On the Small Vessel Detection in High Resolution Retinal Images

Ming Zhang, Di Wu, and Jyh-Charn Liu
Computer Science Department
Texas A&M University
College Station, TX, 77843-3112

***Abstract* – In this paper, we proposed a new scheme for detection of small blood vessels in retinal images. A novel filter called *Gabor Variance Filter* and a modified histogram equalization technique are developed to enhance the contrast between vessels and background. Vessel segmentation is then performed on the enhanced map using thresholding and branch pruning based on the vessel structures. The experiments on high resolution images showed the desirable results with performance of 84.75% true positive rate and 0.15% false positive rate.**

I. INTRODUCTION

BLOOD vessel detection is a critical problem in retina image analysis because the abnormalities of blood vessels are the indicators of many diseases such as hypertension and diabetes. Detection of large vessels is relatively easy due to their strong contrast against background in the images. However, detection of small vessels is much more difficult due to their low contrast and tortuosity in the images. Since the sizes of vessels are usually proportional to the dimensions of the images, the high resolution retinal images should be used for detection of small vessels for better detection performance.

In most medical applications, the structures (trajectory and length) of the small vessels are more important than their precise widths. Moreover, capillary vessels tend to have discontinuous flows. As a result, it is unreliable to detect the precise boundaries of vessels, and we focus on how to capture the central lines of small vessels. For detection of the small vessel boundary and precise width, please refer to [1]

Our new scheme to identify the shallow vessels in the high resolution image includes three major steps. First, the contrast of the raw image is enhanced. Next, a Gabor variance filter is applied for further enhancement and noise removal. Finally, a skeleton extraction algorithm is used to find central lines of vessels and to verify the detection results.

The rest part of the paper is organized as follows. Section II discusses the contrast enhancement scheme. Section III introduces the screening filter based on variance of the Gabor filter. Section IV is for the vessel segmentation algorithm. Section V discusses the experiment result. The paper is concluded in Section VI.

II. CONTRAST ENHANCEMENT

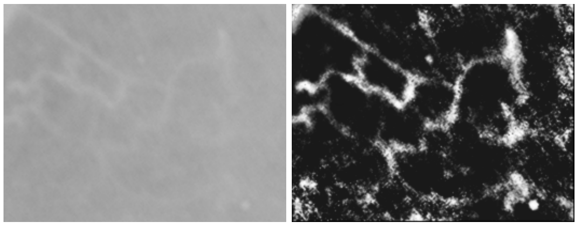

(a) (b)

Figure 1 Contrast enhancement by AHE

(a) Inverted green channel image (b) AHE output, h=80, r=8

Low contrast of small vessels against background causes their detection much more difficult than large vessels. Stark [2] proposed an adaptive histogram equalization (AHE) technique, expressed by $I_1(p) = \sum_{q \in \Omega} \delta(I(p) - I(q)) / h^2$, where Ω is the square filter window centered at p with size h, $\delta(x)$ equals to 1 if $x > 0$, and 0 otherwise.
We improved this method by introducing a new parameter "r": $I_2(p) = [I_1(p)]^r$, which can further sharpen the contrast. The performance of the contrast enhancement using the performance measure $(\mu_v - \mu_b)/(\mu_v + \mu_b)$ is maximized when we choose $h = 81$ and $r = 8$. μ_v and μ_b are the average intensity of background and vessel pixels, respectively.

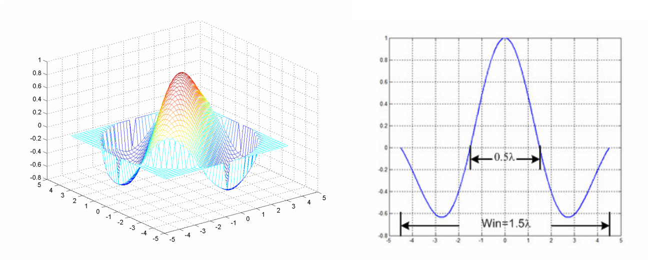
This scheme is found to be highly effective. It brings out the low contrast features of small vessels effectively, but more needs to be done to capture the small vessels correctly. Figure 1 shows the inverted green channel of a retinal image and the output of the modified AHE.

III. VARIANCE OF GABOR RESPONSE FILTER

A set of two-dimensional Gabor filters are proposed by Daughman in [3] to simulate the functionality of the simple cell in human vision system. To achieve our objective of enhancing small vessels, the following expression of Gabor filter is used:

$$G_\theta(x, y) = \exp\left\{ -\left(\frac{x'^2}{\sigma_x^2} + \frac{x'^2}{\sigma_x^2}\right) \right\} \cos(2\pi x'/\lambda),$$

$$\text{where } \begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}.$$



(a) (b)

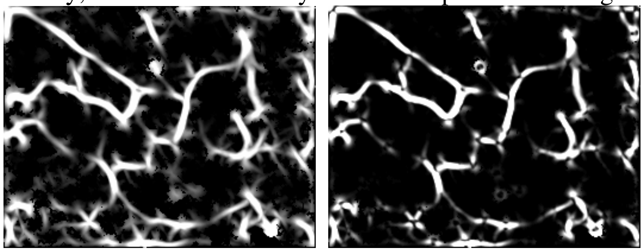
Figure 2 (a) Gabor filter truncated at $x \le 1.5\lambda$, $y \le 1.5\lambda$, (b) The cross section of truncated filter

