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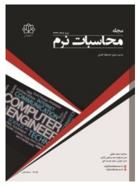

Isolation of vessels in retinal color images ✧

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ABSTRACT

Identifying retinal blood vessels is widely used for diagnosing eye diseases such as diabetic retinopathy, and glaucoma. Currently, doctors manually extract these vessels, which is a challenging and time-consuming process that often leads to errors. In this paper, a new method is proposed for retinal blood vessel extraction, which includes three basic parts. First, the noise in the image is removed. Next, 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 method is applied to the images of the DRIVE test set and its efficiency is evaluated using four different metrics: sensitivity, specificity, accuracy, and precision. The average results for accuracy, specificity, sensitivity, and accuracy in the proposed method are 0.92896, 0.98965, 0.91756, and 0.96578, respectively.

1 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, while 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 the life of a patient [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].

Doctors need 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 has a great impact on the diagnosis process and its results. Therefore, retinal vessel extraction is important for the diagnosis and treatment of retinal diseases [1].

In this paper, 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 a middle filter applied on it. Then, the central lines of the vessel are extracted using a set of filters in four different directions. The central line is

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then marked using a Gaussian filter. The resulting image is thresholded and two images are created: one related to the extraction vessels and the other related to the eyeball area. Using these two images and the image isolated from the combination of center lines to completely regenerate the vessels, the method of expanding the area is applied and the noises in the image are removed by using thresholding.

2 Related work

Due to the importance of identifying vessels in retinal images, more work has been done in the field of retinal vessel separation. In the following, some of these methods are reviewed.

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. In another work, 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 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], 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, which are obtained by the pattern search (PS), are optimized as a local search. In this method, PS, FPSA, and PFCM algorithms are utilized. This method is resistant to healthy and pathological retinal images. The disadvantage 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 multilayer/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. This method can track noisy images and tiny vessels. In this method, the light changes are removed by subtraction of the background component from the selected channel based on Eq. 1:

$$f_C(x) = f_G(x) - f_B(x) \tag{1}$$

where x is a pixel from the green channel and f_B is the background of the retinal image created by applying a low-pass Gaussian blurring of the green channel f_G. However, one of the main challenges of this method is computational complexity.

For delineating small retinal vessel connections on a fundus image, Hakim et al. [13] proposed EC-based regularizers to estimate the number of isolated objects in U-Net-like deep CNN architecture. They investigated the regularizer based on the isolated objects number differences between groundtruth (DISO) and output in delineating the vessel regions. Consider Eq. 2, where E_{LABEL} and E_{OUT} are isolated object numbers of the predicted groundtruth and output, respectively.

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

According to this equation, if the isolated object number between groundtruth and output is not equal, the DISO-based object function leads to a large misclassification error; otherwise, it generates zero misclassification error in the vessel region detection. Then the picture is turned to grayscale, followed by normalization of the data and equalization of adaptive Limited Contrast Histograms (CLAHE). The normalization is applied to keep the picture on the same scale and the CLAHE technique is used to raise the contrast of the grayscale picture.

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

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

In [16], Jafari proposed a new method for retinal blood vessel extraction. This method turns colored images into gray images and then removes the noises of the images using a filter. Next, it utilizes a filter in four different directions to determine the central lines of the vessels. Finally, by using area expansion and noise removal, blood vessels are extracted in the retinal images. The proposed approach is an extension of this method.

3 Proposed approach

In the proposed approach, the adaptive correction function is applied locally to amplify the desired signal and improve the contrast and image quality. Note that, this function prevents noise amplification. The colored images of the retina are changed to gray images (see part b of Fig. 1) based on Eq. 3:

$$img(x, y) = \frac{R(x, y) + G(x, y) + B(x, y)}{3} \quad (3)$$

where $img(x, y)$ is the output image component, $R(x, y)$ 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.

According to Eq. 4, a middle filter is applied to the image (see part c of Fig. 1).

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

In this equation, $img(x, y)$ is the gray image and $image(x, y)$ is the image from the middle filter. The higher-quality images at this stage lead to more precise extraction of veins in the next stage. In the middle filter, the pixel values in a neighborhood are 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 $(2k+1)\times(2k+1)$ or in the shape of a cross are considered. Since the vessels are at the surface of the retina in each direction, the proposed approach requires several patterns in different directions to identify all the vessels. On the other hand, 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. Hence, a set of these filters is used in four directions to extract the center lines.

