

Development of a Method of Feature Space Formation for Assessment of Choroidea Condition from Retinal Angio-OCT Images

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Abstract. This paper presents a technique for selecting regions of interest in retinal angio-OCT images to quantitatively analyze choroidea parameters in order to detect ocular diseases. The significance of this research lies in the fact that choroideas are an important part of the eye responsible for nourishing the retina and maintaining its normal function. Disruptions in the choroidea lead to various eye conditions, including degenerative retina diseases and glaucoma. A method for assessing choriodeal conditions has been developed based on identifying areas without vascular signal in retinal angiographic OCT images. Additional indicators for estimating choriodean status have been proposed. Comparative analysis of parameters between norm and pathological classes was conducted. The results of this work may be useful for ophthalmologists and contribute to improved diagnosis and treatment for eye conditions. © 2024 Journal of Biomedical Photonics & Engineering.

Keywords: biomedical images; optical coherence tomography images; threshold processing; choroid; quantitative features; quantitative analysis.

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1 Introduction

The choroidea is a capillary layer that extends along Bruch's membrane and lies adjacent to the inner vasculature. It plays an important role in supporting the vessels of the retinal pigment epithelium and the outer part of the retina. The choroideas are the main vascular layers of the eye and influence the development of various ocular diseases, such as age-related macular degeneration, polypoidal chorioretinal vasculopathy, central serous choroidopathy, and myopic macular degeneration. The choroids also provide nutrition and waste removal from the retinas, playing an essential role in their health and function. Histological studies have confirmed that pathological processes affect the structure and vascularization of the choroid [1].

Diseases in which changes in choroidal thickness are observed include central serous chorioretinopathy, Vogt-Koyanagi-Harada disease, polypoidal choroidal vasculopathy, and age-related exudative macular degeneration.

Central serous chorioretinopathy (CSC) is characterised by the accumulation of fluid under the retina in the central region of the macula, leading to distortion of the visual field and decreased visual acuity. Changes in the thickness of choroidea are associated with impaired blood supply and drainage in this area [2].

Vogt-Koyanagi-Harada disease (VKH) is a rare inflammatory condition that affects the eyes, skin and other organs. The main symptoms of VKH include inflammation of the eye, changes in skin pigmentation and hair, and visual disturbances. Changes in the choroidal thickness of the retina are associated with an inflammatory process and immune mechanisms that affect blood vessels in the eye [3].

Polypoidal choroidal vasculopathy (PCV) is a type of age-related macular degeneration (AMD) in which abnormal vascular formations resembling polyps develop in the choroid. These polyps can lead to bleeding, swelling, and visual impairment. Changes in choroid thickness in PCV are associated with the formation and regression of these abnormal polyps [4].

Exudative AMD is a form of AMD in which abnormal vascular neoplasms accumulate under the retina, causing a decrease in visual function and distortion of the central field of vision. Changes in the thickness of the choroid in AMD are associated with growth of these tumors and disruption of normal vascular structure [5].

The study of these diseases and choroidal changes helps to expand our understanding of the pathophysiology of ocular pathologies and develop new approaches to diagnosis and treatment. The concept of choroidal vascular index (VI) was introduced to assess the degree of vascular density in the choroid and can serve as an additional tool for monitoring these conditions [6].

Investigations of ocular diseases require accurate and reliable diagnostic methods [7–9]. In recent years, optical coherence tomography (OCT) has become a key tool for evaluating the choroid and other structures of the eye [10–12]. OCT is a non-invasive high-resolution imaging technique that produces cross-sectional tissue slices with micrometre resolution [13]. Unlike other methods, such as fluorescence angiography or indocyanine green angiography, which have gained importance in the diagnosis of ocular diseases, OCT provides more detailed and objective information about the structure and thickness of the choroid [14].

The main features of OCT include the ability to image layers of eye tissues and assess their thickness with high resolution [15, 16]. OCT allows clear visualization of the choroid, detection of changes and determination of various pathological conditions such as choroidal neoplasms. It also monitors the effectiveness of treatment and evaluates the prognosis of disease. Due to its ability to obtain three-dimensional images, OCT provides a more comprehensive study of the structure and changes of the choroids compared to other methods.

