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Automatic Segmentation of Macular Holes in Optical Coherence Tomography Images: A review

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Abstract

Macular holes are a blinding condition that occur due to overuse of the fovea, in which a hole alters the natural retinal structure. Optical Coherence Tomography (OCT) is a way of mapping and shaping retinal sections without physical contact and has become a powerful tool for diagnosing pathologies. This paper deals with a review of automated segmentation of macular holes in OCT images, detailing its varied possibilities. It may be considered something new, no reviews were made about the topic. The purpose of this review is to show the latest trends, through the approaches in preprocessing and segmentation. Recent studies were used to validate the research, 2011 onwards, from the Science Direct, IEEE, PubMed and Google scholar bases. The objectives, methodology, tools, database, advantages, disadvantages, validation metrics and results of the selected material are analyzed and mentioned. Based on this, techniques and their results are compared. From this, future outlook scenarios of automated segmentation of macular holes in OCT images are mentioned.

Keywords

Macular holes, Optical Coherence Tomography (OCT), Segmentation, Preprocessing, Pathology

1. Introduction

In the central region of the retina is the macula, and the fovea is near its center. This system allows detailed view [1]. Some macular pathologies are central serous retinopathy (CSR), age-related macular degeneration (AMD) and macular edema (ME) [2–4]. A distinct macular disease less commonly observed is called macular hole (MH) [5]. Macular holes are blinding conditions, that occur due to overuse of the fovea, in which a hole alters the natural retinal structure [6]. The MH pathology affects about 1 per 500 patients over 40 years [7], and for those over 55 years the number rises to 1.65 per 500 patients [8]. Medical advances make people live longer and this caused an increase number in retinal deseases [9, 10].

The main effects due this pathology is the vision reduction or even total blindness [11]. It can cause negative impacts on the quality of life because the limitations of vision. The treatment or a possible surgery depends of the size and shape of the MH. Other important variables are volume, areas, diameters and height. These measures are important to assess if it is possible the hole closure [12–14]. The identification of MH in OCT images can be made through the top boundaries of the internal limiting membrane (ILM) and the retinal pigment epithelium (RPE) [15–17]. In **Figure 1** is shown some important measures to analysis this pathology. MH can be full-thickness holes (FH) and pseudoholes (PH) [18]. For each situation, there is a different way of treating it [19]. The MH size is the major risk factor in case of complications in surgery [20], and it determine the approach, if just a treatment with enzymatic vitreolysis or surgery [21, 22]. Surgeries has achieved good results in visual restoration of patients [23–25].

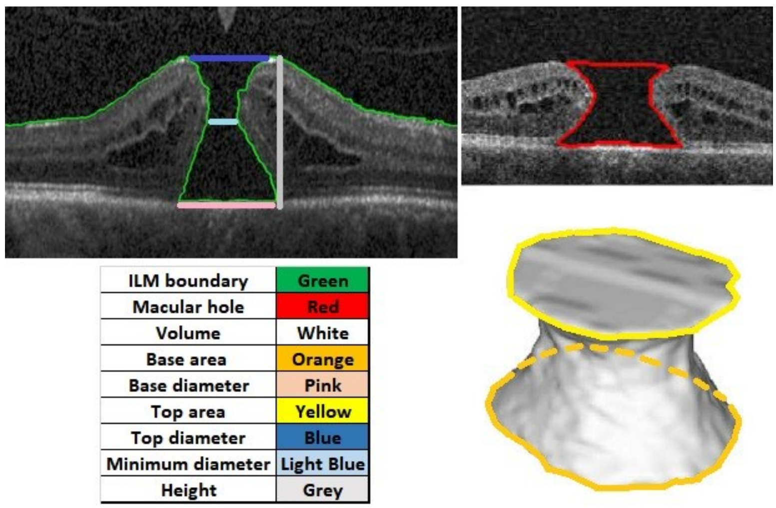

Figure 1. Some measures of MH pathology. Adapted from [26] and [27].

The OCT is a way of mapping and shaping retinal sections without physical contact and has become a powerful tool for diagnosing pathologies [28–30]. OCT provides high quality retinal images. It was first introduced in 1991 [31–33], but it appeared commercially only in 1996 [34]. Now it is standard for medical retinal analysis [35]. Various A scans (1D) build the B scan (2D) image [36], and an aggregation of B-scans constructs a 3D structure [37–39]. These images can have speckle noise, that is a leading problem [40–42], becoming hard to find out how to segment and trace boundaries without this issue compromise the results [43–45]. Shadows caused by retinal blood vessels and some pathologies on retinal structures can challenge even more the segmentation, therefore problems related to a wrong contour are more likely to occur [46, 47].

There are two ways to remove stains on OCT: parallel method, it preserves the resolution, improves contrast, but changes physical structure [48–50]; and serial method, it preserves the physical structure, but is more time cost [51, 52]. Cirrus HD-OCT, 3D-OCT 100 and 2000, RS-3000, Stratus OCT, DRI OCT-1 and Spectralis OCT are some examples of SD-OCT devices [53, 54]. The images of OCT devices are better than those from ultrasound or magnetic-resonance imaging [55]. These images are needful before any conclusion for surgery [56–58], because they provide base to study the development of retinal diseases [59, 60]. There are advantages using OCT: image acquisition quickly [61], great sensitivity to very low light [62] and high resolution for millimeter structures [63].

