



## AN APPROACH OF RETINAL VESSEL DISEASES ANALYSIS USING IMAGE PROCESSING

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### ABSTRACT

Assessment of retinal vessel is an important factor for the many medical disorders. The retinal vessel analysis can be done by first extracting the retinal images from the background. The changes in the retinal vessels due to the pathologies can be easily identified by segmenting the retinal vessels. In this paper we describe the automatic methods for retinal vessel segmentation. Segmentation of retinal vessels is done to identify the early diagnosis of the disease like diabetic retinopathy, hypertensive retinopathy and arteriosclerosis. In this the blood vessel is segmented using morphological operation with the disc shaped structuring element is used. This method is applied on the publicly available DRIVE database.

**Index Terms**— Blood vessels, Fundus images, Morphological operations, Retinal vessel segmentation, Threshold, Blood vessel extraction, Retinal images.

### 1. INTRODUCTION

The retinal vessels segmentation from a retina image is a prominent task for detection of some retinal pathology such as glaucoma, hypertension, arteriosclerosis and diabetes. The glaucoma and diabetes are responsible for blindness [1]. The diagnosis of these diseases is important for early detection and subsequent proper treatment to control the vision loss. The retinal vessels segmentation can help physicians to diagnosing the ocular diseases as well as clinical study and patient screening. However the segmentation of vessels tree structure is important for the registration of retinal images of the same patient taken at different times. The registration of

retinal image is important because, it covers the whole retina, it never change except in case of some diseases, contains sufficient information such as position, size and shape of the vessels which can be used to locate the optic disk and useful for automatic monitoring the progress of certain diseases. The Canny edge detection algorithm is known to many as the optimal edge detector. The first and most obvious is low error rate. It is important that edges occurring in images should not be missed and that there be no responses to non-edges. The second criterion is that the edge points be well localized. In other words, the distance between the edge pixels as found by the detector and the actual edge is to be at a minimum. A third criterion is to have only one response to a single edge. This was implemented because the first two were not substantial enough to completely eliminate the possibility of multiple responses to an edge.

### 2. METHODS

#### 2.1 Overview of the method

The canny edge detector first smoothes the image to eliminate noise. It then finds the image gradient to highlight regions with high spatial derivatives. The algorithm then tracks along these regions and suppresses any pixel that is not at the maximum (non-maximum suppression). The gradient array is now further reduced by hysteresis. Hysteresis is used to track along the remaining pixels that have not been suppressed. Hysteresis uses two thresholds and if the magnitude is below the first threshold, it is set to zero (made a non-edge). If the magnitude is above the high threshold, it is made an edge. And if the magnitude is between the 2 thresholds, then it is set to zero unless there is a path from this pixel to a pixel with a gradient above  $T_2$ .



## 2.2 Process of Canny edge detection algorithm

The Process of Canny edge detection algorithm can be broken down as follows,

- Apply Gaussian filter to smooth the image in order to remove the noise,
- Find the intensity gradients of the image,
- Apply non-maximum suppression to get rid of spurious response to edge detection,
- Apply double threshold to determine potential edges,
- Track edge by hysteresis: Finalize the detection of edges by suppressing all the other edges that are weak and not connected to strong edges.

## 2.3 Eliminate Noise

The first step is to filter out any noise in the original image before trying to locate and detect any edges. Gaussian filter can be computed using a simple mask, it is used exclusively in the Canny algorithm. Once a suitable mask has been calculated, the /Gaussian Smoothing can be performed using standard convolution methods. A convolution mask is usually much smaller than the actual image. As a result, the mask is slid over the image, manipulating a square of pixels at a time. The larger the width of the Gaussian mask, the lower is the detector's sensitivity to noise. The localization error in the detected edges also increases slightly as the Gaussian width is increased.

$$g(m, n) = G_{\sigma}(m, n) * f(m, n)$$

Where,

$$G_{\sigma} = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{m^2 + n^2}{2\sigma^2}\right)$$

The Gaussian mask used in my implementation is shown below.

2	4	5	4	2
4	9	12	9	4
5	12	15	12	5
4	9	12	9	4
2	4	5	4	2

$\frac{1}{115}$

Fig. 1: Discrete approximation to Gaussian function with  $\sigma=1.4$

## 2.4 Edge Strength

After smoothing the image and eliminating the noise, the next step is to find the edge strength by taking the gradient of the image. The Sobel operator uses a pair of 3x3 convolution masks, one estimating the gradient in the x-direction (columns) and the other estimating the gradient in the y-direction (rows). They are shown below:

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

Fig. 2: Sobel Operation

The magnitude, or edge strength, of the gradient is then approximated using the formula:

$$M(n, n) = \sqrt{g_m^2(m, n) + g_n^2(m, n)}$$

Whenever the gradient in the x direction is equal to zero, the edge direction has to be equal to 90 degrees or 0 degrees, depending on what the value of the gradient in the y-direction is equal to. If Gy has a value of zero, the edge direction will equal 0 degrees. Otherwise the edge direction will equal 90 degrees. The formula for finding the edge direction is just:



$$\theta(m, n) = \tan^{-1}[g_n(m, n)/g_m(n)]$$

Once the edge direction is known, the next step is to relate the edge direction to a direction that can be traced in an image.

## 2.5 Non-Maximum suppression

After the edge directions are known, no maximum suppression now has to be applied. No maximum suppression is used to trace along the edge in the edge direction and suppress any pixel value (sets it equal to 0) that is not considered to be an edge. This will give a thin line in the output image.

