Volumetric Segmentation of Human Eye Blood Vessels Based on OCT Images

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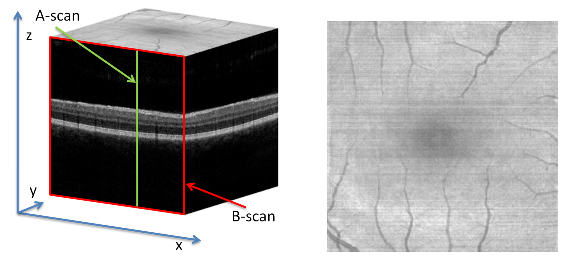
***Abstract*—In this paper we present a method for volumetric segmentation of retinal vessels based on 3D OCT images of human macula. The proposed hybrid method is comprised of two steps: detailed extraction of superficial blood vessels indicators visible in 2D projection of retina layers followed by an axial inspection of inner retina to determine exact depth position of each vessel. The segmentation procedure is improved by application of block-matching and 4D filtering (BM4D) algorithm for noise reduction. The 3D reconstruction of vascular structure was performed for 10 normal subjects examined with Avanti AngioVue OCT device. The automated segmentation results were validated against the manual segmentation performed by an expert giving the accuracy of 95.2%.**

***Keywords*—retina vessels segmentation, fundus reconstruction, optical coherence tomography (OCT), 3D visualization**



(a) OCT volume (b) fundus projection

Fig. 1: Example of macular 3D OCT examination

I. Introduction

A comprehensive analysis of three-dimensional (3D) human retina biometric characteristics is considered essential for proper diagnosis of retinal diseases. One of the important diagnostic tasks is segmentation of blood vessels. Detailed segmentation of retinal vascular network from OCT images have multiple applications including: detection and assessment of various retinal diseases including those affecting the vessels directly [1], atlas generation, taking account of vessel influence in thickness measurement. Vessels segmentation is also frequently performed in order to align multiple retinal images e.g. acquired at various points (like macula and optic nerve head), during multiple clinical visits, with different devices or even with different imaging modalities [2].

Retina vessels segmentation is typically based on images acquired by 2D fundus camera, which requires an unpleasant strong flash of light and takes advantage of high contrast and resolution of the image [3]. While fundus image gives only 2D information about vessels structure, the spectral domain optical coherence tomography (SD-OCT) — a non-invasive imaging technique — provides volumetric analysis of the examined tissue. An example of a 3D scan through the macula is shown in Fig. 1a. Such volumetric scan consists of a set of cross-sections (i.e. B-scans) and each B-scan is composed of a series of A-scans (see Fig. 1a). In the OCT B-scan it is possible to distinguish silhouettes of blood vessels that appear below the vessels [4]. It is caused by absorption of light by the red cells and leaving dark shadows in the underlying layers. Projection of data averaged in the axial direction allows for a simplified reconstruction of the fundus image with vessels as illustrates Fig. 1b. Another indicator of the vessels presence is thickening of retinal nerve fiber layer (NFL) [5]. This information can be used for extraction and parameterization of vasculature.

This possibility was further improved with introduction of optical coherence tomography angiography (OCTA). This technology uses special scan acquisition protocols and advanced image processing algorithms to segment three vascular plexuses of the retina (superficial, deep and choroidal) and visualize vessels as 2D projections [6]. It should be noted, that nowadays the OCT angiography is not so popular yet and majority of the currently used OCT devices is not equipped with this function. It is not possible to evaluate disease evolution with respect to previously acquired scans. Non-angio algorithms for vessel structure determination can be used to analyze such historical data. Furthermore, the OCTA technique, based on decorrelation algorithm to find blood flow, fails to detect the blocked or obstructed blood vessels.

Automatic segmentation of vessels is not commonly available since algorithms have to overcome image processing problems such as: speckle noise, low/uneven data resolution and contrast, crossing of vessels in the axial direction. Additionally, even modern OCT devices do not provide a 3D model or visualization of retina vascular network.