The OCT devices have their own manual segmentation application [64]. Manual segmentation of boundary layers in OCT images is essentially made by experts. This method takes a considerable time and becomes disadvantageous in studies of segmentation and classification [65–69]. Manual segmentation is yet the major technique of segmentation due the lack of trustworthy automated methods [70]. Thus, a fast and low cost segmentation technique is interesting to help these experts with the retina layers analysis. Automatic segmentation and diagnosis of pathologies using OCT is not an easy task, more than one pathology may affects negatively the results. For the same pathology may exist different characteristics. The MH is one example. The guaranty of an identical comparison between regions is not possible in some studies that use more than one device [71, 72].

Despite the challenges encountered in segmentation techniques of MH pathology, the motivation to produce this review is the importance of automated methods to segment OCT images and help the specialists. Besides that, the advances in research involving this theme can contribute to the total acceptance to use this technology in medical practices. This work may be a source of study for researchers, clinicians and engineers wishing to delve into MH segmentation techniques. They are together seeking improvements in retinal image analysis [73, 74]. Different parameters acquired by OCT images contribute with patient diagnosis and with academic researches [75, 76]. Computer-aided diagnosis systems (CAD) may help health professionals making conclusions because they provide information beyond the images [77–79].

A limited amount of researches has been made in this field of study. Therefore, this review can contribute to spread more researches and approaches on segmentation of MH. The main objective of this article is to analyze the latest technologies used for segment MH in OCT images, through the approaches in preprocessing, segmentation and extraction of attributes. Some approaches were performed in order to automatic segment macular holes from OCT scans. As the MH varies according to its size and shape, automatic segmentation becomes more difficult.

A review of these techniques may be considered something new, no reviews were made about the topic. The survey is timely mainly due the recent increase of publications in the field. It is possible to find more works being produced from 2018 to nowadays than in other years. New technology trends, such as machine learning and deep learning have been sprayed in the last three years, as examples: [80], [81] and [82]. This work details the tasks to segment MH and argues the techniques step by step. For each identified approach, the database, the method and the results are discussed.

Automatic segmentation, specifically of MH, are limited in a small quantity of 6 works and there is no review yet in this area. In order to go deeper, this review proposes to examine the main techniques of other works that uses similar techniques to segment other macular pathologies. The principles are the same and they can be applied in MH, segmenting boundary layers from OCT images in order to obtain specific characteristics for certain macular diseases. The review of pulmonary nodule detection made by Valente [83] served as a source of inspiration and learning for this review. As the work of [83], this review seeks to find the best techniques to help with medical imaging diagnostics.

The review is divided into: Section 2 describes the datasets and research methods used in this work. Section 3 details the assessment of CV systems. Section 4 discusses the results, the key words more commonly used and analysis of the works that best match the research. Section 5 is the Discussion section, where an analysis about the advantages and disadvantages of the relevant works is made. Lastly, Section 6, the Conclusion section, summaries the results of this review.

2. Work selection criteria

To develop this review, some steps were necessary: (1) to carry out research of the subject from the Science Direct, IEEE, PubMed and Google scholar bases; (2) choose the works based on the adopted method; (3) synthesize the keywords, in order to ensure relevant research; and (4) evaluate each selected work.

The following logical expression used in the bases was: (segmentation OR classification

OR detection OR ”macular holes” OR MH) AND (”optical coherence tomography” OR OCT). Each base has its own search settings that require adaptation. The search went beyond the expression used, utilizing relevant works found in the references of some studied papers. It was obtained a total of 128 works. From these papers, 32 were chosen to be studied.

Each work was checked aim at divide them with respect to their application: automated segmentation of MH from OCT images (6 articles); automated segmentation of boundary layers with other pathologies in OCT images, similar approach from MH segmentation (21 articles); and segmentation approaches in classification of macular pathologies, correlated works which describe segmentation techniques before the classification step (5 articles). Although only 6 articles are directly linked to segmentation of MH, the other works were supportive because their techniques can be transmitted to macular holes analysis.

3. Computer Vision systems

Diagnosis using medical images are popular trustworthy. Millions of images are produced by hospitals each year. They come from different sources like magnetic, tomography, or ultrasound. These data have features that can allow specialists diagnose pathologies [84]. The CV obtains information through image analysis. To process it, first is required to convert it into a digital image (pixels), which may vary in grayscale or mix of primary colors [85].

Computer vision ensures visual information for a given application. It is a branch of artificial intelligence (AI). Automated systems can take information of data and perform some tasks [86]. This technology is improving several areas: medicine, industry, science, military force etc [87]. There are some levels of vision: low-level vision, gathering and processing of images; intermediate-level vision, segmentation and classification; and high-level vision, AI that generates results [88]. The CV has four phases: acquisition of data, preprocessing, segmentation and classification. Theses phases of the selected works are shown in **Table 1**.

3.1. Acquisition of data

Data is acquired by images from the OCT technique. Images of public databases are used for researches in different applications. Through these databases, researchers can make studies and comparisons between similar works [89]. From this review, most of the works used particular database only or together with some public ones. Other works did not mention the used database.

Some public databases from OCT images are: Duke dataset [90], OCT Retinal IMage Analysis 3D (OCTRIMA-3D) database [91], Mendeley Dataset [92] and Noor Eye Hospital in Tehran database [93, 94]. These databases include the following conditions: normal macula (NM), diabetic macular edema (DME), dry age-related macular degeneration (AMD), choroidal neovascularization (CNV) and Drusen. For the specific case of MH, all of the 6 directly related works utilize particular databases. It was found just one publicly database with MH pathology in OCT scans: Optical Coherence Tomography Image Retinal Database (OCTID) [95].

The Duke database is a publicly available database of Individual spectral domain SD-OCT images with 38400 B-scans with AMD and NM. This database contains their ages, and their corresponding segmentation boundaries on a 5mm diameter centered at the fovea [90]. OCTRIMA-3D dataset is a publicly database that has 10 SD-OCT volume. There are raw images, manual markings of two experts and results. Speckle noise was reduced and contrast enhancement was made in these images [91, 114].

