Retinal Vessels Segmentation Based on Histogram Equalization Combined with Improving Multi-Scale Line Detection

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Abstract In the health care field, doctors usually analyse some details presented in medical images to detect some diseases. If the doctor sees some changes related to the shape, colour or size of the retinal blood vessel. The doctor will guess early stage of dangerous sickness like age-related macular degeneration, diabetes, hypertension, arteriosclerosis. It is a good time for the doctor to build a treatment plan as soon as possible. One of the useful retinal blood vessel analysis ways is segmentation. The task should be done before other works are deployed to cure the patient. The paper proposed a method to segment retinal blood vessels by using histogram equalization combined with improving multi-scale line detection. This method uses histogram equalization to improve the quality of the input image, and then improving multi-scale line detection (MLD) technique to enhance the accuracy of vessels detection. Particularly, using the MLD technique to detect large vessels and small ones with adaptive window sizes finally combined. As a result, our method can work effectively to segment more vessels. The method is tested in quality and quantity on publicly available DRIVE datasets with an average accuracy reaching to 0.9515. The result of the proposed method is better than these other methods.

Keywords Retinal vessels · Segmentation · Line detection · Histogram equalization

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1 Introduction

Nowadays, medical image processing plays an important role in diagnosing some popularly dangerous sickness. Evidence of this, hypertension manifested by changes in vessel calibre [1, 2]. Diabetic retinopathy found out by the onset of neovascularization, which is the first sign of blindness [3]. The stroke often presented by appearing arteriovenous nicking [4, 5]. Therefore, it is very important to detect these retinal vessel changes to intervene immediately at the early stage. Thus, the patients have more chances to avoid losing a major vision. The effective performance of medical diagnosis depends on the accurate vessel segmentation. The result segmentation contributes to the success of the next tasks.

Thus, the medical image segmentation plays an important role in supporting with diagnosing. In fact, some various regions in the image are separated by the segmentation technique based on some features such as [6]: intensity, texture and colour. The segmented image is useful to identify regions of interest. The researchers have used many useful techniques such as threshold [7–9], joined between threshold and domain [10, 11], deep learning [12], filter [13, 14], clustering [15], etc. However, these methods have been very complex calculations. For example, the methods are the poor segmentation in some special cases such as vessel central light reflex, close vessels, small vessels, etc. These problems should be solved as soon as to enhance the quality of retinal vessel segmentation result. In another word, to avoid misunderstanding as two vessels when they consist of the central reflex pixels or prevent from merging two close vessels each other. These drawbacks are going to make vascular network analysis be low accuracy in some cases. Here, they are the identification of single vessel segments, vascular abnormality detection or vessel diameter measurement.

In fact, these disadvantages are easy to find out in some recent methods. Evidence of this, the disconnected vessels, and vessel merging presented by Staal [16] and Soares [17] result, respectively. Moreover, both Staal and Soares cannot avoid losing of objects located in a middle of vessels because of happening central reflection in a vessel. Nguyen [18] had used to improve salient region combined with Sobel operator condition to detect retinal blood vessel. The method is not effective to detect the vessels when the vessel pixels have various saliency levels. Nguyen [19] proposed an effective segmentation method to segment blood vessels in the retinal image. However, this segmentation technique also exists some drawbacks. It cannot detect both major vessels and thin ones at whole. This problem comes from using only one window size to segment all blood vessels. In fact, the line basic detection technique depends on the size of the window. In another word, if the window size is set very small, a major vessel will separate into two vessels.

In contrast, if the window size is set too large, the two close thin vessels will merge as one larger vessel. Mustafa [20] proposed the blood vessel extraction method, which works more effectively than Kirsch templates' detection technique. However, the method cannot detect small vessels.

A useful retinal blood vessel segmentation technique is proposed to solve the drawback mentioned above in the study. Our approach based on the using histogram equalization (HE) combined with improving the multi-scale line detection (IMLD). The proposed algorithm includes two stages: using HE to improve the quality of source image and applying MLD with adaptive window sizes to detect more vessels. The result of the proposed method dominates among recent approaches. This next sections in the paper are presented by following: presenting the basic line detector in section 2, describing the proposed method clearly in section 3, showing the experiment results and conclusion in section 4 and section 5 respectively.

2 Line Detector

To a server for line detector [19], the retinal image is separated into three channels: green, blue, and green. The green channel is the most suitable for line detector work. The vessels presented brighter than the background. A window with size W x W chosen at every pixel position. The grey level average at each pixel calculated as I^W_{avg}.

