RECONSTRUCTION OF VASCULAR STRUCTURES IN RETINAL IMAGES

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ABSTRACT

Vessels in retinal fundus images are useful in revealing the severity of eye-related diseases. In addition, they can act as landmarks for localizing lesions and the central vision area, and guiding laser treatment of neovascularization. In this paper, we propose a two-stage method to identify and extract vascular structure. First, vessels are enhanced by mathematical morphology with respect to their spatial properties. Vessels are differentiated from background patterns through the use of curvature evaluation and linear filtering. However, this may result in missing out some important features of bifurcation and intersection points. To overcome this, a reconstruction process is performed using dynamic local region growing to recover the complete vascular structure. Experiment results indicate that the proposed method is both reliable and effective for detecting the vascular structure in 97% of the retinal images.

1. INTRODUCTION

Ocular fundus image can provide information on the pathological changes caused by local ocular diseases and early signs of certain systemic diseases, such as diabetes and hypertension. Analyzing and interpreting fundus images have become a necessary and important diagnostic procedure in ophthalmology. Among the features in ocular fundus image, the structure of retinal vessels plays an important role in revealing the severity of eye-related diseases [1]. In addition, blood vessels can also act as landmarks for image-guided laser treatment of choroidal neovascularization and for localization of the optic nerve, the fovea and lesions [2]. Thus, reliable methods to extract vascular structures are needed.

Edge detectors such as Sobel and Laplacian of Gaussian cannot be applied to extract vascular structure because vessels in fundus images usually have poor local contrast where edges are never sharp and distinct enough to be readily identified. Moreover, edge detectors can only produce parallel edges. A post-treatment algorithm is needed to extract the complete vascular structure from these parallel edges. There are a lot of research works reported in the literature to identify and extract blood vessels. Generally, they can be categorized into two approaches: the matched filter approach and the mathematical morphology transformations approach.

[3] proposed a method of matching the image by two-dimensional Gaussian filters. An inverted, Gaussian-shaped zero-sum matched filter rotated twelve discrete angles of 15 degree each was designed to detect piecewise linear segment of blood vessels. This filter was performed on the entire retinal image and a threshold was set to differentiate blood vessels from retinal background. This method is able to detect primary (large) vessels, although it tends to give false detection at the boundary of bright objects such as the optic disc region. [4] presented an algorithm that combines morphological filters and curvature evaluation to segment vessel-like patterns. A sum of top-hats morphological transformations was used to highlight vessels with respect to their spatial properties. Curvature evaluation was performed to differentiate vessels from analogous background patterns which also fit the morphological transformations. Vessels were detected as the only features whose curvatures are linearly coherent. After computing the Laplacian transform, an alternating filter was applied to produce the final result. This approach is able to generate a more detailed description of the vascular structure, but tends to miss the important bifurcation and intersection points.

[5] developed an algorithm to track the midline and extract the diameters and the degree of tortuosity of vessel segments. The tracking of a blood vessel proceeded by extending the search in the direction of the last-tracked part of the blood vessel by a certain fixed length. The start and end points, as well as the tracking direction, had to be specified manually by an operator. [6] evaluated the fitness of estimating vessel profiles with Gaussian function and proposed a second-order Gaussian filter for the detection and measurement of vessels. The vessel width measurement was useful for optimizing the matched filter to improve the success rate of detection.

Other techniques to extract vascular structure utilized wave propagation and trace-back mechanism [7] and fuzzy connected object delineation principles [8]. The process is semi-automatic because seed voxels have to be manually specified by an operator interactively. Thus far, the problem of extracting the complete vascular structures in fundus images remains an open problem.

In this paper, we propose a vascular structure reconstruction method using dynamic region growing. We adopt a two-stage process to extract a more complete vascular structure. Experiment results show that the proposed method is able to recover the complete vascular structure in 97% of the retinal images.

2. VESSEL DETECTION

It has been observed that retinal vessels have the following important spatial properties that are useful for vessels analysis: the vessels are usually smooth with slight curvature and may be approximated using piecewise linear line segments. They are typically darker relative to the background (in the green layer of the color fundus images). The cross-section intensity profile of vessels can usually be approximated by a Gaussian curve. In summary, a vessel is defined as a dark pattern with Gaussian-shape cross-section profile, piecewise connected, and locally linear. Morphology transformations of top-hat are suitable for enhancing vessels with respect to this description. However, a lot of details corresponding to background linear features are also highlighted at the same time. In order to differentiate vessels from analogous background patterns, a curvature is evaluated and linear filtering operations are performed.