The Mendeley Dataset has data to train and test algorithms. The images are mixed in four conditions: CNV, DME, Drusen, and NM. This dataset has 5.8 Gigabyte of OCT images [92]. The Reza Rasti database is another publicly available database. It consists of NM, AMD and DME conditions. There are around 512 to 768 A-scans that together make

Table 1. CV phases of the selected works.

Authors	Year	Preprocessing	Segmentation	Classification
Nasrulloh et al. [11]	2018	Yes	Yes	No
Keller et al. [26]	2016	Yes	Yes	No
Miri et al. [96]	2016	Yes	Yes	No
Zhang et al. [5]	2015	Yes	Yes	No
Xu et al. [27]	2013	Yes	Yes	No
Liu et al. [19]	2011	Yes	Yes	Yes
Duan et al. [43]	2017	Yes	Yes	No
Sui et al. [28]	2017	No	Yes	No
Hu et al. [65]	2019	Yes	Yes	No
Hussain et al. [97]	2015	Yes	Yes	No
ElTanboly et al. [98]	2016	Yes	Yes	No
Hussain et al. [99]	2017	Yes	Yes	No
Chiu et al. [100]	2012	Yes	Yes	No
Novosel et al. [101]	2017	Yes	Yes	No
Naz et al. [102]	2017	Yes	Yes	No
Xiang et al. [103]	2019	Yes	Yes	No
Hassan et al. [104]	2018	Yes	Yes	No
González-López et al. [105]	2019	Yes	Yes	No
Stankiewicz et al. [106]	2017	Yes	Yes	No
Athira et al. [107]	2018	Yes	Yes	No
Gopinath et al. [108]	2017	No	Yes	No
Dodo et al. [109]	2019	Yes	Yes	No
Duan et al. [110]	2015	Yes	Yes	No
Lang et al. [111]	2017	Yes	Yes	No
Niu et al. [112]	2014	Yes	Yes	No
Rossant et al. [113]	2015	Yes	Yes	No
Tian et al. [114]	2015	Yes	Yes	No
Huang et al. [80]	2019	No	Yes	Yes
Nath et al. [82]	2018	Yes	Yes	Yes
Hassan and Hassan [81]	2019	Yes	Yes	Yes
Hassan et al. [1]	2016	Yes	Yes	Yes
Fang et al. [115]	2017	Yes	Yes	Yes

the B-scans [93, 94]. The OCTID was the only publicly available database found with only cases of macular holes pathology [95]. This dataset has 102 B-scan OCT images. There is no ground-truth or any manual segmentation made by experts to make comparisons and validate algorithms.

3.2. Preprocessing

Preprocessing image techniques for this review are performed in order to improve their characteristics based on the type of application to the next step, which is the segmentation of a subject in a particular region of interest (ROI). This stage is important due OCT images eventually contain inhomogeneity, speckle noise and shadows caused by retinal blood vessels [116].

The review indicates many types of preprocessing techniques: dilation and erosion [5], median filter [27, 107, 111], gaussian filter [11, 100, 101], wiener filter [11, 81, 99], binary image [26, 100], gradient image [26, 114], anisotropic difusion filter [5, 97, 99], image aligment [19, 98, 103], attenuation coefficient [101], enhanced contrast [1, 105], image flattenig [106, 114], resize the image [1, 107], edge flow [112], sparse filter [112], normalization [81], green channel [81], greyscale [1], morphological operations [1] and others. In **Figure 2** is shown the improvements of preprocessing applied to OCT image.

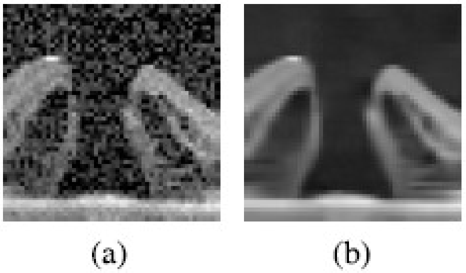

Figure 2. (a) Original OCT image and (b) denoise using the Wiener filter [11].

3.3. Segmentation

Segmentation is a fundamental branch of CV system that collaborates to the automated diagnosis of MH and other pathologies. In the case of MH, this task is challenging because the top boundary of the ILM is irregular and nonlinear. It is not coincidence that there are few works that explore the segmentation or classification for this pathology. Some metrics can be used to validate an algorithm: accuracy, processing time and error variation.

Some segmentation techniques applied to OCT images are: snakes or active contour, it is a method used to circumvent objects in an image [105]; graph search, this technique starts from a starting point to an ending point, repeating the process, trying to find the best path [5, 26, 27]; Dijkstra shortest path search, it is an algorithm that seeks to find the shortest path between two nodes [26, 99, 107]; local gaussian distribution fitting (LGDF), local entropy defines gray level weights [11]; curvature-based surface cutting, it can be flattened into the plane with low metric distortion [11]; ReLayNet, it is an architecture used to segment retinal layers [80, 117]; speed-up robust features (SURF), it is a method used in tasks like object recognition, classification etc [115]; adjusted mean arc length (AMAL), it enables to pass the load limit and turning points, and consequently to follow the post-critical equilibrium trajectories [26]; gradient vector flow (GVF), it is an algorithm that locates object edges [96, 118, 119].