OCT images of the ocular fundus were used to develop algorithms for glaucoma diagnosis registration in Refs. [10, 11]. Also, OCT images of the ocular fundus from [12] were studied and used to determine retinal edema. A classification system was developed based on these studies. Similar studies have been conducted in Refs. [15–21].

The study method chosen was the analysis and processing of ocular fundus angiography images.

2 Materials and Methods

The task of ocular fundus angiography-OCT image processing is to form sets of features for quantitative analysis of the choroidea. To develop a technology for assessing the state of the choroid by identifying areas where vascular signal is absent. The following types of choroidal OCT angiography (angiography) images are used as input data for processing. Angio-OCT images have a size of $3 \times 3 \text{ mm}^2$.

OCT scans with angiography (OCTA), as shown in Fig. 1(a, b), are used to assess the choriocapillary status. The choriocapsular status is determined by the presence of voids in the scans that are larger than $5000 \mu\text{m}^2$

(200 pixels, 1 pixel equals $25 \mu\text{m}^2$). The reviewed literature concludes that people with central serous chorioretinopathy have a greater number of large voids (equal to or greater than $5000 \mu\text{m}^2$) compared to healthy volunteers [22]. Also Fig. 1(a) shows an image without pathology and Fig. 1(b) shows an image with pathology. It can be seen that the images differ in their brightness. Therefore, we proposed a criterion for estimating the transparency of the choroid layer based on image brightness.

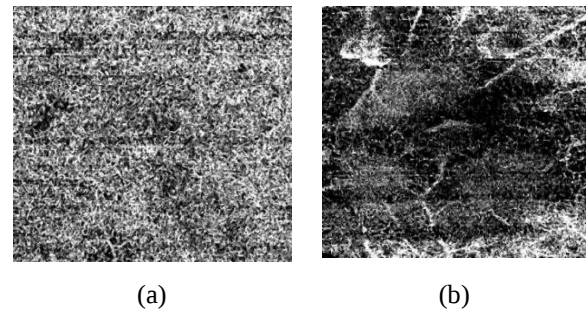


Fig. 1 Angio-OCT of the choroidea: (a) normal, (b) pathology.

For the study, images were taken from 9 to $18 \mu\text{m}$ deep into the vasculature, from Bruch's membrane, and strata of $9 \mu\text{m}$ thickness were experimentally selected. Images at these depths were selected based on the fact that the number of voids is least in images at those parameters [22].

The method itself consists of subjecting OCTA scans to local thresholding using the Phansalkar algorithm, where voids are defined as pixels of black color [23]. A sign to track pathological changes is an increase in the number of large voids or an increase in their size [22].

To further analyze the choroidal index, we selected relevant features on which a detailed analysis was performed. The technology for evaluating diagnostic features to detect pathologies from retina angio-OCT images is presented below.

3 Methods for Evaluating Diagnostic Features for Quantitative Choroideal Analysis

To evaluate the images, textual features need to be extracted [24].

We selected the following features to quantify the choroidea on retinal angio-OCT images:

- 1) the number of voids (K_1),
- 2) the area of voids that are equal to or greater than $5000 \mu\text{m}^2$ (K_2),
- 3) the contour characteristic (K_3),
- 4) the transparency coefficient (K_4).

Transparency is characterized by a positive offset of the mean value of brightness with respect to the median value:

$$I_c = \frac{I_{\max} - I_{\min}}{2}. \quad (1)$$

For opaque media, I_c . The quantitative expression of this parameter is the transparency coefficient. The coefficient is determined by Eq. (2) [25]:

$$K_4 = \frac{(\bar{I} - I_c)}{\bar{I}}, \quad (2)$$

where K_4 is the transparency coefficient, $\bar{I}$ is the mean luminance value, I_c is the median luminance value.

