Article Title

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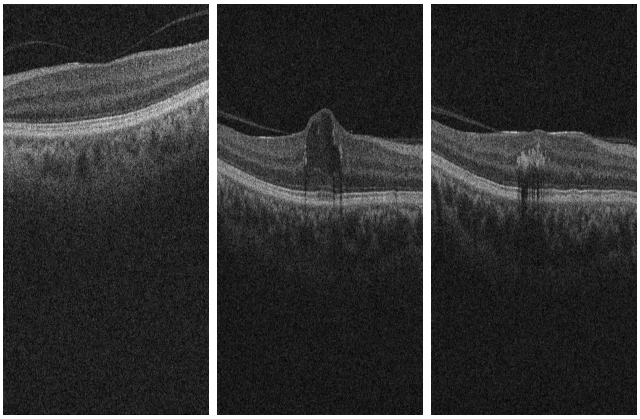
***Abstract*—This paper addresses the problem of automatic classification of Spectral Domain OCT (SD-OCT) data for automatic identification of patients with Diabetic Macular Edema (DME) versus normal subjects. Optical Coherence Tomography (OCT) has been a valuable diagnostic tool for DME, which is among the most common causes of irreversible vision loss in individuals with diabetes. Here, a classification framework with five distinctive steps is proposed and we present an extensive study of each step. Our method considers combination of various pre-processings in conjunction with Local Binary Patterns (LBP) features and different mapping strategies. Using linear and non-linear classifiers, we tested the developed framework on a balanced cohort of 32 patients.**

Experimental results show that the proposed method outperforms the previous studies by achieving a Sensitivity (SE) and Specificity (SP) of 81.2% and 93.7%, respectively. Our study concludes that the 3D features and high-level representation of 2D features using patches achieve the best results. However, the effects of pre-processing is inconsistent with respect to different classifiers and feature configurations.

***Index Terms*—**



(a) Normal (b) DME-cyst (c) DME-exudate

Fig. 1. Example of SD-OCT images for normal (a) and DME patients (b)-(c) with cyst and exudate, respectively.

Introduction

Eye diseases such as Diabetic Retinopathy (DR) and DME are the most common causes of irreversible vision loss in individuals with diabetes. Just in United States alone, health care and associated costs related to eye diseases are estimated at almost $\$500\,\mathrm{M}$ [1]. Moreover, the prevalent cases of DR are expected to grow exponentially affecting over $300\,\mathrm{M}$ people worldwide by 2025 [2]. Given this scenario, early detection and treatment of DR and DME play a major role to prevent adverse effects such as blindness. DME is characterized as an increase in retinal thickness within 1 disk diameter of the fovea center with or without hard exudates and sometimes associated with cysts [3]. Fundus images which have proven to be very useful in revealing most of the eye pathologies [4, 5] are not as good as OCT images which provide information about cross-sectional retinal morphology [6].

Many of the previous works on OCT image analysis have focused on the problem of retinal layers segmentation, which is a necessary step for retinal thickness measurements [7, 8]. However, few have addressed the specific problem of DME and its associated features detection from OCT images. Figure 1 shows one normal B-scan and two abnormal B-scans.

A summary of the existing work can be found in Table I. Srinivasan *et al.* [9] proposed a classification method to distinguish DME, Age-related Macular Degeneration (AMD) and normal SD-OCT volumes. The OCT images are pre-processed by reducing the speckle noise by enhancing the sparsity in a transform-domain and flattening the retinal curvature to reduce the inter-patient variations. Then, Histogram of Oriented Gradients (HOG) are extracted for each slice of a volume and a linear Support Vector Machines (SVM) is used for classification. On a dataset of 45 patients equally subdivided into the three aforementioned classes, this method leads to a correct classification rate of 100%, 100% and 86.67% for normal, DME and AMD patients, respectively. The images that have been used in their paper, are publicly available but are already preprocessed (i.e., denoised), have different sizes for the OCT volumes, do not offer a huge variability in term of DME lesions, and some of them, without specifying which, have been excluded for the training phase; all these reasons prevent us from using this dataset to benchmark our work.

Venhuizen *et al.* proposed a method for OCT images classification using the Bag-of-Words (BoW) models [10]. The method starts with the detection and selection of keypoints in each individual B-scan, by keeping the most salient points corresponding to the top 3% of the vertical gradient values. Then, a texton of size 9×9 pixels is extracted around each keypoint, and Principal Component Analysis (PCA) is applied to reduce the dimension of every texton to get a feature vector of size 9. All extracted feature vectors are used to create a codebook using *k*-means clustering. Then, each OCT volume is represented in terms of this codebook and is characterized as a histogram that captures the codebook occurrences. These histograms are used as feature vector to train a Random Forest (RF) with a maximum of 100 trees. The method was used to classify OCT volumes between AMD and normal cases and achieved an Area Under the Curve (AUC) of 0.984 with a dataset of 384 OCT volumes.

Liu *et al.* proposed a methodology for detecting macular

pathology in OCT images using LBP and gradient information as attributes [11]. The method starts by aligning and flattening the images and creating a 3-level multi-scale spatial pyramid. The edge and LBP histograms are then extracted from each block of every level of the pyramid. All the obtained histograms are concatenated into a global descriptor whose dimensions are reduced using PCA. Finally a SVM with an Radial Basis Function (RBF) kernel is used as classifier. The method achieved good results in detection OCT scan containing different pathology such as DME or AMD, with an AUC of 0.93 using a dataset of 326 OCT scans.

