REPORT

ON

DETECTION OF INTRA-RETINAL HARD EXUDATE IN EYES BY OPTICAL COHERENCE TOMOGRAPHY

BY

Rahul Polisetti 2015AAPS240H

AT

L. V. Prasad Eye Institute

LVPEI

So that all may see

LV Prasad Eye Institute

BIRLA INSTITUTE OF TECHNOLOGY & SCIENCE, PILANI

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A Practice School-I station of

BIRLA INSTITUTE OF TECHNOLOGY & SCIENCE, PILANI

July, 2017

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DETECTION OF INTRA-RETINAL HARD EXUDATE IN EYES BY OPTICAL COHERENCE TOMOGRAPHY

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Rahul Polisetti 2015AAPS240H Electronics and Communication

Prepared in partial fulfillment of the
Practice School-I Course

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Title of the Project: Detection of Intra-retinal Hard Exudate in Eyes by Optical Coherence Tomography

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Key Words: optical coherence tomography(OCT), image processing, intra-retinal hard exudate, diabetic retinopathy, color fundus photography, segmentation

Project Areas: Computers in Biology and Medicine, Image Processing

Abstract

The invention of Optical Coherence Tomography (OCT) imaging has enabled fast and accurate ophthalmologic disease diagnosis. It has improved the detection of various retinal disorders by providing information about changes in the retina and choroid layers. But due to lack of skilled ophthalmologists and the time it takes for manual analysis, patients, especially in rural areas, cannot receive the benefits of OCT imaging. On this note, this project aims to use image processing tools to allow the visualization of hard exudate (HE) formed due to diabetic retinopathy (DR). This will provide a tool to use in diagnosing and preventing DR early. The project uses several image processing techniques to segment the HE and create a three-dimensional image of the HE formation in the eye. The project also compares the result to the previous standard of using color fundus images to diagnose DR, with the OCT imaging method. Results will show whether the proposed technique would be a better tool for quicker diagnoses

Signature of Student Signature of PS Faculty

Contents

1 Introduction

Diabetic retinopathy (DR) is a common complication of diabetes mellitus [1] and is the leading cause of blindness for people aged 20 to 64. In the United States 12 percent of all new instances of blindness are due to DR. [2] The amount of time a person has diabetes directly relates to the chances of the person having ocular problems, with around 80 percent of people with diabetes for more than 20 years having DR. [3, 4]

Diabetes causes damage to the neurons and the small blood vessels of the retina which results in changes including micro aneurysms, intra-retinal hemorrhages and hard exudate formation. [5] Hard exudates (HE), which cause retinal swelling and edema, are due to the leakage of lipids, proteinaceous material, and inflammatory cells from weakened blood vessels into the neural retina. [5] Increasing numbers of HEs results in an increase in risk of blindness. [5] Thus the early detection of HE is an important part of reducing vision loss due to DR.

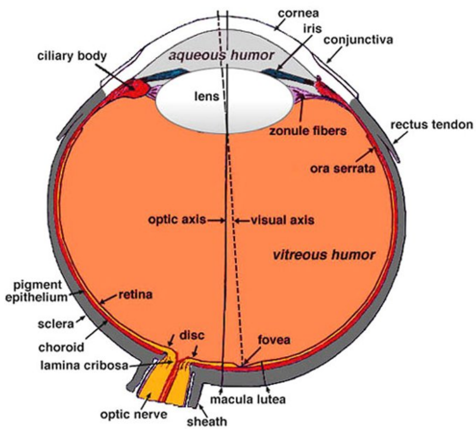

Figure 1: Sagittal cross section of human eye. [6]

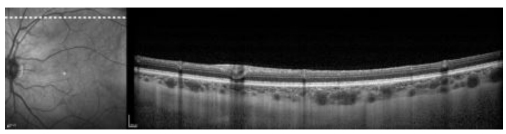

Figure 2: An OCT scan of an normal eye. The dotted line shows where the OCT scan was taken (courtesy Dr. William R Freeman, University of California, San Diego, La Jolla, CA).

