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Automatic Blood Vessel Segmentation Based on Adaptive Thresholding Method

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ABSTRACT

This paper presents a novel unsupervised method of blood vessel segmentation by iterative algorithm using fundus photographs. There are three stages for segment the blood vessels. In first stage, the negative green plane image is pre-processed to extract the vessel enhanced image. Initial estimate of the segmentation is performed by using global thresholding. Tophat morphological reconstruction is used for extract the vessel enhanced image. In second stage, new pixels are added to the existing vessel estimate iteratively by using adaptive thresholding and the residual image is extracted by removing false edge pixels. A stopping criterion is used to terminate the iterations. In third stage, final estimated vasculature is identified at high accuracy and low computational complexity.
Keywords: fundus, tophat morphological reconstruction, stopping criterion, vessel segmentation

I. INTRODUCTION

Fundus image is captured by the fundus camera is a special low power microscope. It is used to capture the interior surface of the eye. Retinal vasculature segmentation is performed on the fundus images that can lead to find blindness such us glaucoma, diabetic retinopathy (DR) [1], retinopathy of prematurity [2], vein occlusions.

The algorithm of automated blood vessel segmentation is classified into two. There are supervised and unsupervised methods. The supervised methods are classified as vessel and non-vessel pixels. Classifiers are used to detect the vessels. Some of the classifiers are Gaussian mixture model (GMM) [3], neural networks [4], k-nearest neighbor [5], support vector machine (SVM) [6], decision trees [7], AdaBoost [8]. These are the classifiers used to separate the vessel pixel from non-vessel pixel. The unsupervised algorithm generally applies on morphological transformations [9]-[11], line detectors [12], matched filtering [13], multiscale segmentation methods [14]-[16] or model-based methods [17]-[19]. Most supervised methods are mainly depends on the training data. For extracting residual image, this method is sensitive to identify the false edge pixels. The most supervised methods are computationally complex for segmenting retinal with pathology. But it is very useful on segmentation of healthy retinal image.

In this paper, the proposed algorithm is very efficient to segment the image and provide low computational complexity and high accuracy for normal and abnormal retinal images. This method proposes the algorithm for extract the major vessels first and followed by addition of finer blood vessels by iteratively execute algorithms. Finer vessel addition is performed by adaptive thresholding in iterative steps. A residual image is extracted by removing the false edge pixels. A special stopping criterion is used to terminate the vessel addition process lead to reducing the false edge pixels. As compared to existing algorithm it provides low computational complexity and high segmentation accuracy for peripapillary blood vessels.

II. METHODS AND MATERIAL

The proposed iterative vessel segmentation algorithm is that segment the finer vessel branches and extracts the enhanced vessel estimated image. First, use the global thresholding to extract the major vessels.

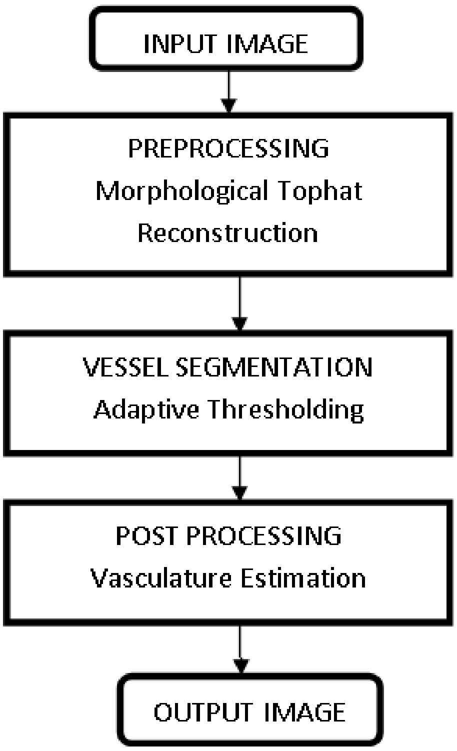
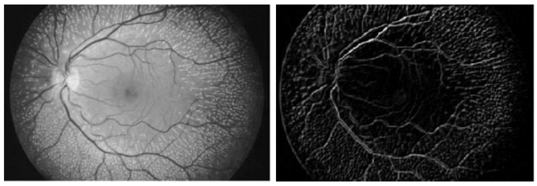


Figure 1 : Block Diagram

Then the vessel enhanced image is extracted by using tophat reconstruction of the negative green plane image. Then the finer vessel pixels are extracted by the iterative adaptive thresholding. Stopping criterion is used to estimate the best vasculature and terminate the iterations.