K_3 is a contour feature, which is defined as the sum of all contour pixels in the image. First, we select the contours using openCV and then we use Eq. (3):

$$K_3 = \sum_{i=1}^H \sum_{j=1}^W I(i, j), \quad (3)$$

where K_3 is the number of pixels representing contours; h is the height of the image, w is the width of the image, the function defining the pixel color $I(i, j) = \{1 \text{ if pixel } (i, j) \text{ is white, } 0 \text{ otherwise}\}$.

For choroidea optical coherence tomography (OCT) angiography images, criteria have been proposed such as the number and area of voids. The presence of voids equal to or greater than $5000 \mu\text{m}^2$ determines the choriocapillary status. Individuals with choriocapillary pathology have a higher number of larger voids compared to healthy patients, according to exploratory studies.

A technology has been developed for processing angio-OCT images.

4 Technology for Choroidea Assessment

To assess the choroidea, a technique was developed consisting of the following steps including pretreatment methods:

- a) median filter processing,

- b) threshold processing,
- c) extreme filter processing,
- d) allocation of voids,
- e) an assessment of their quantitative characteristics.

The first step is to apply the median filter with a window size of 3×3 . The result of image processing by the median filter is shown in Fig. 2 (b).

Thresholding was applied locally using the Phansalkar algorithm, where voids are defined as black-colored pixels [23]. The unique threshold was calculated using the Eq.:

$$\text{threshold}(x, y) = M \left(1 + p e^{-qM} + k \left(\frac{SD}{r} - 1 \right) \right), \quad (4)$$

where (x, y) are the pixel coordinates, M is the mean of all pixels within the radius, SD is the standard deviation of all pixels within the window, p is a constant that the exponential term affects the threshold – for low values of p ($0 \leq p \leq 1$) it behaves like Sauvola's method, too high ($p > 5$) and too many background pixels can be classified as foreground pixels (default $p = 3$), q – constant, and the algorithm behaves like Sauvola's algorithm above a certain values (default $k = 0.25$), r – dynamic range of standard deviation (default $r = 0.5$). The result of the thresholding process is shown in Fig. 2 (c). To sharpen and improve image quality, an extreme filter was used, described by the following Eq.:

$$g = \begin{cases} f_1, & \text{при } f_0 - f_1 < f_N - f_0 \\ f_N, & \text{при } f_0 - f_1 \geq f_N - f_0 \end{cases} \quad (5)$$

where f_i are the numbers of the variation series of the population with N numbers, g is the output value.

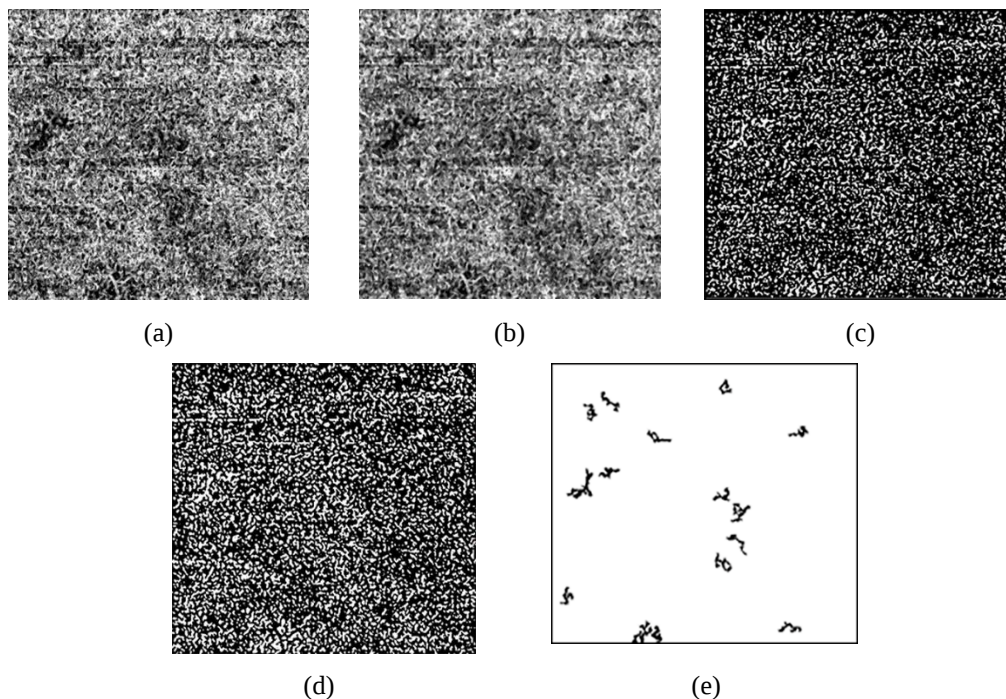


Fig. 2 Voids extraction: (a) original image, (b) median filter result, (c) local thresholding result, (d) extreme filter result, (e) voids image.

