Isolation of vessels in retinal color images

Masumeh Jafari[1]

Computer Engineering Department, Yazd University, Yazd, Iran, masume.jafari@stu.yazd.ac.ir.

Abstract—**Identification of retinal blood vessels is widely used in the diagnosis of eye diseases such as diabetic retinopathy, and glaucoma. Extraction of retinal blood vessels is done manually by a doctor, it is difficult and time-consuming and also many cases are associated with errors. In this article, a new method for the extraction of retinal blood vessels is presented, which includes three basic parts. First, the noise in the image is removed and then the center lines of the vessel are extracted. Finally, the blood vessels of the retinal images are extracted using the area expansion and noise removal method. The proposed algorithm is applied to the images of the DRIVE test set and the efficiency of the algorithm is measured using four different scales of sensitivity, specificity, accuracy, and precision. The average values of accuracy, specificity, sensitivity, and accuracy of the proposed method are 0.92896, 0.98965, 0.91756, and 0.96578, respectively.**

Keywords—Images of the retina, Blood vessels, Extraction of retinal vessels, Noise removal, Disturbance in the Retina

I. INTRODUCTION

Retinal vessels play an important role in the diagnosis of various retinal diseases such as diabetic retinopathy, glaucoma, arteriosclerosis, and hypertension. Chronic hypertension causes gradual narrowing of the retinal arteries, which is not very detectable in the early stages, but gradually, as the disease progresses, the narrowing of the arteries becomes more severe. Diabetic retinopathy is one of the complications of diabetes. With the World Health Organization (WHO), diabetic retinopathy is considered the leading cause of blindness in developed and developing countries [1]. It is one of the most influential cases in a patient's life [2].

Non-Proliferative Diabetic Retinopathy (NPDR) is a type of diabetic retinopathy in which the retinal capillaries are damaged and blood and fluids leak into the eye [3]. Also, in some cases, the center of the retina or macula begins to swell, causing disturbances in a person's normal vision. Another type of retinopathy is called Proliferative Diabetic Retinopathy (PDR). In this condition, the capillaries close and cause new blood vessels to form and grow abnormally on the retina [4]. These abnormal blood vessels form hard tissue and cause the retina to separate from the back of the eye, if left untreated can lead to severe vision loss and blindness [5].

It is very important for doctors to have a correct diagnosis and understanding of the disease in the retinal images, among a large number of vessels and optic nerves [6]. The lesions in the image, as well as the arteries in some places, such as the indentation area, are difficult to detect, and this phenomenon will have a great impact on the diagnosis process and its results. Therefore, retinal vessels extraction is important for the diagnosis and treatment of retinal diseases [1].

In this article, a new method for extracting blood vessels from retinal images is presented. First, the color image of the retina turns into a gray image and then applied a middle filter on it. Then, using a set of filters in four different directions, the central lines of the vessel are extracted. The central line is then marked using a Gaussian filter. The resulting image is thresholded and two images, one related to the extraction vessels and the other to the eyeball area. Using these two images produced and the image isolated from the combination of center lines to completely regenerate the vessels, the method of expanding the area is applied and using thresholding, the noises in the image are removed.

[1] masume.jafari@stu.yazd.ac.ir

Due to the importance of identifying vessels in retinal images, a lot of work has been done in the field of retinal vessel separation, some examples of these methods are mentioned below. Oliveira et al. [7] proposed a method with an unsupervised approach, a matched filter, and a Frangi and Gabor Wavelet filter through a combined average and weight grading to enhance the photographs. They used deformable and FCM models to extract retinal vessels [8].

Mishra et al. [9] proposed a new UCU-Net network with an encoder-decoder architecture that combines U-Net and CUMed-Vision .This method calculates the average width of the retinal input vessels and adapts it to the layer-wise effective receptive fields (LERF) of the deep convolutional neural network (CNN) to find layers that highlight the characteristics of the vessel and then add auxiliary layers there. Using this network, thin retinal veins can be divided.

Wang et al. [10] used the U-Net network, which consists of one encoder and three decoders. Using a decoder, an image is divided into hard or easy areas based on the probability map. The other two decoders are used to independently separate the vessels of the easy and hard zones. Finally, all the outputs consisting of the three decoders are combined to produce the final vessel map.

