AN ADAPTIVE REGION GROWING SEGMENTATION FOR BLOOD VESSEL DETECTION FROM RETINAL IMAGES

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Abstract: Blood vessel segmentation from the retinal images is extremely important for assessing retinal abnormalities. A good amount of research has been reported on blood vessel segmentation, but significant improvement is still a necessity particularly on minor vessel segmentation. As the local contrast of blood vessels is unstable (intensity variation), especially in unhealthy retinal images, it becomes very complicated to detect the vessels from the retinal images. In this paper, we propose an edge based vessel segmentation technique to overcome the problem of large intensity variation between major and minor vessels. The edge is detected by considering the adaptive value of gradient employing Region Growing Algorithm, from where parallel edges are computed to select vessels. Our proposed method is efficient and performs well in detecting blood vessels including minor vessels.

1 INTRODUCTION

Automatic detection of blood vessels in the retinal images can help physicians with diagnosing ocular diseases, patient screening, clinical study, etc. For instance, a patient may exhibit discoloration of the optic nerve, or a narrowing of the blood vessels in the retina. An ophthalmologist (a medical doctor specialized in the structure, function, and diseases of the human eye) uses this information to diagnose the patient, as having for instance Coats' disease or a central retinal artery occlusion. A common procedure to examine the eye health is passing through the procedure of retinal imaging. An optical camera (for instance, Mydriatic and non-mydriatic retinal cameras) is used to see through the pupil of the eye to the rear inner surface of the eyeball. A picture is taken showing the optic nerve, fovea, surrounding vessels, and the retinal layer. The ophthalmologist can then reference this image while considering any observed findings.

The most effective treatment for many eye related diseases is the early detection through regular screening. Assessment of the characteristics of vessels in the retina plays an important role in medical diagnoses. For these tasks measurements are needed of e.g., vessel width, colour, reflectivity, tortuosity, abnormal branching, or have the occurrence of vessels of a certain width. Blood vessel appearance can provide information on pathological changes caused by some diseases including diabetes, hypertension, and arteriosclerosis. Changes in retinal vasculature, such as haemorrhages, angiogenesis; increases in vessel tortuosity, blockages and arteriolar-venular diameter ratios are important indicators of, for example, diabetic retinopathy, and retinopathy of prematurity and cardiovascular risk. Information about blood vessels in retinal images can be used in grading disease severity or as part of the process of automated diagnosis of diseases (Hoover et al. 2000).

The automatic detection of blood vessels is very important as ophthalmologist can potentially screen larger populations for vessel abnormalities. In contrast, manual delineation of vessels becomes tedious or even impossible when the number of vessels in an image is large or when a large number of images are acquired. Furthermore, a detection and segmentation of the vascular tree seems to be the most appropriate representation for the entire retinal image due to three following reasons. Firstly, it maps the whole retina. Secondly, it does not move except in a few diseases. Finally, it contains enough

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information for the localization of some anchor points (Chanwimaluang and Fan 2003).

Automated retinal segmentation is complicated by the fact that the width of the retinal vessels can vary from large to very small, and that the local contrast of vessel is unstable, especially in unhealthy retinal images (Li et al. 2006). Although a large amount of research (Martinez-Perez et al. 1999; Zana and Klein 1999; Hoover et al. 2000; Jiang and Mojon 2001; and Li et al. 2006) has been published for the detection of blood vessels, a huge improvement in detection procedures remains a necessity for the detection of small vessels (branches).

In this paper we propose a novel vessel segmentation technique based on vessel edges. The proposed method employs the adaptive region growing segmentation algorithm to overcome the complexity of edge segmentation, as we cannot trace them with a fixed intensity or gradient direction. The gray values of the vessels in the retinal image are changeable throughout the entire image and gradient direction is not constant due to curvilinear structure of the vessels. Based on these phenomena, it is appropriate to apply the Adaptive Region Growing (ARG) algorithm to detect the edges of vessels. After segmenting the edges, we locate the parallel edges based on gradient direction considering pixel position of each region. These parallel edges are considered as primary vessels and facilitate to remove the noise and other objects. Finally, we map the original retinal image based on pixel positions of that segmented gradient image to detect the blood vessels.

The rest of the paper is organized as follows: section 2 presents a brief background and review of the related segmentation based literature and section 3 discusses our proposed Adaptive Region Growing segmentation based blood vessel detection method. Section 4 provides preliminary results and discussion. Finally, conclusions and future research directions are drawn in section 5.

