Detection of DME by Classification and Segmentation Using OCT Images

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Received August 12, 2021; Accepted November 27, 2021
ISSN: 1735-188X
DOI: 10.14704/WEB/V19I1/WEB19043

Abstract

Optical Coherence Tomography (OCT) is a developing medical scanning technique proposing non-protruding scanning with high resolution for biological tissues. It is extensively employed in optics to accomplish investigative scanning of the eye, especially the retinal layers. Various medical research works are conducted to evaluate the usage of Optical Coherence Tomography to detect diseases like DME. The current study provides an innovative, completely automated algorithm for disease detection such as DME through OCT scanning. We performed the classification and segmentation for the detection of DME. The algorithm used employed HOG descriptors as feature vectors for SVM based classifier. Cross-validation was performed on the SD-OCT data sets comprised of volumetric images obtained from 20 people. Out of 10 were normal, while 10 were patients of diabetic macular edema (DME). Our classifier effectively detected 100% of cases of DME while about 70% cases of healthy individuals. The development of such a notable technique is extremely important for detecting retinal diseases such as DME.

Keywords

OCT, DME, SD-OCT, Completely Automated Algorithm, HOG Descriptors, Retinal Diseases.

Introduction

Macular edema (DME) is one of the several popular macular complications. It is identified by examining cyst fragments inside sub-retinal films. These cysts are created because of fluid collection underneath the macula, leading to the bulging of retinal layers.
The macula is present at the retina center; a rich concentration of cones is located in the area that creates a crisp central visual perception. Macular edema causes inflammation in the region beneath the macula, which deforms one's fundamental vision (Lobo. et al., 2005). DME occurs due to the blood-retinal barrier disruption due to damage occurring in the vascular endothelium of the retina and mural cells in diabetic patients (Kumar, V. et al., 2005), (Metwaly, et al., 2014). Retinal hypoxia is responsible for the enhanced generation of vascular endothelial growth factors (VEGF) together with other signaling systems (Kumar, V. et al., 2005). DME further develops by processes, for example, cytotoxic destruction to retinal fluid transportation cells, the imbalance in vascular spillage and fluid transportation results in DME and eventually to blindness (Bringmann et al., 2006), (Bringmann et al., 2004).

Optical Coherence Tomography (OCT) is extensively practiced in ophthalmology for observing the retina morphology, which is essential for detecting disease and evaluating the efficiency of therapy. It is a clinical image utilized to visualize the eye to perceive and trace a disease. OCT is an across-sectional high-resolution image of biological tissue layers. In clinical practices, OCT scans can be used to detect retinal diseases (Kanagasingam et al., 2014), (Ghorbel et al., 2011). Automatic determination using OCT scanning is yet in experimental stages. Only research practices have been proclaimed, and no practical outcomes are available (Anderson et al., 2002). Most of the researchers working on OCT scanning have concentrated on the difficulty of segmentation of retinal layers (Mayer et al., 2010), (Garvin et al., 2008), (Quellec et al. 2010), (Schlegl et al., 2010). Recently, spectral-domain OCT (SD-OCT) and a comparable range of facts were presented for comparative evaluation of retinal diseases. The most advanced studies showed encouraging consequences of measurable classification of every single segment of an OCT volume. The system depends on morphological and geometrical factors; yet, the strategy requires a normalization scheme to restrain it from being completely automatic (Jayashri N., et al., 2021). It must be recorded that the contributors are presenting the real scans as a standard for society. Only a few studies have been conducted yet to discuss the solution of the problem for detecting DME (Srinivasan et al., 2015), (Venhuizen et al., 2015).

Previously, most of the techniques employed for detecting retinal or other eye diseases used the contrast between segmented layers of the healthy and abnormal retina (Jain, A., et al., 2015). Furthermore, some of the considerations, rather than relating the thicknesses of retinal layers, practiced the segmentation of fluid zones perceived in OCT scans, for instance, cystic formations or edema (Antony et al., 2013), (Farsiu et al., 2014), (Fernandez et al., 2005). Such procedures can recognize the complications just in later
stages. Though various recent systems have been disclosed to detect ophthalmologic or optical complexities, particularly retinal disease, there is still a demand for the evolution of tools to detect disease in early stages. (Fernandez et al. 2005), (Chiu et al., 2012), (Lee et al., 2013). The current study was performed with a fully automated technique for the detection of retinal complications. This technique employs SVMs (Cortes et al., 1995) as well as Histogram Oriented Gradients (HOG) descriptors (Dalal et al., 2005), (Naseri, M., et al., 2015) to classify the images from SD-OCT data sets into normal or having DME. This algorithm examines scans from every SD-OCT volume, and it requires no personal contribution for the detection of retinal diseases (Kalaiselvi, et al., 2018).

