DIRECTIONAL LOCAL CONTRAST BASED BLOOD VESSEL DETECTION IN RETINAL IMAGES

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ABSTRACT

In this paper, we proposed a novel algorithm to detect blood vessels on retinal images. By using *directional local contrast* as its detection feature, our algorithm is highly sensitive, fast and accurate. The algorithm only needs integral computing with very simple parameter adjustments and highly suitable for parallelization. It is much more robust to illumination conditions than intensity based counterparts and equally effective for large and small blood vessel detections.

Traditional blood vessel mapping solutions focused on detecting the most number of blood vessel pixels at the cost of least number of falsely identified background pixels. This performance criterion works for well illuminated images with sharp boundary, but it does not address two major concerns. The first is that it favors detection of large blood vessels, and the second is that for darker images (due to poor illumination or pigment colors) it can be very difficult to generate hand traced maps. To overcome these problems, we propose using central lines of the blood vessels as a new performance measure for blood vessel mapping. The new performance measure is easy to evaluate, and it complements the existing performance measure. Experiment results on two public retinal image databases show that our algorithm outperforms two well known existing algorithms in terms of speeds and accuracy.

Index Terms— directional local contrast, blood vessel detection, retinal images

1. INTRODUCTION

Automated mapping of the blood vessel network is an important function for assessment of the anatomy and pathology of the blood vessel system. Its applications range from long term tracking of vascular changes that could be caused by chronic diseases such as diabetic retinopathy, hypertension, etc., and detection of acute leakage conditions. This is particularly useful for disease conditions that are small in sizes, and located at close proximity of blood vessels, e.g., microaneurysms.

Many solutions have been proposed in the literature [1]-[6], most of which use the green channel of retinal images for blood vessel detection, because it contains most of the blood vessel information. A major challenge faced by blood vessel mapping algorithms is the tradeoff between computing time, detection accuracy and robustness with respect to the photo qualities. The (truncated 2D Gaussian) matched filter solution proposed in [1] pioneered the model based mapping of blood vessels using the intensity. In our previous work [2], we proposed the algorithm that first uses illuminant equalization and image enhancement techniques to improve the image quality, then starting from automatically found initial points, tracking down the vessel. Hoover *et al* [3] proposed to segment vessels by piecewise threshold probing on the filter response of the Gaussian templates [1]. Morphological filters and cross-curvature were used in [4] to segment vessels for both red-free angiography images and color images. In [5], vascular *ridges* extracted from derivatives of a Gaussian function are used as the analysis features to obtain highly accurate results, but this method is computationally expensive. A fast algorithm proposed in [6] maps vessels from multiple localized thresholding results based on the geometric properties of vessels. This method is highly effective for large vessel detection but less accurate for small vessels.

While most images available in the public databases have excellent illumination conditions, images acquired from the field do not always have good illumination because of disease conditions, non-mydriatic procedures, and pigment colors of the subjects. These conditions make intensity based algorithms susceptible to the data conditions, especially when complex parameter setting is required for the algorithms. To overcome this problem we propose using local contrast information for mapping of blood vessels in retinal images. In the green channel of the retinal images, blood vessels are linear objects that have lower intensity values than their background. A blood vessel segment is modeled as a linear segment with constant width. A vessel pixel being tested must lie on a *blood vessel-shape* (*BVS*) *kernel* that is a line of pixels that falls inside the vessel segment. If a BVS kernel that satisfies specific condition can be found for a pixel, it's determined as vessel pixel, or it's marked as background pixel. The BVS kernel model implies

directional search, and therefore tracing of the vessel flow is directly integrated with the contrast analysis step at no computing cost.