The vessel-detection process consists of three steps. The first step is to perform vessel enhancement. This involves designing a set of linear structure elements with length equal to the maximum caliber of the primary (large) vessels. In our experiments, the size of the structure element is set to 12 pixels. We also pose these elements in different orientations using a rotating angle from 0 to 180 degree. A sum of top-hats using these linear structure elements with various orientations allows us to enhance all vessels regardless of their directions, sizes, and even in the low local contrast regions. Equations (1) and (2) give the formulas of the enhancement process.

$$I_{op} = R_{I_o}(Max_{i=1\cdots N}\{O_{L_i}(I_o)\}) \quad (1)$$

$$I_{top} = \sum_{i=1}^{N}(I_{op} - O_{L_i}(I_o)) \quad (2)$$

N denotes the number of structure elements with different rotating angles. If the rotating angle is 15 degree which is used in our experiments, N is equal to 12. $O_{Li}(I_o)$ denotes opening of image I_o with structure element L_i. $R_{Io}(.)$ denotes reconstruction of (.) referring to I_o. This transformation sets the homogeneous areas in the retinal images to zero since they remain unchanged by the top-hat transformations. Furthermore, to eliminate the effect of the background linear patterns being enhanced, a noise reduction process is carried out to remove any isolated round and dark small dot background noise whose diameter is less than the size of the structure element.

In the second step, we perform the evaluation of curvature of the vessel-like patterns enhanced by morphological transformations. Careful observation reveals that the highlighted noise tends to be weak (smaller amplitude) and disorganized whose curvature oscillates between positive and negative values frequently. On the other hand, the curvature of vessels is generally of larger positive amplitudes. This gives rise to the idea of differentiating such noise from vessels by using curvature evaluation. It has been proven that the sign of Laplacian applied to the result image of top-hats can be used as a good approximation of the sign of curvature [4]. A Gaussian smoothing is first performed. The window size of the Gaussian smoothing corresponds to maximum caliber of the primary vessels. Image applied with curvature computation is given by

$$I_{lap} = Laplacian\ (Gaussian\ {}^{width=12}_{\sigma=2}(I_{top})) \quad (3)$$

The third step in the detection process consists of applying a set of linear filters to remove the enhanced noise patterns thereby producing the final images. They include opening by reconstruction and closing by reconstruction with previous structure element and another opening of a larger structure element. These transformations can be expressed as follows:

$$I_1 = R_{I_{lap}}(Max_{i=1\cdots N}\{O_{L_i}(I_{lap})\}) \quad (4)$$

$$I_2 = R_{I_1}(Min_{i=1\cdots N}\{C_{L_i}(I_1)\}) \quad (5)$$

$$I_{final} = (Max_{i=1\cdots N}\{O_{L_i}(I_2)\} \geq 1) \quad (6)$$

$C_{Li}(I_1)$ denotes closing of image I_1 with structure element L_i. Vessels are readily identified as pixels whose values are larger than a small positive value such as 1. Note that smaller vessels and tortuous segments of vessels that are shorter than the structure element during the last opening are removed.

3. VASCULAR STRUCTURE RECONSTRCUTION

Mathematical morphology transformations are known to be sensitive to scale, hence the selection of the size of structure element is critical. This is because during the sum of top-hats, portions of vessels with profiles larger than the structure element will be excluded. To avoid the removal of these vessels, it is necessary to use a larger structure element. However, a larger structure element also means more linear background noise will be highlighted. To achieve a good compromise, we set the length of structure element to be the maximum caliber of the primary vessels. This setting guarantees that we can detect all primary vessels while reducing the background noise to the minimum.

Another limitation of the morphology transformation is that it is unable to effectively highlight bifurcation and intersection points where the profiles are larger than the structure element. In other words, some important bifurcation and intersection points which are indispensable in describing the complete morphology of vascular structure are missing (see Fig. 1(a, b)). In addition, some vessels may have a particularly bright reflection running through their centres. Although such a ‘bump’ at the centre of the intensity profile is small compared to the brightness of its neighbourhood, it is not effectively enhanced like the vessel edges during the top-hats process. As a result, the vessels can only be partially detected (see Figure 1(e, f)).