2 BACKGROUND LITERATURE

Previous methods for blood vessel detection in images of the retina can be categorized into two groups. The tracking based approach and Template or Model based approach. Tracking based approaches work by first locating an initial point and then exploiting local image properties to trace the vasculature recursively. This technique may require user intervention and appear to have proclivity for termination near branch points. Model based approaches apply explicit vessel models to extract the vasculature.

Chaudhuri et al. (Chaudhuri et al. 1989) introduced an algorithm based on directional two-dimensional (2-D) matched filters to detect piecewise linear segments of blood vessels. Twelve different templates were used to search for vessel segments along all possible directions. This method is completely unsupervised and good for initial estimation. However, the detected vessels may not be continuous and small vessels get missed and validity of the detected vessels is not checked.

Tolias and Panas (Tolias and Panas 1998) presented a fuzzy vessel tracking algorithm for retinal images based on fuzzy clustering. Salient regions are initialized as starting point for vessel tracking. Then Fuzzy C-means clustering algorithm determines vessel and non-vessel region along a vessel profile. Then trace the vessel based on thresholding the membership values. This is also an unsupervised technique and performed well on detecting major vessels (98%). Nonetheless, this algorithm still suffers from missing a large number of minor vessels (detection rate only 23.53%).

Mendonca and Campilho (Mendonca and Campilho 2006) proposed an algorithm based on region growing process using vessel centreline as seed point. Multi-scale morphological vessel enhancement applying a modified top-hat transform with variable size structuring elements is performed. In order to obtain binary maps of the vessels a binary morphological reconstruction is used. A set of four directional differences of offset Gaussian filters is used to detect vessel centreline. Vessel filling by region growing process using as initial seeds the pixel within the centrelines is used. The growing is successively applied to the four scales and, in each region growing step; the seed image is the result of the previous aggregation. This technique shows an improved detection rate with accuracy of 94.7%.

Staal et al. (Staal et al. 2004) presented a ridge based vessel segmentation algorithm in color retinal images. The ridge is detected by applying Gaussian scale space technique and grouped by applying region growing algorithm. Therefore, the image is grouped into patches or convex sets. Features of the convex sets and the pixels belonging o the convex sets are considered to construct vectors and classified by the KNN (k-nearest neighbour) classifier. Convex sets' features are height, width and their ratio, curvature, distance between first and last points of a convex set, mean and standard deviation of a green patch, etc. Pixel features are value of red and green plane of the image at the pixel location and their ratio, etc. This technique also shows promising detection rate with maximum accuracy of 0.944.

Wu et al. (Wu et al. 2006) introduced an adaptive detection of blood vessels in the retinal images. At first the blood vessel enhancement is performed by adaptive histogram equalization technique. Then vessels features are extracted using the standard deviation of Gabor filter responses along different orientations. Finally, the vessel is traced using forward detection, backward verification and bifurcation detection. The overall detection rate is 80.15% while small vessel pixel detection rate 42% and small vessel detection rate 75%.

Jiang and Mojon (Jiang and Mojon 2003) presented an adaptive local thresholding technique by verification-based multithreshold probing to detect blood vessels in the retinal images. At first, the original retinal image is converted into binary image through multiple thresholding by considering curvilinear structure and width of the vessels. Then Euclidian distance transformation from candidate vessel point to background point is performed. Following that the vessel candidate is pruned by means of the distance map to only retain centreline pixels (considering distance of two nearest background pixel & angle from these two points) of curvilinear bands. Finally, the curvilinear bands are reconstructed from their centreline pixels. The reconstructed curvilinear bands give the part of the vessel network that is made visible by the particular threshold. The overall detection rate reported is 86.5%. This technique needs further improvement in vessel detection and background noise suppression.

Zana and Klein (Zana and Klein 2001) presented a vessel segmentation algorithm using mathematical morphology and curvature evaluation. At first the vessels are highlighted using their morphological properties (sum of top hats reduces small bright noise and improve the contrast of all linear part). After that the cross curvature is evaluated using the Laplacian operator. Then the alternating filter is used to produce the final result. The technique is not sensitive to sudden changes in the global gray level. However, results in missing pixels of the dilated line because of surrounding texture.

Hoover et al. (Hoover et al. 2000) proposed an algorithm for locating blood vessels in retinal images by piece-wise threshold probing of a Matched Filter Response (MFR). At first, the original image is filtered by MFR. Then the filtered image is thresholded and thinned. Finally, use the probing technique while the probe examines the image in pieces (initial threshold is the MFR image value at the starting pixel, then regions grow using a conditional paint-fill technique), testing a number of region based properties (e.g., segment length). If the probe decides a piece is vessel (if the resulting region belong to a minimum number of threshold pixels but less than maximum or connects two previously probed pieces, then the region is labelled as vessel), then the constituent pixels are simultaneously segmented and classified. The overall detection rate is 90% true positive and 4% false positive. This technique has limitations on detecting background or non vessel removal.

