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Modification of the Adaptive Morphology and Mask Overlapping for Blood Vessel Segmentation

[Arif Muntasa, Indah Agustien Siradjuddin, Mochammad Kautsar Sophan]

***Abstract*—Modification of the Adaptive Morphology and Mask Overlapping is proposed in this research for the blood vessel segmentation of the retinal image. The method consists of five main stages, first, enhancement of retinal image using adaptive enhancement method. Second stage is bottom Hat transformation for the segmentation and noise removal. Third, adaptive thresholding process to remove the remain noise in the image. Morphological operation is applied in the fourth stage, i.e. skeletonization and pruning. Skeletonization is used for the blood vessel thinning process, and pruning is used is to remove unused branches of the segmented blood vessel. The last stage in this research is noise removal using mask overlapping. Experiment is done using the retinal image from the DRIVE dataset. The sensitivity, specificity, and the accuracy of the segmentation method are 78.5%, 95.67%, and 87.12% respectively.**

Keywords*—blood vessel segmentation, morphology, mask overlapping , skeletonization, prunning *(key words)

I. Introduction

Diabetic Retinopathy is one of the cause of the permanently blindness. Hence early detection of the Diabetic Retinopathy will prevent the patient from the irreversible blindness. There are two main classes of Diabetic Retinopathy, i.e. Nonploriferative Diabetic Retinopathy (NPDR) and Proliverative Diabetic Retinopathy (PDR). There three sub classes of NPDR and PDR, i.e. mild, moderate, and severe. Features of the retinal image are required for the classification of Diabetic Retinopathy, they are microaneurysms, exudates, and haemorrhage [1]. Hence the blood vessel and optic disc in the retinal image are eliminated to obtain the three important features of the image to classify the Diabetic Retinopathy. Firstly segmentation of the blood vessel and optic disc of the retinal image is done to accomplish the eliminating process.

Arif Muntasa
Informatics Department, University of Trunojoyo Madura
Indonesia

Indah Agustien Siradjuddin
Informatics Department, University of Trunojoyo Madura
Indonesia

Mochmaad Kautsar Sophan
Informatics Department, University of Trunojoyo Madura
Indonesia

This research is focus on the blood segmentation process of the retinal image. Computational intelligence method is used for the segmentation process [2][3]4]. Modification of the Adaptive Morphology and Mask Overlapping is proposed in this research for the blood vessel segmentation of the retinal image. The remainder of the paper is organized as follows; section two describes the blood vessel segmentation methods in this research. Section 3 explained the result and the discussion. Final section is the conclusion section. .

II. Blood Vessel Segmentation

Five stages are required in the blood vessel segmentation of retinal image in this research, as shown in Figure 1, i.e. image enhancement process, bottom hat transformation, thresholding image, skeletonization, pruning, and overlapping mas. The stages of the segmentation are described in the remainder sub section.

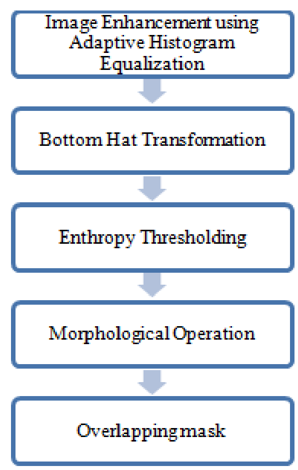


Figure 1. Diagram of the proposed method

A. *Adaptive Histogram Equalization*

First stage of the blood vessel segmentation is image enhancement process. The purpose of this stage is to improve the quality of the retinal image. Since many tiny details, dark regions, and light regions are found in the image, then the local histogram equalization is used in this research, which is Adaptive Histogram Equalization. The enhanced image will reveal the detail information of the retinal image, hence the segmentation process will be easier.

The adaptive histogram equalization (AHE) gives a better result enhancement image compare to the global histogram equalization (HE) in the retinal image enhancement. Since the AHE method works locally in the image, meanwhile the HE is global enhancement method. In the AHE method, image is divided into blocks or regions, then the histogram equalization is applied in each blocks.

The enhanced image using AHE is depicted in Figure 2.

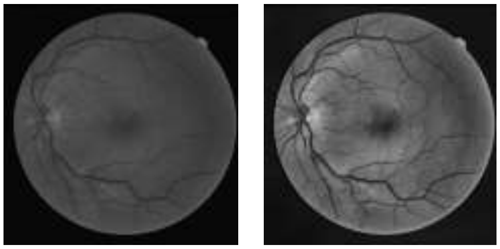


Figure 2. Enhanced Image ; (left) green chanel of the retinal (right) enhanced image using AHE.

Removal of diabetic lesion is applied in the enhanced image using the regional minimum method. The regional minimum is flat region which has similar pixel in the region. The regional minimum is shown in Equation (1)

$$\operatorname{Re} gMin_{SE}\left(f(x,y)\right) = \\ \left(1 \le \left(\left(f(x,y)+1\right)\nabla_{SE} f(x,y)\right) - f(x,y)\right) \vee \left(f(x,y) \le 0\right) \tag{1}$$

where $f(x,y)$ is the enhanced image and SE is the structure element.