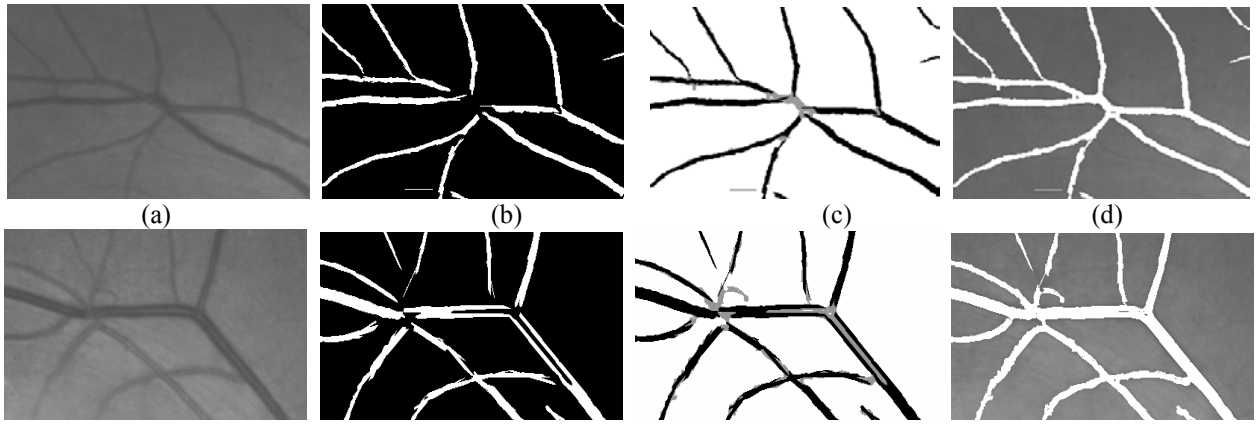

Fig. 1. Morphology reconstruction of vascular structure by local dynamic region growing: original images (a, e), vessels detection results (b, f), region growing pixels in dark gray (c, g), reconstructed vascular structure (white) superimposed to green images (d, h).

In order to recover the complete vascular structure, a morphology reconstruction process is performed based on a dynamic local region growing. The binary detection results of the vessels are superimposed on the grey intensity green images. Boundaries of the binary vessels can be easily specified. Neighbouring pixels of the vessel boundaries in 8-direction that are not vessel pixels are called 'seeds'. The 'seeds' are taken into account in the region growing process in terms of their intensity homogeneity to the vessel pixels. A window is centered at each 'seed' candidate and the average intensity value of all vessel pixels in the window is computed. The window size is set with respect to half of the maximum calibre of the primary vessels. If the difference in intensity between the 'seed' and the average value is smaller than a threshold, then the 'seed' is considered to be intensity homogenous to the vessel and is part of the vessel.

However, if the vessels are in a very noisy region where local contrast is quite low or the 'seeds' are close to false vessel detection area, false growing of massive areas occurs. To overcome this, a contrast limit parameter is applied to guarantee that the process is conducted only in a range of the vessel boundary with reasonable brightness of local contrast. The contrast limit is defined as the average intensity value difference between vessel pixels and non-vessel pixels in the window. A 'seed' is eventually declared to be a vessel pixel when the contrast limit is larger than a threshold. In order to ensure proper growing in lower intensity contrast region, both the contrast and homogeneity parameters are dynamically adjusted according to the vessel darkness. This allows flexible reconstruction of vascular structure. I_{avg} is the average intensity of vessels in the window, then the two thresholds are defined to be: $TH_{hom}=\alpha I_{avg}$ and $TH_{con}=\beta I_{avg}$, where α is 0.03 and β is 0.065 in the experiments.

All 'seeds' that satisfy the two criteria are marked as part of the vessels and another round of region growing begins with the expanded vessels. The growing process will iterate and stop when there is nothing to grow with. Some examples for morphology reconstruction of vascular structure are given in Figure 1(c, d) and Figure 1(g, h). It is observed that false growing usually occurs around optic disc region. This is because the optic disc area has sharp edges while nearby vessels are in very low contrast to background. An optic disc identification algorithm is employed to prevent false growing around the optic disk. First, a fitted ellipse is identified [9], a restriction area is then established between one ellipse of smaller size and one ellipse of larger size in terms of the fitted ellipse. The horizontal and vertical radii of these ellipses are proportional shortened or lengthened to the radium of the ellipse that fits to optic disc. Any vessels inside the band are excluded from the growing process.

4. EXPERIMENT RESULTS

The image database that we use to test the method consists of about 35 normal and abnormal color fundus images. The fundus images were acquired using a fundus camera applied directly to the retina and digitised by image digitizer card. The typical image size was 1500*1152*24 although images of smaller size also appear in our database. Table 1 summarizes the results of vessels detection.

Table 1. Vessel detection results by various methods.

