal disorders, like diabetic retinopathy in medical science and diabetic uropathy and diabetic neuropathy where in the kidneys and the nervous system gets affected.

But in this paper the main concentration has been on general classification into normal and abnormal patterns. More work can be done in specific diseases where in clearly it can be understood what is the difference between artifact, micro-aneurysms, hemorrhages, exudates, where micro-aneurysms, hemorrhages, exudates are diabetic features. Likewise there are different sets of features for glaucoma, hypertension and other diseases. We conclude that, for non-repeating features, performance of our

method is better, in terms of speed, when compared to repeating features.

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