

## ON APPLICATION OF GAUSSIAN KERNEL TO RETINAL BLOOD TRACING

<sup>1</sup>MOHD ASYRAF ZULKIFLEY, <sup>2</sup>AIN NAZARI, <sup>3</sup>SITI KHADIJAH, <sup>4</sup>ADHI HARMOKO SAPUTRO

<sup>1,2,3</sup>Department of Electrical, Electronic & Systems Engineering, Faculty of Engineering & Built Environment Universiti Kebangsaan Malaysia, Bangi, MALAYSIA

<sup>4</sup>Department of Physics, Universitas Indonesia, Depok, INDONESIA

E-mail: <sup>1</sup>[asyraf@eng.ukm.my](mailto:asyraf@eng.ukm.my), <sup>2</sup>[ainnazari@siswa.ukm.edu.my](mailto:ainnazari@siswa.ukm.edu.my), <sup>3</sup>[dijah.zaki@siswa.ukm.edu.my](mailto:dijah.zaki@siswa.ukm.edu.my), <sup>4</sup>[adhi@sci.ui.ac.id](mailto:adhi@sci.ui.ac.id)

### ABSTRACT

Fast disease screening system is becoming very important nowadays as it is useful in minimizing the pain suffered by the patient. Eye is one of the important organs used to screen various diseases such as diabetes, pterygium, glaucoma, stroke and etc. Two popular modalities to capture the visualization information of the eyes are photographed and fundus images. Photographed image captures the exterior appearance of the eyes, while fundus image captures the interior surface of the eye. This study focuses on the fundus image, in which the objective is to extract the retinal blood vessels. Condition of the vessels is a good cue for identifying microaneurysm where a sudden jump in vessels trajectory indicate a blockage in the blood flow. Hence, an edge operator is used to extract the possible lines. Two removal steps, which are outer ring and optic disc removal are performed, so that only the vessels are detected. A filling operation is performed by using gaussian kernel such that areas surrounding existing edges are analyzed to label it as blood vessel or not. The proposed technique is then tested on two databases; DRIVE and STARE. Four performance metrics are calculated based on accuracy, sensitivity, error and specificity where the best results are 0.880, 0.546, 0.120 and 0.912 respectively, obtained based on DRIVE database. The proposed system also works well in STARE database with accuracy of 0.860 and error of 0.140. The system can be further improved by using better detection scheme because the number of false negative is relatively high.

**Keywords:** *Gaussian Kernel, Fundus Image, Blood Vessel Detection, Optic Disc Removal, Outer Ring Removal*

### 1. INTRODUCTION

One of the popular trends for fast disease screening is through analyzing the condition of patient's eyes. The eyes information is usually captured by the fundus camera that photographs the interior surface of the eyes. The main components that can be observed from fundus image are retinal blood vessels, optic disc, macula, posterior pole and etc. Some examples of the disease that can be screened from the fundus image are glaucoma, stroke, diabetic retinopathy and many more. As for glaucoma screening, the sizes of the optic cup and optic disk can be used to infer the possibility of having glaucoma. The ratio between horizontal diameters of the both optics or specifically, the cup-to-disc ratio has been used to grade the glaucoma severity.

More often than not, the presence of retinal blood vessels has reduced the accuracy of

automatic glaucoma screening. The size of the optic disc detected is normally smaller than it supposed to be. The color information of the blood vessels are similar to its surrounding, which makes them to be detected as not a part of the optic disc. The acquired diameter will be less and hence the severity of the glaucoma cannot be determined accurately. To overcome this challenge, a blood vessel removal algorithm has been developed to filter out the vessels so that a better diameter can be observed. Hence, the focus of this paper is to trace the blood vessels automatically from the fundus image. Apart from that, blood vessels tracing will also be useful in clot detection for stroke disease screening. A stroke patient will have a high likelihood of having clot in his eyes which will be observed as sudden discontinuity in the retinal blood vessels.

The main novelty of this paper is to implement Gaussian kernel in detecting and tracing

the retinal blood vessels. A Gaussian kernel is chosen because of its ability to filter noise in varying types and conditions of the fundus image. It works well in the most cases without reducing the accuracy of the blood vessels tracing. The output of this algorithm can be applied easily to blood vessels removal by just subtracting the original input image with the detected blood vessels. The paper is arranged into five sections where the first section is an introduction of the importance of the blood vessels tracing. Section 2 discusses on recent methods in blood vessels tracing in various applications. The third section details out the methodology that we proposed on Gaussian based of blood vessels tracing. The experimental results are discussed in section 4 where the conclusion is given in section 5.