2. CONTRAST BASED BLOOD VESSEL DETECTION

Among several different options, we adopt the Weber's contrast measure $C = \Delta I / I$ as the basis to compute the *directional local contrast (DLC)*, where I is the local background intensity, ΔI the intensity difference between the pixel under consideration and I. Let I_p denote the intensity of a pixel p. p's *DLC* along θ direction is defined as:

$$C_p^{(\theta)} = \frac{I_p - \overline{I}_p^{(\theta)}}{\overline{I}_p^{(\theta)}}, \text{ where } \overline{I}_p^{(\theta)} = \frac{1}{r}\sum_{q \in N_p^{(\theta)}} I_q ,$$

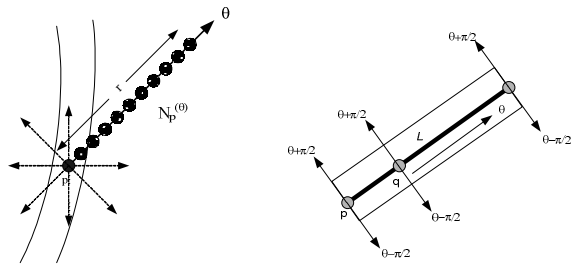
$$N_p^{(\theta)} = \{(x_q, y_q) \mid x_q = \lceil x_p + k\cos\theta \rceil, y_q = \lceil y_p + k\sin\theta \rceil, k = 1...r\}$$

$\overline{I}_p^{(\theta)}$ is the background intensity of p in its θ directional neighborhood $N_p^{(\theta)}$ with size r (See Figure 1 (a)). Negative DLC value indicates that the pixel under consideration has lower intensity than the background along the direction. Some pixels adjacent to p may have to be excluded for DLC measurement when p is located near to the boundary of the blood vessel, as it will become clear shortly.

A *blood vessel-shape (BVS) kernel* is a set of pixels in a linear line, and its length represents the shortest blood vessel to be detected (denoted by *L*), see the illustration in Figure 1 (b). The length of BVS kernel controls the detection resolution on the shortest blood vessel that can be detected. Increasing (Decreasing) the L value will reduce (increase) the false positive rate but the algorithm will be less (more) sensitive.

In determining if a pixel p is on a blood vessel, the BVS kernel originated from p spans along different directions to locate a vessel segment. If p is on the blood vessel segment that flows along direction θ, pixels on the BVS kernel of direction θ (denoted by $B_p^{(\theta)}$) satisfy the condition that they all have negative DLCs along direction $\theta \pm \pi/2$, i.e., for all $q \in B_p^{(\theta)}$, $C_q^{(\theta \pm \pi/2)} \le T$, where T is a given non-positive threshold, in ideal case. The blood vessel direction θ is known if such a BVS kernel can be found. If no such BVS kernel exists, p is considered a background pixel.

To reduce errors caused by noise, most commonly improper exposures, in this paper the decision rule above is relaxed as "p is a blood vessel pixel if there exists a BVS kernel $B_p^{(\theta)}$ that for $\alpha\%$ of all pixels $q \in B_p^{(\theta)}$, $C_q^{(\theta \pm \pi/2)} \le T$". The values of x and T are discussed later in this section.



(a) (b)

Figure 1. (a) A DLC measurement neighborhood of an image pixel, and (b) the BVS along θ of pixel p and DLC measurements in the BVS along directions $\theta \pm \pi/2$.

The DLC definition works well in most cases, but when checking a pixel p around the edge of a blood vessel, its DLC along the direction pointing to the vessel is heavily affected by the vessel because some of p's neighbors used for computing DLC are not on the background, but on the vessel. To solve this problem, first W pixels adjacent to p are not included in the DLC computation as follows:

$N_p^{(\theta)} = \{(x_q, y_q) \mid x_q = \lceil x_p + k\cos\theta \rceil, y_q = \lceil y_p + k\sin\theta \rceil\}$ where $k = W+1..r$, and W is the maximal vessel diameter.

The resulting DLC based vessel detection rules can be summarized as follows.

1. Set parameters for large vessels.
2. For every pixel p, analyze its DLC along n directions. If there's a direction θ such that $C_p^{(\theta \pm \pi/2)} \le T$, and if $C_q^{(\theta \pm \pi/2)} \le T$ for $x\%$ of q in p's L-pixel long BVS kernel $B_p^{(\theta)}$, mark p as vessel pixel. Otherwise mark p as background pixel.
3. Set parameters for small vessels, and rerun step 2.