A. Preprocessing

In the preprocessing stage, green palne image of the fundus image is gives to input to analyze whether the image is affected or not. The green plane image is scaled in [0,1]. The scaled green image I is inverted by making dark regions as brightest. This inverted image I_v is subjected to contrast enhancement by using morphological tophat transformation. 21 pixels length and 1-pixel width of twelve linear structuring elements are used to make tophat transformed image. To generate tophat transformed vessel enhanced image T by select the highest intensity pixels on reconstructed image. Then the output of the image is passed to the input of the vessel segmentation process.



(a) (b)

Figure 1 : (a) Green plane Image (I). (b) Tophat reconstruction vessel enhanced image.

B. Vessel Segmentation

In this stage, the proposed algorithm is used for extract best vasculature by iteratively. First, major vessels V_0 are extracted before the beginning of iteration by using global thresholding from tophat image T. Then the finer vessels are estimated by adaptive thresholding iteratively. In first iteration, major vessels are segmented denoted by V_t. Next, In each iteration false edge pixels are removed from previous iterative image as it is called residual image R_t. At the same time, each iteration add new vessel pixels in the existing vessel estimate V_{Rt}. The union of pixels from existing vessel estimates V_t and new pixels identified image V_{Rt} added to tophat image T. These pixels filled gaps in image are formed the base image B_t.

Vessel addition: There are two threshold parameters are used for vessel segmentation φ_1 (t) and φ_2 (t). The residual image is extracted by the new image thresholded at φ_1 (t) pixel value where "t" is iteration number. This parameter is used for extracting a binary image V_{Rt} that contains new vessels within the region of 10 pixels. Residual image is thresholded at φ_1 (t) gives new vessel pixels in each iteration. First we initialize.

$$\boldsymbol{\varphi_1 (t) = 1 - (0.05*t)}$$

Then the obtained binary image is used for region grown using a threshold pixel value function φ_2 (t). This function φ_2 (t) produce high vessel segmentation accuracy. φ_2 (t) is given by,

$$\boldsymbol{\varphi_2 (t) = 205 + \alpha * (t-1)^k} \qquad \textbf{(1)}$$

$$\boldsymbol{\alpha \in [1,2,...,6],}$$

$$k \in [0,0.2,\ldots,3]$$

The threshold value function used for highest vessel segmentation accuracy within small number of iterations. For every image(l), t_l is the highest segmentation was achieved at iteration t.

Stopping Criterion: A special stopping criterion is used to stop the iteration at a specified interval that achieved a highest accuracy in vessel segmentation. First we split the vessel pixel (i, j) into true positive pixel (tp_t), true negative pixel (tn_t), false positive pixel (fp_t), false negative pixel (fn_t). The calculation of the above pixels are derived by the following equations,

$$\forall(i, j),\ i \in [1,2,\ldots,n1],\ j \in [1,2,\ldots,n2]$$

$$\sum_{i=1}^{n1}\sum_{j=1}^{n2} \mathrm{tpt}\,(i,j) = \mathrm{TPt} \qquad (2)$$

$$\sum_{i=1}^{n1}\sum_{j=1}^{n2} \mathrm{tnt}\,(i,j) = \mathrm{TNt} \qquad (3)$$

$$\sum_{i=1}^{n1}\sum_{j=1}^{n2} \mathrm{fpt}\,(i,j) = \mathrm{FPt} \qquad (4)$$

$$\sum_{i=1}^{n1}\sum_{j=1}^{n2} \mathrm{fnt}\,(i,j) = \mathrm{FNt} \qquad (5)$$

The total number of pixels are derived to the next iterated image is calculated by the following equation,

$$\sum_{i=1}^{n1}\sum_{j=1}^{n2} \mathrm{Vt}\,(i,j) = \mathrm{TPt} + \mathrm{FNt} \qquad (6)$$

$$\mathrm{Ct} = \frac{1}{n1.n2}\sum_{i=1}^{n1}\sum_{j=1}^{n2} \mathrm{Vt}\,(i,j) = \mathrm{V0}\,(i,j) \qquad (7)$$