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A. State of the art

Standard segmentation techniques designed for color fundus images have very low accuracy when applied to OCT images (as will be further shown in Section IIIB). Vessel segmentation techniques based on SD-OCT volumes may be classified into:

- **nonhybrid methods** – dependent only on information from a single OCT examination. This group includes methods based on a supervised k-NN pixel classification of a 2D projection acquired from an automatically segmented retina region [4]. Another classification-based approach utilized training on A-scans characterized as vessel and non-vessel proposed by Xu et al. [7], further extended to 3D boosting learning algorithm utilizing 2D features from the reconstructed OCT fundus image and a Haar-feature calculated from each A-scan [8].
  The first 3D vessel segmentation was performed by Hu et al. [9] with the use of a 3D graph-based approach. However, the volumetric segmentation was only based on a projection image and did not include information about vessels position in the vertical direction.
  Pilch et al. presented a two-step procedure that consists of defining the vessels positions in the lateral direction based on a shadowgraph and using an active shape model to label these contours in the third direction [10].
  Kafieh et al. introduced information of RNFL thickness and shadow position into vessels segmentation procedure [11]. They improved overall accuracy by combining vessels detection based on curvelet transform of 2D OCT projection with their innovative approach.
- **hybrid methods** – multimodal solutions that implement both OCT data and scanning laser ophthalmoscopy (SLO) or fundus images. Hu et al. presented a method based on k-NN pixel classification to segment vessels around the Nerve Canal Opening (NCO) using fundus images and 3D OCT scans [2]. A multimodal approach for vessel segmentation of macular OCT slices along with the SLO image based on brightness variations and curvelet image analysis was proposed by Kafieh et al. [12].
- **methods based on multiple OCT examination (OCTA)** – de-correlation algorithm performed on several subsequent OCT examinations. OCTA takes advantage of differences in the backscattered OCT signal between sequential B-scans taken at the same location [13]. Movement of blood between repeated examination is calculated using split-spectrum amplitude-decorrelation algorithm (SSADA) [6]. It allows for imaging retina vasculature divided into three sections: superficial, deep and choroidal. Unfortunately, this technique although having high potential in vascular disease diagnostics requires special acquisition protocol, higher imaging speed and has lower field of view to achieve high density data in a fixed acquisition time of several seconds. As was mentioned earlier, it is available with the newest OCTA devices only, and it provides projections of each retina section instead of a 3D visualization.

II. VESSELS SEGMENTATION FROM 3D OCT

A. Morphology-based OCT analysis

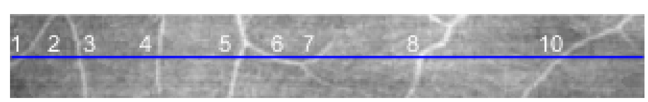
In our method we focus on the inner retina vessels located in the ganglion cell layer (GCL) [14]. Fig. 2 shows an example of a single OCT cross-section with corresponding projection images of the GCL and RPE layers obtained from a 3D scan of a healthy 28-year old volunteer. The horizontal lines in the projection images (Fig. 2a and Fig. 2c) indicate location of the illustrated B-scan (Fig. 2b). Blue, red and green curves in the B-scan represent upper and lower boundaries of the GCL and RPE layers respectively.

As can be seen in Fig. 2b bright areas between GCL boundaries mark positions of superficial vessels, while dark areas between RPE layer boundaries mark shadows of those vessels. It is worth mentioning that not all vessels present in the GCL have shadows in the RPE projection or their shadow is very weak (see vessels number 2 and 7), and not all shadows visible in the RPE represent vessels located in the GCL (see shadow number 9).

