A NEW AND EFFICIENT VESSEL SEGMENTATION METHOD FROM COLOR RETINAL IMAGES

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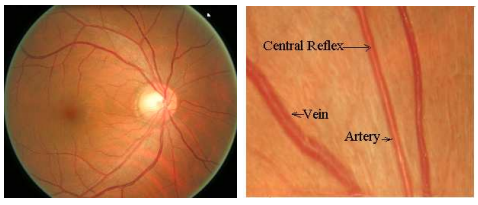
Abstract: Retinal blood vessel changes (e.g., vessel caliber) are important indicators for earlier diagnosis of cardiovascular diseases. To quantify the changes automatically, a reliable vessel detection is essential. However, blood vessel detection in retinal image is complicated by a huge variation in a number of factors such as local contrast, vessel width and vessel central reflex. In this paper, we propose a new technique to detect retinal blood vessels which is able to address these issues. The core of the technique is a new vessel edge selection method which combines the method of finding edge pattern and edge profiling techniques. Experimental results show that 92.40% success rate in the identification of vessel start-points and 88.73% success rate in tracking the major vessels.

1 INTRODUCTION

Recent research suggests that retinal vessel caliber changes can be a predictive factor for cardiovascular diseases (CVDs) which result in a large number of deaths in developed and developing countries every year. According to world health statistics, every year about 17.1 million people die from CVDs. The number is expected to increase to 23.4 million by 2030 (World-Health-Statistics, 2008) due to increases of obesity and aged population. Studies show that retinal arteriolar narrowing is independently associated with risk of stroke (Wong et al., 2001), heart disease (Wong et al., 2002a), diabetes (Wong et al., 2002b) and hypertension (Wong et al., 2004b). Earlier diagnosis of these diseases is possible through periodic screening which can significantly reduce the risk of disease severity and consequently, decrease the number of deaths and other complications. Blood vessel detection is the first step for determining vessel width and analyzing the generalized narrowing of retinal blood vessels.

Although a large number of algorithms (Youssif et al., 2008),(Al-Diri et al., 2009),(Martinez-Perez et al., 2007),(Lam and Yan, 2008),(Sofka and Stewart, 2006) have been proposed for the detection of blood vessels, a huge improvement in detection procedures remains a necessity for the detection of vessels in the presence of central reflex (Figure 1) and poor contrast images. Specifically, these techniques need further improvement to address vessel detection accurately with the presence of vessel central reflex. The central reflex is a bright strip running down the center which causes a complicated intensity cross-section. Locally, this may be hard to distinguish from two side-by-side vessels and has been discussed previously in (Sofka and Stewart, 2006). In this paper, we propose a novel method for vessel segmentation which addresses these challenges in retinal image modality. Our paper is a further improvement on the existing vessel detection algorithm in the presence of vessel central reflex.



(a) (b)

Figure 1: A retinal image (a) and cropped image showing the retinal artery, vein and the central reflex (b).

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The rest of the paper is organized as follows. Section 2 describes our proposed vessel segmentation method which includes the edge detection, edge reconstruction, edge profiling and filtering, and finally, vessel identification. Section 3 provides the Experimental Results and Discussion. Conclusion and future research directions are drawn in section 4.

2 THE PROPOSED METHOD

We have proposed a method for vessel detection through edge tracking which is reported in (Bhuiyan et al., 2010). In this paper, we further improved the method by applying canny edge detection, edge reconstruction and edge profiling method. In our proposed method, blood vessels are extracted based on edge tracking and vessel morphological information. The overall method for vessel detection is shown in Figure 2.

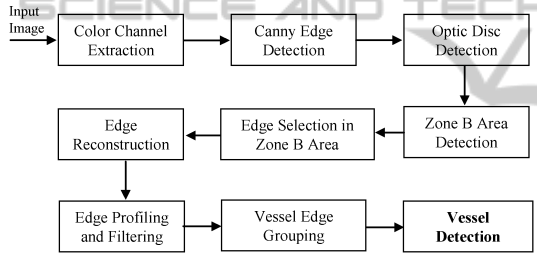


Figure 2: The overall method of retinal blood vessel detection.

2.1 Edge Detection

As our ultimate focus is on the measurement of vessel caliber which requires vessel edge information, therefore, we apply edge based vessel segmentation approach. To detect vessel edges, we apply Canny edge detection algorithm (Canny, 1986). We mentioned that retinal image contrast varies hugely in image local position. For this type of scenario, we consider Canny edge detection algorithm to mark as many real edges in the image as possible. We consider retinal Green channel image which has the highest contrast between vessel and background for all three color channels in an RGB image. To remove impulse noise and other abrupt artifacts from the Green channel image, we apply Median filtering and then apply canny edge detection algorithm. This approach allows us to achieve better results for edge detection.