## 2. LITERATURE REVIEW

Recently, there is an emerging trend of using imaging techniques to achieve an effective visualization of retinal blood vessels. One of the most widely used techniques is segmentation which is used to group the fundus image. In general, segmentation is performed to represent the sub-divide components of an image such as the retinal blood vessels, optic disc and pathology lesions. Therefore, this technique needs to be tuned appropriately in order to obtain a good result as the parameters are very sensitive. Numerous studies have worked on accurate detection of the retinal blood vessels, for instances, Canny Edge-based detector [1], Blood Vessel Operator's Line Segmentation Edge Detection (RBVSLE) [2], histogram matching [3], kernel-Isomap-based feature vasculature analysis [4], and selection method [5].

Generally, canny edge operator has good ability to extract the edges in fundus image and also in eliminating noises [6]. There are three reasons [7] why Canny Operator has been used extensively to detect the vessel, which are good detection, accurate localization and elimination of multiple responses. These three criteria's are simultaneously optimized. A similar approach has also been described in [8] that has become common assessment for the edge detection performance. In [9], the edge detection is used at the beginning to detect the region of interest, which is then combined with the threshold value to eliminate the noise from the detected edges.

Method in [2] traced the blood vessels by using the growing seed function. This method is

known as RBVSLE where the seed coordinate is denoted by  $j$  and  $i$  to represent the location of the pixel. By using this approach, the intensity values in all eight directions are calculated based on eight patterns template. The winning pattern is recognized by the highest accumulated intensity. Then, the pattern with the same direction as the edge seed is acknowledged as the candidate seed. The main limitation of this method is that the small vessels are hardly traced which result in disconnected detection of the vessels.

Another study that tries to improve blood vessel tracing is based on histogram matching method [3]. This method used an adaptive approach from frame to frame by varying the tunable parameters automatically. This technique can cope with low contrast, natural variability in the imaging such as under or over exposure, and artifacts, for instance the glare problem. Furthermore, it did not require connection between the vasculatures since it is able to perform partial tracing of the blood vessels. As consequence, it is simple enough to be applied to a non-specialize hardware. A limitation of this method is the incapability to localize the optic disc center [10].

In addition, a considerable amount of literatures have been published on extracted features from the traced image. Recent evidence suggests that kernel-Isomap based feature selection is ideal for detecting the blood vessels [4]. There is an unambiguous relationship between various types of retinal image identified by the features based on distance test. The features may be divided into four main categories: 1) number of fiber based on distance, 2) angle between the branches, 3) inner product among the branches, and 4) distance between the branches. The results showed that the distance among the branches and between the internal branches were performing the best in real-time biometric application [5].

## 3. METHODOLOGY

A coloured fundus images are used as an input for the retinal blood vessel tracing system. The images were taken from two online databases, which are DRIVE [11] and STARE [12]. Both databases were captured in RGB format. The proposed algorithm converts the image from RGB to gray channel. A gray channel is utilized for its simplicity in representing the blood vessels. A full range of the gray scale of the image is then obtained through histogram normalization. This

will result in a better contrast which can be used to distinguish the vessels from the surrounding.

Firstly, an edge operator is used to detect the blood vessel, which results in detection of outer and inner line of the vessels for the whole image,  $I_{edge}$  (Figure 1).

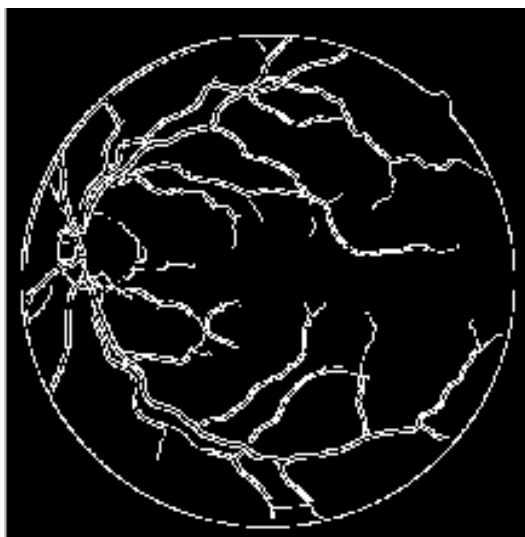


Figure 1: Sample of edge detection

As a result, the detected blood vessels will have hollow region in the middle of the vessels. Apart from that, the outer ring will also be detected. Hence, an optic disc extraction is performed to improve the accuracy of the blood vessel detection. Optic disc is recognized as the brightest region in the image. A piece wise function is used to detect the optic disc region, in which an edge operator is performed to remove the optic disc interference as shown in equation 1.