Figure 2 Blood vessel pixel detection procedure

Only five parameters r, L, T, α, and the number of directions n to search for blood vessels at each pixel need to be considered. Selection of the value r needs to be larger than the width of blood vessels under consideration so that both background and the blood vessel pixels can be captured in each DLC measurement. In 700×600 retinal images the width of small vessels ranges from one to three pixels and that of large vessels four to ten pixels, i.e., W=3 and W=10 for small and large vessels, respectively. As a result, the r value was set at five and 15 respectively for small and large vessels. The value of L is determined by the shortest blood vessel segments to be detected. Two different values ten and 15 are found to be suitable for small and large vessels, respectively.

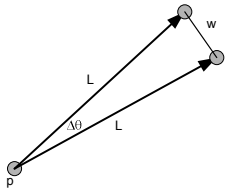


Figure 3 The interdependency between L, *w, and* $\Delta\theta$.

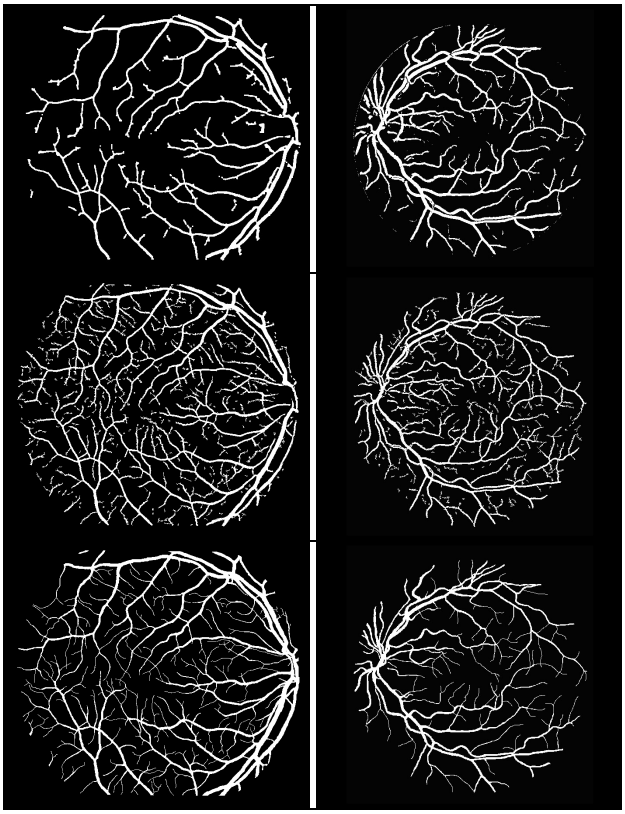
The number of search directions at each pixel is determined by the detection resolution of large and small vessels. Let w denote the smallest width of the vessels under consideration, the angular change $\Delta\theta$ between two adjacent BVS kernels should be small enough so that any blood vessel segment can be covered by one or more adjacent BVS kernels, see Figure 3. When $\Delta\theta$ is small, $L\sin\Delta\theta \approx w$, $\Delta\theta \approx w/L$, and therefore $n = 2\pi/\Delta\theta \approx 2\pi L/w$. In our study, it is found that $n = 32$ and 16 are adequate for small and large vessels, respectively.

The contrast threshold value T determines the lowest level of contrast of the blood vessels that can be detected by the algorithm. When it is set to a value closer to 0, numerous linear patterns can be capture but a significant number of false detections are expected. Instead, we found that Weber's Just-Noticeable-Difference (JND) [8], 2% (or, 0.02), which defines the smallest visual difference that is perceivable by the human eyes, is a much better choice for small blood vessels, i.e., $T = -0.02$ for small vessels. However, for large vessels, due to their high contrast against the background and to avoid high positive false alarms around the boundary of large vessels, $T = -0.05$ was found to be a more suitable threshold value. α is the error tolerance, the smaller the value, the larger the tolerance is. Usually $\alpha\%$ should be near 1 to avoid too much false alarm. In this work, we set α=80.

3. EXPERIMENT RESULTS

We applied our algorithm on two widely used retinal image databases STARE [2] and DRIVE [5], and compared the mapping results with those in two recently published papers [5][6]. The detection outcomes of different algorithms on two sample images are show in Figure 4.

