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FEATURE EXTRACTION AND SEGMENTATION OF RNFL LAYER FROM SDOCT RETINAL IMAGES FOR THE DIAGNOSIS OF DIABETIC RETINOPATHY

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ABSTRACT – Optical Coherence Tomography (OCT) is a non-contact medical imaging technology similar to ultrasound. With OCT, reflected light is used to produce detailed cross-sectional and 3D images of the eye. The Spectral domain OCT (SDOCT) uses a significantly faster, non-mechanical technology which simultaneously measures multiple wavelengths of reflected light across a spectrum, hence the name spectral-domain. Diabetic retinopathy is the most common diabetic eye disease and a leading cause of blindness in adults. It is caused by changes in the blood vessels of the retina. In this proposed work, detection of boundaries is carried out by a two step process viz., edge detection followed by axial gradient calculation. Canny edge detector is used to detect the edges by looking for the local maxima of the gradient of the input image. It calculates the gradient using the derivative of the Gaussian filter. The Canny method uses two thresholds to detect strong and weak edges. It includes the weak edges in the output only if they are connected to strong edges. As a result, the method is more robust to noise, and more likely to detect true weak edges. Following this Retinal Nerve Fiber Layer is segmented and the statistical features are extracted to classify normal and abnormal images

KEYWORDS: Spectral domain optical coherence tomography (SDOCT), Diabetic retinopathy, Retinal layers, Canny edge detector, Micro aneurysm.

I. INTRODUCTION

Diabetes, often referred to by doctors as diabetes mellitus, describes a group of metabolic diseases in which the person has high blood glucose (blood sugar), either because insulin production is inadequate, or because the body's cells do not respond properly to insulin, or both. Patients with high blood sugar will typically experience polyuria (frequent urination), they will become increasingly thirsty (polydipsia) and hungry (polyphagia).

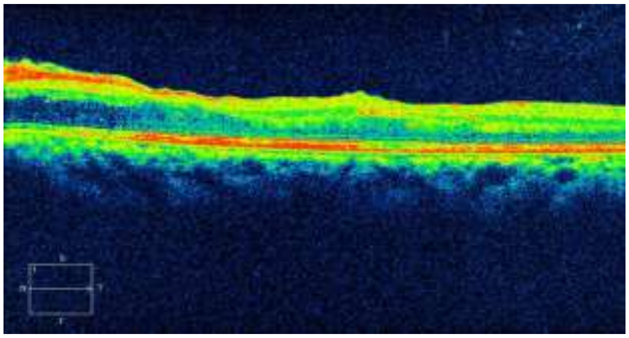

Figure 1.1: SDOCT image with Diabetic Retinopathy

Diabetic retinopathy, also known as diabetic eye disease, occurs when damage occurs to the retina due to uncontrolled diabetes. It can eventually lead to blindness [1]. It is an ocular manifestation of diabetes, a systemic disease, which affects up to 80 percent of all patients who have had diabetes for 10 years or more. Despite these intimidating statistics, research indicates that at least 90% of these new cases could be reduced if there were proper and vigilant treatment and monitoring of the eyes. The longer a person has diabetes, the higher his or her chances of developing diabetic retinopathy[2]. Each year diabetic retinopathy accounts for 12% of all new cases of blindness [3]. It is also the leading cause of blindness for people aged 20 to 64 years.

***Optical coherence tomography (OCT)*:** This is an optical imaging modality based upon interference, and analogous to ultrasound. It produces cross-sectional images of the retina (B-scans) which can be used to measure the thickness of the retina and to resolve its major layers, allowing the observation of swelling [4].