We note that our main focus is to detect the vessel from zone B area, from which the vessel caliber is computed and the original Central Retinal Artery Equivalent (CRAE) and Central Retinal Vein Equivalent (CRVE) formulae are derived (Hubbard et al., 1999). Therefore, we aim to trace the vessels from the zone B area only. Zone B is the circular region which starts at 1*OD-diameter and ends at 1.5*OD-diameter from the OD-center in the retinal image and significantly used for retinal blood vessel analysis (Wong et al., 2004). The zone B area is computed based on optic disc (OD) center and its radius. We have developed an OD detection and center computation method which is reported in (Bhuiyan et al, 2009).

2.2 Edge Tracking from Zone B Area

Once we compute the zone B area, we track the individual edges for profiling and filtering to find the actual vessel edges. From the zone B area, we scan the canny edge detected image and track each of the individual edges and corresponding pixels by region growing technique (Gonzalez and Woods, 2008).

2.3 Edge Reconstruction

Because of the central reflex properties it may be possible that a central reflex edge merge with a vessel edge (Figure 3) or with another central reflex edge. This situation will create noisy profile for a real vessel edge. In order to overcome this situation, once we trace the edges individually, we check if there is any edge which merges with another edge. We check each edge if there is any junction point (which is a merging point of 3 edge-segments) within the edge points. Once we recognize this instance, we map the vessel segments for this point. We measure the slope of the segments locally by considering this point and another short distance point in each of the segments. From this, we select the two edge segments which have the closest slope and discard the other segment.

2.4 Edge Profiling

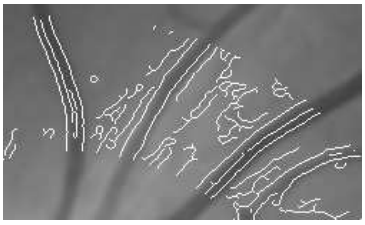
The edge profiling method filters out the noise and backgrounds, and selects the edges which have more likelihood of vessel edges. The method checks the intensity levels on both sides of an edge within a specific direction. For this, each of the edge pixels is considered to obtain two pixels' positions (on both sides of the edge pixel) which are located at a certain normal distance from the edge pixel. For this, each pixel along with its neighboring pixel in the edge are considered as the line end-points. The slope and actual direction of the line are computed to find the points on both sides of the current edge pixel. The method is as follows.

Let us consider the two end-points of the line are (x_1,y_1) and (x_2,y_2), and the angle θ (actual angle in the image) is computed from the slope and direction of the line which are *slope* and *direction*. Let us assume that (x_2,y_2) is the second end-point i.e., located further from the OD compared to the first end point; we find the value of θ as follows. If $\theta < 0$ and if $y_2 \geq y_1$ & $x_2 \geq x_1$ then $\theta = \theta + \pi$. On the other hand, if $\theta < 0$ and if $y_2 \leq y_1$ & $x_2 \leq x_1$ then $\theta = \theta + 2\pi$. If $\theta > 0$ and if $y_2 \geq y_1$ & $x_2 \leq x_1$ then $\theta = \theta + \pi$. Once the actual angle is computed, the point located on left side of the edge point (x_2,y_2) is computed as: $((y_2 - r * sin(\theta + \pi/2)),(x_2 + r * cos(\theta + \pi/2))$ and the point on right side of the edge point is: $((y_2 - r * sin(\theta + 3\pi/2)),(x_2 + r * cos(\theta + 3\pi/2))$ where r is the normal distance from the point (x_2,y_2).

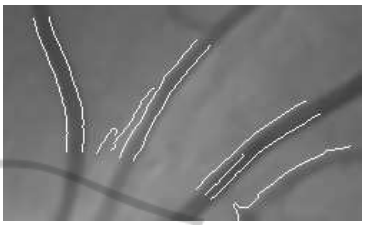
After computing the pixel positions on both sides of each of the edge points, the intensity levels for these position in the image are obtained. For this, we consider the Green channel image after Gaussian smoothing (Gonzalez and Woods, 2008). Usual vessel edge profile is high-to-low for the outside-to-inside pixels' intensity levels and low-to-high for the inside-to-outside pixels' intensity levels. For blood vessels, this profile is consistent, whereas for noise, this profile is random. Therefore, the consistent profile value for each of the potential edges is considered for filtering the true vessel edges and for discarding the noisy edges. Figure 3 shows the traced edges and the edges obtained from edge profiling method.

2.5 Potential Vessel Edge and Position Identification

After profiling the edges the length of an edge is also computed to check if it passes a certain threshold value for a vessel edge. Then an edge is defined as the first edge of a vessel if it returns the profile value for high-to-low. Similarly, the edge is defined as the second edge if the profile value is low-to-high. Following this, we check if there is any disjointed edge by extending the edge based on extrapolation into a certain distance. To control the direction of the extension points, the edge slope is computed by local edge points through the edge end point and another point within 5 pixel distance from it. We merge the edges once the edge type matches. Following this, we sort the edge position to combine the edges as vessel edge. The edge positions are sorted based on angular position of each of the edges around the OD. We consider the OD center and edge start point (closer end point of the edge from OD) to compute the angle. Based on the position we consider each of the edges to merge as vessel edge.