Other techniques are: multi-scale spatial pyramid (MSSP), it captures the geometry of retina at multiple scales [19]; geodesic distance method (GDM), it can locate pixels in boundaries of layers [43]; convolutional neural network (CNN), it is pooling, which is a non-linear down-sampling [28, 108, 120]; dynamic programming (DP), it is a method that divide problems and solves each one separately [65, 100, 102]; canny edge detection, it is an algorithm that detects edges [97, 99, 104]; markov gibbs random field (MGRF), it allows to derive a global texture description by specifying local properties of textures [98]; loosely coupled level sets (LCLS), it is a technique that uses local intensity variations to segment layers [101]; structure tensor, it utilizes the gradient of a point with neighborhood to get directions of segmentation [102, 104]; Randon Forest (RF), that train the data to estimate boundary probabilities [111, 121, 122]; and OTSU algorithm, it is used to perform automatic image thresholding [102, 107, 112]. In **Figure 3** is shown an example of segmentation approach applied to an OCT image, in which the top boundary of the ILM and RPE layers are highlighted. The automatic segmentation methods of MH or similar pathologies are divided and indicated in **Table 2**.

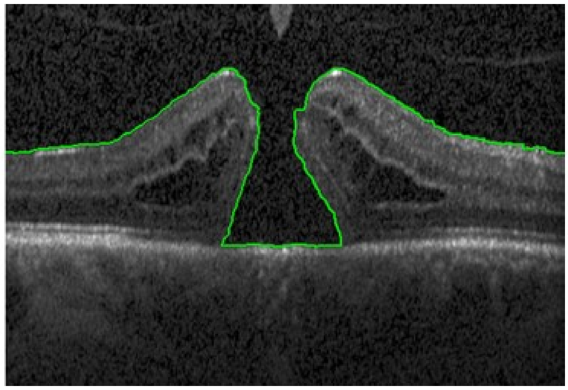

Figure 3. Segmentation of a macular hole [26].

3.4. Classification

Classification is based on information of the observed data. Usually are extracted features that differentiate some patterns. In the case of classification of pathologies in OCT images, the previous step, that is the segmentation, is the focus in these articles. Classification techniques can be performed in segmentation approaches too. Some works in this field combine image processing with techniques of AI [123–125]. The classification of retinal pathologies can be seen in many works [126]. Some examples in this review are: convolutional neural network (CNN) [80], k-nearest neighbour (KNN) [82, 127], suporting vector machine (SVM) [1, 81], multi-instance multilabel learning (MML-LR) [115] and adaboost classifier [5]. In **Figure 4** is given an illustration of some pathologies classified based on their boundary layers.

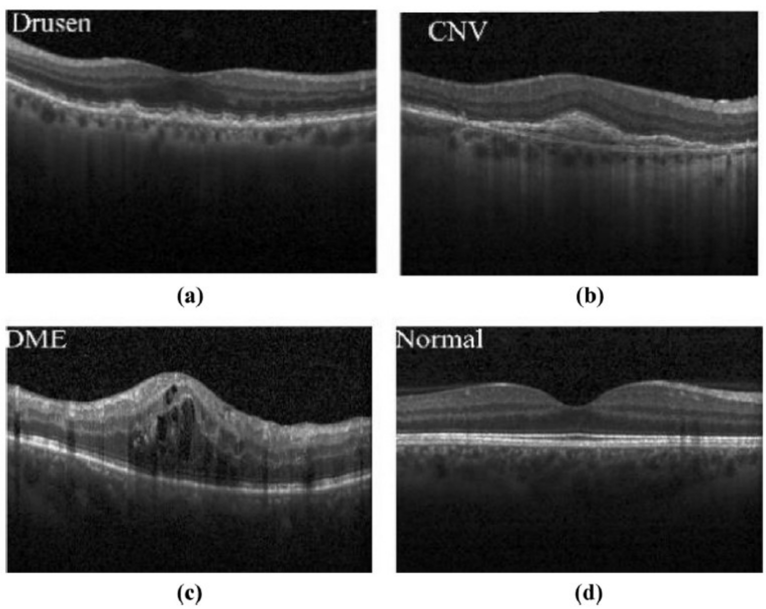

Figure 4. Some retinal pathologies [128].

4. Selected Works

Some metrics of validation were observed in the articles for this review and it is important to understand their meaning, they are: standard deviation (SD), it measures dispersion from the

Table 2. Automatic segmentation of MH or similar boundaries.

Type of segmentation	Segmented boundary layers	Authors	Segmentation technique(s)
Segmentation of MH	1	Nasrulloh et al. [11]	LGDF / Curvature-based Surface Cutting
	1	Keller et al. [26]	AMAL / Graph Search / Dijkstra
	1	Miri et al. [96]	GVF / Graph Theory
	2	Zhang et al. [5]	Graph Cut
	2	Xu et al. [27]	MS-3D Graph Search
	NI	Liu et al. [19]	MSSP
Segmentation of boundary layers	9	Duan et al. [43]	GDM
	2	Sui et al. [28]	CNN / Graph Search
	5	Hu et al. [65]	CNN / Graph Search
	3	Hussain et al. [97]	Graph Search / Dijkstra / Canny Edge
	12	ElTanboly et al. [98]	MGRF
	4	Hussain et al. [99]	Dijkstra / Canny Edge
	3	Chiu et al. [100]	Dijkstra / Graph Theory / DP
	8	Novosel et al. [101]	LCLS
	8	Naz et al. [102]	DP / Structure tensor / Canny Edge / OTSU
	11	Xiang et al. [103]	RFC / Single Graph Live Wire Algorithm
	6	Hassan et al. [104]	Structure tensor / Canny Edge
	4	González-López et al. [105]	Snakes or Active Contour
	2	Stankiewicz et al. [106]	Peak Intensity Analysis / Graph Theory
	NI	Athira et al. [107]	Dijkstra Shortest Path / OTSU
	8	Gopinath et al. [108]	CNN
	9	Dodo et al. [109]	Level Set Method
	12	Duan et al. [110]	Region Growing Method
	8	Lang et al. [111]	RFC / Graph Search
	6	Niu et al. [112]	OTSU / Polynomial Fitting Function
	8	Rossant et al. [113]	Snakes or Active contour
	8	Tian et al. [114]	Graph Search / Dijkstra shortest path
	2	Huang et al. [80]	ReLayNet
	7	Nath et al. [82]	LCLS
	8	Hassan and Hassan [81]	Tensor Grid / OTSU / Canny Edge
	8	Hassan et al. [1]	OTSU / Canny Edge
	2	Fang et al. [115]	SURF