**Materials and Methods**

This section presents the process we used for the detection of DME by SD-OCT image classification. The basic steps are involved as follows:

1. **Study Design**

   i. **SD-OCT Data Sets**

      We perfumed this study by using SD-OCT data sets comprising images obtained from a total of 20 patients. Patients were categorized into groups, i.e. normal and diseased. 10 patients were normal (normal), while 10 were those suffering from DME (diseased). Scanning was performed at Central Lab, Department of Computer Engineering and Application, GLA University, Mathura Uttar Pradesh, INDIA, following the standard protocols.

2. **Protocol Adopted**

   i. **Denoising of Images**

      In the first step, we performed the denoising to remove the impact of noise on the classification as speckle noise may result in corrupted SD-OCT images. Individual B-scans were denoised in the SD-OCT volume via freely available online denoising method, sparsity-based block-matching, and 3D-filtering (BM3D) (Dabov et al., 2007).

3. **Flattening of Retinal Curvature**

   Retinal SD-OCT images are known to possess a usual curvature, which may also be distorted because of the common practices in OCT image procurement and demonstration (Kuo et al., 2013) that fluctuate among patients as well as within every SD-OCT volume.
(Agrawal, N., et al. 2019). So, after the denoising, retinal curvature was flattened in every image was flattened to remove the curvature (Fig 1).

![Figure 1](image1.jpg)

**Figure 1 Flattening of curvature, normal image with curvature (a), curvature Flattened (b)**

4. **Cropping of Images**

SD-OCT images were cropped for focusing the retinal region containing morphological structures showing striking differences among the normal and diseased group before extraction of the feature vector. Every image was cropped in the lateral dimension, to the center 150 columns. Every image was cropped to 40 pixels in the axial dimension, 5 pixels below, and 35 pixels above the mean lower retinal limit (Fig 2b).

5. **Extraction of Feature Vectors**

HOG descriptor algorithm was used for effective description of the shape and the presence of morphological organizations in every image. The HOG descriptor algorithm works by dividing the image into linked sections, known as cells. At the same time, the shapes of morphological organizations are designated by measuring the robustness and alignment of the three-dimensional gradients in every cell. The image is divided into smaller 3-D cells, and a one-dimensional histogram for the 3-D is generated for every cell (Farouk, A., et al. 2015). Then this gradient was standardized over longer coinciding
three-dimensional blocks for causing the descriptors to be invariant to aspects such as light and dark (Figure 2c).

![Image](a)

![Image](b)

![Image](c)

Figure 2 Different OCT images, (a) Normal SD-OCT image, (b) Final cropped image. (c) HOG descriptor visualization

6. High Pixel Removal in RNFL Complex

As the background pixel for all images are similar during the process, therefore, the high pixel was removed in the RNFL complex to assist the RPE layer segmentation.

7. Classification of Images

SVMs were used for multiclass classification of each SD-OCT image aimed at classifying the Normal vs DME group. SVMs work to classify an image by classifying the extracted feature vectors, and the group which gets the maximum votes is selected as the classification for the image.
Segmentation of Images

To improve the classification process from the step mentioned earlier, we performed segmentation for precise separation of group limits. This section uses the method of (Sugmk et al. 2014), (Misra, N.R., et al. 2021) and the description of the method partly reproduces their wording (Sharma, S.K., et al. 2019).

1. Detection of Drusen

The drusen is a shape of abnormality in the RPE layer. The drusen were detected by the formation of the estimated line value of PRE. In this step, the images were enchanted to clarify the RPE layer and obtained median between the highest and lowest boundary of the image and then form another estimate line by mean. Then a different estimate line was formed via estimation in each drusen by comers, and then these estimate line values of PRE were combined, the shape of drusen between both lines was detected.

2. Detection of Bubble

RNFL segmentation was performed to detect a bubble in the RNFL complex. RNFL segmentation was followed by bubble classification. The process to detect the bubble in the RNFL complex and IS/OS layer. As bubble in IS/OS layer is likely to be not linked to DME. RPE layer is used to detect the IS/OS bubble because IS/OS layer is adjacent to the RPE layer. If the bubble is found by computation of the upper RPE layer zone (10 to 15 pixel), this is not in the RNFL complex.

3. Extraction of Features

Feature extraction is the method of obtaining features from image segmentation for classification between Normal and DME images. Features used for classification of both conditions are as follows:

- RPEA detection of RPE layer abnormality. Assigning the binary values either 0 or 1. 0 corresponds to the normal RPE layer, while 1 corresponds to the abnormal RPE layer.
- RNFLA detection of the bubble in the RNFL complex. Assigning the binary values either 0 or 1. 0 corresponds to a bubble in the upper RPE layer, 1 corresponds to the absence of a bubble upper RPE layer.
- AOB Detection of the bubble in the outer RNFL zone adjacent to the RPE layer. Assigning the binary values either 0 or 1. 0 corresponds to the presence of a bubble in the upper RPE layer while 1 corresponds to a bubble in IS/OS layer.
4. Classification of Disease

The binary classification was used to classify the normal and diseased group, i.e. DME. If PREA is given a 0 value for RPE, then this corresponds to normal, and the case is categorized as normal. Whereas if PREA suggests a value of 1 for RPE, RPE is abnormal, and this case is categorized as DME. Similarly, if AOB suggests a value of 0, this means the bubble is a bubble in the upper RPE layer adjacent to the RPE layer. This case is DME (Figure 3).