DR is diagnosed by finding malformations in the retinal images taken by a fundoscope. At present the color fundus photograph is the standard method of detecting the disease. Although fundus images provide a high sensitivity for detecting retinal change it can only provide information in two dimensions, is less accurate in irregular illumination, and can miss faint HEs. [7–13] Optical coherence tomography (OCT) offers cross sectional slices of images of the retinal layer at a high speed and high resolution. [14–16] Due to their opacity and relatively high density, HEs can be easily distinguished as hyperreflective lesions. [17, 18] By stacking OCT layer together they can also create a 3D representation of the retinal layers and the show the extent of HE formation.

Due to the large amount of time and experience required to manually analyze OCT images, an automated approach is required to rapidly extract HE information from a patient's OCT scans. The present study aims to provide a solution to the above problem by using image processing techniques to segment HEs from volumetric OCT scans.

2 Methodology

2.1 Dataset

Two sets of greyscale OCT images from two eyes were provided by LV Prasad Eye institute. Each set contained 256 scans comprising a square area of the retina. Based on ophthalmological examination, the patients were diagnosed with DR and the eyes contained hard exudate formation. Along with the OCT scan, a color fundus image of the corresponding eye was used to test the output for correctness.

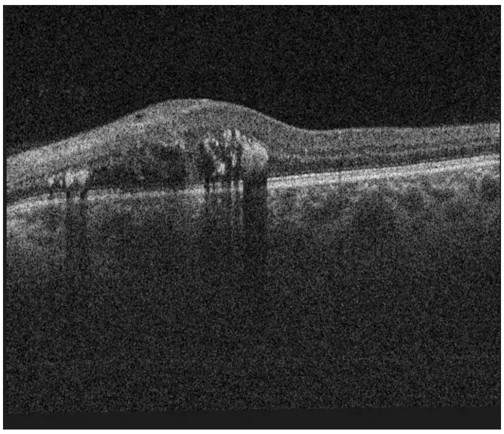

Figure 3: An OCT scan of an eye affected by DR. The HEs are seen as white globules.

2.2 Proposed Automated Methodology

The proposed methodology was implemented in Python using the Scikit Image and Numpy libraries. Explanation of image processing terminology is given in Appendix A.

2.2.1 Shadow Compensation

The presence of HEs creates shadows in the OCT image which manifest as dark areas in the RPE layer. This discontinuity prevents easy segmentation of the complete RPE layer. Shadow compensation is applied to the image to equalize

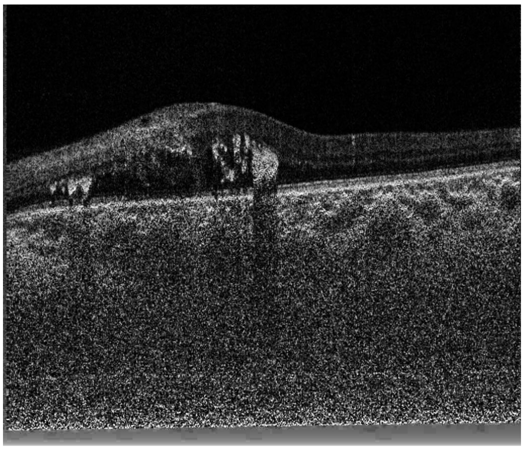

Figure 4: Output of shadow compensation.

the intensity of the RPE, making it easier to remove using edge detection. Shadow compensation is done by increasing the exposure of the column under a HE.(Appendix B)

2.2.2 Median Filter

Generally, the OCT images are noisy, and denoising improve the segmentation accuracy. A median filter with a window pattern consisting of a disk with a radius of 20 pixels was used to reduce the noise of the image.

2.2.3 Edge Detection

To segment the RPE layer a horizontal sobel filter was used to find the horizontal edges of the image. To segment the retinal boundary a canny edge detection algorithm was used with a standard deviation of the Gaussian filter of 0.1.

