A Practical Approach to OCT Based Classification of Diabetic Macular Edema

Samra Naz*, Taimur Hassan†, M. Usman Akram*, Shoab A. Khan*
*Department of Computer Engineering, National University of Sciences and Technology, Islamabad, Pakistan.
samranaz81@ce.ceme.edu.pk, usmakram@gmail.com,kshoab@yahoo.com
†Department of Electrical Engineering, Bahria University, Islamabad
engr.taimoor@bui.edu.pk

***Abstract*—This paper addresses the problem of automatic classification of OCT images for identification of patients with DME versus normal subjects. In this paper a relativity simple and practical approach is proposed to exploit the information in OCT images for a robust classification of Diabetic Macular Edema (DME) using coherent tensors. From the retinal OCT scan top and bottom layers are extracted to find thickness profile. Cyst spaces are also segmented out from the normal and DME images. The features extracted from thickness profile and cyst are tested on Duke Dataset having 55 diseased and 53 normal OCT scans. Results reveal that SVM with Leave-one-Out gives the maximum accuracy of 79.65% with 7.6 standard deviation. However, experiments reveal that for the identification of DME, nearly same accuracy of 78.7% can be achieved by using a simple threshold which can be calculated using thickness variation of OCT layers. Moreover a comparison of the proposed algorithm on a standard dataset with other recently published work shows that our method gives the best classification performance.**

Keywords: Diabetic Macular Edema, OCT, Thickness Profile.

I. Introduction

Optical Coherence Tomography (OCT) Imaging is being used extensively to view and capture small changes in the retina. This three-dimensional imaging technique is now considered as a standard technique in the clinical ophthalmology for examination of retina and assessing the response to treatment [1], [2]. Currently a number of macular disorders such as Age Macular Degeneration (AMD) and Diabetic macular Edema (DME) are diagnosed by visual inspection of the OCT images [3]. Since the early days of OCT imaging automated methods are being proposed to speed up the diagnostic process. Automated systems also enable remote identification of the diseases that is of real help. Macular Edema is one of the most common retinal disease that is usually caused due to diabetes. It is often considered to be a major symptom for Proliferative Diabetic Retinopathy (PDR) [4]. It is highly probable that if a person is suffering from PDR, he may also develop DME. DME is detected by investigating small cyst spaces that are produced due to accumulation of protein within the retinal layers. This fluid accumulation beneath the macula not only causes the retinal layers to swell but also cause hindrance in providing a clear crisp vision [5].Due to accumulation of fluid a clear gap is created between the retinal layers that is known as cyst. Figure 1 shows the presence of cyst space in a diseased eye as compared to the normal human retinal.

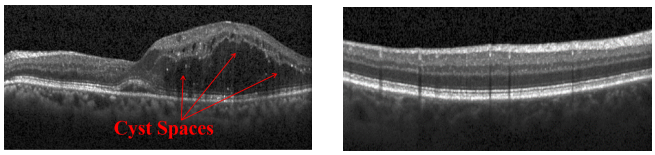

Fig. 1. OCT scans of DME effected retina with cyst space and a normal human retina.

During clinical trials, various treatment modalities have been conducted for DME therapies [6], the significant proportion of subjects that fail to respond to any single therapy suggests that DME pathophysiology is multifactorial, and unfortunately no consensus yet exists for determining which patients are likely to respond to specific therapies. This may be due to the absence of a standard method for stratifying patients based on disease mechanisms. In recent years, the additional depth-resolved dimension of data provided by optical coherence tomography (OCT) imaging has prompted groups to correlate morphological patterns of the retina on OCT with DME and vision outcomes [7]–[9]. For clinical trials, the most commonly used quantitative imaging biomarker of DME severity is currently central subfield thickness, which does not capture details such as edema volume or changes in specific retinal layers. These parameters provide valuable prognostic information to guide treatment decisions. A significant amount of work has been done so far in order to detect different macular disorders. Pratul P.S et al. used multi-scale histogram of oriented gradient descriptors (HOG) to extract features from DME, AMD and Normal OCT images. Using SVM classifiers he correctly classified all the DME images getting 100% accuracy but for healthy case the accuracy came out to be 81.6% [10]. Venhuizen et al. classified the DME and normal images using Bag-of-Words (BoW) models [11]. In [12], A Local Binary Patterns (LBP) are considered as distinguishing features that can separate the Normal OCT scans from DME class. They tested their algorithm on a private dataset thus reporting their Sensitivity (SE) and Specificity (SP) to be 81.2% and 93.7%. The performance of this technique is further improved by combining the BoW models with it [13]. Apart from the private data it is then also tested on publicly

