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Survey On Segmentation Techniques For Retinal Vessel

Ms. Dipali H Kumbhar

Department of Computer Science and Engineering Terna Public Charitable Trust's College of Engineering, Osmanabad

ABSTRACT—

In this paper, the proposed methods of classifying arteries and veins in fundus images are extensively reviewed, which are categorized into automatic and semi-automatic categories. There are some challenges associated with the classification of vessels in images of the retinal fundus, which include the low contrast accompanying the fundus image and the inhomogeneity of the background lighting.

The inhomogeneity occurs as a result of the process of imaging, whereas the low contrast which accompanies the image is caused by the variation between the background and the contrast of the various blood vessels. This means that the contrast of thicker vessels is higher than those that are thinner. Another challenge is related to the color changes that occur in the retina from different subjects, which are rooted in biological features. Most of the techniques used for the classification of the retinal vessels are based on geometric and visual characteristics that set the veins apart from the arteries. In this study, different major contributions are summarized as review studies that adopted deep learning approaches and machine learning techniques to address each of the limitations and problems in retinal blood vessel segmentation and classification techniques.

The purpose of this paper is to provide a comprehensive overview for retinal vessels segmentation techniques. Firstly, a brief introduction to retinal fundus photography and imaging modalities of retinal images is given. Then, the preprocessing operations and the state of the art methods of retinal vessels identification are introduced. Moreover, the evaluation and validation of the results of retinal vessels segmentation are discussed. Finally, an objective assessment is presented and future developments and trends are addressed for retinal vessels identification techniques.

KEY WORDS- Image segmentation and classification Eye-related disorders Retinal disease

INTRODUCTION:

The prevalence of eye-related diseases has witnessed a significant global increase, leading to a rise in the number of individuals experiencing acute conditions. According to the World Health Organization (WHO), approximately 2.2 billion people worldwide suffer from visual impairment. Alarmingly, around 1 billion cases could have been prevented if timely detection had occurred. In the United States alone, an estimated 40 million people are affected by varying degrees of severe eye-related diseases, with a primary focus on conditions related to the retina, such as glaucoma, among others [1,2]. In Africa, visual impairment affects approximately 26.3 million individuals, with 20.4 million experiencing low vision and 5.9 million being blind, contributing to 15.3% of the global blind population. The leading causes of blindness and visual impairment in this region are uncorrected refractive errors and cataracts. While individuals over the age of 50 are more susceptible to visual impairment and blindness, it is important to note that these conditions can affect people of all age groups. The International Classification of Diseases 11 (2018) categorizes visual impairment into two main groups: 1) Distance vision impairment, ranging from mild to blindness, and 2) Near vision impairment, characterized by acuity worse than N6 or M.08 at 40 cm.

Retinal fundus images are photographs that provide a direct optical representation of the eye's internal processes. They capture various morphological and pathological components, including blood vessels, the macula, fovea, optic disk, hemorrhages, arterioles, venules, exudates, and microaneurysms retinal fundus images, highlighting different signs of DR, such as exudates, microaneurysms, hemorrhages, and neovascularization.

To prevent visual loss and maintain healthy eyesight, it is advisable to follow the recommendations outlined below: 1) Maintain stable blood sugar levels to minimize the risk of diabetic complications that can affect vision. 2) Be aware of your family's eye health history as certain eye conditions can have a hereditary component. 3) Adopt a balanced and nutritious diet that includes eye-healthy foods to support overall eye health. 4) Maintain a healthy weight, as obesity and excessive weight can increase the risk of various eye diseases. 5) Wear appropriate protective eyewear, such as safety goggles or sunglasses, to shield your eyes from potential injuries and harmful UV rays. 6) Incorporate regular exercise into your routine, as it promotes overall well-being and good blood circulation, which is beneficial for eye health. 7) Reduce or eliminate tobacco usage, as smoking has been linked to several eye diseases and can exacerbate existing visual impairments. 8) Practice proper eye hygiene, including resting your eyes periodically and ensuring clean hands and eye lenses to reduce the risk of infections and other eye-related issues [[7], [8], [9]].

The main purpose of identifying and localizing the vessels of the retina is to distinguish the diverse vasculature structure tissues of retina, (which could be tight or wide) from the background of the fundus image as well as other retinal anatomical structures like abnormal lesions, macula, and optic disc.

The attention of researchers has been continuously focused on the area of retinal vessels identifcation because of the presence of non-invasively fundus imaging techniques and the important details that are obtainable from the vasculature structure for the recognition and diagnosis of a wide range of retinal pathology such as age-related macular degeneration (AMD), hypertension, diabetic retinopathy (DR) and glaucoma

Generally, vessel segmentation is one of the major areas in medical image segmentation (Lesage 2009; Kirbas 2004) and the retinal vessel segmentation falls under this category. Within the context of retina vessels segmentation, there are many methodologies and algorithms that are improved and applied for the automated localization method, segmentation technique and RVS for feature extraction (Fraz 2012; Aparna and Rajan 2017; Arunkumar 2018). In the current study, a review of recent and early literature has been made, covering the techniques and methodologies that have been proposed for detecting and segmenting retinal vasculature shapes in 2-D retinal fundus cases. In the previous studies, the theoretical underpinning of each category of segmentation is presented, as well as the benefts and limitations of each category.