Quality (number of images)	poor	moderate	good	excellent
Matched filter	11	16	8	0
Zana's Algorithm	5	14	14	2
Proposed method	1	7	15	12

Our method is able to recover an almost perfect vascular structure extraction for high contrast images as shown in Figure 2(a, b). It also works well for fundus images containing massive lesions and low local contrast as shown in Figure 2(c, d) and 2(e, f) respectively.

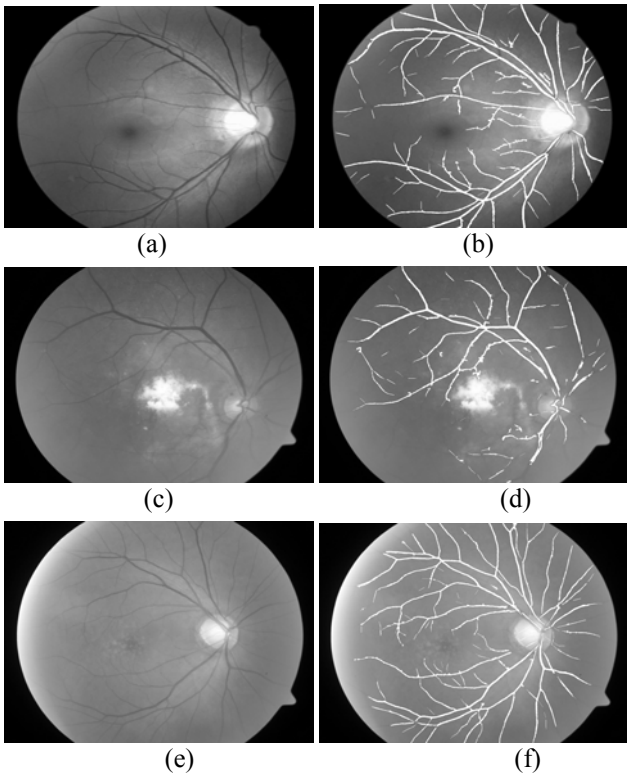

Fig. 2. (a) High contrast image, (b) reconstructed vascular structure for (a), (c) image with lesions, (d) reconstructed vascular structure for (c), (e) low contrast image, (f) reconstructed vascular structure for (e).

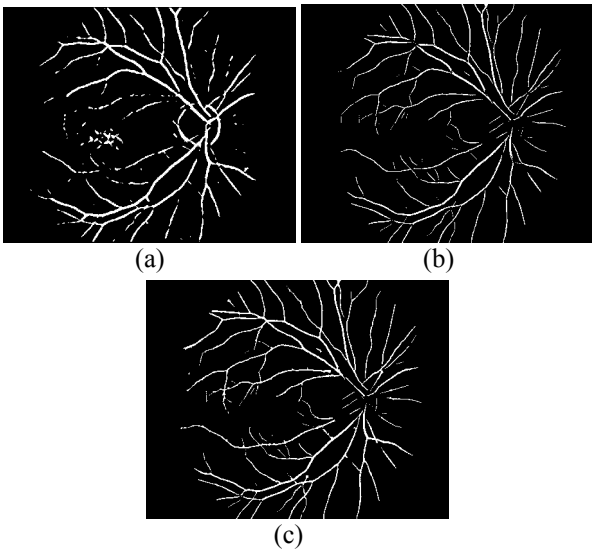

Fig. 3. Vessel extraction for Fig. 2(e). (a) Matched filter, (b) Zana's algorithm, (c) Proposed method.

For the purpose of comparison, we also implement two other existing methods for vessel identification and segmentation [3 ,4]. Figure 3(a) shows the extracted result of the matched filter method applied to Figure 2(e). It is clear that the matched filter is unable to deal with the presence of bright objects such as lesions and the optic disc and it tends to highlight many linear structures in the background. This leads to a rather large number of false detection. The approach proposed by Zana [4] is in principle the same as the first stage of our method to enhance and detect vessels with results shown in Figure 3(b). However, it is unable to recover the important bifurcation and intersection points as well as deal with vessels with bright reflection in the center (see Figure 1). Our method employs the idea of region growing to recover the complete morphology of vascular structure. This leads to higher recovery rate of vascular structure than Zana's algorithm (see Figure 3(c)).

5. CONCLUSIONS

In this paper, we propose a reliable method to reconstruct morphology of the complete vascular structure in fundus images. First, vessels are enhanced by morphological transformations and are detected by curvature evaluation and linear filters. Next, a reconstruction process is performed using dynamic local region growing to recover missing bifurcation and intersection points and partially detected vessels. Results show that the method performs well in reconstructing complete vascular structure.

6. REFERENCES

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