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Small Retinal Blood Vessel Tracking Using an Adaptive Filter

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Abstract. *The problem of extracting small retinal blood vessels using a Canny edge detection method is addressed. It shows that using the Canny edge detector to detect retinal blood vessels, especially small vessels, can be significantly improved if an adaptive edge detection filter is incorporated. The filter is designed as a local dynamic hysteresis thresholding value generator. It adapts knowledge of the location of major vessels to define a small neighborhood and to generate the local hysteresis threshold values to detect meaningful edges, especially the edges of small blood vessels that may be missing, using Canny edge detector alone. The effectiveness of the adaptive edge detection filter is demonstrated by the preliminary experimental results obtained with the proposed method. A comparative test is also presented to highlight the performance differences between the Canny edge detector with the adaptive edge detection filter and the one without the filter.*
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INTRODUCTION

In vessel segmentation, tracking based approaches represent an important class of algorithms.[1] There are two key issues on vessel tracking and measurement in retinal image analysis: localization of the vessel boundaries and computation of the center line positions of the vessels to measure the width of the vessel at each center point. Both edge detection and matched filter have been used to track the retinal vessels. Edge detectors such as the Canny detector[2] and Sobel detector[3] are widely used to detect vessel boundaries. Morphological detector,[4] gradient operator,[5] directional matched low-pass differentiator template,[6] and optimized Canny's detector[7] were also shown to be effective for the extraction of blood vessels. To detect edges on both sides of the vessels, parallel edge detection makes use of a bar-shaped model of lines.

The Canny[8] edge detection technique is based on the magnitudes and orientations of local gradients. It can detect major anatomical features in retinal images robustly without additional enhancement and compensation for illumination irregularities by Gaussian smoothing, and has been widely used to extract the boundaries of vessels.[9–14] Other important advantages of using the Canny edge detector for vessel localization include the reduction of false positives and false negatives, the detection of edges close to the vessel walls, and the linking and recovery of fragmented edge pixels. However, there is also a major limitation in current Canny detector applications in retinal vessel extraction. Hysteresis thresholding values for defining an edge point are empirically prespecified. There is no systematic solution to find the best hysteresis thresholding values in these applications. While the edge properties for the small retinal edges very often are local, the hysteresis thresholding values to determine an edge point are chosen globally. As a consequence, higher hysteresis thresholding values may lose information about the small vessel; on the other hand, lower hysteresis thresholding values may pick up noises. In addition, since the gradient magnitude and orientation estimation are based on local derivatives of vertical and horizontal directions, the changes of orientation of the gradient from one edge point to another may not be continuous. In most cases of blood vessel extraction, the edge positions are far from smooth comparing with the actual physical blood vessels. The continuity of retinal vessel positions detected by the Canny detector can be achieved by smoothing the vessel wall vector field.[15]

In this paper, we focus on the issue of determining the hysteresis thresholding values. Two threshold values are used in Canny detector to determine an edge: a high threshold value (HTV); and a low threshold value (LTV). A pixel is declared as an edge pixel if the gradient at the pixel is larger than the HTV, or is between the HTV and the LTV and is connected to a declared edge pixel. The use of the HTV and the LTV picks up more meaningful edges compared with other edge detectors using only a single threshold. Hysteresis thresholding with a smaller HTV and/or a smaller LTV can

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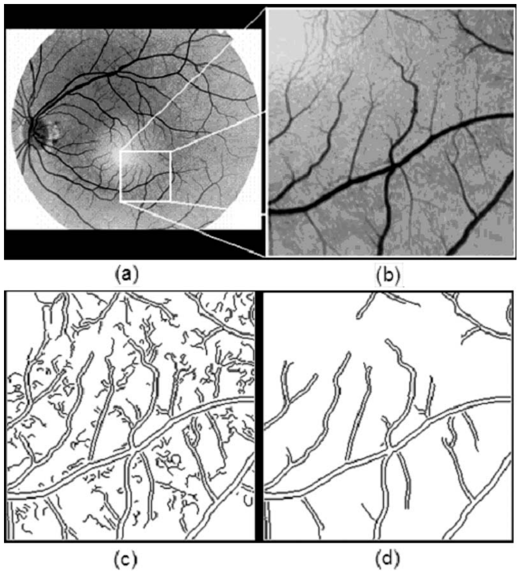