Literature Survey :

Hand gesture recognition has attracted considerable interest in the domains of human-computer interaction (HCI), computer vision, and machine learning. Scholars have investigated diverse methodologies and techniques to facilitate precise and effective recognition of hand gestures across a range of contexts and applications.

Traditional Approaches: Initial methods for hand gesture recognition predominantly depended on manually crafted features and template matching algorithms. These techniques encompassed the extraction of pertinent features from hand images, such as edges, corners, and texture descriptors, which were then compared with pre-established templates to discern gestures. Although successful in controlled settings, these methods frequently encountered challenges with the diversity in hand shapes, poses, and lighting circumstances.

Machine Learning Techniques: With the rise of machine learning algorithms, scholars started investigating data- centric methods for hand gesture recognition. Supervised learning algorithms, including Support Vector Machines (SVMs), decision trees, and random forests, have been extensively employed for classification purposes. These algorithms utilize labeled training data to discern discriminative features and patterns linked to various hand gestures. Despite their effectiveness, these approaches typically necessitate substantial feature engineering and might encounter difficulties with intricate gestures and variations in hand poses.

Deep Learning Architectures: In recent times, advanced deep learning models, notably convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have risen as formidable tools for hand gesture recognition. CNNs are adept at acquiring hierarchical features from raw input data, rendering them particularly suitable for tasks involving image-based gesture recognition. Through automatic learning of patterns and correlations from hand images, CNNs can attain high levels of accuracy even in challenging conditions marked by noise and variability.

Conversely, RNNs are adept at capturing temporal relationships within sequences of gestures. Long Short-Term Memory (LSTM) networks, a subtype of RNN, have proven notably successful in capturing temporal dynamics in hand gestures, facilitating the recognition of intricate sequences of gestures.

Sensor Technologies: Progress in sensor technologies, including depth cameras, inertial sensors, and wearable devices, has significantly enhanced the precision and resilience of hand gesture recognition systems. Depth cameras like Microsoft Kinect and Intel RealSense offer depth data alongside RGB imagery, enabling more accurate hand tracking and gesture recognition. Inertial sensors integrated into wearable devices capture motion data, facilitating gesture recognition in mobile and wearable computing contexts.

Challenges and Future Directions: Despite notable progress, several challenges persist in hand gesture recognition. These challenges encompass issues such as occlusion, variations in hand shapes and poses, lighting conditions, and the need for real-time processing capabilities. Overcoming these challenges necessitates the development of innovative algorithms, robust feature extraction methods, and the utilization of multimodal fusion approaches. Future directions in hand gesture recognition research involve the exploration of novel architectures, the integration of multimodal sensor data, and the utilization of transfer learning techniques to enhance system performance across diverse domains and applications. Moreover, ongoing research efforts aim to devise more natural and intuitive interaction paradigms, such as gesture-based interfaces for augmented reality and virtual reality environments. In summary, hand gesture recognition remains a dynamic field of study with abundant applications and prospects for innovation. Through tackling existing challenges and exploring novel methodologies, researchers aspire to improve the capabilities and user-friendliness of gesture-based interfaces across various computing environments.

Retinal vessel segmentation :

The aim of identifying and localizing the retinal vessels is to distinguish the retina's diverse vasculature structure tissues (which could be tight or wide) from the background of the fundus image as well as other retinal anatomical structures like abnormal lesions, macula, and optic disc. The attention of researchers is continuously focused on the area of retinal vessels identification, because of the presence of non-invasively fundus imaging techniques and the important details that are obtainable from the vasculature structure for the recognition and diagnosis task of a wide range of retinal pathology such as age-related macular degeneration (AMD hypertension, diabetic retinopathy (DR) and glaucoma. Recently, there has been advancement in the development of innovative computer-aided techniques for the segmentation of retinal vessels, and in recent times, the application of these techniques is justified in clinical applications. Ophthalmologists obtain relevant information from the retinal vasculature structure (RVS), which helps them to detect and diagnose of a wide range of retinal pathology like diabetic retinopathy, glaucoma, age-related macular degeneration and retinopathy of prematurity. Ophthalmologists also use such vital information to diagnose diseases associated with the heart or brain, which are linked to non-standard differences in retinal vascular shape. Thus, the variations that occur in venules morphology and the retina's arterioles are of identification assessment as they are key pointers of certain abnormalities. Generally, vessel segmentation is one of the major areas in medical image segmentation (Lesage 2009; Kirbas 2004) and the retinal vessel segmentation falls under this category. Within the context of retina vessels segmentation, there are many methodologies and algorithms that are improved and applied for the automated localization method, segmentation technique and RVS for feature extraction (Fraz 2012;