Several studies have been performed to assess the diagnostic capability of SD-OCT in perimetric glaucoma [5]. One representative study compared the diagnostic capability of SD-OCT to TD-OCT RNFL thickness scans in subjects with early and moderate glaucoma as well as normal age-matched subjects [6]. When using the average RNFL thickness at the 5% level compared to the normative database (yellow coloring on RNFL deviation map), SD-OCT had a sensitivity of 83% and a specificity of 88% compared to 80% and 94% respectively for TDOCT. When using the average RNFL thickness at the 1% level (red coloring on RNFL deviation map), the specificity for both SDOCT and TDOCT was 100% but the sensitivity was only 65% in SDOCT and 61% in TDOCT. ONH parameters have also been found to have excellent ability to discriminate between normal eyes and eyes with even mild glaucoma. These ONH parameters were found to be as good as RNFL thickness parameters in diagnosing glaucoma. Similarly, GCA parameters have been found to be comparable to ONH and RNFL parameters [7].

The parameters found to be most diagnostically useful are minimum, inferotemporal sector, average, superotemporal sector, and inferior sector ganglion cell complex thickness [7]. It is well known that significant structural RNFL loss occurs prior to the development of functional visual field loss. In such preperimetric disease, SDOCT RNFL is especially useful in helping to diagnose glaucoma prior to the onset of visual field loss [8].In the presence of perimetric disease, finding RNFL bundle loss on SD-OCT with a corresponding abnormality in the visual field served by those retinal ganglion cells can help confirm the diagnosis of glaucoma.

II. MATERIALS AND METHODS

MATLAB stands as an interactive environment for numerical computation, visualization, and programming. MATLAB can be used to analyze data, develop algorithms, and create models and applications. This helps to reach a solution faster than with spreadsheets or traditional programming languages, such as C/C++ or Java. MATLAB is used for a range of applications, including signal processing and communications, image and video processing, control systems, test and measurement, computational finance, and computational biology.

Edge detection, especially step edge detection has been widely applied in various computer vision systems, which is an important technique to extract useful structural information from different vision objects and dramatically reduce the amount of data to be processed.

The general criteria for edge detection includes

1. Detection of edge with low error rate, which means that the detection should accurately catch as many edges shown in the image as possible
2. The edge point detected from the operator should accurately localize on the center of the edge.
3. A given edge in the image should only be marked once, and where possible, image noise should not create false edges.

Steps followed in Canny Edge Detection Algorithm

The Process of Canny edge detection algorithm can be broken down to 5 different steps:

1. Apply Gaussian filter to smooth the image in order to remove the noise
2. Find the intensity gradients of the image
3. Apply non-maximum suppression to get rid of spurious response to edge detection
4. Apply double threshold to determine potential edges
5. Track edge by hysteresis: Finalize the detection of edges by suppressing all the other edges that are weak and not connected to strong edges.

Gaussian Filter

Since all edge detection results are easily affected by image noise, it is essential to filter out the noise to prevent false detection caused by noise. To smooth the image, a Gaussian filter is applied to convolve with the image. This step will slightly smooth the image to reduce the effects of obvious noise on the edge detector. It is important to understand that the selection of the size of the Gaussian kernel will affect the performance of the detector. The larger the size is, the lower the detector's sensitivity to noise. Additionally, the localization error to detect the edge will slightly increase with the increase of the Gaussian filter kernel size. A 5×5 is a good size for most cases, but this will also vary depending on specific situations.

Finding the Intensity Gradient of the Image

An edge in an image may point in a variety of directions, so the canny algorithm uses four filters to detect horizontal, vertical and diagonal edges in the blurred image. The edge detection operator (Roberts, Prewitt, Sobel for example) returns a value for the first derivative in the horizontal direction (G_x) and the vertical direction (G_y). From this the edge gradient and direction can be determined:

$$G = \sqrt{Gx^2 + Gy^2} \qquad (2.1)$$

$$\theta = a\ \tan 2(G_x, G_y) \qquad (2.2)$$

where G can be computed using the hypot function and atan2 is the arctangent function with two arguments. The edge direction angle is rounded to one of four angles representing vertical, horizontal and the two diagonals (0°, 45°, 90° and 135° for example). An edge direction falling in each color region will be set to a specific angle values, for example alpha lying in yellow region (0° to 22.5° and 157.5° to 180°) will be set to 0°.

Non-Maximum Suppression

Non-maximum suppression is an edge thinning technique. Non-Maximum suppression is applied to "thin" the edge. After applying gradient calculation, the edge extracted from the gradient value is still quite blurred.