2.2.4 Smoothing

In order to smoothen both the RPE and the Retinal boundary edge, a 2D implementation of the savitzky golay filter was used.

2.2.5 Morphological Operations

To remove small speckles in the image, morphological erosion was done. The structuring element was taken as a square of side length 4 pixels. To remove gaps in the image, morphological closing was done with the structuring element being a square of side length 10 pixels.

2.2.6 Polynomial Fit

To further improve the segmentation accuracy of the RPE a polynomial curve is fit through the points of the smoothened edge. Any gaps in the RPE edge due to improper shadow compensation are approximated using this polynomial curve. The degree of the polynomial is chosen as 1st or 2nd by visually identifying the shape of the RPE.

2.2.7 3D Median Filter

The above steps are applied to all 256 images and the layers between ILM and RPE are segmented. A 3D median filter with a spherical radius of 2 pixels is used in order to improve HE segmentation. The use of a 3D space is to increase information about the surrounding pixels, thus creating a better image.

2.2.8 Thresholding

In order to remove the HEs, the Otsu thresholding method was use. The image histogram was taken as the histogram of all 256 images in a 3D image space.

2.3 Image Analysis

To create a 3D model of the HEs, ImageJ was used to stack the 256 processed scans. The 3D image viewer plug-in for ImageJ allowed for free rotation of the HE structure along all three axises. The 3D image was then projected from the top in order to compare the OCT extraction with the corresponding color fundus image. Using retinal vessels as landmarks, the dimensions of the OCT projection were adjusted to the size and orientation of the respective color fundus image.

3 Results

Figure 6 shows the RPE layer boundary detected using horizontal sobel edge detection on the shadow compensated image, which has been denoised using a median filter and smoothened using a Savitzky Golay filter. The result of morphological erosion and closing is seen in Figure 7. There is a gap in the line caused due to improper shadow compensation under the large central hard exudate. This improper compensation can be seen in figure 4. In order to account for gaps in the sobel edge detection, a polynomial line (in this case a first degree polynomial) is fit through the points of figure 6. This line is shown in figure 8. Figure 9 shows the combination of the sobel edge detection and polyfit line. This was created by considering the polynomial fit line whenever there is a gap in the sobel edge detected curve.

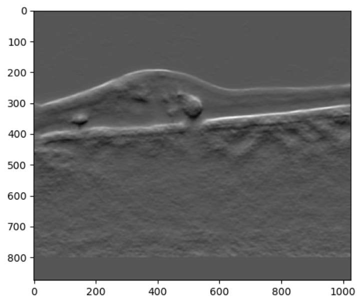

Figure 5: Output of sobel edge detection and Savitzky Golay filtering.

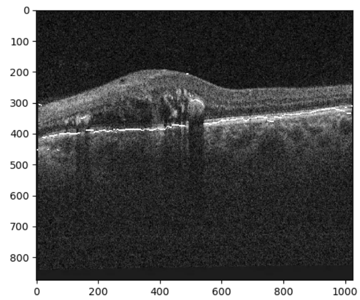

Figure 6: Detected boundary.

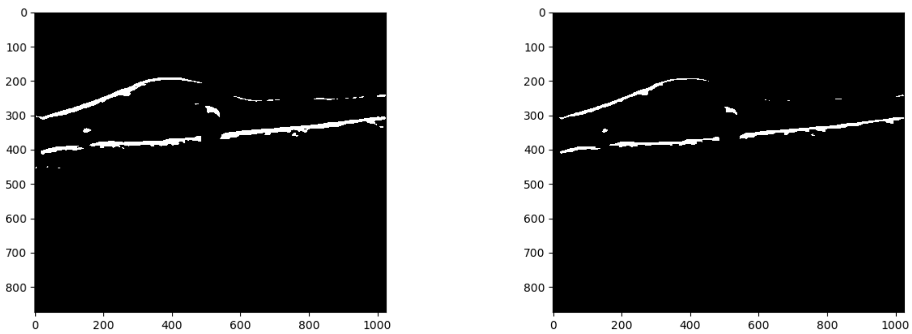

Figure 7: Before and after morphological operations.