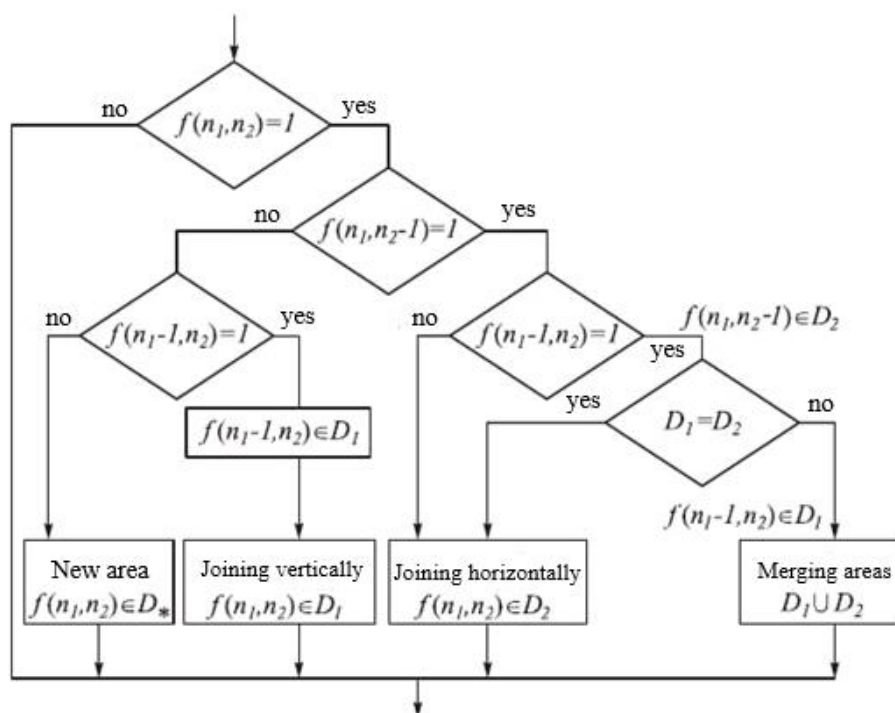


Fig. 3 Scheme of the algorithm of voids selection [16].

Table 1 Static characteristics for “normal” and “pathology” classes.

Feature group	Norma		Patalogy	
Parameter	RMS deviation	Mathematical expectation	RMS deviation	Mathematical expectation
K ₁	588.174	7302.2	217.459	7935.8
K ₂	6.786	6,4	4.962	67.2
K ₃	885.687	818.7	2613.857	16105.1
K ₄	0.074	0.08	0.035	-0.619

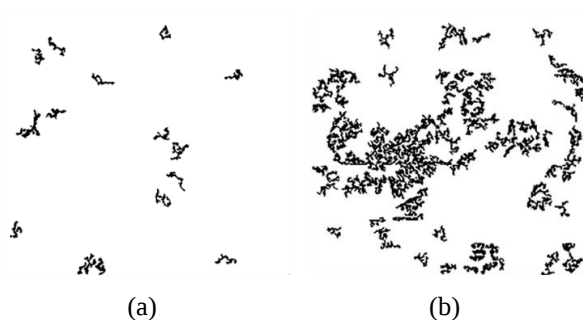


Fig. 4 Visualisation of the foramen: (a) normal, (b) pathology.

The result of applying the extreme filter is shown in Fig. 2 (d).