Double Threshold

After application of non-maximum suppression, the edge pixels are quite accurate to present the real edge. However, there are still some edge pixels at this point caused by noise and color variation. In order to get rid of the spurious responses from these bothering factors, it is essential to filter out the edge pixel with the weak gradient value and preserve the edge with the high gradient value [9]. Thus two threshold values are set to clarify the different types of edge pixels, one is called high threshold value and the other is called the low threshold value. If the edge pixel's gradient value is higher than the high threshold value, they are marked as strong edge pixels. If the edge pixel's gradient value is smaller than the high threshold value and larger than the low threshold value, they are marked as weak edge pixels. If the pixel value is smaller than the low threshold value, they will be suppressed. The two threshold values are empirically determined values, which will need to be defined when applying to different images.

Edge Tracking by Hysteresis

So far, the strong edge pixels should certainly be involved in the final edge image, as they are extracted from the true edges in the image. However, there will be some debate on the weak edge pixels, as these pixels can either be extracted from the true edge, or the noise/color variations. To achieve an accurate result, the weak edges caused from the latter reasons should be removed. The criteria to determine which case does the weak edge belongs to is that, usually the weak edge pixel caused from true edges will be connected to the strong edge pixel. To track the edge connection, Binary Large Object-analysis is applied by looking at a weak edge pixel and its 8-connected neighborhood pixels. As long as there is one strong edge pixel is involved in the BLOB, that weak edge point can be identified as one that should be preserved [11].

Image Gradient

An **image gradient** is a directional change in the intensity or color in an image. Image gradients may be used to extract information from images. Image gradients can be used to extract information from images [12]. **Gradient images** are created from the original image for this purpose. Each pixel of a gradient image measures the change in intensity of that same point in the original image, in a given direction.. These gradients are less susceptible to lighting and camera changes, so matching errors are reduced [13].

III. RESULTS AND DISCUSSION

The original SDOCT image being considered is displayed below.

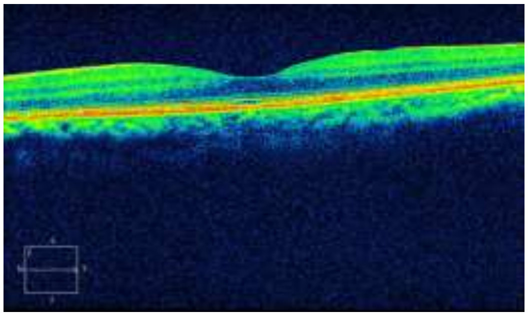

Fig 4.1: SDOCT Image

The image is being blurred and the noises are removed after performing Gaussian filter operation. The image is displayed below.

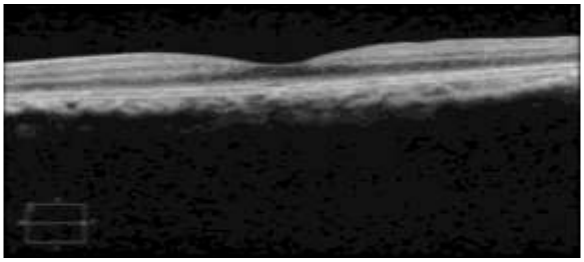

Fig 4.2 Filtered Image

The resultant images after convolution with horizontal and vertical filter is displayed below.