mean of a dataset; sensitivity, or true positive rate (TPR), or recall, it indicates the amount of correctly identified actual positives; specificity, or true negative rate (TNR) indicates the amount of correctly identified actual negatives; accuracy, it indicates how close the values are measured to a target; signed error (SE), it is a sample statistic that summarizes how well a set of estimates match the quantities that they are supposed to estimate; unsigned error (UE), it is the opposite of signed error.

Other important metrics are: jaccard Index, it is used in understanding the similarities between sample sets; Dice similarity coefficient (DSC), it is a reproducibility validation metric; operator characteristic curve (AUC) or ROC curve, it evaluates the binary classifier as its discrimination threshold varies.; average deviation distance (AD) or mean absolute deviation (MAD), it is the average distance between each data point and the mean; first-order agreement coefficient (AC1), it is the probability of agreement of evaluators; Pearson correlation, it indicates how two variables are linearly related; and signal to noise ratio (SNR), it is a comparison between desired signal and the level of background noise.

During research, many keywords were found. In **Figure 5** is shown the most relevant keywords to this field of study. This section analysis the best works exploring the most recent and important approaches for automated segmentation in OCT images.

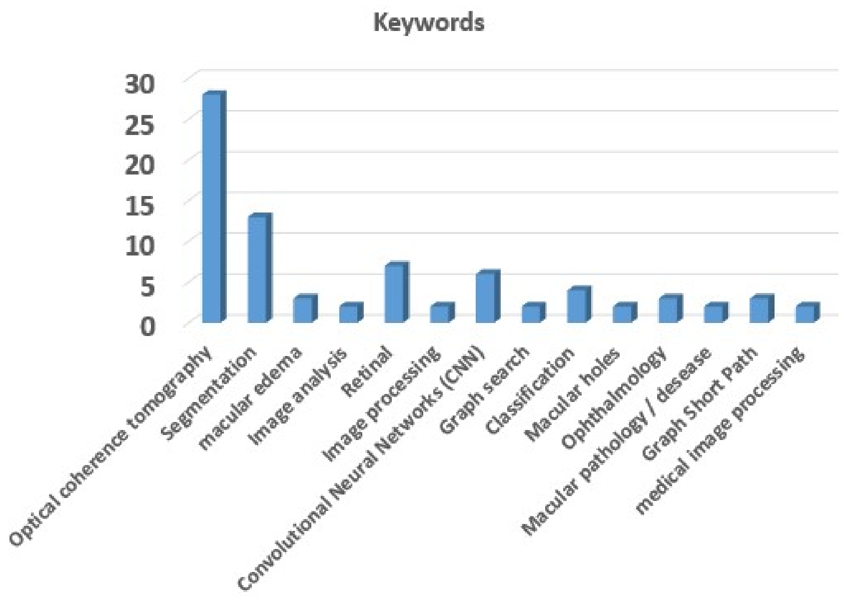

Figure 5. The best and most effective keywords.

Nasrulloh [11] developed a technique to extract measurements from the automated segmentation of MH. In this technique, after the preprocessing step, the segmentation is processed by LGDF and Curvature-based Surface Cutting. A total of 30 images of MH cases were used and the average segmentation performance was of 19.84 seconds per image. The algorithm had an accuracy of 99.19%, sensitivity of 85.18%, Jaccard Index of 76.34% and DSC of 86.19%. Keller [26] also created an algorithm to segment MH. The technique used was AMAL. It was necessary 10 different patients (24 images from each one). The mean, SD and the time to segment MH with the Dijkstra Shortest Path Search were of 0.043 mm, 0.013 mm, and 0.039 s, respectively.

Miri [96] proposed an algorithm to perform the automatic segmentation of the ILM boundary within optic nerve head (ONH). The method identified the ILM surface using a Graph Theory and GVF methods. A total of 44 patients were used. The mean and SD were of 1.9 ± 0.475 mm and the Pearson correlation was of 99.94%. Zhang [5] proposed a technique similar to Miri [96] to segment CME for the retina with MH pathology. The coarse segmentation was made by AdaBoost classifier and the fine segmentation used Graph Cut algorithm. To evaluate the technique, 18 3D OCT volumes with MH and CME were used. The accuracy of TPR was of 84.5%, FPR was of 1.8% and accuracy rate was of 98.6%.

Xu [27] suggested a method for segmentation of 2D and 3D MH. The segmentation was performed using Multi-scale 3D Graph Search. A total of 51 eyes contained 128 B-scans were used. Patients with other diseases were excluded. The accuracy was of 96% and the mean error between the two experts was of 6.1%. Different from Xu [27], Liu [19] developed a classification method of multiple macular pathologies, they were NM, ME, MH, and AMD. The segmentation approach was MSSP. A total of 326 macular SD-OCT scans were used. The algorithm achieved an AUC of 0.93 for all pathologies.