Figure 1. Retinal vessel extraction using Canny edge detection method: (b) shows an enlarged region from a retinal image of (a); (c) shows the edge information using Canny edge detection with HTV=0.1141 and LTV=0.0557 shows selected noises of small vessels; (d) edges detected using a Canny edge detector with HTV=0.2954 and LTV=0.1183 delineate the true boundaries of the blood vessel as well as false edges due to noises. A Gaussian smoothing kernel of 1 was used in both detections.

certainly pick up more edges, but may also collect a larger portion of noise edges. On the other hand, a larger HTV and/or a larger LTV can certainly pick up high quality edges at the expense of losing some true edges. In Canny's method, choosing the HTV and the LTV is based on the analysis of an entire image. This can result in the loss of weak edges. It is very common that a noisy gradient value of a pixel in one area can be larger than a real edge gradient value in another area. In retinal fundus images, the gradient values of larger retinal vessels can be much higher than that of smaller retinal vessels. The gradient values of noise edges related to a large vessel can be higher compared to the gradient values for the smaller vessel. In other words, selecting higher hysteresis thresholding values may lose the edges of smaller vessels while lower hysteresis thresholding values can pick up noises as illustrated in Figure 1. From the figure, one can see that smaller retinal vessels on the upper left region of the image of Fig. 1(a) show weak signal contrast compared with the bigger vessel on the bottom right region of the image. The edge locations detected shown in Fig. 1(c) show a large portion of noise information picked up by the lower HTV and LTV pair, while the edge locations detected in Fig. 1(d) show major, but somehow incomplete, vessel information picked up by a higher HTV and LTV pair.

To overcome or at least to alleviate this problem, in this article we employ the idea of adaptive edge detection filtration[16] to automatically generate local hysteresis thresholding values based on local gradient information. With this idea, the values of the HTV and the LTV are selected based on a local neighborhood of a pixel as opposed to the whole image. While edge thresholding is often selected and applied globally over the whole image, it has often been suggested that local thresholding can be appropriate. This can be done locally to normalize the image gradients, which can then be globally thresholded as before. The local average of the image intensity was first calculated and then the gradient was normalized by dividing by the local average.[17] On the other hand, the edges in low intensity regions were estimated from intensity information of its neighborhood rather than by boosting their contrast directly.[18] The gradient was effectively normalized by dividing by the local average of the gradient.[19] Canny[8] estimated the mean from the bottom 80% of the histogram. Alternatively, a histogram is generated[18] from the average gradient magnitudes calculated over each connected edge curve, from which the parameters of the Gaussian distribution may be estimated.

THE ADAPTIVE EDGE DETECTION FILTER USING DYNAMIC LOCAL HYSTERESIS THRESHOLDING

In the Canny hysteresis thresholding edge detection method, when both LTV and HTV are specified, an edge can be determined from the gradient field of the image by the following tests:

- if the gradient at the pixel is above the HTV, the pixel is declared an "edge pixel;"
- if the gradient at the pixel is below the LTV, then the pixel is declared a "non-edge pixel;"
- if the gradient at the pixel is between the LTV and the HTV, then it is declared an edge pixel if and only if it is connected to an edge pixel directly or via pixels between the LTV and HTV.

In retinal blood vessel detection, both LTV and HTV can be selected empirically by simple experiments. By inspecting the outputs of edge detection using different threshold values, a suitable pair of LTV and HTV can be determined for detecting large blood vessels. However, it is much more difficult to select a suitable pair of LTV and HTV for detecting not only the large vessels but also small vessels within the entire image due to the local intensity variability and low contrast of the small vessels against the background.

Figure 2 illustrates such an example in which a subimage is used to show the detection of the small vessels and the selection of a pair of LTV and HTV values. Both sides of a small vessel shown in the location "d" of the subimage have gradients smaller than 0.05 from the plot of the gradient profile. On the other hand, a noise signal located at "c" of the subimage also has a gradient larger than 0.05 on the left of the plot of the gradient profile. By selecting a HTV smaller than 0.05, the small vessel located in "d" of the subimage can be successfully extracted; however, the noise signal located at "c" can be also mistakenly selected as a vessel edge point. By selecting a LTV smaller than 0.05 and a HTV much larger than 0.05, we can exclude the noise signal at "c," but also we can miss the edge signal at "d" where there is no connection to any edge point.