The number of lines passing through the centre pixel depends on the angular resolution. Each line has its average value of pixels. A line has the highest value considered as

'winning line' and this figure presented by $I^W_{\max}$. Each pixel has a line response calculated as Eq. (1):

$$R_W = I^W_{\max} - I^W_{avg} \tag{1}$$

A pixel will consider as the vessel pixel if the line response is large. The winning line is arranged along the vessel. In opposite, the pixel will be background pixel if the difference between the average grey level of the surrounding window and the winning line is tiny. The performance of the technique is depended on the size of window W. It is ideal for window size with a balance between the number of the vessel and background pixels. In another word, the window size should be double vessel calibre.

The line detector can work well in the case; there are the light reflection phenomena in the middle vessel. In fact, the middle pixel value is usually lower than the others. The performance of classification is not accurate because of the similar intensity values. However, these pixels recognized by the technique as a part of the vessel. The winning line consists only a few central reflex pixels. Therefore, the average value not reduced significantly by these pixels. As a result, these pixels considered as vessel pixels because of large responses. Additionally, most of the other pixels classified as background ones because of using long-length lines.

The basic line detector demonstrated its benefits. But it also consists of a few limitations such as merging close vessels, extending at crossover points and causing misclassification when the background pixels located near strong vessels.

3 IMLD for Retinal Vessels Segmentation

In the section, we proposed an efficient retinal blood vessel segmentation method that uses HE combined with IMLD. The generalized block diagram of our retinal blood vessel segmentation technique presented in Fig. 1.

The method includes two stages: histogram processing and improving multi-scale line detection. Each stage will be explained in more details in its subsection.

3.1 Histogram Processing

Firstly, the input image enhanced by using HE technique [21]. The task helps to improve the contrast between the vessels and others. This technique explained by the following:

1. Calculate the histogram of the source image by Eq. (2)

$$h(r_k) = n_k \tag{2}$$

   where r_k is the k^{th} value of intensity, n_k is the number of pixels in the range of intensity r_k.
2. Calculate the Cumulative Distributive Function (CDF) of the source image. The probability $P(r_k)$ of intensity level r_k is calculated by Eq. (3):

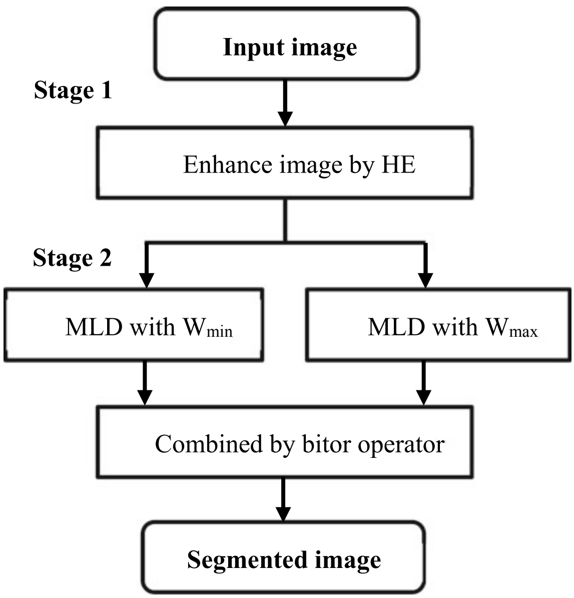

Fig. 1 Block diagram of the retinal blood vessel segmentation technique

$$P(r_k) = \frac{n_k}{MN} \quad k = 0, 1, 2, \dots L - 1 \tag{3}$$

where MN is the sum of pixels, and L is the number of intensity levels.
A particular transformation function in image processing described by equation (4):

$$s = T(r) = (L - 1) \int_0^r \Pr(w)dw \tag{4}$$

where w is an integration dummy variable. The CDF of random variable r is computed by Eq. (4). The discrete form of previously mentioned transformation is described by Eq. (5):

$$s_k = T(r_k) = (L - 1) \sum_{j=0}^{k} \Pr(r_j) \quad k = 0, 1, 2, \dots, L - 1 \tag{5}$$

Thus, each pixel in the source image will be mapped with intensity r_k into a corresponding pixel with level s_k in the output image. The transformation $(r_{k)}$ is called a histogram equalization.

3. The histogram of the source image computed by Eq. (6):

$$I_p = T(I_p) \tag{6}$$

where I_p is pixel intensity value.