Sui [28] developed a choroidal segmentation algorithm. The techniques used were deep multi-scale CNN and Graph Search. A total of 23972 images were necessary. The mean and SD of absolute error in pixels were of 8.5 $\pm$ 7.6. Hu [65] sugested a segmentation technique of multiple retinal layer boundaries using the same techniques as Sui [28]. The method included 50 OCT images. The UE value in pixels for the mean, max, and SD were of 0.99, 1.13, 0.10, respectively.

Hussain [97] created an automatic method to segment the ILM and the Bruch's Membrane Opening (BMO). The techniques used were Canny Edge Detection, Dijkstra Shortest Path Search and Connected Component Analysis. A total of 18 SD-OCT volumes were used. The precision was of more than 95%. The UE difference for BMO location and BMO-MRW were of 54.18 $\pm$ 53.74 µm and 58.62 $\pm$ 43.12 µm (mean $\pm$ SD), respectively. Hussain [99] created an automatic method to identify 4 boundaries layers in the presence of 3 pathologies using the same techniques as Hussain [97]. A total of 3 datasets were used and 2 of them are public. The mean and SD of the root-mean-square error in pixels were of 1.57 $\pm$ 0.69.

Novosel [101] developed a segmentation method in 3D OCT volumes of retinal layers and focal lesions. The LCLS framework and Locally Adaptive Likelihood were applied. A total of 97 B-scans were used. The method achieved TPR of 93% for fluid segmentation, DSC of 68% and MUE ranging from 4.9 to 8.3 µm for drusen segmentation. Stankiewicz [106] sugested the segmentation of ERM from 3D volumes too. The used techniques were Peak Intensity Analysis and Graph Theory. A total of 141 B-scans were used. The results with Pixel Intensity Analysis in MSE and SD were 46.07 and 11.44 µm. The results with Graph Search technique in MSE and SD were 26.55 and 8.81 µm.

Naz [102] sugested the automatic segmentation of retinal layers using two techniques and compared using 108 OCT images: Kernel regression + GTDP (mean and SD of 0.004 $\pm$ 0.0001 µm) and Structure tensor (mean and SD of 0.289 $\pm$ 0.0659 µm). Hassan [104] proposed an algorithm to detect fovea in OCT scans. The segmentation of six retina layers also used Structure Tensor and Canny Edge Detection. The dataset contains 120 OCT B-scans with three conditions: NM, ME and CSR. The overall accuracy was of 97.5%.

Chiu [100] proposed the segmentation of three retinal boundaries from images with AMD, RPE and drusen. The segmentation were based on Dijkstra's Shortest Path Search, Graph Theory and DP. A total of 100 B-scans were used. The mean and SD were of 4.2 $\pm$ 2.8 µm. This work was one of the most compared and studied articles by researchers in this field. Tian [114] created an algorithm called OCTRIMA-3D that segments retinal layer boundaries of OCT volume. It is based in Dijkstra Shortest Path proposed by Chiu [100]. A total of 10 SD-OCT volume datasets were used. In addition, 100 SD-OCT images were necessary too. The MSE $\pm$ SSE for the ILM surface were of 0.6 $\pm$ 1.14 pixels.

Athira [107] developed a technique to detect ME based on fractal texture analysis. Layers detection also used Dijkstra Shortest Path Search, and also Sparse Matrix and OTSU algorithm. A total of 100 normal and 100 ME images were used. The algorithm had an accuracy of 97.5%, sensitivity of 98.9% and specificity of 98.05%. Dodo [109] created an algorithm to segment nine layers. Different from the others that used Dijkstra's Shortest Path in segmentation step, in this work it was applied to the preprocessing step. The initialisation used Fuzzy image processing. The segmentation was made by Level Set methods. A total of 200 images were used. The mean and SD in pixels were of 0.9643 ± 0.014.

Xiang [103] created a method to segment retinas with CSR. The technique used was RFC and Single Graph Live Wire Algorithm. A total of 48 images with 128 B-scans were used. The TPF, FPF and DSC in % were of 92.73 ± 15.03, 0.05 ± 0.09 and 92.73 ± 14.21, respectively. Lang [111] created a segmentation method for retinal layers in retinitis pigmentosa (RP). It also used RFC and Graph Search algorithm. A total of 512 A-scans and B-scans varying from 19 to 49 for each patient were used. The boundary errors in µm over all subjects were specified in signed error and absolute error of $- 0.9 \pm 2.65$ and 4.22 ± 2.44, and the layer thickness errors over all subjects were of $- 0.03 \pm 3.33$ and 5.14 ± 2.69.

González-López [105] developed an automatic segmentation method for retinal boundary layers. The proposed technique was based on Snakes or Active Contours and it used 40 OCT images. The overall DSC was of 91.25% and the mean and SD for unsigned boundaries were of 1.27 ± 1.06 pixels. Rossant [113] sugested a segmentation method of layers for RP subjects using another approach of snakes, the PDS. The database included 95 images. Comparisons between the automatic segmentation to manual segmentation and comparisons of PDS model against Twin Snakes, Ribbon Snakes and Ribbon of Twins (ROT) were made. The PDS technique leaded to the best results with mean and SD of 1.3 ± 0.33 pixels.