(a)



(b)

Figure 3: Image showing the detected edges of noise and central reflexes (left), and detected actual edges after profiling (right).

2.6 Vessel Identification and Centerline Detection

For merging the vessel edges we check the sorted edges and consider the first edge and second edge in a sequence and within a certain distance. Generally, after applying the edge detection, two edges are obtained for any blood vessel if there is no central reflex. If there is a central reflex in the vessel, it may be two or three or four edges based on the intensity levels of the central reflex edges. We consider this information for merging edges into blood vessels.

In general, the central reflex is approximately 1/3 of the vessel width (Kaushik et al., 2007). Considering this, we merge the edge labeled as first and second edge if there is no other first or second or first-second combination within approximately same distance. The distance is measured as the Euclidian distance between the two edge start-points. If we have first-first-second combination of the edges, we check the overall distance between the first and last edge, and between the middle and last edge. If the conditions satisfy the edges to be part of a vessel, we define the edges belong to an individual vessel. Similar approach is applied for first-second-second combination. For the first-second-first-second combination we check all the distances; the first first-second pair, the second first-second pair, the second-first (i.e., the second and third edge which is the width of the central reflex) and the first and last edge pair (i.e., the width of that cross-section). If these distances satisfy the vessel edge-central reflex properties, we define these as a single vessel. Otherwise, the first first-second

Table 1: Results of edge start-point detection.

	Large Vessels	Small Vessels
Total Number (manual)	292	164
Automatic Detection	270	116
Accuracy	92.47%	70.73%

edge pair is defined as one vessel and the second first-second starts to compute the next vessel edge merging process. Figure 4 and 5 shows the output images for vessel detection in different circumstances. Once we define the vessel and its edges we then track the centerline from averaging the edge-pixels' locations.

3 EXPERIMENTAL RESULTS AND DISCUSSION

We analyzed fifteen retinal images obtained from the Singapore Malay Eye Study (SiMES) dataset (Wong et al., 2004c) which are randomly selected by retinal image graders and applied our method to produce the output images indicating the detected vessels. Each image size of 2048x3072 was taken from using a digital non-mydriatic retinal camera (Canon CR-DGi with a 10D SLR backing). It has taken approximately 8.47 seconds on MATLAB 7.8 to produce each output image on a 2.53 GHz Pentium(R) 4 CPU with 3.2 GB of RAM. Experimental results of the accuracy of starting point detection are shown in Table 1. Large vessels are defined as those vessels which are more than 45 μm in diameter. We note that we compute the vessel diameter in microns by considering the distance between the pixels in microns (from calibrating the camera). After computing the vessel diameter in microns, those vessels with diameter less than 45 μm are defined as small vessels and are ignored for the CVD prediction (Hubbard et al., 1999). We observe that vessel start-point detection accuracy is 92.47% for large vessels and overall vessel start-point (i.e., both major and minor) detection accuracy is 81.60%. Based on these start-points, overall large vessel detection accuracy is 88.73% (Table 2).

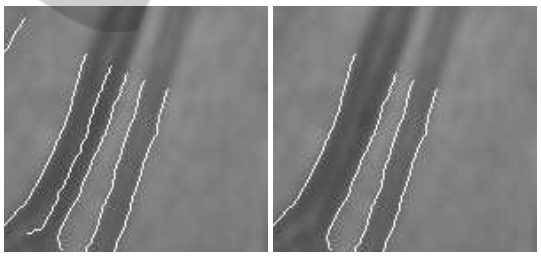
Table 2: Results of Vessel Tracking.

	Number of Vessels
Actual	142
Detected	126
Accuracy	88.73%

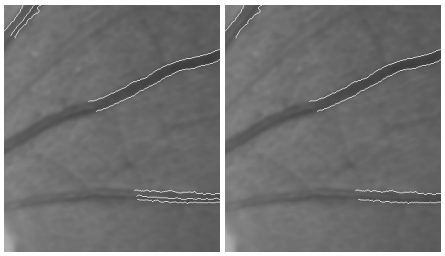
(a)

(b)

Figure 4: Image showing the detected edges with noise and central reflexes (left), and detected vessels (right).



(a) (b)



(c) (d)

Figure 5: Cropped image showing detected vessel and central reflex edges (a) and (c), and their corresponding detected vessel images (b) and (d). Image showing correctly detected vessels within the positions of two side-by-side vessels with central reflexes (b).

4 CONCLUSIONS AND FUTURE WORK

In this paper, we discussed a novel method for detection of blood vessels from color retinal images. Our method is highly accurate in detecting blood vessels with central reflex. The novelty of our method lies in the detection of blood vessels with vessel and central reflex edge tracking with varying contrast. A user friendly interface is developed to select the missing start points and to identify the missing vessels from which the width will be measured automatically. Based on the method, we are in the process of developing a new technique for vessel width measurement. The results for vessel width measurement and CVD prediction model will be reported later.

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