3.2 Improving Multi-scale Line Detection

Nguyen [19] proposed the segmentation method in a retinal image using MLD. The result improved significantly compared with the basic line detection method. However, the improvement is not enough accuracy. In fact, this method can only detect all large vessels and some small ones. In another word, the method is false to detect a few smaller vessels. It is clear if we use only a window size, the result will get low accuracy. We, therefore, proposed IMLD by using MLD with various window sizes to detect better. The MLD also reuse the basic line detector with using various the length of the aligned lines. The line detector calculated by equation (7):

$$R_W^L = I_{\max}^L - I_{avg}^W \tag{7}$$

where $1 \le L \le W$, $I_{\max}^L$ and I_{avg}^W are the same role in the previous section. The line detectors at various scales are implemented by controlling the values of L.

In our proposed method, we use two window sizes to detect major vessels and minor ones by maximum and minimum window size. We define maximum window size and minimum ones as $W_{\max}$ and $W_{\min}$ in orderly. The $W_{\max}$ approximates double large vessel calibre. And the approximates double small vessel calibre.

Large vessels are detected by equation (7) with $W_{\max}$ and $1 \leq \mathrm{L} \leq W_{\max}$. Parallel, the small vessels are detected by equation (7) with $W_{\min}$ and $1 \leq \mathrm{L} \leq W_{\min}$. Moreover, the $W_{\max}$ is applied to avoid separating the large vessel into two small ones. Additionally, $W_{\min}$ also used to get more small vessels and reduce some drawbacks when a background pixel located at a special position. It is a fact that if line length reduced, the more background noise would appear. To solve this limitation, the line responses at various scales are linearly combined. We should note that line detector at each scale returns the raw response values that are in a limited range. As a result, the difference between the background and the vessels be very low. To improve the contrast in the images, the raw response image values standardized to create the unit standard deviation distribution and zero mean as equation (8):

$$R' = \frac{R - R_{mean}}{R_{sdt}} \tag{8}$$

where R is the value of the raw response, $R^{'}$ is the value of the standardized response, R_{mean} and R_{std} are the mean and standard deviation of the raw response values orderly. The standardization is useful for the distribution of the intensity values. It needs to apply to the response images produced by line detectors at different scales because its result is helpful for linearly combination process.

In the combination technique, each scale assigned the same weight. The line responses with various scales combined linearly to create the segmentation. This response at every pixel defined by equation (9):

$$R_{combined} = \frac{1}{n_L + 1}\left(\sum_L R_w^L + I_{igc}\right) \tag{9}$$

where I_{igc} is the inverted green channel value at the corresponding pixel, n_L is the number of scales used, and ${R_w}^L$ is the line detector response at scale L. The green channel integrated into the combination to distinguish similarity among the blood vessels and other structures easier.

Finally, we applied bitor operator to combine between the segmented image with $W_{\max}$ and segmented image with $W_{\min}$ for creating the final segmented image.

4 Experiment and Results

The experiment uses DRIVE dataset [22], which includes the colour images focusing on eyes and result of segmented images. It considered as a useful benchmark to appreciate the efficiency among the method and others.

Obviously, the segmentation method's result is the classification of pixels, which are either as a vessel or background tissue. Consequently, on the positive side, the events are true positive (TP) and true negative (TN) as a pixel accurately segmented as a vessel or non-vessel. In the negative side, the two misclassifications are false negative (FN), and false-positive (FP) as a pixel is incorrectly segmented.

To evaluate algorithms' performance, we use two widely known statistical measures, including sensitivity and specificity [23]. The sensitivity is a normalized measure of true positives as equation (10), while specificity measures the percentage of true negatives as equation (11):

$$\text{sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{10}$$

and,

$$\text{specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{11}$$

The binary classification accuracy described by equation (12):

$$\text{accuracy} = \frac{\text{TP} + \text{TN}}{\text{P} + \text{N}} \tag{12}$$

With N and P show the sum of negatives (non-vessel) and positives (vessel) pixels in during segmentation. The accuracy is the homogeneity level, which compares binary classification and the ground truth. Accuracy presents the degree of effective segmentation. Therefore, it used to evaluate and compare our method and others.

We implemented the proposed approach in Sect. 3. It is a truth that the original image includes three channels such as red, green, and blue. To prepare for the first stage, processing the green channel of an image extracted. In the green channel, the difference of intensity between the blood vessel and background is higher than the rest of channels. In this paper, the ground truths vessel extracted from DRIVE is considered a measurement standard to compare the method's effective performance and recent others [19, 20]. We test all images in DRIVE. In the study, we show two typical cases.

The segmented images presented in Figs. 2 and 3. Figure 2a presents the source image, segmented image by the method in Fig. 2b, the Nguyen [19] in Fig. 2c and the Mustafa [20] in Fig. 2d. Furthermore, in the Fig. 3a presenting the source image, segmented image by the method in Fig. 3b, the Nguyen [19] in Fig. 3c and the Mustafa [20] in Fig. 3d.