Huang [80] proposed a classification method called ReLayNet for four conditions: NM, DME, drusen, and CNV. Two datasets were used. The first one contains 84484 OCT B-scans (averaged overall accuracy and SD were of 88.4 and 1.3). The second one contains a total of 8904 (averaged overall accuracy and SD were of 89.9 and 0.6). Nath [82] also proposed a segmentation and classification method to classify pathologies in normal or abnormal OCT images. The ROI was detected using attenuation coefficients by LCLS. There are no information about the database. The mean deviation for all interfaces were of 1.9 and 8.5 µm. Duan [110] created a technique to segment retinal layers using Region Growing method. Just as in Nath [82], nothing about the database was mencioned. The results shown were only qualitative. A visual comparison was made between the proposed method and other three techniques. It was possible conclude empirically that the proposed method had the best segmentation.

Niu [112] proposed a technique to segment retinal boundary layers using OTSU algorithm, Polynomial Fitting Function and Top-hat Filtering. A total of 3200 B-scans were necessary. The mean and SD in µm were of 0.22 ± 0.24. Hassan [81] developed an algorithm to classify macular conditions in NM, CSR and ME. Preprocessing and layer segmentation were necessary. For the segmentation step was also needed OTSU algorithm, also other methods, such as Tensor Grid and Canny Edge Detection. A total of 90 OCT volumes were necessary. The accuracy, sensitivity and specificity were of 97.78%, 96.77% and 100%, respectively.

Gopinath [108] proposed an algorithm using deep learning, CNN and LSTM. Three datasets were used. For normal cases: dataset of Chiu (110 B-scans) and OCTRIMA3D (100 B-scans). For pathology cases: Chiu (220 B-scans). The mean and SD in pixels were of 1.78 ± 0.78 for Chiu-path, 1.16 ± 0.46 for Chiu-norm and 0.92 ± 0.31 for OCTRIMA-3D. Hassan [1] also developed a deep learning classification technique for three retinal conditions: ME, CSR and NM. The segmentation step was performed based on Canny Edge Detection and OTSU algorithm. The dataset was composed by 90 time domain OCT (TD-OCT). The accuracy, sensitivity and specificity were of 97.77%, 100% and 93.33%, respectively. Other work with similar approach was proposed by Fang [115]. It is a detection and recognition technique of multiple macular lesions: ERM, edema, and drusen in OCT images with Multi-instance Multilabel Learning. The segmentation of ROIs for different lesions was performed by SURF. A total of 823 clinically labeled OCT images were used. The results in % were: accuracy of 88.72 ± 0.84, recall of 91.21 ± 0.53 and precision of 92.83 ± 0.74.

El Tanboly [98] sugested the segmentation of the largest number of retinal layers, twelve, considering healthy and deseased subjects. The methods used were LCDG and MGRF. A total of 200 normal and diseased OCT scans were used. The accuracy using DSC, AC1 in %, and AD in µm represented as mean and SD were of 0.763 ± 0.1598, 73.2 ± 4.46 and 6.87 ± 2.78. Besides segment twelve layers, Duan [43] also created an algorithm to detect 3D retinal boundary layers based on GDM. A total of 50 B-scans were used. The mean and SD of SE were of - 0.11 ± 0.22 µm, absolute error (AE) were of 1.43 ± 0.2 µm and Hausdorff distance (HD) were of 7.3 ± 0.67 µm. To compare and divide the articles in this review, some attributes were used. A total of 32 articles were utilized. The comparison is shown in **Table 3**.

Table 3. Comparison between the related works.

Authors	Accuracy (%)	Mean ± SD (mm)	Response time
Nasrulloh et al. [11]	99.19	0.9644 ± 0.0015	19.84 s/image
Keller et al. [26]	NI	0.043 ± 0.013	0.039 s/image
Miri et al. [96]	99.94	1.9 ± 0.475	NI
Zhang et al. [5]	98.6	NI	NI
Xu et al. [27]	96	0.061 ± 0.0	38 s/image
Liu et al. [19]	93.1	NI	NI
Duan et al. [43]	NI	0.0014 ± 0.0002	0.415 s/image
Sui et al. [28]	NI	8.5 ± 7.6 in pixel	3.4 s/image
Hu et al. [65]	NI	0.99 ± 0.1 in pixel	27.5 s/image
Hussain et al. [97]	97.27	0.059 ± 0.0431	NI
ElTanboly et al. [98]	NI	0.0069 ± 0.0029	NI
Hussain et al. [99]	NI	1.57 ± 0.69 in pixel	NI
Chiu et al. [100]	NI	0.0042 ± 0.0028	1.7 s/image
Novosel et al. [101]	89	0.0049 ∼ 0.0083	NI
Naz et al. [102]	NI	0.004 ± 0.0001 in µm	NI
Xiang et al. [103]	92.73 ± 14.21	NI	NI
Hassan et al. [104]	97.5	NI	5 s/image
González-López et al. [105]	91.25	1.27 ± 1.06 in pixel	NI
Stankiewicz et al. [106]	NI	0.0026 ± 0.0088	NI
Athira et al. [107]	97.5	NI	NI
Gopinath et al. [108]	NI	0.92 ± 0.31 in pixel	4 s/volume
Dodo et al. [109]	NI	0.96 ± 0.01 in pixel	NI
Duan et al. [110]	NI	NI	NI
Lang et al. [111]	NI	0.0042 ± 0.0024	NI
Niu et al. [112]	99.96	0.0022 ± 0.0024	NI
Rossant et al. [113]	87.4	1.3 ± 0.33 in pixel	NI
Tian et al. [114]	NI	0.6 ± 0.0 in pixel	26.1 s/volume
Huang et al. [80]	89.9	NI	NI
Nath et al. [82]	NI	0.0019 ± 0.0085	NI
Hassan and Hassan [81]	97.78	NI	NI
Hassan et al. [1]	97.77	NI	8 s/image
Fang et al. [115]	88.72	NI	0.25 s/image

5. Discussion

The main objective of this review is approach the segmentation techniques of macular holes in OCT images, however the amount of works in this field is limited. Therefore, some works involving boundary layers segmentation in OCT images were used. Since the ILM layer is the most important layer for MH segmentation in OCT images, many of these works use techniques to segment it, but for other pathologies. A study of the selected works shows that many possibilities for segmentation of MH in OCT images are possible. Some approaches obtained accuracy upper 95%, as examples: [11], [96], [5], [27], [99], [104], [107], [112], [81] and [1].

