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Automatic macular edema identification and characterization using OCT images

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Background and objective: The detection and characterization of the intraretinal fluid accumulation constitutes a crucial ophthalmological issue as it provides useful information for the identification and diagnosis of the different types of Macular Edema (ME). These types are clinically defined, according to the clinical guidelines, as: Serous Retinal Detachment (SRD), Diffuse Retinal Thickening (DRT) and Cystoid Macular Edema (CME). Their accurate identification and characterization facilitate the diagnostic process, determining the disease severity and, therefore, allowing the clinicians to achieve more precise analysis and suitable treatments.
Methods: This paper proposes a new fully automatic system for the identification and characterization of the three types of ME using Optical Coherence Tomography (OCT) images. In the case of SRD and CME edemas, multilevel image thresholding approaches were designed and combined with the application of ad-hoc clinical restrictions. The case of DRT edemas, given their complexity and fuzzy regional appearance, was approached by a learning strategy that exploits intensity, texture and clinical-based information to identify their presence.
Results: The system provided satisfactory results with F-Measures of 87.54% and 91.99% for the DRT and CME detections, respectively. In the case of SRD edemas, the system correctly detected all the cases that were included in the designed dataset.
Conclusions: The proposed methodology offered an accurate performance for the individual identification and characterization of the three different types of ME in OCT images. In fact, the method is capable to handle the ME analysis even in cases of significant severity with the simultaneous existence of the three ME types that appear merged inside the retinal layers.

1. Introduction

Visual impairment represents a major worldwide health concern which, besides its effects on the normal vision, carries a significant loss of life quality and an important economic cost both to the patients and the healthcare systems. According to the World Health Organization (WHO), it is estimated that 253 million people suffer from visual impairment in the world, where 36 million are blind and 217 million present low vision [1,2]. In the last 10 years, despite the progress that was made in surgical procedures, cataracts still remains as the leading cause of visual impairment affecting a 47.9% of the population with vision difficulties. Macular Edema (ME), especially diabetic ME, is also among the main causes of vision loss, being listed as the second [3]. It is defined as a swell in the macular region caused by the leak of fluid from the retinal blood vessels. This swelling changes the morphology of the retinal tissues, fact that is directly linked to the central vision loss, disabling the individuals to correctly perceive shapes, colors or even details of the objects [4]. In the last decades, the average lifespan has increased, yielding an older population where the vi-

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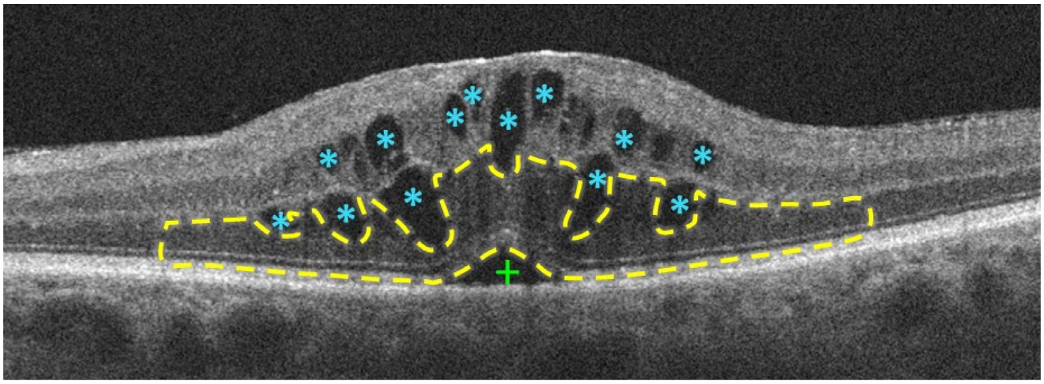

Fig. 1. Example of OCT retinal image with the specified three types of ME: SRD (+), CME (*) and DRT (- -).

sion problems are more frequent. For that reason, it is estimated that the number of people with visual impairment could be triplicated by 2050. It is important that the early detection and treatment of retinal diseases become one of the major health issues in all the countries, especially in the developed ones.

Nowadays, Computer-Aided Diagnosis (CAD) systems are used in ophthalmology as important tools that support the clinical evaluations of several types of eye fundus images. One of the most widely used is the Optical Coherence Tomography (OCT) image modality. This acquisition technique, that is increasing its popularity and use, provides images of a cross-sectional visualization with high-resolution of the retinal layers. It is a non-invasive and contactless technique that evaluates in vivo the histopathology of the retinal tissue.