$$I_{WOD}(x,y) = \begin{cases} 1 & \text{if } I_{OD}(x,y) > \tau_1 \\ 0 & \text{if } I_{OD}(x,y) \leq \tau_1 \end{cases} \quad (1)$$

$I_{WOD}$  is the image without optic disc while  $I_{OD}$  is the input image with optic disc. A sample output of optic disc edge is shown in Figure 2. A threshold  $\tau_1$  signifies the intensity that is regarded as optic disc region. The detected edge inside the optic disc region is then subtracted from the  $I_{edge}$  to obtain more accurate representation of the vessels, which is represented as  $I_{edge_C}$ . The size of the edge/line is thickened through neighborhood information such as in equation 2. Let  $I_{edge_T}$  be the thickened line,  $r$  be the radius of the line and  $(x_0, y_0)$  be coordinate of the closest  $I_{WOD}$  pixel that has high value.

$$I_{edge_T}(x,y) = \begin{cases} 1 & \text{if } (x-x_0)^2 + (y-y_0)^2 > r \\ 0 & \text{if } (x-x_0)^2 + (y-y_0)^2 \leq r \end{cases} \quad (2)$$



Figure 2: Sample of optic disc edge

The outer ring is finally removed from the image by finding the outmost edge based on colour information. In order to fill the inner region of the blood vessels, red channel is utilized. Only the inner regions need to be filled, whereas the outer regions will remain as it is. Hence, the red channel is used due to colour difference between the inner and outer of the vessel wall. A Gaussian kernel is used to give the weightage on the colour information used to fill up the inner region. The distribution of the weightage,  $W$  is as follows where  $P(x,y)$  is the anchor position.

$$W(x,y) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-P_x)(y-P_y)}{2\sigma^2}} \quad (3)$$

The advantage of the Gaussian kernel can be observed in the noisy image. Sometimes, the region will have a mixture of brown and red coloured pixel in the inner part of the blood vessels. Some of these pixels are actually the blood vessels but with low intensity. Hence, a decision can be made by considering the neighborhood information application through Gaussian kernel instead of relying on a specific pixel value only. Finally, the inner part is confirmed to be part of blood vessels if the following equations are observed.

$$I_0(x, y) = \begin{cases} 1 & \text{if } P(x, y) > \tau_2 \\ 0 & \text{if } P(x, y) \leq \tau_2 \end{cases} \quad (4)$$

where

$$P(x, y) = \sum_{i=0}^n W_i I_{RED}(x, y, i) \quad (5)$$

$n$  is the total number of neighbourhood considered and  $\tau_2$  is a threshold value that represents the presence of blood vessel.

#### 4. RESULTS AND DISCUSSION

Coloured fundus images were used to verify the proposed algorithm. Both, STARE and DRIVE databases are in RGB format which can be obtained at [www.ces.clemson.edu/~ahoover/sater/](http://www.ces.clemson.edu/~ahoover/sater/) and [www.isi.uu.nl/Research/Databases/DRIVE/](http://www.isi.uu.nl/Research/Databases/DRIVE/) respectively. A total 60 images were tested that comprises of 20 images from STARE database while 40 images from DRIVE database.

Figure 3 shows some output samples of the detected blood vessels tested on DRIVE database while Figure 4 depicts the outputs tested on STARE database. Figure 3(a) and 4(a) are the ground truth while figure 3(b) and 4(b) are the output of automated detection system. From qualitative perspective, the proposed system has managed to detect the majority of thick retinal blood vessels but only a few of fine blood vessels. For quantitative assessment, four performance metrics are used, which are accuracy, specificity, error and sensitivity. Table 1 shows the performance of the algorithm with variable value of  $\tau_2 = 75$  and  $\tau_2 = 100$ .

In general, the results for images taken from DRIVE database return better performance compared to STARE database. The main reason is the images from STARE database was taken in a brighter environment. It is hard to detect the tiny blood vessels since pixel intensity distribution has skewed towards the high value. On the other hand, DRIVE database was taken under better lighting environment where the blood vessels can be easily discerned even with bare eyes.