In order to detect the retinal boundary, canny edge detection was used due to better accuracy. The upper image of figure 10 shows the output of a Savitzky Golay filter applied on the result of canny edge detection. The curve outlining the retinal boundary is shown in the lower image of figure 10.

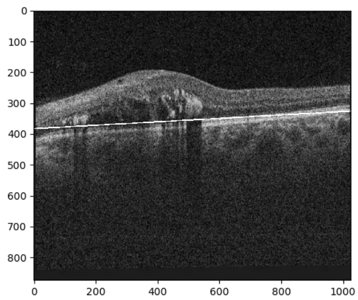

Figure 8: Output of polynomial fitting.

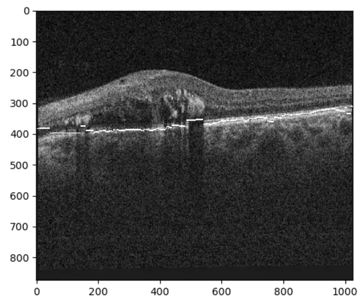

Figure 9: Combination of polyfit and sobel edge detection.

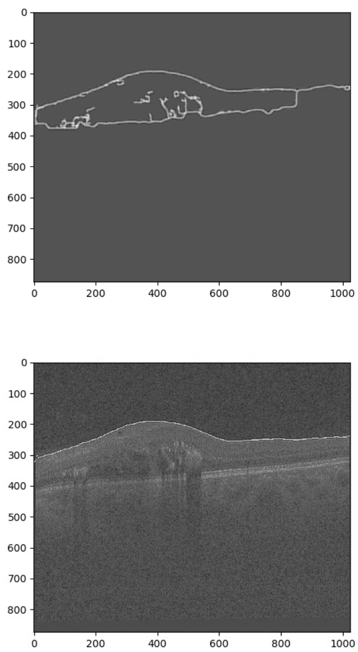

Figure 10: Output of canny edge detection and Savitzky Golay filtering(top). Detected retinal boundary(bottom).

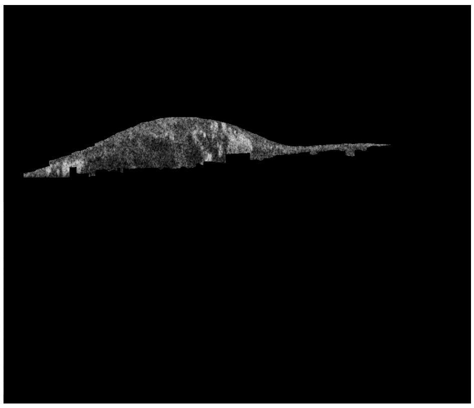

Figure 11: Separated image.

To improve thresholding accuracy, the separated image (figure 11) is passed through an 3D median filter. The output (figure 12) is the result of applying a median filter on the entire 3D space consisting of all 256 images. Considering all images provides us with more information about the surrounding pixels, significantly improving accuracy.

The HEs are then segmented out (figure 13) by using the Otsu thresholding method. The histogram for this method is considered from the entire 3D space of 256 images.

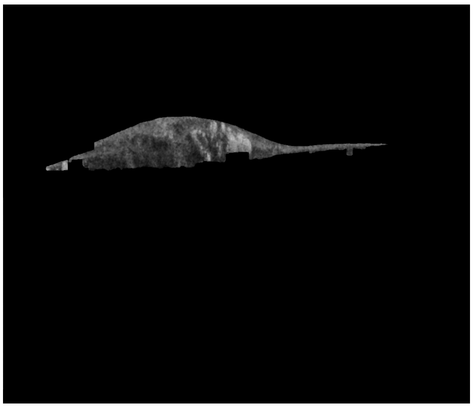

Figure 12: Output of 3D median filter.

Figure 13: Output of Otsu thresholding.