Aparna and Rajan 2017; Arunkumar 2018). In the current study, a review of recent and early literature has been made, covering the techniques and methodologies that have been proposed for detecting and segmenting retinal vasculature shapes in 2-D retinal fundus cases. In the previous studies, the theoretical underpinning of each category of segmentation is presented, as well as the benefits and limitations of each category. In general, there is a variety of algorithms and techniques available for segmentation, because situations and cases vary. However, all the techniques of retinal segmentation share the same stages, which are pre-processing, processing and post-processing tasks. The papers reviewed in our study are classified according to the technique or algorithm utilized in the processing phase, resulting in six main groups, which include the following: (1) machine learning (2) kernel-based techniques; (3) the multi-scale methods; (4) the model-based methods; (5) the adaptive local thresholding techniques; and (6) the mathematical morphology-based techniques. These six classifications are further clustered into two main categories (machine learning techniques or rule-based techniques) as presented in Fig. 1. There are particular rules that must be followed in an algorithm outlined in the group of rule-based techniques. On the other hand, in the machine learning category, the pre-segmentation retinal case (gold standard or ground truth) is used to create a labeled dataset which is utilized during the process of training. Nevertheless, when the problem of image analysis is faced by a non-image processing specialist, he/she quickly understands that an independent image processing technique or a one image transformation technique is often not the way out. Thus, this is represented in Fig. 1, where the hybrid nature of these techniques is denoted by nested lobes. A majority of the problems associated with image analysis are complex, especially, medical ones. However, these problems can be solved by combining a variety of basic techniques and transformations to achieve high-performance hybrid.

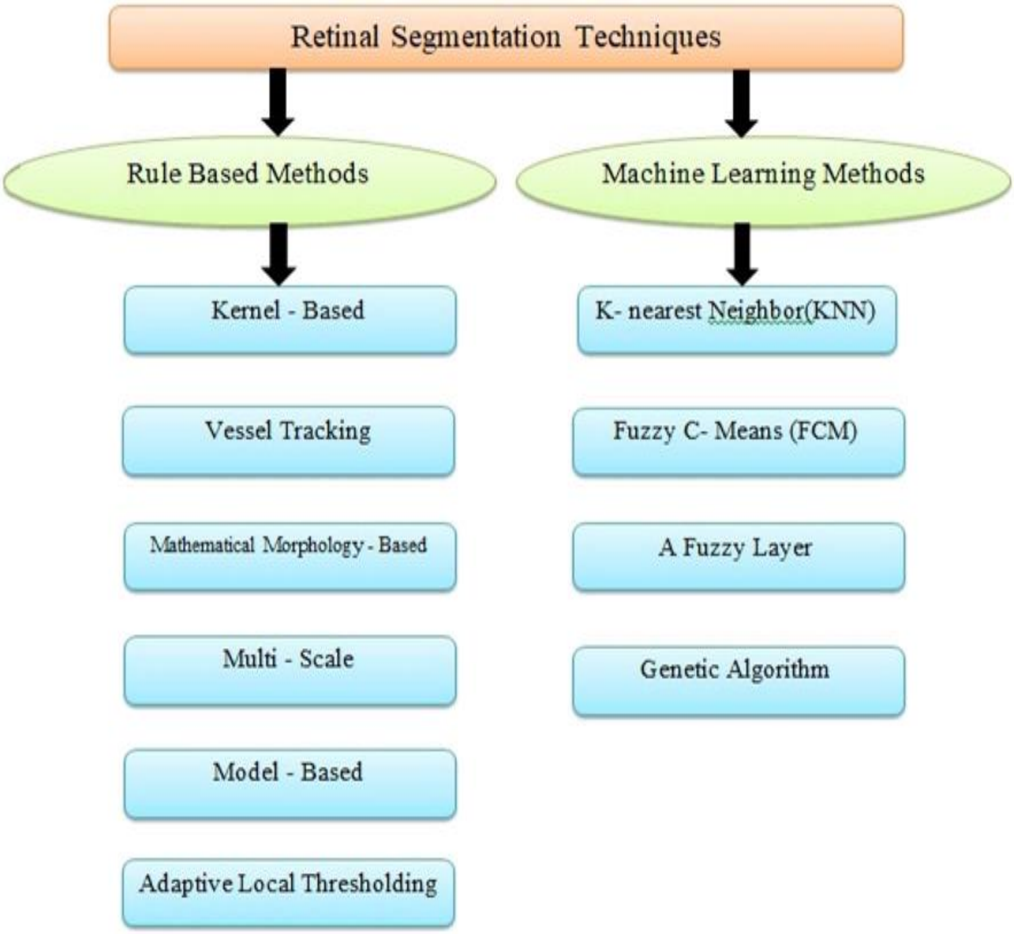

Fig. 1 Retinal vessels segmentation techniques

Retinal vessel classification techniques:

There are some challenges associated with the classification of vessels in images of the retinal fundus, and some of those challenges include the low contrast accompanying the fundus image, and the inhomogeneity of the background lighting. The inhomoge- neity occurs as a result of the process of imaging, whereas the low contrast is caused by the variation between the background and the contrast of the various blood vessels. This means that the contrast of thicker vessels is higher than those that are thinner. Another challenge is related to the color changes that occur in the retina for different sub- jects which are rooted in biological features. Most of the techniques used for the classification of the retinal vessel are based on geometric and visual characteristics that set the veins apart from the arteries. Basically, there are four areas in which the veins differ from the arteries: the shade of veins is darker than that of arteries, veins are thicker than arteries which are lighter, and the arteries are easily recognized by the central flex. In addition, there is often an alternation between veins and arteries close to the optic disc and before branching off. Nevertheless, in many situ- ations, these variations do not adequately distinguish the arteries from the veins. For instance, in situations when the quality of images is low, the central flex in the exter- nal areas is eliminated. A very dark shade is contained by the external regions of the image due to the effect of shading that arises from the inhomogeneity of the image's lighting. Such situations create resemblance between the arteries and the veins, resulting in the misclassification of some vessels. In addition, since thickness varies from the highest value close to the optic disc to the smallest value in the external areas, it cannot be relied upon as a suit- able classification feature.

Retinal vessel semi-automatic techniques:

An approach, in which the conditional optimization is employed, as proposed by (Rothaus et al. 2007, 2009), in their work. This approach, which is an extended version of the work of Martinez- Perez, is based on the anatomical properties of veins and arter- ies. In their method, the propagation of labels is carried out during the creation of vessel graph through the use of some starting segments that have been manually labelled. In the work by Estrada et al. (Estrada 2015), a semi-automatic- approach is presented, in which a combination of domain- specific knowledge and graph-theoretic methods are used. With the approach, which is dependent on the estimation of the vascular topology, the whole vasculature is analyzed. The method is regarded as an extended version of the tree topology estimation framework that is proposed by (Estrada et al. 2014), because it is dependent on the estimation of vascular tree topology, and combines expert domain-spe- cific features for the construction of likelihood model. In the next step of their proposed framework, the space of prob- able solutions that correspond with the projected vessels is searched repeatedly so that the model can be maximized. Four datasets [WIDE (Estrada et al. 2014), AV-DRIVE (Qureshi et al. 2013), CT-DRIVE (Qureshi et al. 2013) and AV-INSPIRE (Niemeijer et al. 2011)] are used to measure the performance of the presented method.

Retinal vessel automatic techniques:

The two main problems associated with retinal images are the inhomogeneity in contrast and the lighting as a result of changes that occur in intra- and inter-images. However, these changes must be removed so that useful color information is obtained. It is for this reason that authors like (Grisan 2003) perform an analysis of the background image to enable the correction of these changes by statistically estimating their characteristics. The work by (Grisan 2003) in 2003 was one of the earliest works in the area of automatic methods, which were designed for the automatic classification of retinal ves- sels. One of the main steps involved in the analysis of fundus image is the extraction of vessel network, which requires the implementation of a vessel tracking process as well as a set of vessel segments. In their work, the vessel network is extracted automatically using the sparse tracking method. Vessel network symmetry and local features are exploited by dividing the retinal image into different portions having the same number of veins and arteries. The assumption is that the local features of the two types of vessels within these zones are quite different. This approach involves the division of an area around the optic disc (within 0.5–2 of the optic disc diameter from its centre) into four zones, with each zone containing one of the main arches. Despite the pres- ence of several features, the mean of the hue channel, and the difference of the red channels in each vessel segment are regarded as the most unique and suitable features that can be used for classification. Given two adjacent vessels, within the clinical context, the darker vessel is regarded as the vein, and in the absence of a significant difference in the red val- ues, the vessel which possesses more color homogeneity is regarded as a vein. Subsequent to the extraction of features, the fuzzy clustering algorithm is used in the classification of vessels. The criterion for classification is the Euclidean dis- tance between each pixel and the mean value of features in each class. Lastly, the labels of pixels found in each segment are merged based on major voting, and then the classifica- tion of the entire is carried out.

Challenges and Future Directions

Regarding retinal segmentation categories shown in Figure 1, there is neither a best technique or algorithm to face all performance metrics in high segmentation achievement, nor a best mathematical scheme to do so. Deciding whether the methodology is best depends on a set of factors including: (1) *Achieved accuracy*, which in turn, depends on the achieved specificity and sensitivity, where segmentation is considered the best if it achieves the highest possible sensitivity value (or shows low false detection to other retinal structures), while also maintaining the specificity at optimal level. On the other hand, the optimality of the method increases as detection capability of the method records high performance in pathological retinal images; (2) *Time and computational complexity*: The time and computational power required by the methods tend to be low, as the accuracy has increased tendency on the condition that high performance of high accuracy has achieved; (3) *Robustness*: The method is considered to be best if it shows robustness against method parameters variation.