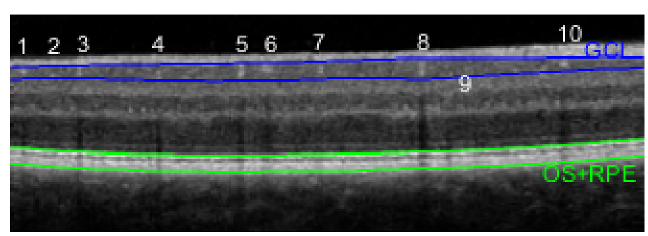
From the detailed analysis of 3D OCT scan it can be stated that vessel segmentation based only on shadow detection leads to erroneous results. In order to perform precise segmentation we search for the vessels themselves instead of their indicators. We propose a hybrid algorithm that detects superficial vessels incorporating local brightness variations wih focusing on inner retina areas. The general scheme of the proposed solution is illustrated in Fig. 3.

B. Preprocessing

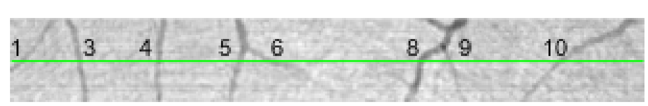
Prior to applying image analysis algorithm we perform noise reduction as a pre-processing procedure. Our previous research showed that both anisotropic diffusion and wavelet-based approaches give good results for improving quality and preserving structural characteristics in OCT images [15]. In



(a) Fragment of a GCL layer projection image



(b) B-scan image with segmented GCL and RPE layers



(c) Fragment of a RPE layer projection image

Fig. 2: Example of B-scan image with corresponding projections of segmented GCL and RPE layers

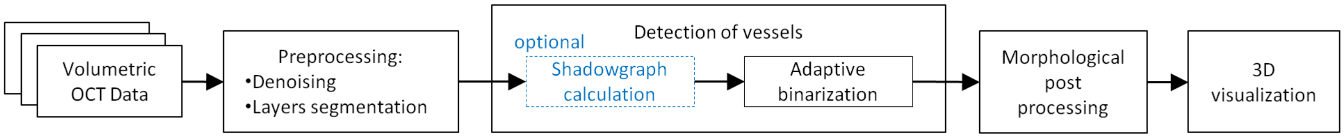


Fig. 3: General scheme of the algorithm

the following experiments we used block-matching and 4D filtering (BM4D) algorithm proposed by Maggioni et al. [16]. This is a novel method incorporating collaborative Wiener filtering of a 3D data, that provides very good denoising effectiveness for medical images.

Since detection of vessels in the next steps is narrowed to specific retina layers, the preprocessing step includes also segmentation of upper and lower boundaries of 2 retina layers: GCL and RPE. We segment those layers using our modified graph theory-based approach [17].

C. Segmentation of superficial retina vessels

1) Shadowgraph-based approach: Since thicker vessels, that lie in the GCL layer, can cause lower illumination response of outer retina layers, the majority of methods proposed so far are those based on shadow detection for lateral vessels segmentation. A very fast and robust method for calculation of lateral vessel position is based on shadowgraph — a function of the B-scan column-wise intensity values. The region of intereset for this procedure vary between algorithms. We tested three approaches: two from references [10], [18] and our solution. The main features of these approaches are as follows:

- shadowgraph s_1 computed for the width of the B-scan as a sum of intensities of image $I(x,z)$, where x denotes the index in transversial direction and z is index in the axial direction [18]. The calculation includes only the region below inner retina (up to the segmented outer segments border $L_{IS/OS}$) and can be described by

$$s_1(x) = \sum_{z=0}^{L_{IS/OS}(x)} I(x,z) \tag{1}$$

- shadowgraph s_2 created by calculating grey-level centers of each A-scan, where h describes the vertical resolution of the B-scan image [10]:

$$s_2(x) = \frac{\sum\limits_{z=0}^{h-1} z * I(x,z)}{\sum\limits_{z=0}^{h-1} I(x,z)} \tag{2}$$

- shadowgraph constructed as a function of the normalized projections of GCL and RPE layers as describe (3)–(5). Taking into account intensities of tissue reflectance in the GCL layers allows for emphasizing those vessels that exist in the superficial vascular complex and are too small to leave a significant shadow trace. The influence of shadows can be weighted by parameters w_1 and w_2.