978-1-5090-6748-0/17/$31.00 ©2017 IEEE

available dataset by Duke [14]. In this paper we propose an automated classification method to detect DME using OCT images. Useful information present in the retinal layers is extracted in the form of feature vector. Different approaches are followed to analyze the extracted features individually and the combined effect is also evaluated. SVM classifier is employed to test the combined effect of features whereas the separate most distinguishing features are separated by setting a threshold that gives maximum classification accuracy. In the end the best technique is also compared to other The paper is organized as follows. The proposed methodology used to detect the presence of macular edema is described in Section 2. Sections 3 describes the performance evaluations and their results for the proposed system. At the end section 4 concludes the study.

II. Proposed Methodology

Many methodologies have been introduced so far for the segmentation of retinal layers to detect different macular and ocular diseases. We propose a relatively simpler and practical approach for the diagnosis of DME. The block diagram in Figure 4 illustrates the proposed structure tensor based method. Numerous classes of features that were employed in this study are briefly outlined in the following.

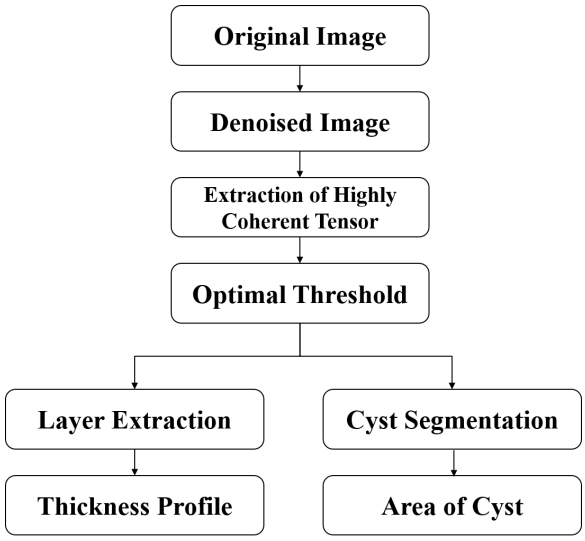

Fig. 2. Block Diagram for Thickness Profile Extraction and Cyst Segmentation.

A. Thickness Profile

OCT images provide a 3 dimensional cross sectional view of the retinal layers thus revealing the maximum information about the inter layer difference. We generate three features from the layers information. The retinal layers are segmented using highly coherent structure tensor [14]. Structure tensor is a matrix that is derived from the gradient function. Being an advanced edge detector, it summarizes the prominent directions of the gradient in a specified neighborhood of a point, and the degree to which those directions are coherent [15]. Two dimensional structure tensor are computed by applying the 2D convolution sum of image gradients and calculating at different orthogonal orientations by using a Gaussian window w(x,y) [15]. Structure tensor is also referred as second moment matrix because it summarizes the coherence and depicts the predominant orientation of gradients in the specified neighborhood of a pixel [15]. Eq. (1) shows the 2D discrete structure tensor.

$$S_w(x,y) = \begin{bmatrix} I_{XX}(x,y) & I_{XY}(x,y) \\ I_{YX}(x,y) & I_{YY}(x,y) \end{bmatrix} \quad (1)$$

$S_w(x,y)$ shows a 2x2 structure tensor matrix. In this matrix the first entry $I_XX(x,y)$ shows the horizontal tensor that is computed by convolving the square of horizontally oriented gradient with the Gaussian window $w(x,y)$, $I_XY(x,y)$ and $I_YX(x,y)$ are both computed by convolving the Gaussian window with the sum of product of horizontally and vertically oriented gradients, and the fourth entry i.e. $I_YY(x,y)$ is computed by convolving the product of vertically oriented gradients with the Gaussian window $w(x,y)$.