Emary et al. [11] have presented a framework for the classification of multi-purpose retinal vessels using the combination of the possibilistic fuzzy C-means (PFCM) algorithm and the flower pollination search algorithm (FPSA). The FPSA uses the PFCM algorithm to localize the retinal vessel network. In the second optimization level, the cluster centers obtained using pattern search (PS) are optimized as local search. In this method, using PS, FPSA, and PFCM algorithm were used. This method is resistant to healthy and pathological retinal images. Among the disadvantages of this method is the lack of efficiency for large data sets.

Al Shehhi et al. [12] proposed a graph-based method for extracting retinal vessels. A multi-layer/multi-purpose structure has been used to enhance the contrast and create basic features due to the sensitivity of the vessel patterns. To reduce computational processing, they used graph-based segmentation. In this method, black top hat (BTH), graph cut and segmentation, and Dijkstra's shortest path algorithms are used. Using this method, it is possible to track noisy images and tiny vessels. In this method, subtraction of the background component from the selected channel is used to remove light changes using equation 1.

$$f_C(x) = f_G(x) - f_B(x) \qquad (1)$$

In the relation above, x is a pixel from the green channel, f_B the background of the retinal image created by applying a low-pass Gaussian blurring of the green channel f_G. One of the problems of this method is computational complexity.

Hakim et al. [13] for delineating small retinal vessel connections on a fundus image proposed EC-based regularizers to estimation the number of isolated objects in U-Net-like deep CNN architecture. The is investigate the regularizer based on the isolated objects number differences between groundtruth (DISO) and output in delineating the vessel regions. A discrepancy of MISO, isolated objects number between the groundtruth and the output forces to be equal or more closer. According to equation 2

$$L_{DISO} = L_{BCE} + \alpha|E_{OUT} - E_{LABEL}| \qquad (2)$$

where E_{LABEL}, E_{OUT} is isolated object number of the predicted groundtruth and output, respectively. If the isolated objects number between groundtruth and output is not equal, the DISO based object function leads to large misclassification error. Otherwise, it generates zero misclassification error in the vessel regions detection.

Then the picture is turned to greyscale, followed by normalization of the data and equalization of adaptive Limited Contrast Histograms (CLAHE). The normalization to keep the picture into the same scale is applied and CLAHE technique to raise the contrast of the grayscale picture is applied.

Uysal et al. [14] Propose a hybrid method which combines of data augmentation and preprocessing methods with a deep learning model. Preprocessing used to create an opposition between the background and retinal blood vessels and to the irregular clarification problems solve. Then a convolutional neural network (CNN) designs and for the retinal blood vessel extraction is trained. In the training step, for improving training performance, data augmentation is performed.

Wang et al. [15] for blood vessel segmentation a novel Context Spatial U-Net (CSU-Net) propose. They designed a two-channel encoder include a context channel with multi-scale convolution to capture more receptive field and a spatial channel with large kernel to retain spatial information. Also, they introduced for strengthen and combine the extracted features from two paths, a feature fusion module (FFM) and an attention skip module (ASM).

Jafari [16] first turns the color image into gray and then the noises in the image are removed using a filter. Then, using the filter in four different directions, the central lines of the vessels are obtained. Finally, by using the method of area expansion and noise removal, blood vessels are extracted in retinal images. The proposed method is an extension of this method.