The accurate detection and segmentation of the retinal vascular structure forms the backbone of a variety of automated computer aided systems for screening and diagnosis of ophthalmologic and cardiovascular diseases. Even though many promising methodologies have been developed and implemented, there is still room for research improvement in blood vessel segmentation methodologies, especially for noisy and pathological retinal images outside the limited number of retinal images available in public datasets. In real-life applications, retinal vessels segmentation systems will not replace the experts' role in diagnosis; rather, they will enhance the diagnosis accuracy and reduce the workload of the ophthalmologists. Therefore, large volume of patients' images can be processed with high diagnosis accuracy and comparable time.

RESULTS :

The results of the performances of the methods are compared and the authors evaluate the performance of their methodologies using publicly available datasets. The different methodologies for the segmentation of reti- nal vessels follow similar procedures. The first step in each methodology is the pre-processing step, which involves the extraction of the green or grey layer (from the image of raw color retinal, followed by the enhancement of the image's contrast. The next step is the processing step which is the nucleus of the algorithm, involving the use of the various techniques that are categorized in the previous section. In the last step of post-processing, the initial segmented image is submitted to be processed for smoothing and edge pre- serving and improvements. With regard to the categories of retinal segmentation provided in Fig. 5, there is no best algorithm, mathematical scheme, or technique that meets all the performance metrics for achieving high segmentation. However, there are a number of factors that help in determining the most appropriate methodology, and some of them include (1) achieved accuracy that in turn, lays on the resulting sensitivity and specificity. With this metric, segmentation is regarded as the best if it is able to attain the biggest potential value of sensitivity, or shows small false detection for other retinal structures, while the specificity is maintained at optimal level. However, when the performance of the method is high in terms of the detection of pathological retinal images, then the method's optimality increases; (2)time and computational complexity: with a higher level of accuracy, the computational time and power needed by the techniques tend to decrease; (3) robustness: a technique is considered to be superior than other methods. This approach aims to enhance the dining experience while respecting the importance of maintaining a pleasant restaurant environment.

CONCLUSION :

In summary, the existing retinal blood vessel segmentation methodologies are categorized, and described in the last section. We discussed various techniques used in these methodologies for the segmentation of blood vessels in retinal image and compare performance result of the methods. These methodologies were evaluated using publicly available datasets. Various retinal vessels segmentation methodologies follow similar procedures: each methodology initiates by *pre-processing* step, where the green layer (or grey) is extracted from the raw color retinal image, and then the contrast of the image is enhanced. *Processing* step represents the heart of algorithm, where the different techniques categorized in last section are used. Finally, in the *post-processing* step, the initial segmented image undergoes steps of smoothing and edge preserving and enhancement.

REFERENCES:

1. Lesage, D.; Angelini, E.D.; Bloch, I.; Funka-Lea, G. A review of 3D vessel lumen segmentation techniques: Models, features and extraction schemes. Med. Image Anal. 2009, 13, 819–845. [Google Scholar] [CrossRef] [PubMed]
2. Kirbas, C.; Quek, F. A review of vessel extraction techniques and algorithms. ACM Comput. Surv. CSUR 2004, 36, 81–121. [Google Scholar] [CrossRef]
3. Kirbas, C.; Quek, F.K. Vessel extraction techniques and algorithms: A survey. In Proceedings of the the Third IEEE symposium on Bioinformatics and Bioengineering, Bethesda, MD, USA, 12 March 2003; pp. 238–245. [Google Scholar]
4. Suri, J.S.; Liu, K.; Reden, L.; Laxminarayan, S. A review on MR vascular image processing: Skeleton versus nonskeleton approaches: Part II. IEEE Trans. Inf. Technol. Biomed. 2002, 6, 338–350. [Google Scholar] [CrossRef] [PubMed]
5. Fraz, M.M.; Remagnino, P.; Hoppe, A.; Uyyanonvara, B.; Rudnicka, A.R.; Owen, C.G.; Barman, S.A. Blood vessel segmentation methodologies in retinal images—A survey. Comput. Methods Program Biomed. 2012, 108, 407–433. [Google Scholar] [CrossRef] [PubMed]
6. Srinidhi, C.L.; Aparna, P.; Rajan, J. Recent Advancements in Retinal Vessel Segmentation. J. Med. Syst. 2017, 41, 70. [Google Scholar] [CrossRef] [PubMed]
7. Dash, J.; Bhoi, N. A Survey on Blood Vessel Detection Methodologies in Retinal Images. In Proceedings of the 2015 International Conference on Computational Intelligence and Networks, Bhubaneshwar, India, 12–13 January 2015; pp. 166–171. [Google Scholar]
8. Mansour, R. Evolutionary Computing Enriched Computer Aided Diagnosis System For Diabetic Retinopathy: A Survey. IEEE Rev. Biomed. Eng. 2017, 10, 334–349. [Google Scholar] [CrossRef] [PubMed]
9. Pohankar, N.P.; Wankhade, N.R. Different methods used for extraction of blood vessels from retinal images. In Proceedings of the 2016 World Conference on Futuristic Trends in Research and Innovation for Social Welfare (Startup Conclave), Coimbatore, India, 29 February–1 March 2016; pp. 1–4. [Google Scholar]
10. Singh, N.; Kaur, L. A survey on blood vessel segmentation methods in retinal images. In Proceedings of the 2015 International Conference on Electronic Design, Computer Networks & Automated Verification (EDCAV), Shillong, India, 29–30 January 2015; pp. 23–28. [Google Scholar]
11. Kolb, H. Simple Anatomy of the Retina, 2012. Available online: http://webvision.med.utah.edu/book/part-i-foundations/simple-anatomy-of-the-retina/ (accessed on 22 January 2018).
12. Oloumi, F.; Rangayyan, R.M.; Eshghzadeh-Zanjani, P.; Ayres, F. Detection of blood vessels in fundus images of the retina using gabor wavelets. In Proceedings of the 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Lyon, France, 22–26 August 2007; pp. 6451–6454. Available online: http://people.ucalgary.ca/~ranga/enel697/ (accessed on 12 September 2017).
13. Saine, P.J.; Tyler, M.E. Ophthalmic Photography: Retinal Photography, Angiography, and Electronic Imaging; Butterworth-Heinemann: Boston, MA, USA, 2002; Volume 132. [Google Scholar]
14. Kolb, H. Simple Anatomy of the Retina. In Webvision: The Organization of the Retina and Visual System; Kolb, H., Fernandez, E., Nelson, R., Eds.; University of Utah Health Sciences Center: Salt Lake City, UT, USA, 1995; Available online: http://europepmc.org/books/NBK11533;jsessionid=4C8BAD63F75EAD49C21BC65E2AE5F6F3 (accessed on 22 January 2018).
15. Ophthalmic Photographers' Society. Available online: www.opsweb.org (accessed on 22 January 2018).
16. Ng, E.; Acharya, U.R.; Rangayyan, R.M.; Suri, J.S. Ophthalmological Imaging and Applications; CRC Press: Boca Raton, FL, USA, 2014. [Google Scholar]
17. Patel, S.N.; Klufas, M.A.; Ryan, M.C.; Jonas, K.E.; Ostmo, S.; Martinez-Castellanos, M.A.; Berrocal, A.M.; Chiang, M.F.; Chan, R.V.P. Color Fundus Photography Versus Fluorescein Angiography in Identification of the Macular Center and Zone in Retinopathy of Prematurity. Am. J. Ophthalmol. 2015, 159, 950–957. [Google Scholar] [CrossRef] [PubMed]