Lemaître *et al.* [12] proposed to use 2D and 3D LBP features extracted from denoised volumes and dictionary learning using the BoW models [13]. In the proposed method all the dictionaries are learned with same size of "visual words" ($k = 32$) and final descriptors are classified using RF classifier.

The work described in this paper is an extension of our previous work [12]. In this research, beside the comparison of 2D and 3D features, we explore different possible representations of the features, and different pre-processing steps for OCT data (i.e. aligning, flattening, denoising). We also compare the performances of different classifiers.

This paper is organized as follows: the proposed framework is explained in Sect. II, while the experiments and results are discussed through Sect. **??** and Sect. **??**. Finally, the conclusion and avenue for future directions are drawn in Sect. **??**.

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I. Related Work

This section reviews the works straightly addressing the problem of classifying OCT volumes as normal or abnormal. A summary can be found in Table I.

Srinivasan *et al.* [9] proposed a classification method to distinguish DME, AMD and normal SD-OCT volumes. The OCT images are pre-processed by reducing the speckle noise by enhancing the sparsity in a transform-domain and flattening the retinal curvature to reduce the inter-patient variations. Then, HOG are extracted for each slice of a volume and a linear SVM is used for classification. On a dataset of 45 patients equally subdivided into the three aforementioned classes, this method leads to a correct classification rate of 100%, 100% and 86.67% for normal, DME and AMD patients, respectively.

Venhuizen *et al.* proposed a method for OCT images classification using the BoW models [10]. The method starts with the detection and selection of keypoints in each individual B-scan, by keeping the most salient points corresponding to the top 3% of the vertical gradient values. Then, a texton of size 9×9 pixels is extracted around each keypoint, and PCA is applied to reduce the dimension of every texton to get a feature vector of size 9. All extracted feature vectors are used to create a codebook using *k*-means clustering. Then, each OCT volume is represented in terms of this codebook and is characterized as a histogram that captures the codebook occurrences. These histograms are used as feature vector to train a RF with a maximum of 100 trees. The method was used to classify OCT volumes between AMD and normal cases and achieved an AUC of 0.984 with a dataset of 384 OCT volumes.

Liu *et al.* proposed a methodology for detecting macular pathology in OCT images using LBP and gradient information as attributes [11]. The method starts by aligning and flattening the images and creating a 3-level multi-scale spatial pyramid. The edge and LBP histograms are then extracted from each block of every level of the pyramid. All the obtained histograms are concatenated into a global descriptor whose dimensions are reduced using PCA. Finally a SVM with an RBF kernel is used as classifier. The method achieved good results in detection OCT scan containing different pathology such as DME or AMD, with an AUC of 0.93 using a dataset of 326 OCT scans.

As stated in the previous section, our current research is an extension of our previous work [14] with further contributions and evaluations at every stages of our classification framework.

TABLE I
SUMMARY OF THE STATE-OF-THE-ART METHODS.

Ref	Diseases			Data size	Pre-processing				Features	Representation	Classifier	Evaluation	Results
	AMD	DME	Normal		De-noise	Flatten	Aligning	Cropping					
[9]	✓	✓	✓	45	✓	✓		✓	HOG		linear-SVM	Accuracy (ACC)	86.7%,100%,100%
[10]	✓		✓	384					Texton	BoW, PCA	RF	AUC	0.984
[11]	✓	✓	✓	326		✓	✓		Edge, LBP	PCA	SVM-RBF	AUC	0.93
[12]		✓	✓	62	✓				LBP-LBP from Three Orthogonal Planes (LBP-TOP)	PCA, BoW, histogram	RF	SE,SP	87.5%, 75%

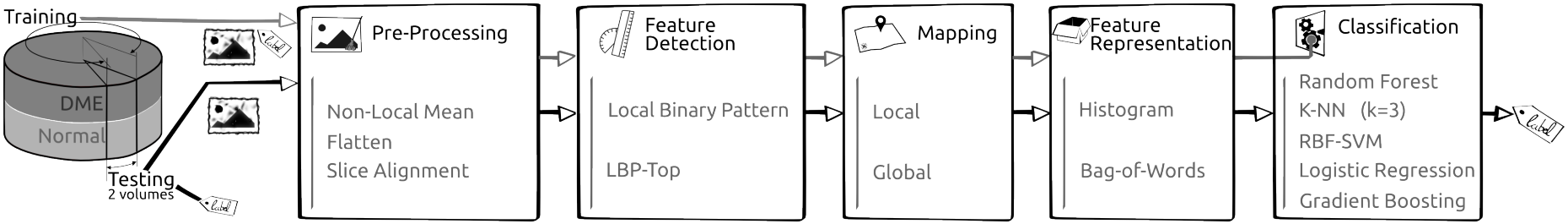

Fig. 2. Our proposed classification pipeline.

II. Materials and Methods

The proposed method, as well as, its experimental set-up for OCT volume classification are outlined in Fig. 2. The methodology is formulated as a standard classification procedure which consists of five steps. First, the OCT volumes are pre-processed as presented in details in Sect. **??**. Then, LBP and LBP-TOP features are detected, mapped and represented as discussed in depth in Sect. **??**, Sect. **??**, and Sect. **??**, respectively. Finally, the classification step is presented in Sect. **??**.

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