## 2.6 Applying Threshold

After application of non-maximum suppression, remaining edge pixels provide a more accurate representation of real edges in an image. However, some edge pixels remain that are caused by noise and color variation. In order to account for these spurious responses, it is essential to filter out edge pixels with a weak gradient value and preserve edge pixels with a high gradient value. This is accomplished by selecting high and low threshold values. If an edge pixel's gradient value is higher than the high threshold value, it is marked as a strong edge pixel. If an edge pixel's gradient value is smaller than the high threshold value and larger than the low threshold value, it is marked as a weak edge pixel. If an edge pixel's value is smaller than the low threshold value, it will be suppressed. The two threshold values are empirically determined and their definition will depend on the content of a given input image.

Finally, hysteresis is used as a means of eliminating streaking. Streaking is the breaking up of an edge contour caused by the operator output fluctuating above and below the threshold. If a single threshold, T1 is applied to an image, and an edge has an average strength equal to T1, then due to noise, there will be instances where the edge dips below the threshold. Equally it will also extend above the threshold making an edge look like a dashed line. To avoid this, hysteresis uses two thresholds, a high and a low. Any pixel in the image that has a value greater than T1 is presumed to be an edge pixel, and is marked as such immediately then any pixels that are connected to this edge pixel and that have a value greater than T2 are also selected as edge pixels. If

you think of following an edge, you need a gradient of T2 to start but you don't stop till you hit a gradient below T1.

## 3. RESULTS

Figures shows the sample results of the segmentation process obtained from the fundus image taken from DRIVE database.

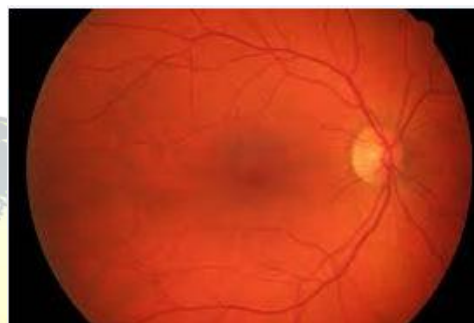


Fig. 3: Sample Image

Images from the databases of DRIVE is taken and used to test the automatic segmentation of retinal vessels with the proposed algorithm for segmentation. Canny's detection is better than all with improved performance.

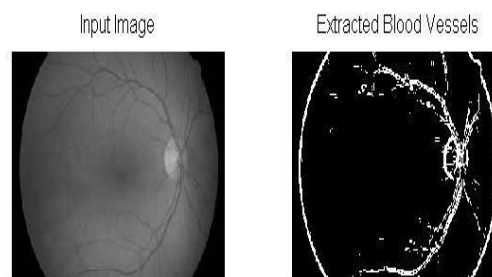


Fig. 3.1 Simulation result of sample image



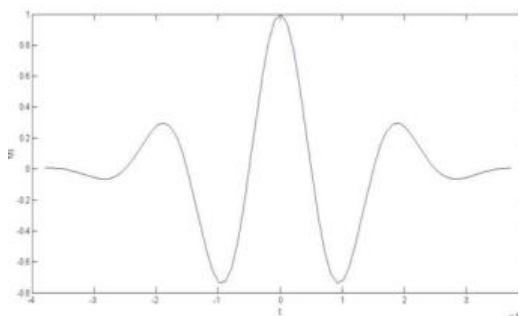


Fig. 3.2 Maximum Captured

Clearly, the derivative shows a maximum located at the center of the edge in the original signal. This method of locating an edge is characteristic of the “gradient filter” family of edge detection filters and includes the Sobel method. A pixel location is declared an edge location if the value of the gradient exceeds some threshold. As mentioned before, edges will have higher pixel intensity values than those surrounding it.

So once a threshold is set, you can compare the gradient value to the threshold value and detect an edge whenever the threshold is exceeded. Furthermore, when the first derivative is at a maximum, the second derivative is zero. As a result, another alternative to finding the location of an edge is to locate the zeros in the second derivative. This method is known as the Laplacian and the second derivative of the signal is shown below:

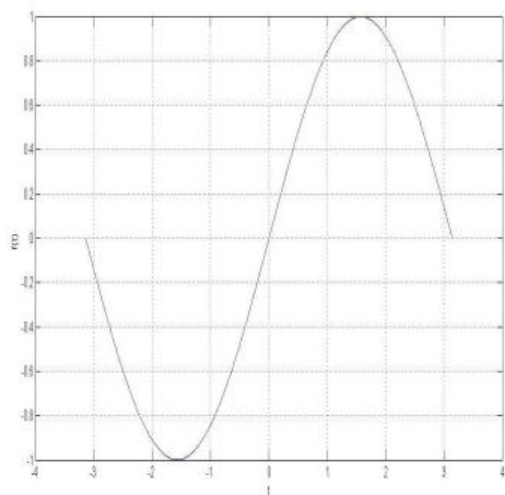


Fig. 3.3 Plot of Threshold

## 4. CONCLUSION

Automatic method of retinal vessel segmentation described in this paper is based on Canny's edge detection algorithm. Segmentation of retinal vessels has been presented in this paper. Segmenting the retinal vessels helps to identify the diseases like diabetic retinopathy and hypertensive retinopathy. Canny's edge detection algorithm is computationally more expensive compared to Sobel, Prewitt and Robert's operator. However, the Canny's edge detection algorithm performs better than all these operators under almost all scenarios.

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