B. Bottom Hat Transformation

The second step in this research is the segmentation process using bottom hat transformation. Creating the masking process using the Gaussian mask filter is the beginning process in the bottom hat transformation. The Gaussian mask filter is shown in Equation (2).

$$G(x) = \frac{1}{2\pi\sigma^2} e - \frac{x^2 + y^2}{2\sigma^2} \tag{2}$$

The enhanced image is convolved using the Gaussian filter which is obtained by Equation (2). Morphological operation is required in the next process of Bottom Hat Transformation. The Bottom hat transformation is the substraction between the morphological closing of the image and the convolved image. The result of the bottom hat transformation is depicted in Figure 3.

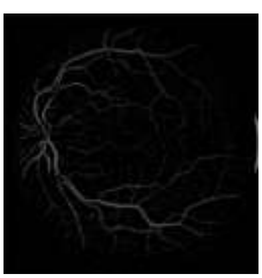


Figure 3. Result of the Bottom Hat Transformation

C. Thresholding

Output of the segmentation process is the binary image. Hence the thresholding process is required in the next process of the segmentation of the blood vessel. The gray image of the result of bottom hat transformation is threshold using entropy threshold. The entropy is used to determine the threshold value shown in Equation (3), Equation (4), and Equation (5) [5][6].

$$Entropy_{Upper} = -\frac{1}{2}\sum_{i=1}^{RowU}\sum_{j=1}^{ColU} Mat_{i,j} * \log 2\left(\sum_{i=1}^{RowU}\sum_{j=1}^{ColU} Mat \ + C\right) \tag{4}$$

$$Entropy_{Lower} = -\frac{1}{2}\sum_{i=1}^{RowL}\sum_{j=1}^{ColL} Mat_{i,j} * \log 2\left(\sum_{i=1}^{RowL}\sum_{j=1}^{ColL} Mat \ + C\right) \tag{5}$$

$$Entropy_{Total} = Entropy_{Upper} + Entropy_{Lower} \tag{6}$$

Result of the thresholding process is shown in Figure 4.

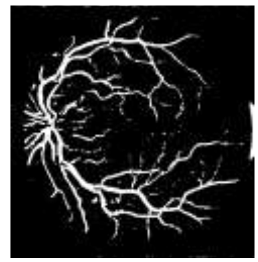


Figure 4. Threshold Image using Entropy thresholding

D. Morphological Operation

The next step in this research is the morphological operation which is consists of skeletoning and pruning process.

To reduce the thickness of the blood vessel, skeletonization process is used in this research. The skeletonization is the combination of the morphological operator erosion and opening as shown in Equation (6).

$$S(X)\bigcup_{\rho>0}\bigcap_{\mu>0}\left[\left(X \otimes \rho B\right) - \left(X - \rho B\right) \oplus \mu\bar{B}\right] \tag{6}$$

Pruning is used to eliminate the unused branches of the blood vessel. In General, the unused branches are the result of the skeletonization process.

E. Mask Overlapping

The last stage of the blood vessel segmentation in this research is mask overlapping. The objective of this stage is to remove the remain noise of the retinal image. The DRIVE dataset provide the masking image in each retinal image as shown in Figure 5.

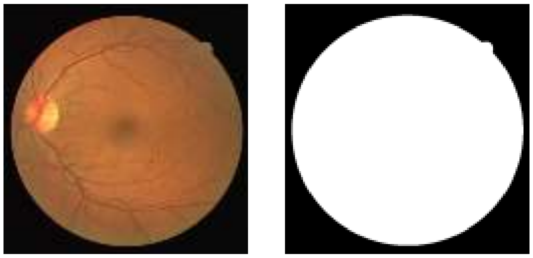


Figure 5. DRIVE dataset, (left) : retinal image ; (right): masking image.

The overlapping process is shown in Equation (7).

$$Overlapping = \sim M + \sim E \qquad (7)$$

where M is the masking image and E is the binary image.

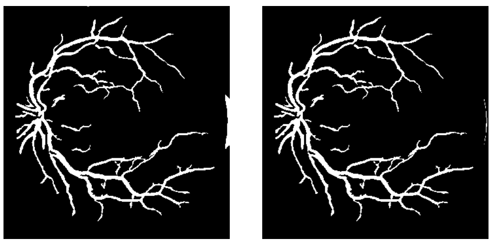


Figure 6. Mask Overlapping process to remove the noise

Figure 6 shows the result of the mask overlapping process which is applied to binary image. As seen in the image, noise outside the blood vessel ring is reduced after the overlappping process.

III. Result and Discussion

Digital Retinal Image for Vessel Extraction (DRIVE) [7] dataset is used for the experiment in this research. Retinal image, ground truth, and the masking image are provided in the dataset as seen in Figure 7.