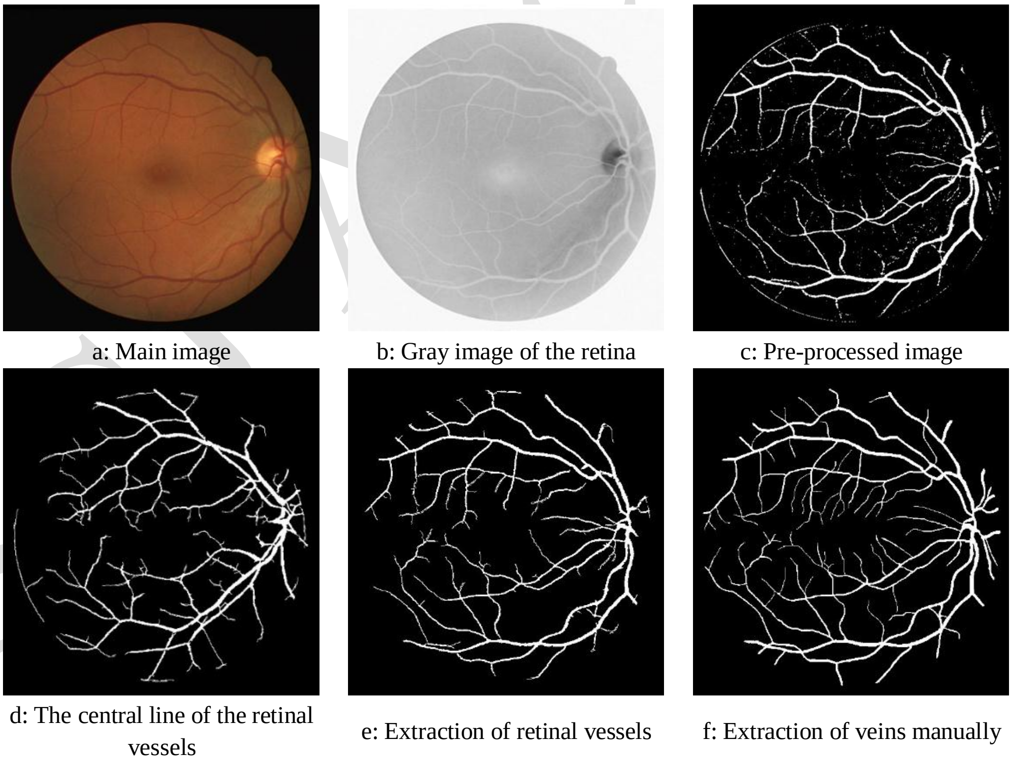
II. JPROPOSED ALGORITHM

The DRIVE dataset was used to evaluate the proposed method. The images in this collection were obtained by screening people with diabetes in the Netherlands. The screening population included 400 people with diabetic retinopathy. From this collection, 40 images have been randomly selected and published. In this data set, 33 images have no diabetic complication and 7 images include this complication. These images are categorized into two equal sets of educational and experimental. There is a mask image (eye area) for each image in the training dataset.

First, by applying the adaptive correction function locally, in addition to amplifying the desired signal and improving the contrast and image quality, noise amplification is also prevented. According to figure1, the color image of the retina is changed to a gray image using equation 3 (figure 1b).

$$img(x, y) = [R(x, y) + G(x, y) + B(x, y)] / 3 \quad (3)$$

In equation 3, *img(x, y)* is the output image component and *R(x, y)* is the red component of the image matrix, *G(x, y)* is the green component of the image matrix, and *B(x, y)* is the blue component of the image matrix.



a: Main image | b: Gray image of the retina | c: Pre-processed image

d: The central line of the retinal vessels | e: Extraction of retinal vessels | f: Extraction of veins manually

Figure 1. Extraction of blood vessels by the proposed method

$$image(x, y)= medianfilter(img(x, y)) \quad (4)$$

Then, according to the above relation, a middle filter is applied to the image (figure 1c). In equation 4, *img(x, y)* is the gray image and *img(x, y)* is the image from the middle filter (figure 1c). The better the quality of the image obtained at this stage, the more accurately the veins are extracted in the next stage. In the middle filter, the pixel values in a neighborhood are first sorted in ascending order. The center pixel value is then replaced by the middle value of the sorted group. The two-dimensional middle filter removes salt and pepper noises without adversely affecting the edges of the image. In this filter, square windows of size (2k + 1) × (2k + 1) or in the shape of a cross are considered.

Since the vessels are at the surface of the retina in each direction, this algorithm requires several patterns that are set in different directions to identify all the vessels. To extract the center lines, the fact is used that by applying the first-order derivative filter in the direction perpendicular to the direction of the vessel, the output values of the filter have a special order, because the vessels in the retina are in different directions, a set of these filters is used in four directions.