This process is done to all the OCT images, which are then stacked together using ImageJ to provide a 3D model of the HE formation. The 3D image viewer plugin for ImageJ is used to provide a free hand view of the HE formation (figure 14). Figure 15 shows the top view of the 3D model. The top view is then overlaid onto the color fundus image for comparison (figure 16).

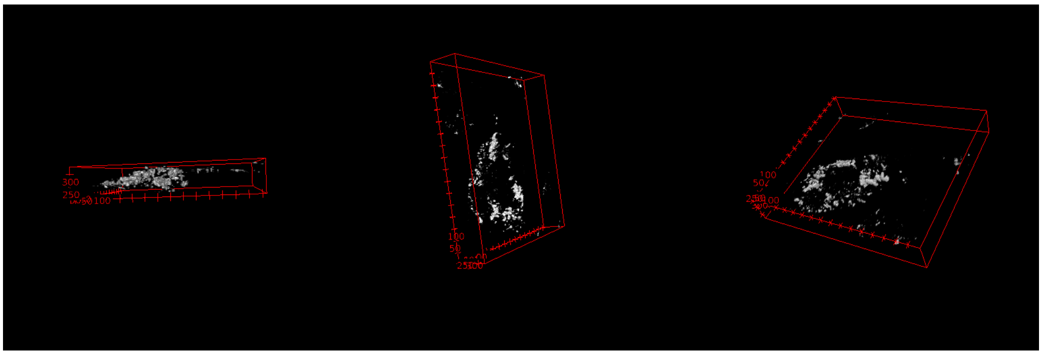

Figure 14: HE formation seen at different angles.

4 Conclusion

The HEs detected using the OCT images show excellent correlation with the fundus image. But due to improper detection and segmentation of the RPE and the retinal boundary, several extra artifacts are present in the OCT created volume. These include parts of the RPE and retinal vessels. Due to this the volume does not purely consist of hard exudates.

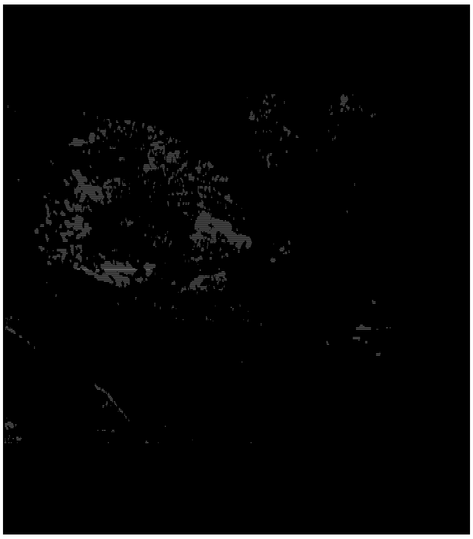

Figure 15: Top view projection of HEs after combining 256 slices.

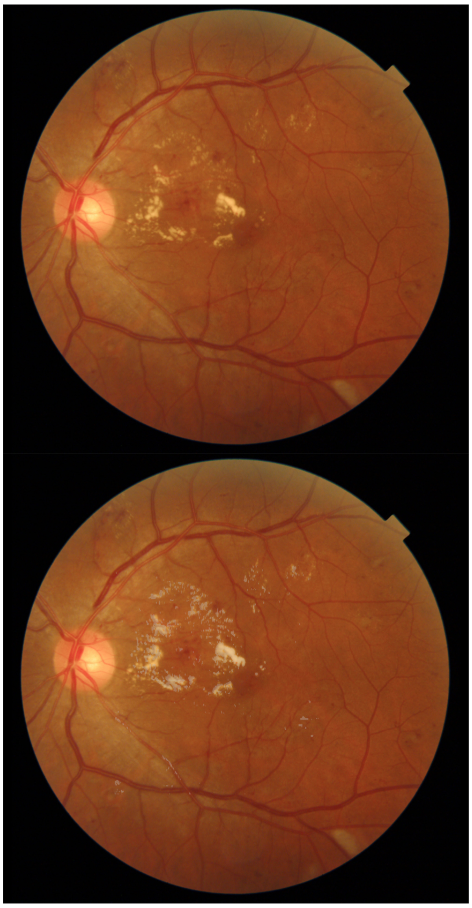

Figure 16: Original fundus image(top). Overlay of HEs on fundus image(bottom).