For the detection of macular edema only the top and bottom layers, ILM and choroid layer respectively, are important. Due to the presence of macular edema a considerable amount of difference is created between ILM and choroid layer that can be analyzed in order to detect the ME effected eye. The gradient calculated in the vertical direction gives the maximum information about the edges in the OCT image. After the extraction of highly coherent tensor, it is converted into binary image by using OTSU algorithm. The top and bottom layer are segmented out by extraction the first and last white pixel in an image. After layer segmentation, the difference between the top and bottom layer is computed that gives the layer thickness or thickness profile. The thickness profile is analyzed to extract suitable features. The description of each feature is given below:

*1) **Maximum Thickness** (f_1) :* Maximum peak in the B-scan thickness profile or the point of maximum difference between the ILM and choroid layer.

*2) **Minimum Thickness** (f_2) :* The shallowest point in the B-scan thickness profile or the point of minimum difference between the ILM and choroid layer.

*3) **Thickness Variation** (f_3) :* The shallowest point in the B-scan thickness profile or the point of minimum difference between the ILM and choroid layer.

Figure 3 provides a complete step by step illustration of thickness profile extraction from an OCT scan using highly coherent structure tensor.

B. Cyst Area

Macular cyst is the major symptom of Diabetic Macular Edema that develops when the macular capillaries are leaked and the fluid accumulates between the retinal layers [16]. Using the highly coherent structure tensor, a binary image is obtained having a clear cyst space between the retinal layers. To segment out the cyst space from the binary image, the hole is filled using morphological operations and then

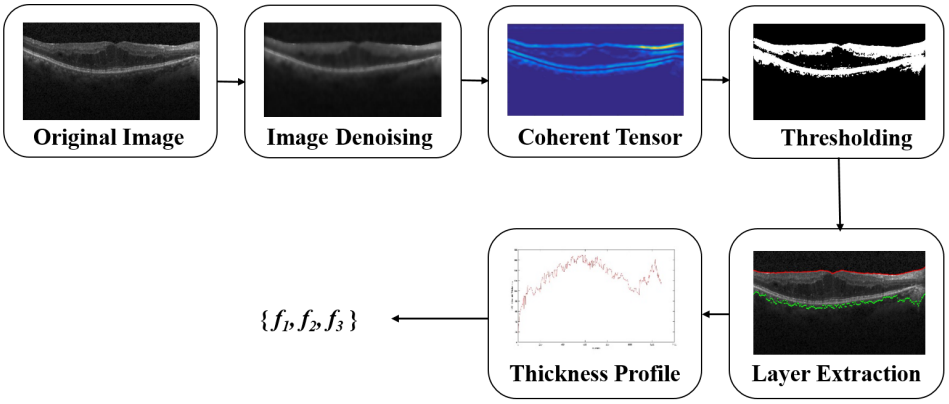

Fig. 3. Block Diagram for thickness profile extraction.

subtracted from the original binary image. The area of the cyst is calculated and is considered the fourth feature f4 in the feature vector. Figure 3 Shows a complete overview of the steps required to segment out the cyst spaces.

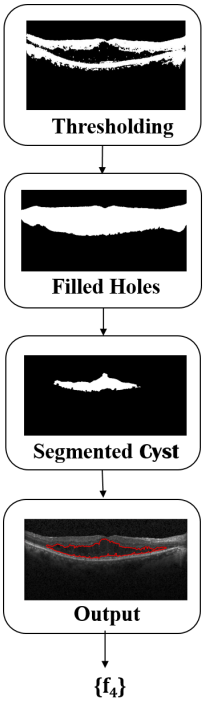

Fig. 4. Segmentation of Cyst Spaces in Oct images.

From both the method a total of three features from thickness profile and one feature from cyst segment is extracted out. These features are tested separately and the combined effect is analyzed as well.