The image of the retina is represented by a three-dimensional surface, the x and y directions represent the dimensions of the image and z represents the brightness level of the image points. The center line is a linear vessel with a width of one pixel, a thinner morphology operator is used to have a line one pixel wide. In this algorithm, the interconnected components are determined by an octet neighborhood, and the pixels that are part of the components whose number of pixels is more than a predefined constant value are confirmed as external stud points. By removing the verified pixels, the interconnected components are determined by the four-dimensional neighborhood of the resulting image. Specify the center pixel for each component, and from the image from which the outer stud points are extracted, a window with predefined dimensions is separated to the center of the middle pixel. In this window, the average and maximum values are calculated and the threshold value is obtained using equation 5 and is used to binary the window.

$$Threshold = \sqrt{max(w) \times mean\ (w)} \qquad (5)$$

The resulting binary image is multiplied by the window obtained from the stud point image to the center of the middle pixel of the component under study. If the sum of the pixels with a value of 1 in the resulting window is more than half the number of pixels in the component being examined, the pixels of this component are approved as external stud points, otherwise all pixels of the noise component are recognized and deleted.

Any pixels in one of the four directions are retained, and pixels that do not fit in this combination are removed. Thus, an image with the initial candidate points for the center lines is obtained. The result of applying the centerline detection algorithm to each of the directions is combined in the final image. Gaussian filter is used to mark the center line. The resulting image is thresholded and converted to a binary image. In the next step, this binary image is used to start the area expansion algorithm. The threshold value is calculated based on the statistical information of the image as follows.

$$T_{seed} = \mu - \alpha\sigma \qquad (6)$$

In the above relation, μ and σ are the mean and standard deviation of the brightness of the pixels in the window, respectively. In the next step, two binary images are obtained by thresholding the image at two different levels, the image of the smaller threshold results as blood vessels and the image of the larger threshold results in the eye area. Using these two binary images along with the binary image reset operation, the vessels with different diameters are reconstructed in the image. The isolated image is obtained by combining the center lines with the images from the previous step using the area expansion method, provided that the two pixels are adjacent (figure 1d).

In the last step, noise removal is applied. In this operation, pixels less than 20 are cleared and fill in small empty spaces. Figure 1e shows the final result of the separation of retinal blood vessels. As can be seen, a number of very small veins have been removed. Figure 1f shows the separation of retinal vessels manually by specialist doctors.

III. RESULTS

The algorithm is implemented in a MATLAB environment on DRIVE data set images. Four criteria of sensitivity, specificity, accuracy, and precision were used to evaluate the performance. The evaluation criteria for the images in the DRIVE data set are reviewed and the average of these results is given in Table 1.

TABLE I. RESULTS OF RETINAL BLOOD VESSELS EXTRACTION FOR ALL IMAGES IN THE DRIVE DATASET

Performance evaluation quantities	**sensitivity**	**specificity**	**accuracy**	**precision**
Proposed method	0/92896	0/98965	0/96578	0/91756

Table 2 compares the proposed algorithm with some of the available methods. The results show that the proposed method has satisfactory results using three steps (pre-processing, extraction of vessel center lines and separation of vessels).

TABLE II. QUANTITATIVE COMPARISON OF THE PROPOSED ALGORITHM WITH SOME OF THE AVAILABLE METHODS

method	**accuracy**	**sensitivity**	**specificity**
Oliveira et al. [7]	0/9464	0/8644	0/9367
Mishra et al. [9]	0/9540	0/8916	0/9601
Wang et al. [10]	0/9581	0/7991	0/9813
Emary et al. [11]	0/9368	0/9378	0/8994
Al Shehhi et al. [12]	0/934	0/850	0/944
Hakim et al. [13]	0/9600	0/8463	0/9759
Uysal et al. [14]	0/9527	0/7778	0/9784
Wang et al. [15]	0/9565	0/8071	0/9782
Proposed method	0/96578	0/92896	0/98965

IV. CONCLUSION

Extraction of blood vessels from retinal images is critical for the diagnosis of eye diseases. This article describes a new method for extracting blood vessels from retinal images. To evaluate the proposed method, the images in the DRIVE data set were used and the average values of sensitivity, specificity, accuracy, and precision indicate the satisfactory performance of the method. In future work, can be used of fuzzy logic based on the FBMF median filter algorithm to remove gray image noise. Also, the proposed method may for non-medical application such as palmprints segmentation for biometric systems and lung vessel detection in CT scans be beneficial.