Improvements must be made in the algorithm in order to fully segment out the HEs without any artifacts. A method to do this would be to use the shadow compensation algorithm on an inverted and non inverted image, and adding the result to provide a segmentation mask. This could provide a reliable outline of the RPE.

While stacking the slices of the HEs taken from the OCT scan, scale information could also be used to prevent dependence on using landmarks such as blood vessels for scaling and alignment.

In conclusion, lipid HE may be reproduced from OCT images of the retina. The output from this approach appears to correlate well with those obtained from the fundus image. Automatic OCT-based quantification of HE may provide an low cost and faster way to detect DR in a clinical setting.

Appendix

Appendix A

Median Filter The principle behind the median filter is to go through the picture pixel by pixel, supplanting every pixel with the median of neighboring pixels. The neighbors are known as the "window", which slides, pixel by pixel, over the whole picture.

Sobel Filter It is a discrete differentiation operator, approximating of the gradient of the image intensities at every point. The Sobel operator is based on convolving the image with a small, divisible, and integer-valued filter in the horizontal and vertical directions and is generally cheap as far as calculations are concerned.

Canny Edge Detection It is a multi-stage algorithm consisting of:
1.noise reduction using Gaussian filter.
2.Finding the Find the intensity gradients of the image.
3.After getting gradient magnitude and direction, a full scan of image is done to remove any unwanted pixels which may not constitute the edge.
4.Apply double threshold to determine potential edges.
5.Finalize the detection of edges by suppressing all the other edges that are weak and not connected to strong edges.

Savitzky-Golay Filter An approach for smoothing a series by replacing each value of the series with a new value which is obtained from a polynomial fit to 2n+1 neighboring points (including the point to be smoothed), with n being equal to, or greater than the order of the polynomial.

Image Histogram An image histogram is a type of histogram that plots the number of pixels for each tonal value.

Morphological Image Processing is a collection of non-linear operations related to the shape or morphology of features in an image.

Morphological Dilation this operation causes bright regions within an image to grow

Morphological Erosion This operation causes bright regions within an image to get thinner

Morphological Closing The morphological close operation is a dilation followed by an erosion, while keeping the structuring element for both operations the same.

Appendix B

The code below contains the implementation of the shadow compensation algorithm in MATLAB. (courtesy Mr. Kiran Kumar Vupparaboina, Technical Lead - Signal Processing Lab, LVPEI)

```
% the path to the image is stored in variable name
img = imread(name);
n = 2;
Ig1=(double(img)/255).^4;

% cumtrapz is the Cumulative trapezoidal numerical
    integration function
L=(Ig1.^n)./ (flipud(cumtrapz(flipud(Ig1.^n))));

% output is shadow compensated
output = uint8(255*(L).^(1/4));
```

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Glossary

choroid also known as the choroidea or choroid coat, is the vascular layer of the eye, containing connective tissue, and lying between the retina and the sclera.

diabetic retinopathy is a diabetes complication that affects eyes. It's caused by damage to the blood vessels of the light-sensitive tissue at the back of the eye (retina).

exudate a mass of cells and fluid that has seeped out of blood vessels or an organ, especially in inflammation.

globule a small round particle of a substance; a drop.

inner limiting membrane (ILM) is the boundary between the retina and the vitreous body.

optical coherence tomography is an established medical imaging technique that uses light to capture micrometer-resolution, three-dimensional images from within optical scattering media (e.g., biological tissue).

retina is the third and inner coat of the eye which is a light-sensitive layer of tissue.

retinal pigment epithelium (RPE) is the pigmented cell layer just outside the neurosensory retina that nourishes retinal visual cells, and is firmly attached to the underlying choroid and overlying retinal visual cells.