The algorithm is found to be highly sensitive. It can capture the linear pattern that has the just-noticeable-difference from the background. In evaluation of the detection performance of the proposed algorithm, we do not follow the pixel count based performance measure proposed in [2] because it strongly favors detection of large blood vessels and therefore not an effective measure in assessing an algorithm's ability in detection of small vessels. In stead, we propose a performance measure based on detection of



(a) **(b)**

Figure 4 Detection outcomes for (a) im0082 in STARE and (b) test image 00 in DRIVE. In (a), the top graph is Jiang's detection map, the middle graph is that of ours, and the bottom one the 2nd manually labeled map (label-vk) in STARE. In (b), the top graph is Staal's detection map, the middle graph that of ours, and the bottom graph the 2nd manually labeled map.

visible blood vessel count. Each blood vessel can be represented by its central line, which can be obtained by applying any thinning algorithm on the detected blood vessel map, e.g., [9]. Given that assessment of the blood vessel boundary is highly subjective, as one can see from the two set of manually drawn blood vessel maps in STARE and other sources, the proposed new performance measure can avoid this problem in evaluation of both large and small vessels detection.

Let M_t denote the ground truth, M denote the automatic detection outcome. The *true vessel positive rate* and *false vessel positive rate* of the new performance measure are defined as follows.

$$TVPR = \frac{\ell(\{p \mid C(p) \neq 0, M_t(p) \neq 0\})}{\ell(\{p \mid C_t(p) \neq 0\})}$$

$$FVPR = \frac{\ell(\{p \mid C(p) \neq 0, M_t(p) = 0\})}{\ell(\{p \mid C_t(p) = 0\})},$$

where $\ell(\bullet)$ is the length of the central line. C_t and C denote the central line of M_t and M, respectively. This definition has a similar format as those in [2], when $\ell(\bullet)$ is replaced by pixel count of the whole vessel.

Using the new performance measure we compared the performance of our algorithm with that of Jiang's algorithm on STARE (ground truth: labels-vk), and with that of Staal's algorithm on DRIVE (ground truth: 2nd manual). And the result is summarized in Table 1.

Table 1 True and false positive rates of different algorithms based on central line detection.

Data	scheme	TVPR(%)	FVPR(%)	Time(s)
STARE	Jiang's[6]	54.09	0.13	8
	Ours	81.06	0.87	7
DRIVE	Staal's [5]	82.2	0.54	900
	Ours	82.6	0.45	5

The proposed new performance measure represents a new approach to evaluate blood vessel detection algorithms. In the pixel based performance measure, a single pixel width difference in large blood vessel boundary can lead to significant performance results. It is also much more useful in assessing the performance of small vessel detection, which is crucial to automated analysis of micro-vascular changes, e.g., neovasculization detection.

In addition to its high sensitivity, a major advantage of the proposed algorithm is its simplicity, speed and ease of parallelization. The calculation of DLC's of every pixel and decision procedure for every pixel can both be done independently. The key step in the algorithm is to compare the directional local contrast to a given threshold T, i.e., to check if the following inequation is true:

$$\frac{I_p - \overline{I}_p^{(\theta)}}{\overline{I}_p^{(\theta)}} \le T, \text{ where } \overline{I}_p^{(\theta)} = \frac{1}{r}\sum_{q \in N_p^{(\theta)}} I_q$$

Through some simple algebraic manipulations, the computation can be translated into the inequality condition:

$$\sum_{q \in N_p^{(\theta)}} (I_p - (1+T) I_q) \le 0$$

The value of I_q is in range [0, 255], T is usually fixed for specific photo taking equipment, thus a lookup-table technique is feasible to hold rounded values of $(1+T)I_q$, so that only integer add/subtract operations would be needed for fast implementation.

7. CONCLUSION

In this paper, we introduced a simple, fast, highly sensitive algorithm for mapping of blood vessels, based on directional local contrast in retinal images. The algorithm is faster and more accurate than two recently published algorithms. With minor modifications to the shape descriptor, the algorithm can be expanded to detect other objects in retinal images, e.g., microaneurysms. For a pixel p on microaneurysm, if we set the neighborhood size large enough to reach outside the microaneurysm, p's DLC's along all directions should be less than T. So the decision rule of microaneurysm is: a pixel p is microaneurysm pixel if $C_p^{(\theta)} \le T$ for all directions. Preliminary results show that this approach is promising. More comprehensive study is being pursued to make the algorithm complete and robust.

8. REFERENCES

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