REFERENCES

[1] Mane, D., Londhe, N., Patil, N., Patil, O., & Vidhate, P. (2022). A survey on diabetic retinopathy detection using deep learning, Data engineering for smart systems, 238, 621-637. https://doi.org/10.1007/978-981-16-2641-8_59

[2] Antonetti, D. A., Silva, P. S., & Stitt, A. W. (2021). Current understanding of the molecular and cellular pathology of diabetic retinopathy, Nature reviews endocrinology, 17(4), 195-206. https://doi.org/10.1038/s41574-020-00451-4

[3] Monisha Birlin, T., & Divya, C. (2022). Comparison of various segmentation techniques in diabetic retinopathy-a review, Modern approaches in machine learning & cognitive science: a walkthrough, 1027, 73-79. https://doi.org/10.1007/978-3-030-96634-8_7

[4] Prouski, G., Jafari, M., & Zarrabi, H. (2017). Internet of things in eye diseases, introducing a new smart eyeglasses designed for probable dangerous pressure changes in human eyes, 2017 International conference on computer and applications, 364-368. https://doi.org/10.1109/COMAPP.2017.8079762

[5] Crabtree, G. S., & Chang, J. S. (2021). Management of complications and vision loss from proliferative diabetic retinopathy, Current diabetes reports, 21(9), 1-8. https://doi.org/10.1007/s11892-021-01396-2

[6] Jafari, M. (2017). Internet of things in eye diseases using smart glasses, International journal of engineering education, 9, 1034–1042.

[7] Oliveira, W. S., Teixeira, J. V., Ren, T. I., Cavalcanti, G. D., & Sijbers, J. (2016). Unsupervised retinal vessel segmentation using combined filters, PloS one, 11(2), 1-12. https://doi.org/10.1371/journal.pone.0149943

[8] Abdellahoum, H., Mokhtari, N., Brahimi, A., & Boukra, A. (2021). CSFCM: an improved fuzzy C-Means image segmentation algorithm using a cooperative approach. Expert systems with applications, 166, 114063–114085. https://doi.org/10.1016/j.eswa.2020.114063

[9] Mishra, S., Chen, D. Z., & Hu, X. S. (2020). A data-aware deep supervised method for retinal vessel segmentation. 2020 IEEE 17th international symposium on biomedical imaging, 1254-1257. https://doi.org/10.1109/ISBI45749.2020.9098403

[10] Wang, D., Haytham, A., Pottenburgh, J., Saeedi, O., & Tao, Y. (2020). Hard attention net for automatic retinal vessel segmentation, IEEE journal of biomedical and health informatics, 24(12), 3384-3396. https://doi.org/10.1109/JBHI.2020.3002985

[11] Emary, E., Zawbaa, H. M., Hassanien, A. E., & Parv, B. (2017). Multi-objective retinal vessel localization using flower pollination search algorithm with pattern search, Advances in data analysis and classification, 11(3), 611-627. https://doi.org/10.1007/s11634-016-0257-7

[12] Al Shehhi, R., Marpu, P. R., & Woon, W. L. (2016). An automatic cognitive graph-based segmentation for detection of blood vessels in retinal images. Mathematical problems in engineering, 2016, 1-15. https://doi.org/10.1155/2016/7906165

[13] Hakim, L., Kavitha, M. S., Yudistira, N., & Kurita, T. (2021). Regularizer based on euler characteristic for retinal blood vessel segmentation, Pattern recognition letters, 149, 83-90. https://doi.org/10.1016/j.patrec.2021.05.023

[14] Uysal, E., & Güraksin, G. E. (2021). Computer-aided retinal vessel segmentation in retinal images: convolutional neural networks, Multimedia tools and applications, 80(3), 3505-3528. https://doi.org/10.1007/s11042-020-09372-w

[15] Wang, B., Wang, S., Qiu, S., Wei, W., Wang, H., & He, H. (2020). CSU-Net: a context spatial U-Net for accurate blood vessel segmentation in fundus images, IEEE journal of biomedical and health informatics, 25(4), 1128-1138. https://doi.org/10.1109/JBHI.2020.3011178

[16] Jafari, M. (2022). A new way to extract blood vessels in digital images of the retina, Soft computing journal. https://dx.doi.org/10.22052/scj.2022.243171.1000