Some advantages can be mentioned in the works selected for this review. Liu [19] was the first study showing satisfactory results in automatic diagnosis in OCT images. It was important to serve as starting point to other works. Chiu [100] created one of the most compared and studied articles by researchers in this field. Xu [27] proposed a method that classify MH in four classes, this is an important step for the surgical aid. Keller [26] developed a method that can be applied to segment MH and other subjects in medical images. Zhang [5] created an algorithm that can segment CME excluding MH and blood vessels. The work of Miri [96] had smaller border errors than the comparative methods. Nasrulloh [11] developed a technique 61 times faster (2.46 minutes) than the original LGDF implementation. El Tanboly [98] had the first work segmenting twelve layers with all kinds of condition.

Duan [43] outperformed the Active Contour and Graph based approaches for segmenting retinal layers in both healthy and pathological images. Sui [28] developed a deep learning method which is unique in choroid segmentation. Hu [65] obtained more reliable probability maps using neural network. Novosel [101] developed an algorithm to segment layers and lesions. González-López [105] created an algorithm tolerant to noisy scenarios. Gopinath [108] developed a method that not requires any preprocessing step. Duan [110] successfully segmented the OCT image that contains some broken retinal layers. Tian [114] created an algorithm that not requires advanced denoising techniques.

Disadvantages can also be mentioned in the proposed works. In the preprocessing phase of Zhang [5], the delineation of MH was rough and contained failures. In Keller [26], the algorithm had data to find parameters like MH height and base width, but did not. In Xu [27], MH edge segmentation errors could be adjusted and patients with other diseases were excluded. Liu [19] found out that in their algorithm texture features may decrease effectiveness of the classifier. The work of Sui [28] spends about 10 h for each loop in training algorithm. Hussain [97] could not give a comparative analysis with other existing methods, because do not exist public database with segmentation of BMO or BMO-MRW.

Chiu [100] found a tradeoff between functionality and accuracy. Comparisons between the method of Novosel [101] and others was difficult, because there was no pattern of images and reference standard. González-López [105] sugested a model in which a completely fair comparison with the states-of-the-art seems extremely complicated because they used more than one dataset, each one with their own setting. Duan [110] created a method in which there is not quantitative analysis of the results and nothing about the database was mencioned. Tian [114] developed a methodology that sometimes has problem to segment the ILM boundary. The review showed that the latest segmentation techniques of MH in OCT images have not solution for all issues yet, and more research and improvement needs to be done.

5.1. Future prospects

Further researches are necessary to find out new approaches or improve the existing ones. A closer relationship between the medical community and the researchers strengthens the subject. Future prospects can allow the total use of MH segmentation systems in daily medical practices, they are:

- CV systems with a better accuracy and robustness to speckle noises;
- development of techniques that can automatically measure features of MH and classify them according with their classes;
- creation of a publicly database of OCT images with MH containing segment and feature information to help researchers on their works;

- promoting a closer relationship between the involved parties in the system, such as engineers, physicians, technicians and government.

6. Learned lessons

Segmentation techniques are fundamental to aid in the diagnosis of medical pathologies. Researchers are constantly looking for the best segmentation techniques. The advancement of computing is allowing practices with increasing levels of accuracy. Image preprocessing is almost always required before applying some segmentation technique, but some deep learning tools already do not require image preprocessing. Despite the growth of deep learning techniques, new preprocessing and segmentation techniques are constantly appearing.

There are some softwares that can be used for CV tasks, but the predominance is the Matlab and Python as integrated development environment. There are numerous public and private databases for macular pathologies, but for macular holes there is still no well-defined database with manual segmentation for comparison porpuse, per example. The number of experts working on the ground truth of articles can range from one to five. Comparisons for validation work may use one to eight state-of-the-art. Advantages and disadvantages can be observed in each work, depending on the technique used. A perfect result for segmentation of MH or similar pathology has not been found yet. Validation metrics can vary, this will depend on what kind of parameter you want to focus on.

7. Conclusion

This paper elaborated a review of CV techniques applied to segmentation of macular holes and similar techniques that can be applied on this pathology. The work used papers published from the year 2011 to nowadays on Science Direct, IEEE, PubMed and Google scholar bases, which makes a recent review. Progress has been performed in this field. However, though the area of diagnostics requires more studies. The issue is important to the scientific community, due the need of boundary segmentation in other tasks too.

In general, the revised papers show potential for the joining of CV technology with medical diagnostics. Many challenges still need to be overcome for their full admission in medical practices. For this, a good partnership between researchers and physicians is needed. The total acceptance to use this technology in medical practices will only work by joining forces between health professionals, researchers, government, engineers and partners. Thus, with these efforts will be possible to spread this technology and make it operational. The reduction of errors is a requirement for the acceptable use of these technologies.

The best results could be analyzed due to well done research, considering the best keywords, in well-known scientific bases. This work may be a source of study for researchers wishing to delve into MH segmentation techniques. This review may serve as a basis for studies and developments of techniques even more robust than those mentioned here, with the aim of solving the problems that still exist in automatic MH segmentation.

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Conflicts of Interest

There is no conflict of interest.

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