By selecting the LTV smaller than 0.05, such as 0.0016, and HTV much higher than 0.05, such as 0.06, most of noise

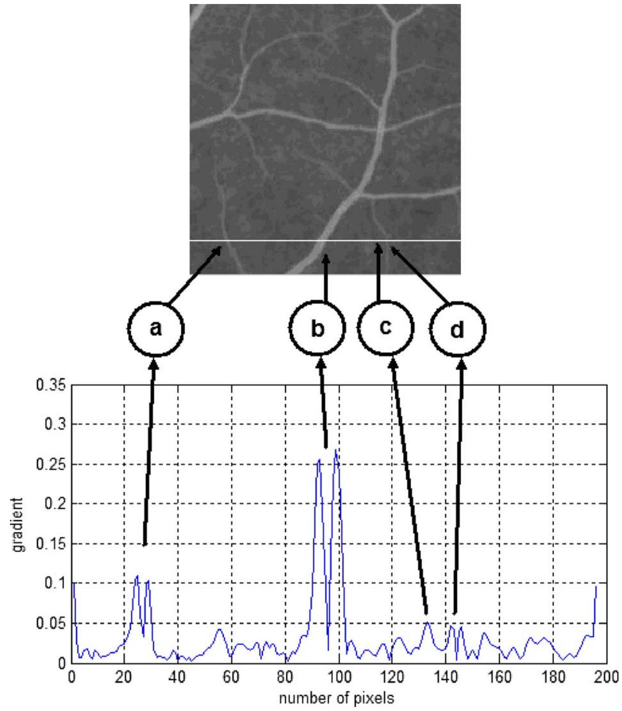

Figure 2. Row 176 of the subimage (top) is highlighted to show that there are a large vessel located at positions "b," two small vessels located at "a" and "d," but there is no vessel located in "c." However, the corresponding gradient at "c" shows a larger gradient than the gradient values located in "d" where a small vessel should be picked up.

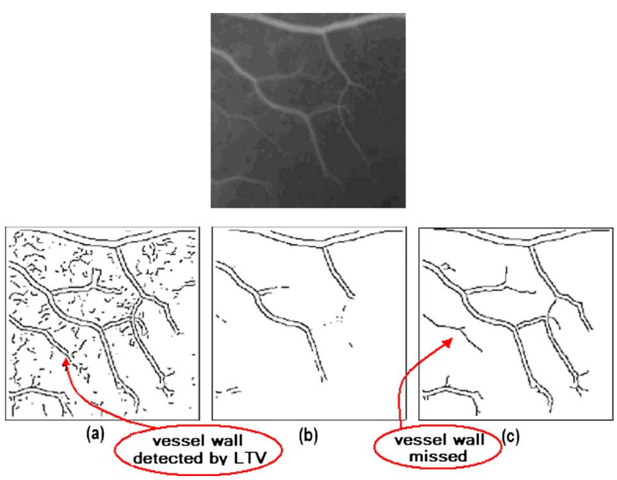

Figure 3. (a) The edge locations picked up with the LTV of 0.016; and (b) the edge locations picked up with a HTV of 0.06; and (c) the final results of the edge search and linking based on (a) and (b).

from a subimage of the origin image in Fig. 1(a) can be filtered out, as shown in Figure 3(c). However, some parts of small vessels are missing from the results. The vessel edges detected by LTV at (a) are later lost in the final detection because there exists no connection between the missed edge with the edges picked up by the LTV at (a). A possible solution to recover the missing edges is to select a lower HTV.

By lowering the LTV, the Canny hysteresis thresholding edge detection method can pick up some edges of small

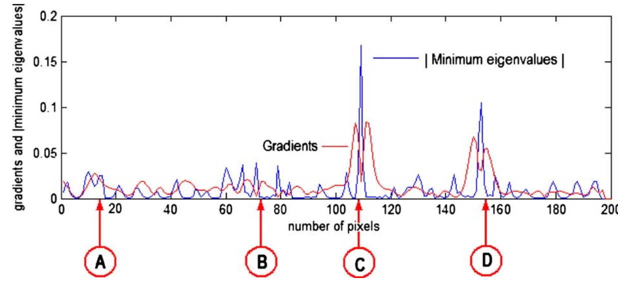

Figure 4. The eigenvalue map is plotted against its corresponding gradient profile for the same row highlighted in Fig. 2. The absolute value of eigenvalues in "A" corresponding to a larger gradient value with no vessel is much smaller than the eigenvalues corresponding to vessel signals, even though the gradient values are larger, such as the gradients on "C" and "D," or smaller, such as the gradient value at "B."