The image of the retina is represented by a three-dimensional surface, the x and y directions show the dimensions of the image and z denotes the brightness level of the image points. The center line is a linear vessel with a width of one pixel. Hence, a thinner morphology operator is used to have a line one pixel wide. In this approach, the interconnected components are determined by an octet neighborhood. 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. By Specifying the center pixel for each component and 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. Then the threshold value is obtained using Eq. 5:

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

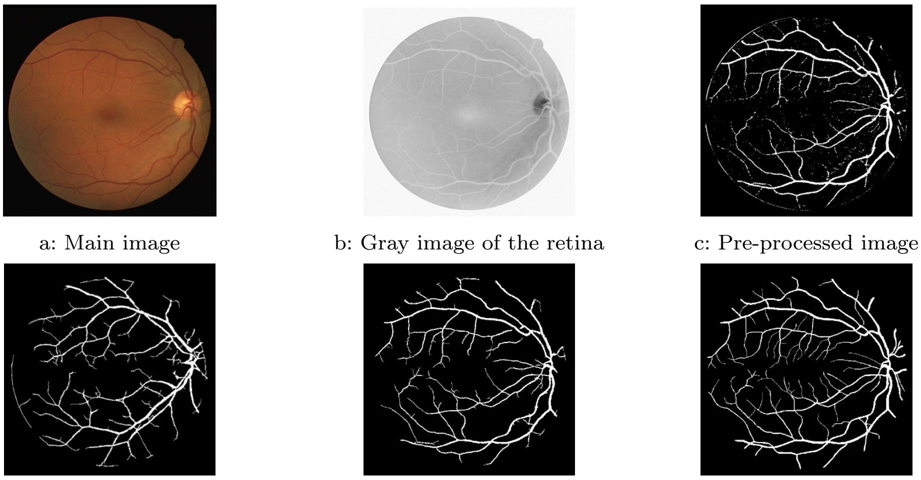
This equation is used to binarize the window. The resulting binary image is multiplied by the window obtained from the stud point image to the center of the middle pixel of the component. If the sum of the pixels with value 1 in the resulting window is more than half the number of pixels in the component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

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:

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

where 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 in 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 previous step images through the area expansion method, provided that the two pixels are adjacent (see part d of Fig. 1).

In the last step, noise removal is applied. In this operation, pixels with a value less than 20 are cleared. Part e of Fig. 1 shows the final result of the separation of retinal blood vessels, where some of the very small veins are removed. The manual separation of retinal vessels is demonstrated in Part f of Fig. 1.



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

d: Central line of the retinal vessels e: Extraction of retinal vessels f: Extraction of veins manually

Fig. 1. Extraction of blood vessels by the proposed method.

4 Results

The DRIVE dataset is used to evaluate the proposed method. The images in this collection are obtained by screening people with diabetes in the Netherlands. The screening population included 400 people with diabetic retinopathy. From this collection, 40 images are 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: educational and experimental. There is a mask image (eye area) for each image in the training dataset. Moreover, the proposed approach is implemented in a MATLAB environment and four metrics sensitivity, specificity, accuracy, and precision are used to evaluate the performance. Table 1 shows the average of the results.

Table 1. Results of retinal blood vessels extraction for all images in the drive dataset.

Approach	Performance evaluation quantities			
	sensitivity	specificity	accuracy	precision
Proposed	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 2. Quantitative comparison of the proposed algorithm with some of the available methods.

Approach	Performance evaluation quantities		
	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]	0.9340	0.8500	0.9440
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	0.96578	0.92896	0.98965

5 Conclusion

Extraction of blood vessels from retinal images is critical for the diagnosis of eye diseases. This paper proposed a new method for extracting blood vessels from retinal images. To evaluate the proposed method, the images in the DRIVE data set are used and the average values of sensitivity, specificity, accuracy, and precision indicate the satisfactory performance of the proposed method. For future work, we plan to use fuzzy logic based on the FBMF median filter algorithm to remove gray image noise. Furthermore, the efficiency of the proposed method can be evaluated on non-medical applications such as palmprint segmentation for biometric systems and lung vessel detection in CT scans.

Conflict of interest

The authors declare that they have no conflict of interest.

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