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AUTOMATIC BLOOD VESSEL DETECTION ON RETINAL IMAGE USING HYBRID COMBINATION TECHNIQUES

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ABSTRACT

A blood vessel in the retinal is one of the important organs especially to diagnose diseases such as diabetic retinopathy and glaucoma. In this study, a new method for automatic segmentation of blood vessels in retinal images was presented. The proposed method is based on a hybrid combination between Gray-Level and Moment Invariant techniques. There are consists four stages of processing, (1) preprocessing, (2) feature extraction, (3) classification, and (4) post-processing. The proposed method was compared to the Vascular Tree and Morphological method. Based on the objective evaluation, the proposed method successfully achieved a sensitivity of 98.589% and specificity of 55.544% compared to the others.

Key words: Automatic, segmentation, retinal, gray-level, moment invariant

INTRODUCTION

The blood vessel is one important part in retinal image and it is also used as landmarks for identification. Over the past decade, blood vessel examinations enable the determination of several eye diseases. However, the retinal image may encounter variation in intensity which occurred due to general imperfection during the image acquisition process (Mustafa & Yazid, 2016b; Mustafa & Yazid, 2016a). Recent developments have proposed many approaches for automated retinal blood vessel segmentation (Fan *et al*., 2017; Yang *et al*., 2017; Jiang *et al*., 2017; Mustafa *et al*., 2017; Mustafa & Yazid, 2018). The study by Chaudhuri *et al.* (1989) suggested a 2-D matched filtering implemented by which vessel is figured out from the Gaussian kernel. To load into a vessel with a different structure, the kernel was then rotated at many different angles. After that, the threshold process is applied in the image from the background to differentiate the vessel silhouette. This proposed method was successful in poor local contrast, compared to other edge detection algorithms, where this operation provides an excellent output result. Otherwise, in the last step, the process of post-processing should be done as this filter detection method is available to use in stationary processes only. Another disadvantage of this filter is that the thin vessels are not detected as the length of the segment needed is larger to reduce he noise (Zhou *et al.*, 2012). This is supported by a study by Al-Rawi and colleagues (2007) which demonstrated the improvement of 2D matched filter method. This study made a comparison of vessel detection between red and blue channel with a green channel output performance. This vessel segmentation method was presented based on the threshold value. The resulting images were produced by getting the number of connected components in a sample vessel images and compared with another image acting as a reference.

Jiang and Mojon (2003) proposed a common framework based on a verification-based multi-threshold plan. The extraction of a blood vessel in the retinal is done by combining the appropriate details associated with retinal vessels in the validation process. However, this algorithm operation requires a long computational time, hence is the most expensive operation as opposed to others. Another study by Martinez-Perez *et al.* (2007) proposed a rule-based method by multi-scale feature extraction. The segment vessel was tested from both red-free and fluorescein images. The size

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and width of the vessel were determined using this method and the results were obtained from the multiple pass region growing procedure. In a different study, Mendonça and Campilho (2006) proposed a method based on the segmentation of retinal blood vessels by combining the detection of centerlines and morphological reconstruction. This method utilized an automated protocol for the segmentation of vascular network in retinal images. Chanwimaluang and Fan (2003) described the effectiveness of Local Entropy Thresholding techniques to detect blood vessel on retinal images. This approach, however, is complicated since it involves multiple steps namely; (1) matched filtering to enhance the image, (2) local entropy thresholding to remain the blood vessel structure, (3) length filtering to remove misclassified pixels, and (4) vascular intersection to solve the link of the blood vessel. In another study, Mustafa *et al.* (2014) proposed a new method based on morphological approach. The input image was divided into two main phases, green channel, and image conversion. In the green channel, the image was applied to valley detection, while the image conversion part was for peak detection. The results obtained after applying the two types of detection above were superimposed to produce the final image and compared to the Local Entropy Thresholding method (Chanwimaluang & Fan 2003).

In this current paper, a new supervised method for blood vessel detection in digital retinal images was proposed. Basically, this method uses a gray-level and moment invariants-based features for the pixel. The resulting performance was compared to the Vascular Tree method (Chanwimaluang & Fan 2003) and Morphological method (Mustafa *et al.,* 2014). Several image quality assessments such as sensitivity and specificity were performed to compare the effectiveness of each method.