Also calculate the change of the vessel estimate C_t at each iteration from the above equation. Error of the vessel estimate E_t and accuracy of the vessel segmentation ACC_t defined by the following equation,

$$\mathrm{Et} = \frac{\sum_{i=1}^{n1}\sum_{j=1}^{n2}[\mathrm{fpt}\,(i,j) + \mathrm{fnt}\,(i,j)]}{\mathrm{TPt} + \mathrm{TNt} + \mathrm{FPt} + \mathrm{FNt}} \qquad (8)$$
$$= 1 - ACC_t$$

As error rate (Et) decreases the accuracy of the vessel segmentation (ACC_t) increases. When changes of the vessel estimate give the negative result then the stopping criterion is met. So, it stops the iteration and gives highest accuracy for blood vessel segmentation.

III. RESULTS AND DISCUSSION

The vessel segmentation proposed algorithm performance is evaluated with ground truth values of manually marked segmentation. Three sets of ground truth value experimental results

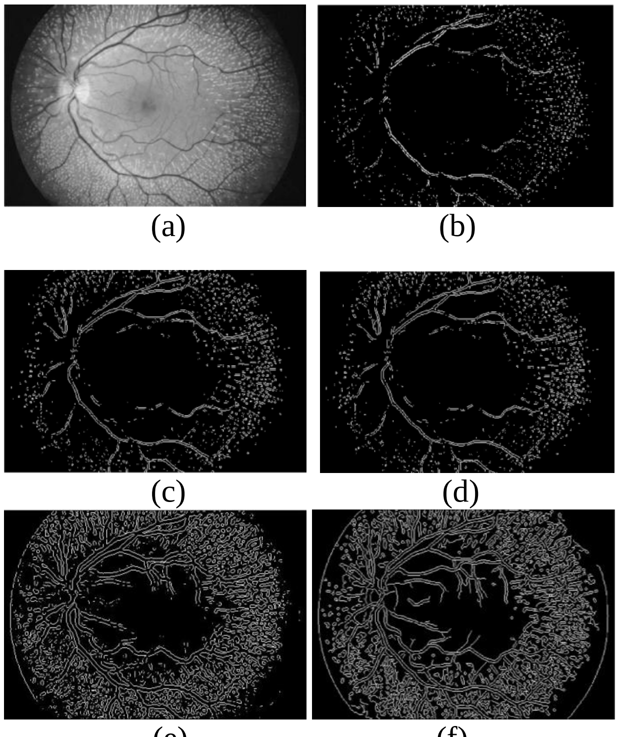


Figure 2 : Images of iterative vessel segmentation. (a) Green plane image (b) Tophat reconstruction vessel enhanced image (c) Residual removed image (d) Thresholding image (e) Using threshold value new vessel pixels are identified image (f) Vessel extracted after region growing are used to compare the performance of the proposed algorithm.

In first, the performance of the vessel segmentation is more as compared to existing methods. The proposed algorithm is computationally simple. Second, the proposed algorithm is used for abnormal images also, but existing supervised and unsupervised method gives poor performance metrics for abnormal image segmentation. Third, It also gives good performance to extract the peripapillary blood vessels from both normal and abnormal images.

IV. CONCLUSION

This paper presents a fully automated blood vessel segmentation by using iterative adaptive thresholding method. First perform the initial segmentation which gives to extract the major blood vessels from the fundus image. Then find out the positive and negative vessel pixels by using adaptive thresholding iteratively. In each iteration new vessel pixels are identified and removed unnecessary pixels called as residual image. A novel stopping criterion is used to terminate the iterations which give final vasculature estimate at high accuracy. The method has lower computational complexity than other existing methods.

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