Table 1: Performance analysis of the automated detection of blood vessels

Performance Analysis	Database			
	DRIVE		STARE	
	$\tau_2 = 75$	$\tau_2 = 100$	$\tau_2 = 75$	$\tau_2 = 100$
Accuracy (Ac)	0.880	0.875	0.860	0.853
Sensitivity (Se)	0.546	0.616	0.523	0.580
Error (Er)	0.120	0.125	0.140	0.147
Specificity (Sp)	0.912	0.900	0.886	0.874

The formulas for all four performance metrics are given below:

$$Ac = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

$$Se = \frac{TP}{TP + FN} \quad (7)$$

$$Er = \frac{FP + FN}{TP + TN + FP + FN} \quad (8)$$

$$Sp = \frac{TN}{FP + TN} \quad (9)$$

Where TP is the true positive, TN is the true negative, FP is the false positive and FN is the false negative. As for threshold variation,  $\tau_2=75$  performed better than  $\tau_2=100$  for both databases. In average, the fundus images from DRIVE database return accuracy, sensitivity, error and specificity values of 0.880, 0.546, 0.120 and 0.912 respectively for  $\tau_2=75$ . The accuracy and specificity values are high but the sensitivity value need to be improved. There are too many false negative compared to the true negative that makes the sensitivity value low. The error rate is relatively low for both threshold values, which is less than 0.13.

For STARE database, all metrics return worse performance for both threshold values. However, the sensitivity value is still relatively low since the number false negative is also high. In qualitative perspective, a high false negative is the result of the algorithm inability to detect the fine blood vessels. Most of the fine blood vessels not even detected during the edge detection stage. Hence, a better detection module can be explored for future work such as by adding colour constancy module [13].

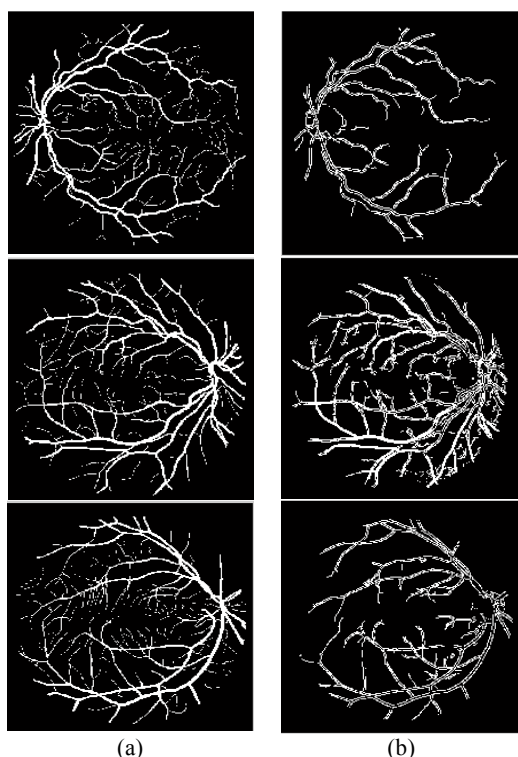


Figure 3: Sample outputs from DRIVE database: (a) Ground truth (b) Detected blood vessels

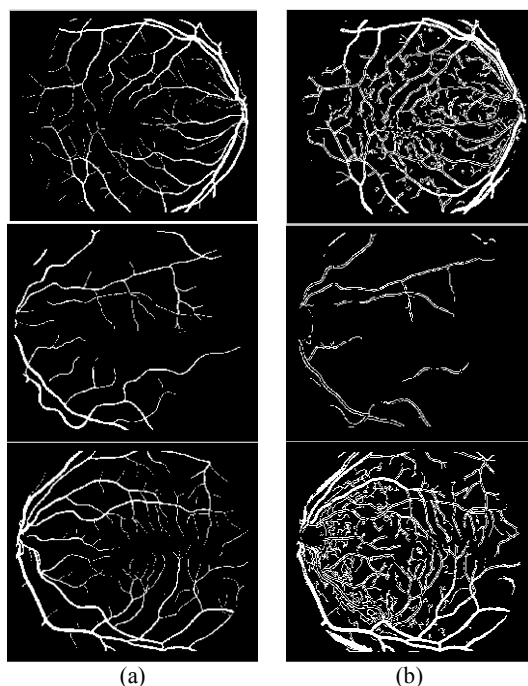


Figure 4: Sample outputs from STARE database: (a) Ground truth (b) Detected blood vessels

## 5. CONCLUSION

This paper describes the application of Gaussian kernel on blood vessels tracing. The nature of the Gaussian kernel allows a better label allocation since the neighbourhood information is taken into consideration. Moreover, the weightages are distributed normally, which is in line with the importance of each neighbourhood pixel. This work can be further improved by enhancing the initial detection module, which is the edge detection. A better tracing of the blood vessels based on tracking algorithm can be explored [14].

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