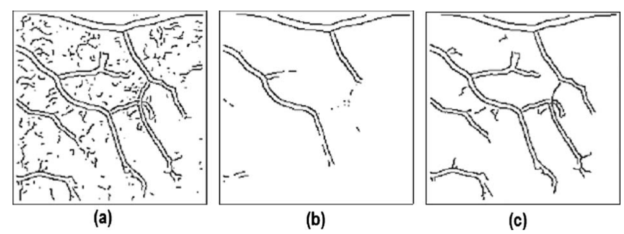

Figure 5. (a) and (b) The edge locations picked up using the same LTV and HTV as shown in Fig. 3; (c) the final results using the adaptive filter.

vessels, as long as the edges selected by the LTV are linked directly or indirectly to any declared edge picked up by the HTV. However, a lower HTV can pick up noise, as shown in Fig. 1(d). The possible solution is a lower local HTV that may satisfy some constraints where a vessel exists. Therefore, the key factor of setting a local HTV is first to find the location of a vessel and then establish pixel linkages between the known vessel edges and the missing edges.

A very useful property of a blood vessel in a two-dimensional fundus image is that the boundaries along both sides of the blood vessel are more-or-less parallel. But the gradient of an edge on one side can be quite different from the gradient of the edge on the opposite side. Furthermore, the density distribution of a blood vessel cross-sectional profile can be estimated using a Gaussian-shaped function. The orientation of such cross sections taken perpendicular to the central line of the blood vessel varies continuously, being a smooth continuous function.[20] The eigenvalues of a matrix representing such a Gaussian-shaped function can be used to define a spatial relationship between the two sides of a blood vessel.

The minimum eigenvalues for a small neighborhood containing both vessel walls are much smaller than those for a small neighborhood of a pixel with no vessel signal close by. For a given matrix size, an eigenvalue map can be obtained from a gradient field of an image by taking only the minimum eigenvalues of each matrix. By using the eigenvalue map, the noise gradient shown in "A" location of Fig. 2 and Figure 4 can be removed, and the weak vessel gradient values shown in location "B" in the both figures

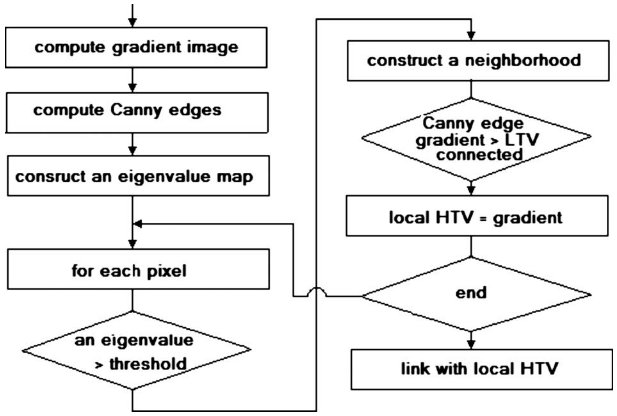

Figure 6. Diagram of the algorithm.

may be selected. The algorithm is design based on this idea. As an example, Figure 5(c) shows the results of small vessel detection using the adaptive filter.

THE ALGORITHM

The adaptive edge detection filter is developed to determine the HTV and LTV based on local connection of any selected edge point. The algorithm is stated as:

Step 1: Edge points are detected using Canny hysteresis thresholding.

Step 2: The gradients of all edge points are selected as local dynamic HTV.

Step 3: Edge points between the LTV and the edge points are selected as candidate points.

Step 4: An eigenvalue map of the image is calculated as follows:

a) A matrix size is selected to cover the largest sizes of blood vessel;

b) The eigenvalue of a pixel is the minimum eigenvalue of the matrix of the neighborhood centered at the pixel.

Step 5: A threshold value of the eigenvalue map is selected.

Step 6: For any pixel with corresponding eigenvalues less than the threshold value, if its neighborhood contains a candidate point and a point pixel across from the pixel, then the gradient of the candidate point is selected as a local dynamic HTV.

Step 7: Select new edge points using the local dynamic HTV and the LTV.

The algorithm is charted in Figure 6.