MATERIALS AND METHODS

The experiment involves two main stages; (1) Pre-processing and (2) Feature Extraction.

A. Pre-Processing

The green channel was extracted from the original retinal image in Red, Green, and Blue (RGB) colour and is used for further processes. The green channel was selected as it provides the best contrast between vessels and background of the RGB image (Gonzalez & Woods 2008). This process is important to enhance the image as most of the retinal images consist of noise with unstable illumination and contrast. Next, the vessel central light reflex removal was applied. Blood vessels usually appear darker than the background as it has lower reflectance. Since some of the blood vessels are present with unwanted light reflex, this step is necessary to eliminate the bright strip from the green channel image. In this process, a morphological opening filter was used to remove the brighter strip that exists in the green channel image. Morphological opening generally smoothes the contour of the object whereby erosion gets rid of small objects, followed by dilation to restore the shape of remaining objects. The process was proceeded with homogenizing the background. Non-uniform illumination in the image will create a variation of background intensity which must be reduced or it will later affect the vessel segmentation performance. The shade-corrected image was performed to eliminate the background lightning variations. Subtraction method was used in shade-correction which calculates the difference between background image, I_B and the original image, I_Y as shown by equation (1).

$$I_H(x, y) = I_Y(x, y) - I_B(x, y) \tag{1}$$

The last step in the preprocessing process, vessel enhancement whereby the homogenized image I_H, was complemented forming I_H^c. Next, the top-hat transformation was performed to enhance the blood vessels by correcting uneven illumination for a dark background. As shown by equation (2), γ is the morphological operation fixed to a disc of eight pixels in radius. The operation results in bright structures in retinal such as an optic disc, the possible presence of exudates or reflection artifacts to be removed. Otherwise, the darker structures such as blood vessels, fovea and the possible presence of microaneurysms or hemorrhages retain.

$$I_{VE} = I_H^c - \gamma\left(I_H^c\right) \tag{2}$$

B. Feature Extraction

After preprocessing, segmentation was performed. This process was divided into two features extraction which is gray-level-based features and moment invariants-based features. In the gray-level approach, the difference between the gray-level candidate pixel and a statistical value representative of its surroundings was obtained. Since the blood vessels are always darker than their surroundings, gray level features appear as the better choice. The features can be divided into several sets of gray-level, which were then classified the features of the homogenized image that concerning only small pixel region centered on the described pixel *(x, y)*. The set of gray-level comprised of minimum, maximum, mean, standard deviation and homogenized of gray-level value. These features appropriate choice to segment the blood vessel. The set of these descriptors can be expressed by equations (3) – (4).

$$f_1(x,y) = I_H(x,y) - \min\left[I_H(s,t)\right] \tag{3}$$

$$f_2(x,y) = \max\left[I_H(s,t)\right] - I_H(x,y) \tag{4}$$

$$f_3(x,y) = I_H(x,y) - mean\left[I_H(s,t)\right] \tag{5}$$

$$f_4(x,y) = std\left[I_H(s,t)\right] \tag{6}$$

$$f_5(x,y) = I_H(x,y) \tag{7}$$

The second feature was based on moment invariant. Hu moment consisting of seven sets which include size, translation and rotation were adopted. Since the piecewise linear structure of the vessel in the retinal are connected with many of line segments, it is difficult to detect whether it is a vessel or non-vessel. In order ti examine the structure shape, a descriptor invariant to translation, rotation and scale change is useful. For the task, the logarithm of moment one and moment two were used to test the accuracy performance in detecting the vessels. These combinations provide a high degree of characteristics of moment output. However, those characteristics cannot distinguish the central pixel of vessel and non-vessel. Thus, a new sub-image of Hu moments was computed by multiplying the original vessel with an equal-dimension matrix by Gaussian in a certain value. The results will then show the difference value between the vessel and non-blood vessel. A feature based on moment invariants appear to be a good selection in the extraction of a blood vessel in the retinal as shown by the following equations:

$$f_6(x,y) = \left|\log(\phi 1)\right| \tag{8}$$

$$f_7(x,y) = \left|\log(\phi 2)\right| \tag{9}$$

In the feature extraction stage, each pixel of a retinal image is classified by a vector in a 7-D feature space as demonstrated by equation 10.