III. Results and Discussion

We tested our proposed methodology on a publicly available dataset by Duke used in [17]. Among the data we use 55 images from ME effected patients and other 53 from the people belonging to normal class. To classify the images

TABLE I
Classification with SVM, Naive Bayes and KNN

	SVM	Naive Bayes	KNN
Accuracy ± STD	70.9±4.5	64.65±10.8	51.92±12.9

TABLE II
Classification using SVM

	10-fold Cross Validation	Leave-One-Out (100 iterations)
Accuracy ± STD	70.96 ± 4.5	79.25 ± 7.7

a simpler approach is considered initially. Layer thickness being one of the most differentiating feature is tested using simple threshold method. A value of 48 gives the maximum accuracy of 78.7% while classifying 37 out of 55 ME images correctly. Similarly area of cyst is also considered as one of the distinguishing feature and a threshold of 1.5 microns is applied to gain maximum accuracy of 70.3%. Figure 6 shows the samples classified

We employed different classifiers with 10 fold cross validation to get maximum accuracy while combining all four features f1, f2, f3 and f4. Table 1 clearly shows that SVM outperforms Nave Bayes and KNN. SVM is again tested using Leave one out approach. Table 2 depicts that Leave on out with 100 iteration outdoes the performance of 10 fold cross validation. Leave one out provides the maximum accuracy of 79.2%. Experiments reveal that using a single feature vector of thickness variation with threshold base approach can give almost equal accuracy obtained by using a combined feature set with SVM based classifier. However, only cyst area based classification gives a slightly less accurate results.

For comparison purpose, the proposed algorithm is also tested and evaluated on another Duke Data set. The data set contains 15 images from the Normal class and remaining 15 belonging to the DME class. The OCT images are already filtered using BM3D method to remove speckle noise [10].In [11], Venhuizen et al. uses Bag-of-Words model based

TABLE III
COMPARISON WITH OTHER TECHNIQUES

	SE	SP
Venhuizen et al. [11]	71.42	68.75
Lemaitre et al. [13]	86.67	100
Thickness Variation	93.3	100

approach to classify OCT images. Later on, a texture and dictionary learning model (LBP+BoW) based approach is also tested on the same data set [13]. For evaluation purpose, all the results are reported in the form of Sensitivity (SE) and Specificity (SP). Table 3 presents the comparison of our Thickness variation-threshold based method with the best approaches of [11] and [13].

Results reveal that our method is the best resulted in giving the maximum accuracy in terms of sensitivity and specificity thus outperforming all other methods introduced so far.

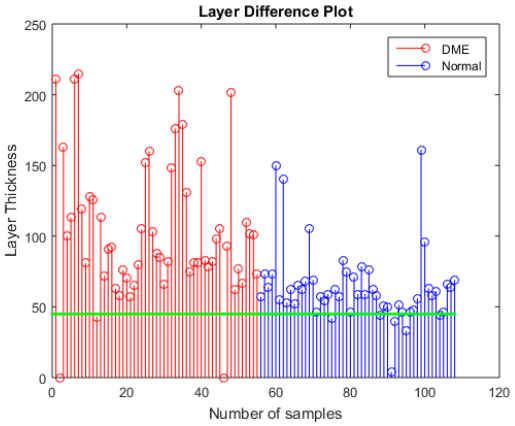

Fig. 5. Thickness variation.

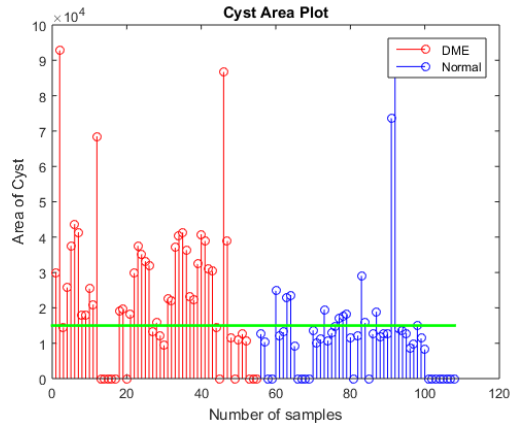

Fig. 6. Plot for area of cyst based

IV. CONCLUSION

This paper addresses an automated method to identify Diabetic Macular Edema using different set of features. Results show that the accuracy obtained using all the four features with SVM classifier (79.25%) is almost the same that is achieved by a simple threshold based approach (78.7%) applied on thickness variation. The comparison of threshold based technique against different dataset and methodologies highlights that our technique gives the maximum classification rate for normal vs DME volumes.