EXPERIMENTAL RESULTS

The adaptive edge detection filter is implemented using MATLAB and tested with retinal fundus images. A set of 24 test images of 1032×1302 pixels was randomly selected. A subset of sample images is shown in Figure 7(a).

A Gaussian filter with kernel of 1 is used to smooth the image. Then, a Canny edge detector with a HTV of 0.1 and a LTV of 0.04 are used to detect the edge points. The outputs of the set of sample images are shown in Fig. 7(b). The adaptive filter is then added to the Canny edge detector with the same parameters of HTV of 0.1 and LTV of 0.04. The outputs of the set of sample images are shown in Fig. 7(c).

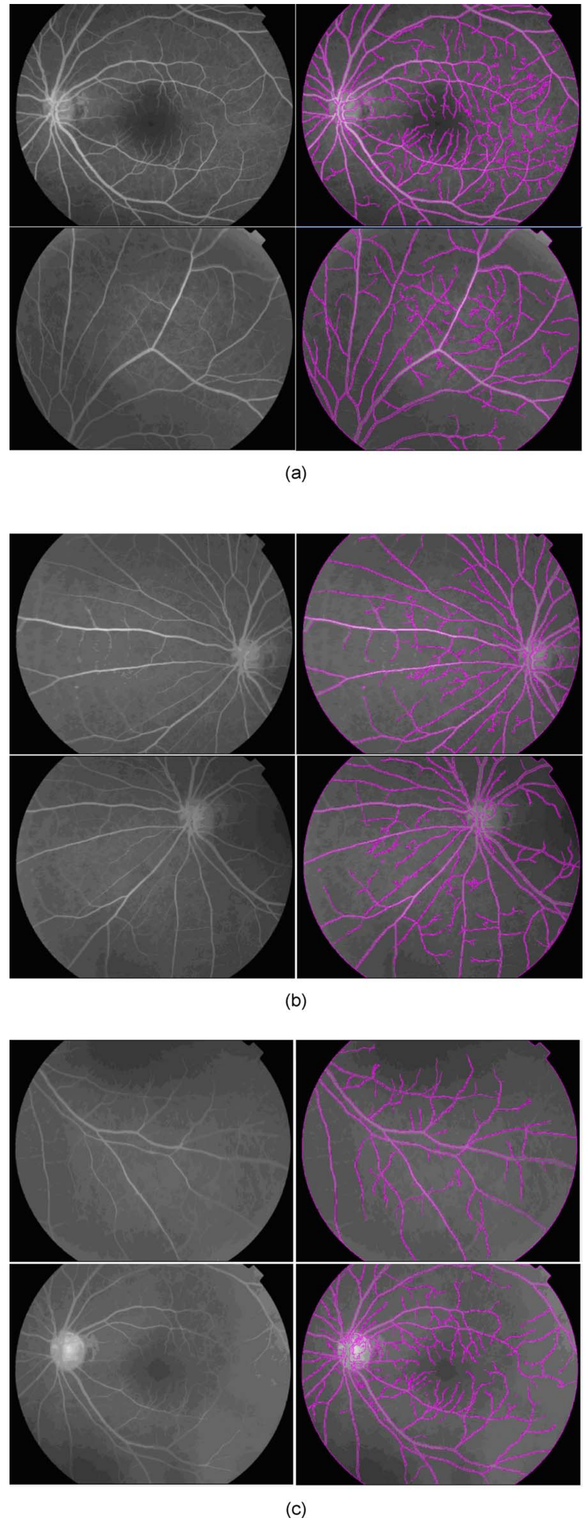

Figure 7. (a) Original retinal blood vessel image; (b) output of detected blood vessels using Canny edge detection method without adaptive filter and with parameters of LTV=0.04 and HTV=0.1; and (c) output of detected blood vessels using Canny edge detection method with adaptive filter and with parameters of LTV=0.04 and HTV=0.1.

The improved effectiveness of edge detection with the addition of the adaptive filter is visually apparent.

CONCLUSIONS AND FUTURE WORK

In this paper, the application of an adaptive edge detection filter for detecting small blood vessels from a retinal image is discussed. In this method, the filter is design based on dynamic hysteresis thresholding and its HTV is determined by local connection of possible vessel wall points. The effectiveness of the proposed method has been demonstrated through experiments. Future work will be directed toward improving the tracking and measurement of center lines of small vessels.

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