Regarding the ME disease, a clinical classification was proposed by Otani et al. [5] using OCT images, being widely used worldwide by the specialists as a way to classify the different types of ME based on the properties of the OCT image modality. Hence, considering the clinical characteristics that are present in these images added to retinal properties as thickness, reflectivity or the area of the intraretinal fluid accumulation, MEs were categorized in three main types: Serous Retinal Detachment (SRD), Diffuse Retinal Thickening (DRT) and Cystoid Macular Edema (CME). Posteriorly, Panozzo et al. [6] extended this classification with a new proposal that better characterizes these clinical conditions. The new classification takes into account five parameters for the same defined ME types: retinal thickness, diffusion, volume, morphology and presence of vitreous traction [7]. Fig. 1 illustrates the complexity and heterogeneity of this retinal pathology, given the significant variability in terms of morphology, shape or the relative position that each ME type normally presents within the retinal tissue. Typically, the SRD type is characterized by a dome shape at the inferior retinal layers whereas the CME type is defined by the presence of the intraretinal cystoid spaces of low reflectivity separated by highly reflective boundaries that represent the intraretinal cystoid-like cavities [8]. Finally, the DRT type is commonly characterized by a "sponge-like" swelling appearance as a result of a regional fluid spread with reduced intraretinal reflectivity [4,9].

An automatic detection and extraction of these ME regions is a crucial task as it significantly helps in the evaluation of the disease severity, aiding the clinicians to determine more accurate diagnosis and treatments [10].

In recent years, most of the proposed computational works using OCT images have focused their studies on a general or partial analysis of the presence of the intraretinal fluid. Sidibé et at. [11] proposed a technique that allows the classification of the entire OCT volume. This approach is based on modeling the appearance of normal OCT images using Gaussian Mixture Models (GMM), detecting as outliers the images with intraretinal fluids. In the work of Montuoro et al. [12], the authors proposed an automatic method based on graph theory that allows the simultaneous segmentation of the retinal layers and the existing fluid-filled regions. Following a similar idea, Alsaih et al. [13] used learning strategies to identify normal volumes versus volumes with the ME presence. The dataset was assessed by trained graders and the method identified the volume types in the OCT images based on the evaluation of the retinal thickening, hard-exudates, intraretinal cystoid space formation as well as subretinal fluid. Deep learning was also recently introduced in the issue mainly for cystoid edemas, as the work of Lu et al. [14] that proposed a methodology using a Fully Convolutional Neural Network (FCN) for the segmentation of abnormal fluid regions within the retinal tissue. Lee et al. [15] proposed a method for the automatic segmentation of fluid regions by the application of a Convolutional Neural Network (CNN). Using a similar strategy, Gopinath and Sivaswamy [16] proposed a method also using a CNN implementation for the segmentation of CMEs followed by a post-processing step using clustering to refine the previously identified cystoid regions. Roy et at. [17] also implemented a convolutional architecture based on the RelayNet to simultaneously segment the retinal layers as well as the fluid regions that are present in the OCT images. Schlegl et al. [18] used a neural network comprising two processing components, an encoder that transforms an input image into an abstract representation and a decoder that maps the abstract representation to an output image assigning each pixel to a class as normal or abnormal fluid regions. In the work of Girish et al. [19], the authors proposed a FCN to automatically capture both micro and macro-level features for the characterization of the cystoid structures. Rashno et al. [20] proposed the application of a neutrosophic transformation and a graph-based shortest path method to segment fluid-associated and cystoid regions. González et al. [21] proposed a strategy for the automatic detection of CME edemas. This approach applies a flooding process and a texture analysis, within the retinal region, to identify the presence of these ME type. In the work of Moura et al. [22], a method for the automatic identification of intraretinal fluid regions was designed based on a set of features that characterize the analyzed regions, including intensity and texture-based features. Girish et al. [23] proposed a benchmark study for the automated intra-retinal CME segmentation. In particular, the authors introduced a modular approach integrating different segmentation algorithms, facilitating the comparative analysis between the obtained quantitative and qualitative results of the experiments. Esmaeili et al. [24] proposed a methodology to detect dark pixels between the pigmented epithelium and the nerve fiber layer considering them as cystoid spaces. This approximation was based on a K-SVD dictionary learning [25] in the curvelet transform [26] to help reducing speckle noise, facilitating the set of thresholds that are posteriorly applied to the regions of