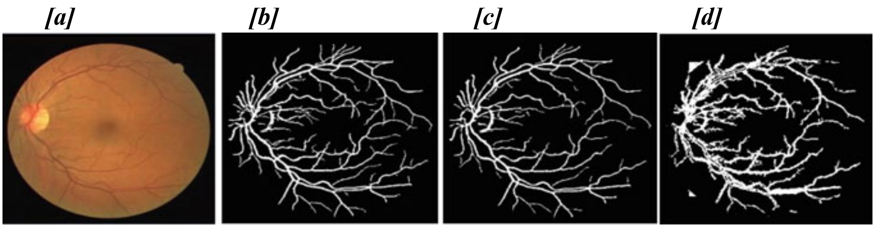

Fig. 2 The result images of the method and other methods

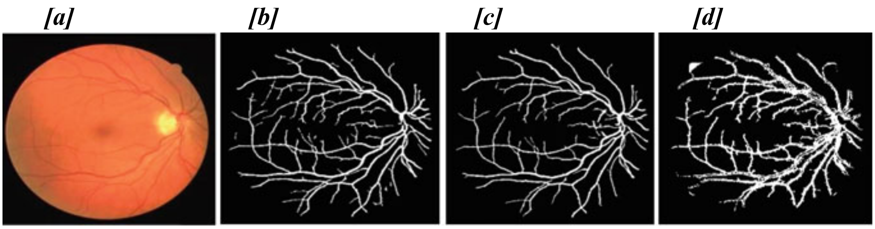

Fig. 3 The result images of the method and other methods

To look insight Figs. 2 and 3 show the quality of our result images (Figs. 2b and 3b) is more effective than results of other methods because of consisting more vessels. Thanks to using HE to improve the quality of source image and choose adaptive window sizes to detect all kinds of vessels.

The performance measures like sensitivity, specificity, and accuracy presented in Table 1. The segmented image is considered as better when these parameters value gets higher, which written by italics.

According to the number in Table 1, we can observe that the method's sensitivity and accuracy values are the highest in all cases. While in Table 2, our specificity values are higher than those in the Mustafa method [20]. In fact, our proposed method is less

Table 1 The first image

Measures	Sensitivity	Specificity	Accuracy
Nguyen et al. method [19]	67.90	*98.93*	95.50
Mustafa et al. method [20]	68.41	94.82	91.53
Proposed method	*74.40*	98.52	*95.85*

Table 2 The second image

Measures	Sensitivity	Specificity	Accuracy
Nguyen et al. method [19]	71.91	*98.37*	96.00
Mustafa et al. method [20]	65.02	95.54	92.44
Proposed method	*78.43*	98.06	*96.30*

Table 3 The average performance of various segmentation techniques regarding sensitivity, specificity, and accuracy on DRIVE dataset

Measures	The average performance		
	Sensitivity	Specificity	Accuracy
Nguyen et al. method [19]	62.90	*98.78*	94.86
Mustafa et al. method [20]	61.07	95.39	91.17
Proposed method	*69.35*	98.32	*95.15*

effective than Nguyen method [19] in specificity parameter. However, the difference is very tiny and related background pixels.

To evaluate the performance of these methods mentioned above, we test all images in DRIVE dataset. The average of sensitivity, specificity, and accuracy presented in Table 3. According to the figures in the table, we can say that our proposed method is more advantageous than the rest two methods. Ours can segment vessel pixels better. Evidence of this, in term of sensitivity and accuracy, our results are highest, and the difference of sensitivity is very great (69.35 compared to 62.90 and 61.07). However, ours is less effective than Nguyen method [19] in term of specificity. In fact, our drawback is very small because the difference is very light (98.32 compared to 98.78) and the figure related to background pixels. In our method, we focus on vessel pixels.

5 Conclusions

Retinal blood vessel segmentation is the main work in images processing. Because its result is very useful for doctors to diagnose some dangerous diseases. Based on the segmented image result, the doctor easily finds out some main symptoms of the disease. In our paper, a novel method proposed to segment retinal blood vessel using HE combined with IMLD. The proposed method includes two stages: using HE to enhance the input image and apply MLD with various window sizes to detect vessels. Thanks to the using the adaptive window size, the method can detect both large vessels and small ones. It concludes that our proposed method is more effective than recent other algorithms according to computing sensitivity, specificity and accuracy.

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Conflict of Interest The authors declare that they have no conflict of interest.

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