The selection of voids is based on the criterion of four-connectivity, i.e., only samples adjacent to the sides of an object are considered neighbors. The algorithm consists in processing the image matrix line by line. An arbitrary sample (n_1, n_2) is selected, if it

belongs to the background and is equal to zero, then the next sample is processed. If it does not belong to the background (i.e., it is equal to one), then its belonging to any object is analyzed. For this purpose, two neighboring samples already processed are taken into account. Depending on the values of these neighboring samples, the current sample may be attached to an object. If neighboring samples belong to background, a new object is created [25]. The algorithm is shown in Fig. 3.

Experimental investigations of the proposed technique on natural images are presented below.

5 Analysis of the Results of Image Processing of Chorioid Angio-OCT Images

For the analysis, we took images at depths of 9–18 μm from the Bruch's membrane, with a step size of 9 μm .

Figs. 5–8 show the distribution graphs of the obtained values of the signs.

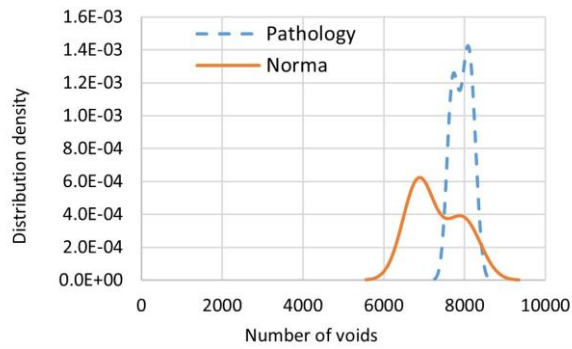


Fig. 5 Void distribution density plot.

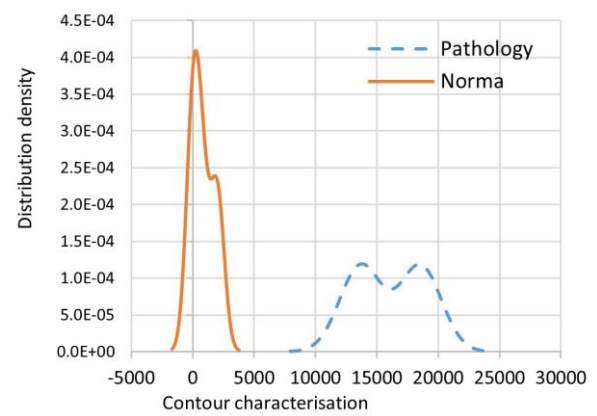


Fig. 7 Contour characteristic distribution density plot.

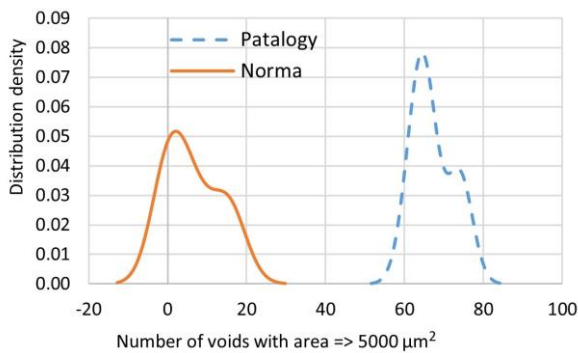
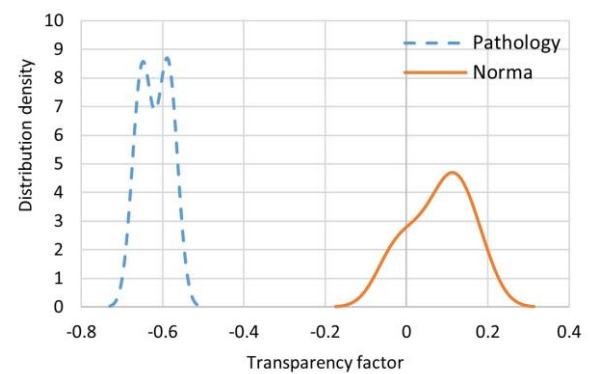
Fig. 6 Density plot of the distribution of voids with an area equal to or greater than 5000 μm^2 .

Fig. 8 Transparency ratio distribution graph.