The parameter $\epsilon \in \langle 0,1 \rangle$ is used for enhancing intensity values of the projections.

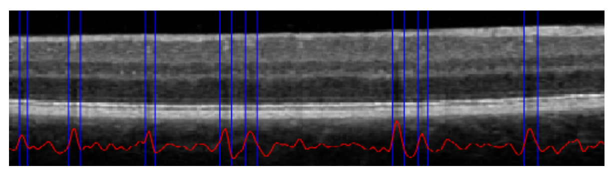
$$s_3 = w_1 \frac{P_{GCL}}{max(P_{GCL})} - w_2 \frac{P_{OS-RPE}}{max(P_{OS-RPE})} + \epsilon \tag{3}$$

$$P_{GCL}(x,z) = \sum_{z=L_{IPL/INL}(x)}^{L_{GCL/IPL}(x)} I(x,z), \tag{4}$$

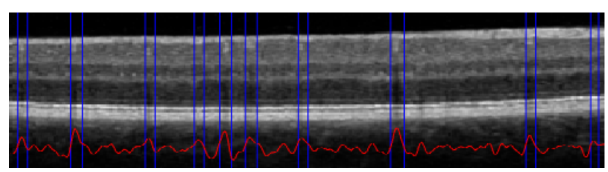
$$P_{OS-RPE}(x,z) = \sum_{z=L_{IS/OS}(x)}^{L_{RPE/CHR}(x)} I(x,z) \tag{5}$$

Each calculated shadowgraph is subjected to smoothing (using Savitzky-Gola filter, length = 3, weighing factor = 21), removing low freqency component and normalization. Next, the obtained shadowgraphs are thresholded with a parameter $t_1 \in \langle -1,1 \rangle$ to detect the vessels. Figs. 4a-4c present shadowgraphs calculated for the image in Fig. 2b using $t_1 = 0.4$.

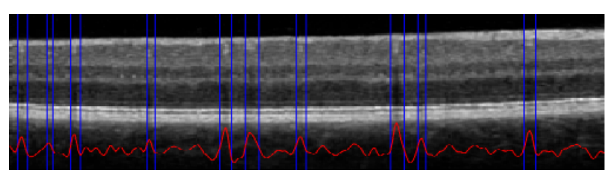
Such pre-segmented vertical sections are next evaluated in axial direction to obtain full volumetric structure. The search was performed between upper and lower boundaries of the GCL using adaptive binarization approach with threshold t_2.



(a) shadowgraph obtained from summarized axial intensity values of the outer retina [18]



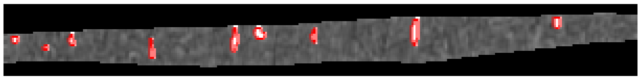
(b) shadowgraph obtained from axial grey-level centers [10]



(c) shadowgraph obtained from normalized layers projections

Fig. 4: Example of lateral vessels segmentation: B-scan image with overlayed shadowgraph (red curve) and detected shadow regions (blue vertical lines) for each the evaluated method

(a) Shadowgraph-based method



(b) Volumetric adaptive binarization method

Fig. 5: GCL section of B-scan image with manualy segmented vessels (white areas) and borders of automatically segmented vessels (denoted in red)

Fig. 5a illustrates effect of this procedure using shadowgraph s_3 with parameters $w_1 = 1.1$, $w_2 = 0.8$, and $\epsilon = 0.5$. White spots depict manualy segmented vessels, the detected vessel areas are enclosed with red circles. The threshold was selected as 0.05 over a median value of the analyzed shadow-defined image region. All vessels are correctly identified in their volumetric space. The vessel number 9 was correctly detected near the lower boundary of GCL.

2) Volumetric adaptive binarization-based approach: As was indicated in Fig. 3 the shadowgraph calculation can be ommited. In this case the adaptive binarization is performed directly on volumetric data in the area of GCL and does not rely on indicators such as shadows. First, the area between upper and lower boundaries of GCL is extracted, then we calculate the median value of pixels in this area and perform thresholding, leaving out pixels of intensities lower than the selected treshold t_3. Fig 5b illustrates a result of this approach for $t_3 = 0.15$. This method gives narrower detection of vessels, than the methods based on the shadowgraph.