![Image](a)

![Image](b)

**Figure 3** Disease classification via OCT images, (a) Normal SD-OCT image from one of Healthy Retina, (b) OCT image from one of DME Retina

Results

Like (Srinivasan et al., 2014) for obtaining the precision of the classification algorithm and its capability to normalize to the data set, leave-two-out cross-validation we applied for proficient usage of all data sets as well as to escape bias in the results by the exclusion of any data (Ghai, et al., 2020). In the current study, 20 experiments were performed using 20 SD-OCT images obtained from SD-OCT data sets. The multiclass classifier was trained for 18 volumes for every experiment, excluding one from every group, and examined the 2 volumes omitted. This method causes the classification of each volume out of 20 SD-OCT volumes at least once, each utilizing 18 other volumes as training data. Table 1. This completely automated algorithm, coded in MATLAB, examined on a PC with a Windows-10 (Intel i7-8565U 4-Core, 40GB RAM, 256GB PCIe SSD, Quadro P520).
## Table 1 SD-OCT Imaging Parameters for the Studied Groups

<table>
<thead>
<tr>
<th>Sr. no</th>
<th>Group</th>
<th>AR (µm)</th>
<th>LR (µm)</th>
<th>Image Dimensions (mm × mm)</th>
<th>B-scans</th>
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<tr>
<td>1</td>
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<td>2.96</td>
<td>12</td>
<td>5.6 × 5.6</td>
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<td>11</td>
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<td>95</td>
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<tr>
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<td>6.0 × 6.0</td>
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<td>8.8 × 7.3</td>
<td>63</td>
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</table>

## Discussion

The current study validated the use of an effective method for retinal disease recognition by using OCT. This study was aimed at the detection of DME. The suggested technique not only depends on the inner retinal layer’s segmentation; instead, it also employs a classification scheme using SVM classifiers and HOG descriptors. Such classification is highly valuable for detecting diseases that change the inner layers of the retina, due to which segmentation of layer boundary becomes extremely challenging. Furthermore, our study accomplished a highly sensitive and specific detection of DME while using scans obtained by common scanning procedures. Results obtained from current studies are consistent with previously performed studies.

Some workers conducted the classification of retinal diseases using SD-OCT scanning employing specificity and sensitivity fulfillment computations. They presumed that SD-OCT is extremely sensitive to some of the retinal diseases (Mokwa et al., 2013). OCT scanning can be used for the investigation and control of DME (Wei et al., 2006).
The images used in the study were taken by different scanning tools, thereby producing the images having varying pixel pitch and resolutions. However, resizing images to obtain images of similar sizes proved to be a striking feature and strength for our study.

Another salient feature of the current study is using the simplest and robust way to approximate the retinal curvature. Hence, the present study provides an efficient and simpler way for retinal approximation and classification compared to commonly used complex methods. Most of the algorithms used for segmentation of retinal layer utilize, etc., employ much more complicated designs and methods for approximating retinal curvature and classification (Srinivasan et al., 2014). The current study investigated that this algorithm provides an excellent disease detection rate indicating DME occurrence even when only 35% of the images are categorized as DME. We achieved the best disease detection rate. It is sensible to predict that such a detection rate must be lowered for detection of the very premature phases of DME or other retinal or optical diseases (Mittal, P et al., 2020), (Wang, M. M., et al., 2015).

Conclusion

Previously, most of the methods used to detect retinal or other eye diseases utilized the comparison between segmented layers of the normal and diseased retina. Moreover, some of the studies, rather than comparing the thicknesses of retinal layers, used the segmentation of fluid zones observed in OCT scans, for example, cystic structures or edema (Mittal, P et al., 2020), (Mittal, P et al., 2020). Such approaches can identify the diseases only in later stages. Though several modern techniques have been developed to detect ophthalmologic or optic complications especially retinal disease, there is still a need for the development of mechanisms for the detection of disease in the early stages. (Mittal, P. et al., 2021). We think that the validation of the utmost effective, a completely mechanized isolated indicative scheme for retinal diseases will include both methods. The progress of such an ample technique is part of continuing research.

1. Conflicts of Interest

“The authors declare that there is no conflict of interest regarding the publication of this paper.”

2. Funding Statement

I want to thanks GLA University for providing us resources for such a long and expensive research out of which these results came.
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segmentation of retinal surfaces in SD-OCT volumes. *Biomedical optics express, 4*(12), 2712-2728.