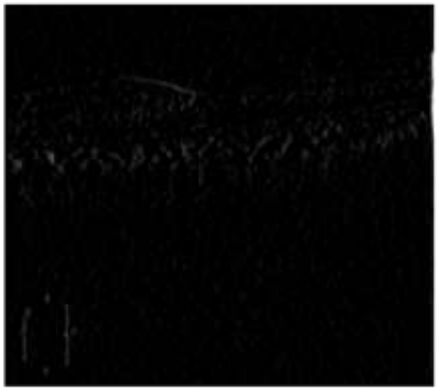

Figure 4.3: Image after the application of horizontal filter

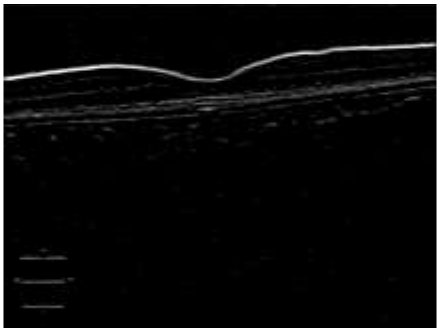

Figure 4.4: Image after the application of vertical filter

Adjustments for directions are made to nearest 0, 45, 90, or 135 degree and the result is displayed as shown below

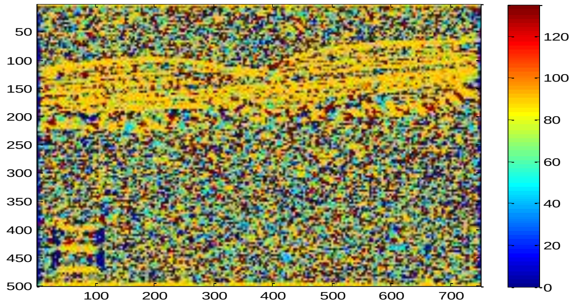

Figure 4.5: Image after adjustments of directions

The image after Non-maximal suppression is shown as below.

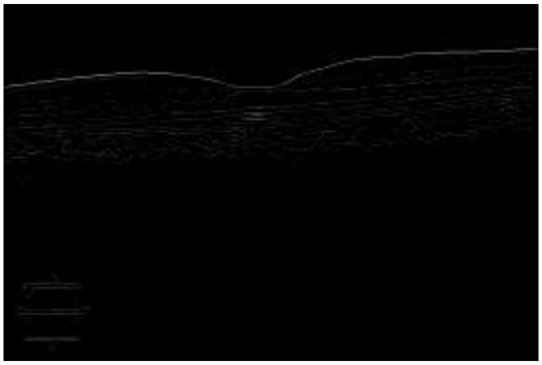

Figure 4.6: Image after Non-maximal suppression

The thresholds for edge detection are extracted from the image. The final image after hysteresis thresholding is displayed below.

Figure 4.7: Edge detected image

The axial gradient of the image is obtained and displayed as shown below.

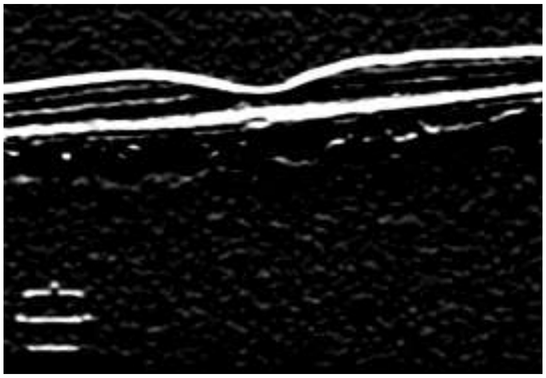

Figure 4.8: Axial gradient of the image

The required complex containing the GCL+IPL layer is obtained and the statistical texture features are extracted.

Figure 4.9:The extracted complex

EXTRACTED FEATURES:

Skewness:
It is the measurement of inequality of the intensity level distribution about the mean. It can be both positive and negative.

Kurtosis:
It is used to measure the peak of the distribution of the intensity values around the mean.

Entropy:
The entropy measures the randomness of the distribution of coefficients values over the intensity levels.

Energy:
The energy feature measures the uniformity of the intensity level distribution.

IV.CONCLUSION AND FUTURE WORK

CONCLUSION

The resultant images are obtained by the sequential steps including filtration, convolution with horizontal and vertical filter, adjustments of directions, Non-maximal suppression followed by the detection of edges. The directional axial gradient of the image is calculated using appropriate Gaussian kernel. The features are extracted from the obtained complex for classification.

FUTURE WORK

Linear and Non linear classification has to be done for the analysis of data and for the detection of abnormality and thus leading to the classification of diabetic retinopathy at initial stage.

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