III. Experiments and Results

A. Data and processing

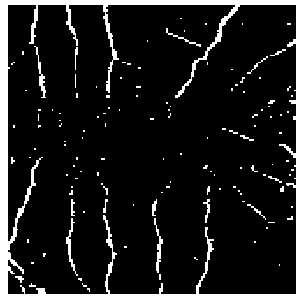
The reconstruction of vascular network was performed for 10 normal subjects examined with Avanti AngioVue device (Optovue Inc., USA). The volumetric scan consisted of $304\times304\times640$ data points representing $3\times3\times2$ mm of tissue what gives an axial resolution of $3.1\,\mu$m and transversal resolution of $9.9\,\mu$m. The experiments were performed in Matlab/Simulink environment on raw data exported from OCT.

B. Vessels detection in the lateral direction

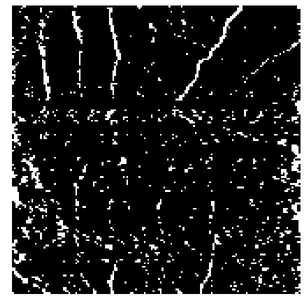
We evaluated precision of the methods based only on the shadow detection ([10], [18]) and compared them to our two proposed solutions as well as to the line tracking method designed for color fundus images [19]. First experiment was set to evaluate the accuracy of vessels segmentation in the lateral direction. Table I presents results of this experiment. It can be derived that shadowgraph s_1 provides better segmentation accuracy than shadowgraph s_2, and both of our approaches give better results, although the volumetric adaptive binarization method has the best performance. The line tracking method has very low accuracy and cannot be utilized for OCT images without considerable adjustments.

TABLE I: Results of lateral segmentation procedure for superficial vessels complex

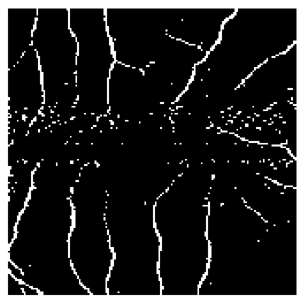
Method	Accuracy [%]	Precision [%]	Specificity [%]
Shadowgraph s_1	92.9	53.7	95.1
Shadowgraph s_2	90.0	34.6	95.0
Shadowgraph s_3	94.8	75.2	98.6
Volum. adapt. bin.	95.2	78.7	98.8
Line tracking	27.6	8.7	22.2



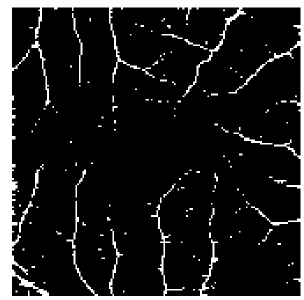
(a) Shadowgraph s_1



(b) Shadowgraph s_2



(c) Shadowgraph s_3



(d) Volumetric adaptive binarization

Fig. 6: Projections of detected superficial vessels

The parameters for shadowgraph s_3 were selected empirically for one volumetric scan and gave the best accuracy for values: $w_1 = 1.2$ and $w_2 = 0.7$ and $\epsilon = 0.5$. We tested thresholds t_2 and t_3 for adaptive binarization steps in the range of $\langle 0, 0.5\rangle$. The best results were obtained for $t_1 = 0.42$, $t_2 = 0.43$ and $t_3 = 0.14$. Examples of binary representations of segmented vessels for each tested method illustrates Fig. 6. As can be seen from Fig. 6d the volumetric adaptive binarization method preserves connections between branches, what is important for clinicians. Fig. 7 presents Receiver Operating Characteristic of lateral segmentation.

C. Vessels detection in 3D

The second experiment was focused on the analysis of the algorithm accuracy for segmenting volumetric data. The test was performed by binary comparizon of reference data with automatically calculated vessels network. Table II presents results of this experiment. The volumentric approach gives the best results here as well.