$$F(x,y) = \left[f_1(x,y), \ldots\ldots\ldots\ldots, f_7(x,y)\right] \tag{10}$$

To determine whether the selective pixel was characterized as vessels or non-vessels, the decision tree has been chosen as a classification technique. In this paper, the candidate pixels were segmented into two classes, namely vessels or non-vessels. The pixel of the retinal images was classified based on the seven features. If the selective pixels of the image is more than the specified value based on the features, the pixel will be considered as vessels. For example, in this work for the first feature, *f1,* the pixel was characterized by an average threshold range of 80 values. Any values of the pixels that were less than 80 were considered as non-vessels and more than 80 were considered as vessels. The average threshold value was selected based on each feature in order to evaluate the candidate pixels of the image whether vessels or non-vessels. Thus, the use of threshold value is one of the ways to differentiate the pixel that belongs to vessels or otherwise.

RESULTS AND DISCUSSION

The proposed method experimented with 20 retinal images from DRIVE online database. The size of each image is 300 x 300 pixels with 96 dpi and 24-bit depth. To improve the result, post-processing protocol was performed. The process comprised of two steps first was filling pixel gaps in the detected blood vessels and second, the images were enhanced by removing the falsely detected isolated vessel pixels. To prove the effectiveness, the results of the proposed method were compared to the Vascular Tree method (Chanwimaluang & Fan 2003) and Morphological method (Mustafa *et al.,* 2014). Figure 1 presents the resulting images between three comparison methods. The Vascular Tree method produced thicker vessels and the details of blood vessels were also lost compared to the Morphological method and proposed method. While the morphological results were satisfactory and quite good, they still fail to detect the small blood vessels. Based on this observation, our proposed method proved effective and successful to segment blood vessels on retinal images.

Next, quantitative measurements to assess sensitivity and specificity were conducted to evaluate the overall performance of different segmentation techniques. The quality of the segmented images was determined based on the pixels similarity of the resultant segmented image against the manually segmented image (Mustafa *et al.,* 2014; Mustafa *et al.*, 2017). The equation of sensitivity and specificity were referred to Mustafa *et al.* (2014) and Mustafa *et al.* (2017). The overall performance results comparing the sensitivity and specificity of the three segmentation methods were shown in Table 1 based on 20 retinal images from DRIVE database. The highest sensitivity was achieved by the Morphological method, followed by the Vascular Tree method with 99.578 and 99.125 respectively. The proposed method obtained slightly lower scores with 98.589. In terms of