18. Orlando, J.I.; Prokofyeva, E.; Blaschko, M.B. A discriminatively trained fully connected conditional random field model for blood vessel segmentation in fundus images. IEEE Trans. Biomed. Eng. 2017, 64, 16–27. [Google Scholar] [CrossRef] [PubMed] [Green Version]
19. Zhang, J.; Dashtbozorg, B.; Bekkers, E.; Pluim, J.P.; Duits, R.; ter Haar Romeny, B.M. Robust retinal vessel segmentation via locally adaptive derivative frames in orientation scores. IEEE Trans. Med. Imaging 2016, 35, 2631–2644. [Google Scholar] [CrossRef] [PubMed]
20. Abbasi-Sureshjani, S.; Zhang, J.; Duits, R.; ter Haar Romeny, B. Retrieving challenging vessel connections in retinal images by line co-occurrence statistics. Biol. Cybern. 2017, 111, 237–247. [Google Scholar] [CrossRef] [PubMed]
21. Abbasi-Sureshjani, S.; Favali, M.; Citti, G.; Sarti, A.; ter Haar Romeny, B.M. Curvature integration in a 5D kernel for extracting vessel connections in retinal images. IEEE Trans. Image Process. 2018, 27, 606–621. [Google Scholar] [CrossRef] [PubMed]
22. Gu, L.; Cheng, L. Learning to boost filamentary structure segmentation. In Proceedings of the IEEE International Conference on Computer Vision, Santiago, Chile, 7–13 December 2015; pp. 639–647. [Google Scholar]
23. De, J.; Cheng, L.; Zhang, X.; Lin, F.; Li, H.; Ong, K.H.; Yu, W.; Yu, Y.; Ahmed, S. A graph-theoretical approach for tracing filamentary structures in neuronal and retinal images. IEEE Trans. Med. Imaging 2016, 35, 257–272. [Google Scholar] [CrossRef] [PubMed]
24. Maninis, K.-K.; Pont-Tuset, J.; Arbeláez, P.; Van Gool, L. Deep retinal image understanding. In International Conference on Medical Image Computing and Computer-Assisted Intervention; Springer International Publishing: Berlin/Heidelberg, Germany, 2016; pp. 140–148. [Google Scholar]
25. Sironi, A.; Lepetit, V.; Fua, P. Projection onto the manifold of elongated structures for accurate extraction. In Proceedings of the IEEE International Conference on Computer Vision, Santiago, Chile, 7–13 December 2015; pp. 316–324. [Google Scholar]
26. Solouma, N.; Youssef, A.-B.M.; Badr, Y.; Kadah, Y.M. Real-time retinal tracking for laser treatment planning and administration. In Medical Imaging 2001: Image Processing; SPIE—The International Society of Optics and Photonics: Bellingham, WA, USA; pp. 1311–1321.
27. Wang, Y.; Lee, S.C. A fast method for automated detection of blood vessels in retinal images. In Proceedings of the Conference Record of the Thirty-First Asilomar Conference on Signals, Systems & Computers, Pacific Grove, CA, USA, 2–5 November 1997; pp. 1700–1704. [Google Scholar]
28. Can, A.; Shen, H.; Turner, J.N.; Tanenbaum, H.L.; Roysam, B. Rapid automated tracing and feature extraction from retinal fundus images using direct exploratory algorithms. IEEE Trans. Inf. Technol. Biomed. 1999, 3, 125–138. [Google Scholar] [CrossRef] [PubMed]
29. Li, H.; Chutatape, O. Fundus image features extraction. In Proceedings of the 22nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Chicago, IL, USA, 23–28 July 2000; pp. 3071–3073. [Google Scholar]
30. Yang, Y.; Huang, S.; Rao, N. An automatic hybrid method for retinal blood vessel extraction. Int. J. Appl. Math. Comput. Sci. 2008, 18, 399–407. [Google Scholar] [CrossRef]
31. Zhao, Y.; Rada, L.; Chen, K.; Harding, S.P.; Zheng, Y. Automated vessel segmentation using infinite perimeter active contour model with hybrid region information with application to retinal images. IEEE Trans. Med. Imaging 2015, 34, 1797–1807. [Google Scholar] [CrossRef] [PubMed]
32. Yu, H.; Barriga, E.S.; Agurto, C.; Echegaray, S.; Pattichis, M.S.; Bauman, W.; Soliz, P. Fast localization and segmentation of optic disk in retinal images using directional matched filtering and level sets. IEEE Trans. Inf. Technol. Biomed. 2012, 16, 644–657. [Google Scholar] [CrossRef] [PubMed]
33. Aibinu, A.M.; Iqbal, M.I.; Shafie, A.A.; Salami, M.J.E.; Nilsson, M. Vascular intersection detection in retina fundus images using a new hybrid approach. Comput. Biol. Med. 2010, 40, 81–89. [Google Scholar] [CrossRef] [PubMed]
34. Wu, C.-H.; Agam, G.; Stanchev, P. A hybrid filtering approach to retinal vessel segmentation. In Proceedings of the IEEE International Symposium on Biomedical Imaging: From Nano to Macro, Arlington, VA, USA, 12–15 April 2007; pp. 604–607. [Google Scholar]
35. Siddalingaswamy, P.; Prabhu, K.G. Automatic detection of multiple oriented blood vessels in retinal images. J. Biomed. Sci. Eng. 2010, 3. [Google Scholar] [CrossRef]
36. Wang, S.; Yin, Y.; Cao, G.; Wei, B.; Zheng, Y.; Yang, G. Hierarchical retinal blood vessel segmentation based on feature and ensemble learning. Neurocomputing 2015, 149, 708–717. [Google Scholar] [CrossRef]
37. Kauppi, T.; Kalesnykiene, V.; Kamarainen, J.-K.; Lensu, L.; Sorri, I.; Raninen, A.; Voutilainen, R.; Uusitalo, H.; Kälviäinen, H.; Pietilä, J. The DIARETDB1 Diabetic Retinopathy Database and Evaluation Protocol. In Proceedings of the British Machine Vision Conference 2007, Coventry, UK, 10–13 September 2007; pp. 1–10. [Google Scholar]
38. Walter, T.; Klein, J.-C.; Massin, P.; Erginay, A. A contribution of image processing to the diagnosis of diabetic retinopathy-detection of exudates in color fundus images of the human retina. IEEE Trans. Med. Imaging 2002, 21, 1236–1243. [Google Scholar] [CrossRef] [PubMed]
39. Hanley, J.A.; McNeil, B.J. The meaning and use of the area under a receiver operating characteristic (ROC) curve. Radiology 1982, 143, 29–36. [Google Scholar] [CrossRef] [PubMed]
40. Metz, C.E. Receiver operating characteristic analysis: A tool for the quantitative evaluation of observer performance and imaging systems. J. Am. Coll. Radiol. 2006, 3, 413–422. [Google Scholar] [CrossRef] [PubMed]
41. Staal, J.; Abràmoff, M.D.; Niemeijer, M.; Viergever, M.A.; Van Ginneken, B. Ridge-based vessel segmentation in color images of the retina. IEEE Trans. Med. Imaging 2004, 23, 501–509. [Google Scholar] [CrossRef] [PubMed]
42. Niemeijer, M.; Staal, J.; van Ginneken, B.; Loog, M.; Abramoff, M.D. Comparative study of retinal vessel segmentation methods on a new publicly available database. In Proceedings of the Medical Imaging 2004: Physics of Medical Imaging, San Diego, CA, USA, 15–17 February 2004; pp. 648–656. [Google Scholar]
43. Hoover, A.; Kouznetsova, V.; Goldbaum, M. Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response. IEEE Trans. Med. Imaging 2000, 19, 203–210. [Google Scholar] [CrossRef] [PubMed]