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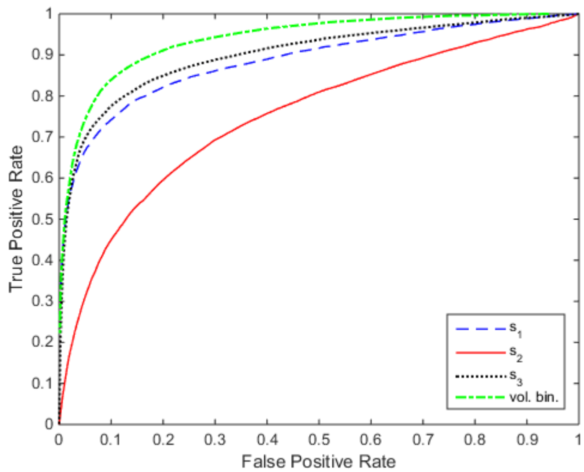

Fig. 7: ROC curves of lateral segmentation procedure

TABLE II: Results of volumetric segmentation procedure

Method	Accuracy [%]	Precision [%]	Specificity [%]
Shadowgraph s_1	99.91	24.94	99.93
Shadowgraph s_2	99.90	20.77	99.93
Shadowgraph s_3	99.90	27.25	99.93
Volum. adapt. bin.	99.95	44.86	99.98

IV. Conclusions

We presented a method for volumetric segmentation of retina vasculature. This algorithm is useful for evaluation of disease history of the patients examined prior to development of the OCTA technology as well as for detection of obstructed blood vessels undetected by OCTA. This approach can also be used for the analysis of large, older datasets of OCT scans obtained with standard acquisition protocols.

Segmentation methods based only on detection of vessels shadow are able to segment only thick superficial vessels, since thinner vessels do not leave a significant shadow trace. Furthermore the approaches detecting shadows in the RPE layer have larger error rate for volumetric segmentation due to erroros in the lateral direction.

Our adaptive binarization approach allows for detection of vessels crossing each layer (e.g. from superficial to deep vessel bed). It also preserves connections between branches what is important for ophthalmologists. It is possible to extend the presented algorithm to a three-dimensional hierarchic vasculature model, that can be further used in diagnostic procedures, such as evaluation of blood flow and analysis of retina vessels structure with respect to pathological changes among layers.

Out future research will involve further improvements, application of the developed methods to the deep vessels bed, and comparison with other state of the art methods for vessels detection from OCT (such as k-NN pixel classification).

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References

[1] C. Heneghan, J. Flynn, M. O'Keefe, M. Cahill, *Characterization of changes in blood vessel width and tortuosity in retinopathy of prematurity using image analysis*, Med. Image Anal., vol. 6, pp. 407–429, 2002.

[2] Z. Hu, M. Niemeijer, M. Abramoff, M. Garvin, *Multimodal retinal vessel segmentation from spectral-domain optical coherence tomography and fundus photography*, IEEE Trans. Med. Imag., vol. 31, no. 10, pp. 1900–1911, Oct. 2012.

[3] M. M. Fraz, P. Remagnino, A. Hoppe, et al. , *Blood vessel segmentation methodologies in retinal images – A survey*, Comput. Methods Programs Biomed., vol. 108, pp. 407–433, 2012.

[4] M. Niemeijer, M. K. Garvin, B. van Ginneken, M. Sonka, M. D. Abràmoff, *Vessel segmentation in 3D spectral OCT scans of the retina*, in Proc. SPIE Medical Imaging 2008: Image Processing, 2008, vol. 6914, pp. 69141R1-69141R8.

[5] D. C. Hood, B. Fortune, S. N. Arthur, et al., *Blood vessel contributions to retinal nerve fiber layer thickness profiles measured with optical coherence tomography*, J. Glaucoma, vol. 17, pp. 519–528, 2008.