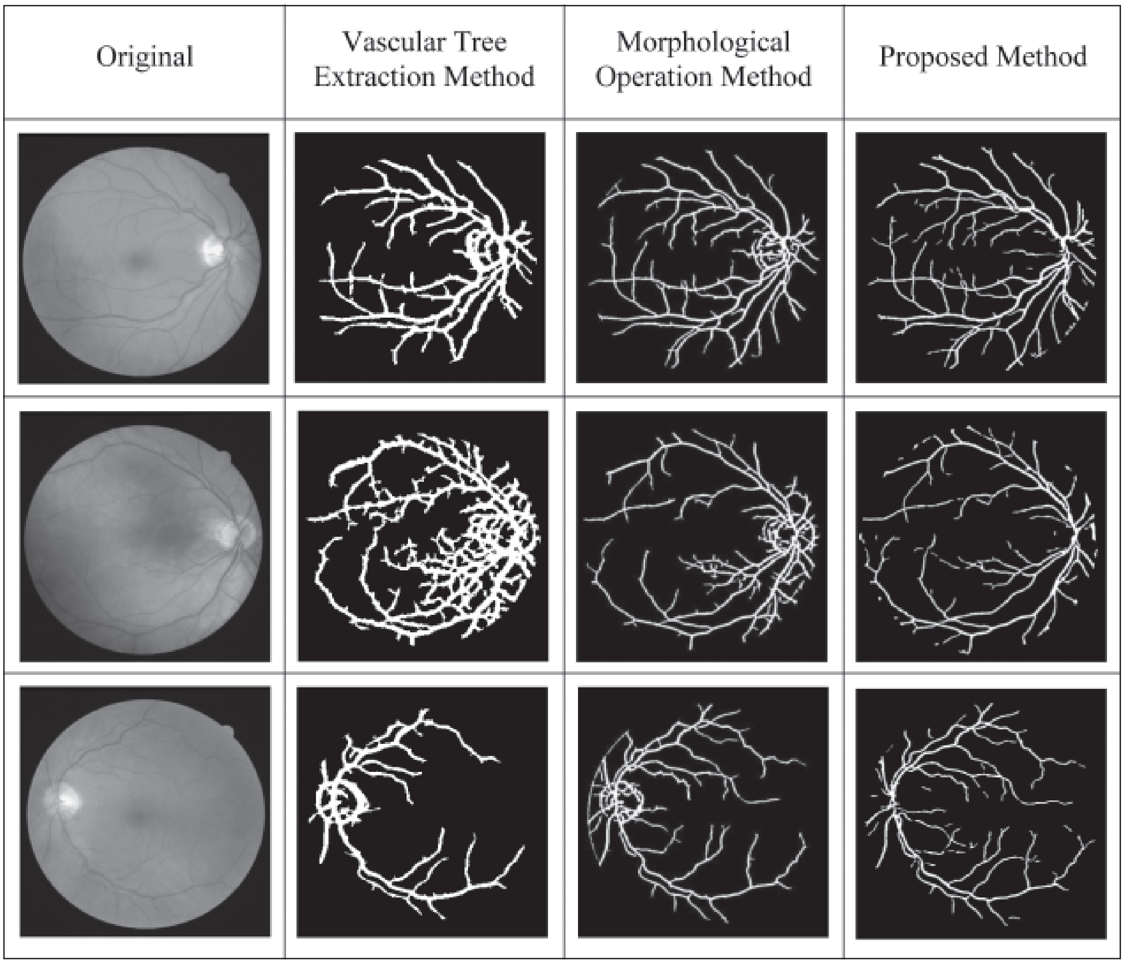

Fig. 1. Comparison of resulting image for three different segmentation approaches.

Table 1. Performance results of the different segmentation method on a DRIVE database image

Image	Vascular Tree Extraction method		Morphological Operation method		Proposed Method	
	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity
1	98.645	72.207	99.439	57.578	98.739	60.139
2	99.221	62.598	99.774	52.770	98.340	62.376
3	99.350	50.645	99.498	43.657	98.029	47.791
4	99.487	49.818	99.929	37.619	98.231	56.572
5	99.399	54.335	99.556	46.082	99.378	50.388
6	99.441	45.961	99.402	48.680	98.674	49.085
7	99.151	52.137	99.666	40.210	98.416	53.389
8	98.784	49.732	99.472	40.829	98.410	47.610
9	99.350	47.132	99.507	46.778	99.242	51.307
10	99.412	49.169	99.759	43.850	99.104	53.237
11	99.553	37.618	99.435	52.849	97.360	57.883
12	99.306	49.713	99.604	48.143	98.925	54.528
13	99.081	56.049	99.825	44.527	98.867	53.610
14	99.166	58.504	99.435	54.830	98.368	61.379
15	97.307	74.127	99.342	45.820	98.187	54.942
16	99.184	50.097	99.821	44.262	98.936	58.511
17	99.336	40.085	99.516	51.020	98.447	54.463
18	99.558	38.183	99.496	51.897	98.851	58.021
19	98.354	76.446	99.705	53.772	98.477	67.535
20	99.416	45.472	99.378	52.940	98.801	58.108
Average	**99.125**	**49.391**	**99.578**	**47.906**	**98.589**	**55.544**

specificity, the highest scores came from the proposed method (55.544), followed by Vascular Tree method (49.391) and the morphological method (47.906).

CONCLUSION

The blood vessels are important components in retinal images and are also used as landmarks for registration of the images. Determination of blood vessels must be accurate as incorrect detection will lead to improper treatment. In current this work, the images undergo several image processing stages such as preprocessing, feature extraction and classification. In preprocessing, several methods were utilized such as image enhancement using top-hat transformation, while in feature extraction, gray level and moment invariant were used.

In the classification stage, the decision tree was adopted. Our current method proposed shows a good performance (sensitivity = 98.589% and specificity = 55.544%) compared to the Vascular Tree method and Morphological method. In future, research should be concentrate on the investigation of the small and overlapping blood vessel.

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