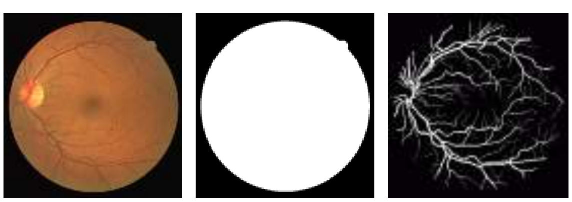


Figure 7. DRIVE dataset. (left) retinal image; (middle) masking image; (right) groundtruth image

Twenty retinal images were conducted as the experiment data in this research. Since each retinal image has its own groundtruth image, hence we can calculate the performance of our proposed method. Three performance measures are used in this research; they are sensitivity, specificity, and the accuracy. These measures can be seen in Equation (8), Equation (9), and Equation (10).

$$Sensitivity = \frac{TP}{TP + FN} \qquad (8)$$

$$Specificity = \frac{TN}{TN + FP} \qquad (9)$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \qquad (10)$$

where TP=True Positive, TN=True Negative, FP=False Positive, and FN=False Negative

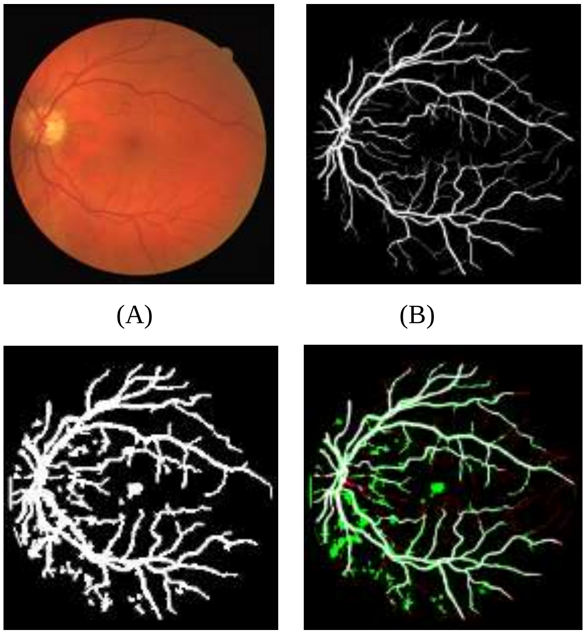
True Positive is number of pixel which is detected as the blood vessel pixel based on the ground truth image. True Negative is number of pixel which is detected as the background on retinal image based on the ground truth image, False Positive is number of pixel which is detected as the blood vessel object meanwhile the pixel is a background in the groundtruth image. False Negative is a number of pixel which is detected as background pixel on the retinal image meanwhile the pixel is an object in the ground truth image.

Size of Gaussian filter in the experiment is 5 x 5 with the value of standard deviation is 3. Diamond with r=15 is used for the structure element in the Bottom Hat transformation. The result of the experiment is shown in Table 1.

TABLE 1. THE PERFORMANCE OF THE PROPOSED METHOD.

Image	Sensitivity	Specificity	Accuracy
1	0.887999	0.931222	0.909610
2	0.834336	0.963177	0.898757
3	0.868933	0.939847	0.904390
4	0.765662	0.965538	0.865600
5	0.875471	0.944745	0.910108
6	0.702805	0.969585	0.836195
7	0.699577	0.969787	0.834682
8	0.728265	0.971589	0.849927
9	0.763188	0.945791	0.854489
10	0.799713	0.964677	0.882195
11	0.714754	0.969829	0.842292
12	0.844723	0.944658	0.894690
13	0.682150	0.974266	0.828208
14	0.852877	0.939528	0.896202
15	0.831695	0.908978	0.870336
16	0.758741	0.976441	0.867591
17	0.861260	0.937687	0.899474
18	0.691831	0.985132	0.838481
19	0.791046	0.963922	0.877484
20	0.759385	0.966704	0.863044
Average	**0.78572**	**0.956655**	**0.871188**

The result of the segmentation of the retinal image is shown in Figure 8.



(A) (B)

(C) (D)

Figure 8. Result of the experiment. (A) input of the Retinal Image, (B) Ground truth image, (C) the result of the proposed method, (D) the performance measure of the proposed method

Figure 8 (D) shows that many pixels are detected as the blood vessel pixel (False Positive), since the result of the proposed method is over detection. To overcome this problem, another noise removal method is required in the segmentation process.

Meanwhile figure 8(D) also shows that some pixels are detected as background (False Negative). This can be explained that some pixel is disconnected with the blood vessel pixel, hence our proposed method recognize the disconnected pixel as the noise of the image. Since the pixel is considered as the noise, then the pixel is eliminated and detected as the background pixel.

IV. Conclusion

Modification of the Adaptive Morphology and Mask Overlapping for Blood Vessel Segmentation is proposed in this research. The average of the sensitivity, specificity, and the accuracy is 78,6%, 95,7%, 87,1% respectively. The segmentation of the blood vessel is required for the classification of Diabetic Retinopathy from the retinal image. In the future research, the blood vessel is eliminated from the retinal image, hence the remain features of the retinal image, i.e. exudate, microaneurysms, and haemorrhage are used as a feature for the Diabetic Retinopathy classification.

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