[6] Y. Jia, et al., *Split-spectrum amplitude-decorrelation angiography with optical coherence tomography*, Optics Express, vol. 20, no. 4, pp. 4710-4725, 2012.

[7] J. Xu, D. Tolliver, H. Ishikawa, C. Wollstein, J. Schuman, *Blood vessel segmentation with three-dimensional spectral domain optical coherence tomography*, International Patent no. WO/2010/138645 (Feb. 12, 2010).

[8] J. Xu, D. A. Tolliver, H. Ishikawa, G. Wollstein, J. S. Schuman, *3D OCT retinal vessel segmentation based on boosting learning*, in Proc. World Congr. Medical Physics Biomedical Engineering, IFMBE, O. Dössel and W. C. Schlegel, Eds., Munich, Germany, Sep. 2009, vol. 25/XI, pp. 179–182.

[9] Z. Hu, M. Niemeijer, M. D. Abramoff, K. Lee, M. K. Garvin, *Automated segmentation of 3-D spectral OCT retinal blood vessels by neural canal opening false positive suppression*, in Proc. Med. Image Comput. Comput.-Assisted Intervention Conf., New York, 2010, pp. 33–40.

[10] M. Pilch, Y. Wenner, E. Strohmayr, et al., *Automated segmentation of retinal blood vessels in spectral domain optical coherence tomography scans*, Biomed. Opt. Exp., vol. 3, pp. 1478–1491, 2012.

[11] R. Kafieh, H. Danesh, H. Rabbani, M. Abramoff, M. Sonka, *Vessel Segmentation in Images of Optical Coherence Tomography Using Shadow Information and Thickening of Retinal Nerve Fiber Layer*, ICASSP 2013, pp. 1075-1079.

[12] R. Kafieh, H. Rabbani, F. Hajizadeh, M. Ommani, *An Accurate Multimodal 3-D Vessel Segmentation Method Based on Brightness Variations on OCT Layers and Curvelet Domain Fundus Image Analysis*, IEEE Transactions on Biomedical Engineering, vol. 60, no. 10, pp. 2815-2823, 2013.

[13] T. E. de Carlo, A. Pomano, N. K. Waheed, J. S. Duker, *A review of optical coherence tomography angiography (OCTA)*, International Journal of Retina and Vitreous, vol. 1, no. 1, DOI: 10.1186/s40942-015-0005-8, pp. 1-15, 2015.

[14] J.P. Campbell, M. Zhang, T.S. Hwang, et al., *Detailed Vascular Anatomy of the Human Retina by Projection-Resolved Optical Coherence Tomography Angiography*, Scientific Reports, 7:42201, DOI: 10.1038/srep42201, 2017.

[15] A. Stankiewicz, T. Marciniak, A. Dąbrowski, et al. , *Denoising methods for improving automatic segmentation in OCT images of human eye*, Bulletin of the Polish Academy of Sciences, Technical Sciences, vol. 65, no. 1, DOI: 10.1515/bpasts-2017-00ZZ, 2017.

[16] M. Maggioni, V. Katkovnik, K. Egiazarian, A. Foi, *A Nonlocal Transform-Domain Filter for Volumetric Data Denoising and Reconstruction*, IEEE Trans. Image Process., vol. 22, no. 1, pp. 119-133, DOI: 2013.

[17] A. Stankiewicz, T. Marciniak, A. Dąbrowski, et al., *Improvement of 3D Retina Layers Segmentation Based on Graph Theory Approach for Low Quality OCT Images*, Metrology and Measurement Systems, vol. 23, no. 2, pp. 269-280, 2016.

[18] H. Wehbe, M. Ruggeri, S. Jiao, et al. *Automated retinal blood flow calculation using spectral domain optical coherence tomography*, Opt. Express, vol. 15, no. 23, pp. 15193-15206, 2007.

[19] M. Vlachos, E. Dermatas, *Multi-scale retinal vessel segmentation using line tracking*, Computerized Medical Imaging and Graphics, vol. 34, pp. 213-227, 2010.

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