44. Bankhead, P.; Scholfield, C.N.; McGeown, J.G.; Curtis, T.M. Fast retinal vessel detection and measurement using wavelets and edge location refinement. PLoS ONE 2012, 7, e32435. [Google Scholar] [CrossRef] [PubMed] [Green Version]
45. MESSIDOR: Methods for Evaluating Segmentation and Indexing Techniques Dedicated to Retinal Ophthalmology, 2004. Available online: http://www.adcis.net/en/Download-Third-Party/Messidor.html (accessed on 22 January 2018).
46. Decencière, E.; Zhang, X.; Cazuguel, G.; Laÿ, B.; Cochener, B.; Trone, C.; Gain, P.; Ordonez, R.; Massin, P.; Erginay, A. Feedback on a publicly distributed image database: The Messidor database. Image Anal. Stereol. 2014, 33, 231–234. [Google Scholar] [CrossRef] [Green Version]
47. Odstrcilik, J.; Kolar, R.; Budai, A.; Hornegger, J.; Jan, J.; Gazarek, J.; Kubena, T.; Cernosek, P.; Svoboda, O.; Angelopoulou, E. Retinal vessel segmentation by improved matched filtering: Evaluation on a new high-resolution fundus image database. IET Image Process. 2013, 7, 373–383. [Google Scholar] [CrossRef]
48. Chaudhuri, S.; Chatterjee, S.; Katz, N.; Nelson, M.; Goldbaum, M. Detection of blood vessels in retinal images using two-dimensional matched filters. IEEE Trans. Med. Imaging 1989, 8, 263–269. [Google Scholar] [CrossRef] [PubMed]
49. Chanwimaluang, T.; Fan, G. An efficient algorithm for extraction of anatomical structures in retinal images. In Proceedings of the 2003 International Conference on Image Processing (Cat. No.03CH37429), Barcelona, Spain, 14–17 September 2003; Volume 1091, pp. I-1093–I-1096. [Google Scholar]
50. Al-Rawi, M.; Qutaishat, M.; Arrar, M. An improved matched filter for blood vessel detection of digital retinal images. Comput. Biol. Med. 2007, 37, 262–267. [Google Scholar] [CrossRef] [PubMed]
51. Villalobos-Castaldi, F.M.; Felipe-Riverón, E.M.; Sánchez-Fernández, L.P. A fast, efficient and automated method to extract vessels from fundus images. J. Vis. 2010, 13, 263–270. [Google Scholar] [CrossRef]
52. Zhang, B.; Zhang, L.; Zhang, L.; Karray, F. Retinal vessel extraction by matched filter with first-order derivative of Gaussian. Comput. Biol. Med. 2010, 40, 438–445. [Google Scholar] [CrossRef] [PubMed]
53. Zhu, T.; Schaefer, G. Retinal vessel extraction using a piecewise Gaussian scaled model. In Proceedings of the 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Boston, MA, USA, 30 August–3 September 2011; pp. 5008–5011. [Google Scholar]
54. Kaur, J.; Sinha, H. Automated detection of retinal blood vessels in diabetic retinopathy using Gabor filter. Int. J. Comput. Sci. Netw. Secur. 2012, 12, 109. [Google Scholar]
55. Zolfagharnasab, H.; Naghsh-Nilchi, A.R. Cauchy Based Matched Filter for Retinal Vessels Detection. J. Med. Signals Sens. 2014, 4, 1–9. [Google Scholar] [PubMed]
56. Singh, N.P.; Kumar, R.; Srivastava, R. Local entropy thresholding based fast retinal vessels segmentation by modifying matched filter. In Proceedings of the International Conference on Computing, Communication & Automation, Noida, India, 15–16 May 2015; pp. 1166–1170. [Google Scholar]
57. Kumar, D.; Pramanik, A.; Kar, S.S.; Maity, S.P. Retinal blood vessel segmentation using matched filter and laplacian of gaussian. In Proceedings of the 2016 International Conference on Signal Processing and Communications (SPCOM), Bangalore, India, 12–15 June 2016; pp. 1–5. [Google Scholar]