The window size of the filter is critical to balance of computing costs and detection precisions. Through various experiments, it is found that the window size of $h = 1.5\lambda$ (i.e., the main lobe and the adjacent two side lobes are kept) gave satisfactory results. The Gaussian function part of the Gabor filter becomes neglectable (<0.1) at point $\pm 1.5\sigma_x$. Thus, we set $\sigma_x = \sigma_y = 0.5\lambda$. Figure 2 shows the truncated Gabor filter**.**

To maximize the response, when the filter is tuned to the direction of vessel, where the main lobe of the truncated Gabor filter should cover the vessel, that is, $0.5\lambda \ge d$, where d is the diameter of the vessel. Let the Gabor filter be centered at a pixel on a vessel. If the direction of the Gabor filter is tuned to that of the vessel, the filter response is maximal. On other directions, the responses are relatively smaller. Moreover, if the filter is centered at a background pixel, the responses along all directions are similar because of the uniform intensity of the background. This motivates us to use the variance of the filter responses as the feature to differentiate vessels and background. If the pixel is on a vessel, because of the significant difference of the Gabor filter responses in vessel direction and other directions, the variance of the responses along all quantized orientations is much larger than that of a pixel on the background. We call this new filter *Gabor variance filter*, abbreviated as *vGabor*. The maps obtained by applying the Gabor maximum filter (maximal value of Gabor filter responses along all orientations) and vGabor filter on the same image are shown in Figure 3. Comparing the two images, one can see that the response map of vGabor filter contains little background noise, making it an ideal detection indicator for small vessels. The output of vGabor filtering is denoted by I_3.

IV. VESSEL SEGMENTATION

Small vessels were significantly enhanced on I_3. A simple hard thresholding operation with threshold m can be used for segmentation, and then a thinning algorithm [4] can be employed to extract the skeletons of vessels. Short segments whose lengths are less than l are eliminated because most of them are essentially background noise. Finally, branches from every bifurcation points with length less then a specified threshold l_b are also pruned. The pruning operation eliminates small branches formed around small vessels during thinning operation.



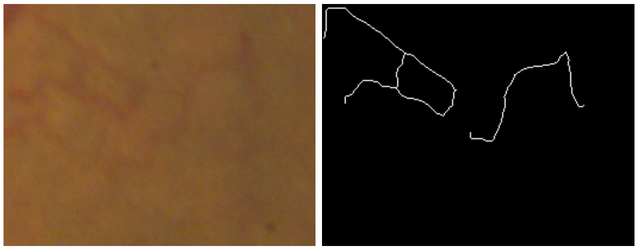
(a) (b)

Figure 3 The outputs of different filtering (a) Gabor maximum filter (b) Gabor variance filter

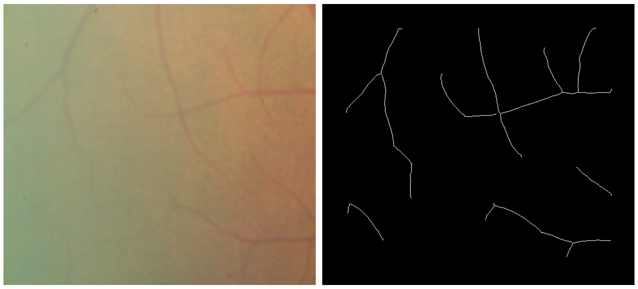
V. EXPERIMENT RESULT

The dimension of each test image (I_L) is 250x200, which were cropped from a set of high resolution images (I_H) whose original size is 3060x2036 pixels. The diameters of blood vessels in these images range from 5 pixel to 20 pixels. As stated in Section III, $0.5\lambda \ge d$. Thus, we set $\lambda = 12, \sigma_x = \sigma_y = 6$. In the vessel segmentation step, we choose $m = 80$, $l = 100$, and $l_b = 20$, empirically.

We tested 10 images cropped from a set of retinal images with various illumination and pathology conditions. Two images and their detection results, which are denoted as I_r, are shown in Figure 4. Using manually labeled blood vessel maps as ground truth (denote as I_t), the experiments over the 10 images showed that the average performance of our scheme is 84.75% in true positive rate (TPR) and 0.15% in false positive rate (FPR) (see Figure 5). TPR is defined as the ratio between the number of pixels on our result images that also appear on the ground truth, and the total pixel number on the thinned ground truth. FPR is defined as the ratio between the number of vessel pixels on our results but not on the ground truth, and the number of pixels on the background of the thinned ground truth. Note that here we use only pixels on the vessel centerlines to calculate the performance, so the large number of background pixels makes the false positive rate very small.



(a) (b)



(c) (d)

Figure 4 Detection Result (a, c) Two original images (b, d) the corresponding detection result

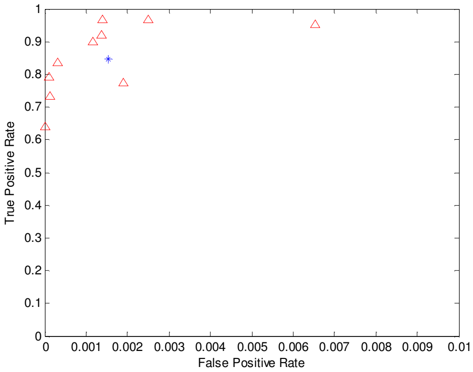


Figure 5 Performance of proposed algorithm

VI. CONCLUSION

In this paper, we presented a solution to detect the shallow small vessels in high resolution retinal images. The original image is first enhanced with the improved adaptive histogram enhancement technique and the vessels are then further enhanced with a novel Gabor variance filter. Finally, the structure of the vessel is extracted using thresholding and branch pruning. Tested on 10 images, the proposed algorithm achieves 84.75% TPR and 0.15% FPR.

REFERENCES

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