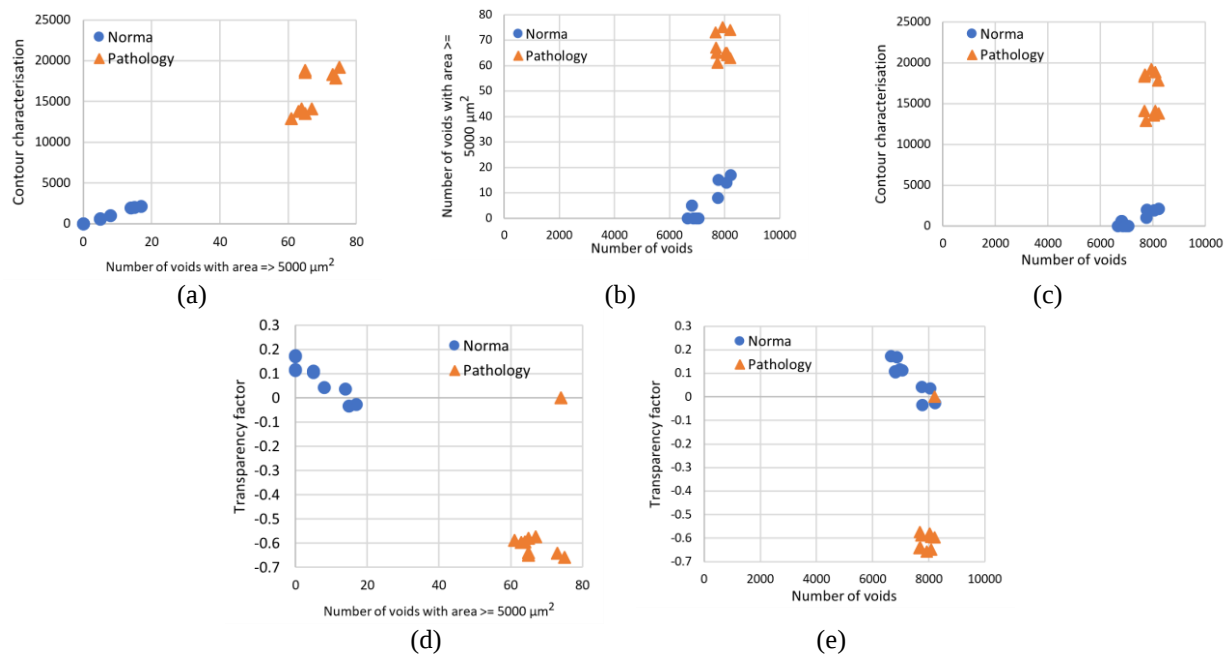


Fig. 9 Graphs of distribution of objects of two classes in the space of Contour characteristic: (a) for the number of voids with area greater than 5000 μm^2 , (b) the ratio of the number of voids with area greater than 5000 μm^2 to the number of all voids, (c) for the number of all voids; Transparency coefficient: (d) for the number of voids greater than 5000 μm^2 , (e) for the number of all voids.

This choice was based on previous studies, which showed that the lowest number of voids were found in formations at these depths [22]. Fig. 4 shows a visualisation of voids for normal and pathological conditions.

According to the above graphs, we can already say that there is a clear separation between the classes of normal and pathological objects. We also plotted the distribution of objects in the two classes, and the results are presented in Fig. 9. Table 1 shows the static characteristics of features for the “normal” and “pathology” classes.

6 Conclusion

This paper presents a technique for selecting regions of interest in retinal angio-OCT images for quantitative analysis of choroid parameters to detect various ocular diseases. In this work, features of the choroid were

studied and algorithms for extracting parameters and counting were reviewed.

During the study, a method was developed to assess the condition of the choroids by finding areas with no vascular signal (voids) in angio- OCT images of the choroidal region, as well as a set of features was formed for quantitative assessment of choroid: contour characteristics, transparency coefficient, number of voids, and number of void areas greater than or equal to 5000 μm^2 . The results obtained were analyzed. On the angio-OCT images, the contour and transparency coefficients showed clear separation between classes.

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Disclosures

The authors declare that they have no conflict of interest.

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