3 PROPOSED METHOD

As we mentioned earlier that the automated retinal segmentation is complicated by the fact that the local contrast of vessels is unstable, the width of retinal vessels can vary from very large to very small especially unhealthy ocular fundus images. We present a method for the segmentation of blood vessels in retinal images based on the partial derivative of intensity image, which gives information about its topology and also overcome the problem of image intensity variation. We use STARE (Hoover 2002) retinal imaging dataset. Our proposed method performed much better in detecting both major and minor vessels.

The procedure is as follows: at first we enhance the contrast of the original retinal image by applying Adaptive Histogram Equalization method then we apply the first order directional derivative operator, normalize it and convert the original image into gradient image. Each vessel will show up as parallel edges, which will be segmented by applying Adaptive region growing algorithm. Since the contrast of the vessels is unstable it is not viable to apply a threshold value to segment the edges of a vessel. Due to the curvilinear structure of the vessels the gradient direction is also changeable. So, we apply Adaptive value of gradient magnitude with region growing process to segment the edges. Parallel edges are selected considering the gradient direction of each pixel belonging to the parallel regions. We can, therefore, segment the vessels and remove the background noise and other objects. Finally, we map the vessel pixels from the original retinal image based on the segmented gradient image to show the detected vessels.

Figure 1 displays the overall technique of our proposed method. We describe each step in detail in the following subsections.

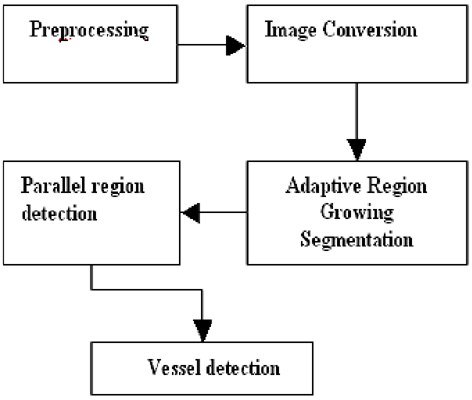

Figure 1: The vessel segmentation model.

3.1 Preprocessing of Retinal Image

In the preprocessing step the aim is to enhance the contrast of the original retinal image. The Adaptive Histogram Equalization method is implemented, using MATLAB, to enhance the contrast of the image intensity by transforming the values using contrast-limited adaptive histogram equalization. It operates on small regions in the image, called tiles, rather than on the entire image. Each tile contrast is enhanced, so that the histogram of the output region approximately matches the histogram specified by the 'Distribution' parameter. The neighboring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries.

3.2 Image Conversion

The enhanced retinal image is converted into gradient image using first order partial differential operator. The gradient of an image *f(x,y)* at location *(x,y)* is defined as the two dimensional vector (Gonzalez and Wintz 1987)

$$G\,[f(x,y)] = [G_x\ G_y] = \left[\frac{\partial f}{\partial x}\ \frac{\partial f}{\partial y}\right] \quad (1)$$

It is well known from vector analysis that the vector G points in the direction of maximum rate of change of *f* at location *(x,y)*. For edge detection, we are interested in the magnitude of the vector, generally referred to simply as the gradient and denoted G [*f(x,y)*] and commonly takes the value of

$$G\,[f(x,y)] \approx |G_x| + |G_y|. \quad (2)$$

The direction of the gradient vector is calculated as follows. Letting $\alpha(x, y)$ represent the direction angle of G at location *(x,y),*

$$\alpha(x, y) = \tan^{-1}(G_y / G_x) \quad (3)$$

where the angle is measured with respect to the x-axis.

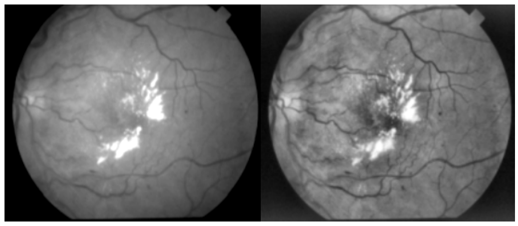

Figure 2: Original retinal green channel image (left) and its Adaptive Histogram Equalized Image (right).

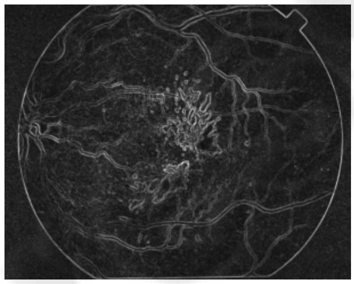

Figure 3: Gradient image of the Adaptive histogram equalized of Figure 2.