REFERENCES

[1] Wolfgang Drexler and James G Fujimoto. State-of-the-art retinal optical coherence tomography. *Progress in retinal and eye research*, 27(1):45–88, 2008.
[2] Taimur Hassan, M Usman Akram, Bilal Hassan, Ammara Nasim, and Shafaat Ahmed Bazaz. Review of oct and fundus images for detection of macular edema. In *2015 IEEE International Conference on Imaging Systems and Techniques (IST)*, pages 1–4. IEEE, 2015.
[3] George Trichonas and Peter K Kaiser. Optical coherence tomography imaging of macular oedema. *British Journal of Ophthalmology*, 98(Suppl 2):ii24–ii29, 2014.
[4] JN Olayiwola, DM Sobieraj, K Kulowski, D St Hilaire, and JJ Huang. Improving diabetic retinopathy screening through a statewide telemedicine program at a large federally qualified health center. *Journal of health care for the poor and underserved*, 22(3):804–816, 2011.
[5] Conceiç ao Lobo, Isabel Pires, and José Cunha-Vaz. Diabetic macular edema. *For further volumes*, page 1.
[6] Wei-Chun Chan, Shawn H Tsai, Ai-Ching Wu, Lee-Jen Chen, and Chi-Chun Lai. Current treatments of diabetic macular edema. *International Journal of Gerontology*, 5(4):183–188, 2011.
[7] S Ben Yahia, A Maalej, W Turki, R Messaoud, S Gabsi, and M Khairallah. Diabetic macular edema. an oct-based classification. *Investigative Ophthalmology & Visual Science*, 49(13):3467–3467, 2008.
[8] Desislava Koleva-Georgieva. *Optical coherence tomography findings in diabetic macular edema*. INTECH Open Access Publisher, 2012.
[9] Bartosz L Sikorski, Grazyna Malukiewicz, Joanna Stafiej, Hanna Lesiewska-Junk, and Dorota Raczynska. The diagnostic function of oct in diabetic maculopathy. *Mediators of inflammation*, 2013, 2013.
[10] Pratul P Srinivasan, Leo A Kim, Priyatham S Mettu, Scott W Cousins, Grant M Comer, Joseph A Izatt, and Sina Farsiu. Fully automated detection of diabetic macular edema and dry age-related macular degeneration from optical coherence tomography images. *Biomedical optics express*, 5(10):3568–3577, 2014.
[11] Freerk G Venhuizen, Bram van Ginneken, Bart Bloemen, Mark JJP van Grinsven, Rick Philipsen, Carel Hoyng, Thomas Theelen, and Clara I Sánchez. Automated age-related macular degeneration classification in oct using unsupervised feature learning. In *SPIE Medical Imaging*, pages 94141I–94141I. International Society for Optics and Photonics, 2015.
[12] Guillaume Lemaıtre, Mojdeh Rastgoo, Joan Massich, Carol Y Cheungc, Tien Y Wongc, Ecosse Lamoureuxc, Dan Mileac, Fabrice Mériaudeau, and Désiré Sidibé. Classification of sd-oct volumes using local binary patterns: Experimental validation for dme detection. 2016.
[13] Taimur Hassan, M Usman Akram, Bilal Hassan, Adeel M Syed, and Shafaat Ahmed Bazaz. Automated segmentation of subretinal layers for the detection of macular edema. *Applied optics*, 55(3):454–461, 2016.
[14] Bilal Hassan, Gulistan Raja, Taimur Hassan, and M Usman Akram. Structure tensor based automated detection of macular edema and central serous retinopathy using optical coherence tomography images. *JOSA A*, 33(4):455–463, 2016.
[15] Josef Bigun. Optimal orientation detection of linear symmetry. 1987.
[16] CG Keith. Retinal cysts and retinoschisis. *The British journal of ophthalmology*, 50(11):617, 1966.
[17] Stephanie J Chiu, Michael J Allingham, Priyatham S Mettu, Scott W Cousins, Joseph A Izatt, and Sina Farsiu. Kernel regression based segmentation of optical coherence tomography images with diabetic macular edema. *Biomedical optics express*, 6(4):1172–1194, 2015.