3.3 Adaptive Region Growing Technique

The edges of vessels are segmented using region growing procedure that groups pixels or sub regions into larger regions based on gradient magnitude. As the gradient magnitude is not constant for the whole vessel we need to consider an adaptive gradient value that gradually increases or decreases to append the pixel to a region. We call it an adaptive procedure, as the difference of neighbouring pixels intensity value is always adapted for the region growing process.

The region growing process starts with appending the pixels that pass certain threshold value (Gonzalez, Woods et al. 2004). For region growing we find the intensity difference between a pixel belonging to a region and its neighbouring potential region growing pixels. The pixel is considered for appending in that region if the difference is less than a threshold value. The threshold value is calculated by considering the maximum differential gradient magnitude for any neighbouring pixels with equal (approximately) gradient direction. Region growing should stop when no more pixels satisfy the criteria for inclusion in that region. In the region growing process each region is labelled with a unique number. For that purpose we construct a cell array with region number and its pixel position. The image is scanned in a row-wise manner until its end, and each pixel that satisfies our criteria is taken into account for growing a region with its 8-neighborhood connectivity.

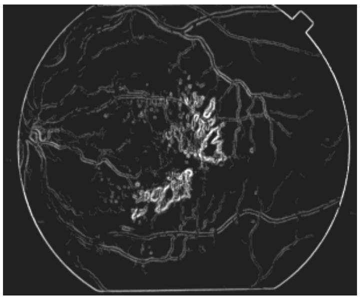

Figure 4: Output image after applying adaptive region growing with minimum pixel number.

3.4 Parallel Region Detection

We calculate the parallel edges (regions) by considering pixel orientation belonging to each region. At first, we pick the region number and belonging pixel coordinates from the constructed cell array. Then we grouped the region/regions parallel to each region, which is calculated by mapping the pixels gradient direction. For each region every pixel is searched from its potential parallel region and once a maximum number of pixels match with the other region we consider it as parallel to that region. We consider all regions and once a region is considered we assigned a flag value to that region so that it will not be considered again. In this way we can only filter the vessels from the region and discard all other regions, which are background noise or other objects like haemorrhage, macula, etc in the retinal image.

3.5 Vessel Detection

We mapped the original retinal image with the pixels from the segmented gradient image to show the vessels. We can also find the centreline of each vessel (parallel region pixels) edges and then expand it with setting the stopping criteria of facing edge pixels to determine the total pixels of each vessel. For simplicity, we only produce the images with mapping the original retinal images. Figure 5 below displays two examples of images from the dataset and their output.

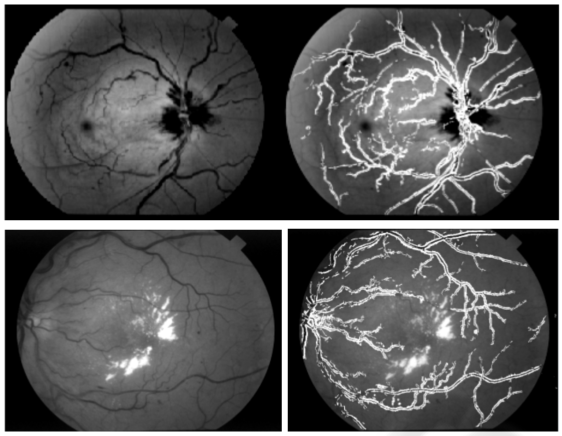

Figure 5: Original retinal image (left) and detected vessels (right).

4 RESULTS AND DISCUSSION

Figure 5 shows two example images and the output after blood vessel segmentation using the proposed method. The first retinal image is almost a normal eye and we observe that 99% vessels are detected properly. However, the second retinal image suffers from noise and the detection rate falls to approximately 90%. This fall in detection rate is due to the fact that if any part of the retinal image suffers from noise like block (eg. haemorrhage) then the whole area is removed as we consider only the parallel regions. Therefore, it is possible to miss vessels from that particular part of the retinal image. Table 1 displays observations of vessel detection for five different images.

5 CONCLUSION AND FUTURE WORK

In this paper we proposed a novel approach for adaptive region growing technique and applied to retinal gradient images. The results obtained are promising. Currently, we are working on to produce the retinal output binary image by expanding the vessel centreline, which can be used as a vessel width and crossover measurement.

Table 1: Vessel detection accuracy.

Image	Total Number of vessels	Number of detected vessels	Accuracy
Image 1	93	92	98.92
Image 2	74	70	94.59
Image 3	85	79	92.94
Image 4	81	76	93.82
Image 5	75	71	94.66

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