AN AUTOMATIC TRACKING METHOD FOR RETINAL VASCULAR TREE EXTRACTION

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ABSTRACT

In this paper, we propose an automatic tracking method to extract blood vessels in retinal images. Seed points are firstly picked out on a retinal image for initialization. Our algorithm detects vessel edge points iteratively based on a statistical sampling model using a Bayesian method. At a given step, local vessel's sectional intensity profile is approximated by a Gaussian model. New vessel edge points are detected by using local grey level statistics and expected vessel structures. For evaluation purpose, we use the STARE public database. Experiments results show effective detection of blood vessels when using the proposed method.

Index Terms— blood vessel extraction, Bayesian tracking, retinal image

1. INTRODUCTION

The automatic analysis of retinal blood vessels is a very important task in many clinical investigations and scientific research. The early diagnosis of several pathologies, such as arterial hypertension, arteriosclerosis or diabetic retinopathy could be achieved by analyzing the vascular structures. Many vessel extraction methods have been reported in the literature. The techniques related to retinal vessel extraction may be roughly categorized into methods based on matched filters [1,2], adaptive thresholds [2], [3], intensity edges [4], [5], region growing [6], statistical inferencing [7], mathematical morphology [8], and Hessian measures [9].

Most of the work on vessel segmentation techniques can be divided into two main groups: Pixel-based methods and tracking methods. An advantage of tracking based methods is the guaranteed connectedness of vessel segments whereas in pixel processing based methods, connectedness is not guaranteed. Besides, as vessels are connected in the retina, tracking methods can follow a whole vascular tree without examining the vast majority of the image that does not contain vessel. Among tracking methods, few probabilistic approaches have been reported in the literature of vessel segmentation [10].

In a previous work [11], a statistical-based method was introduced for retinal vessel segmentation, which needed manual initialization. In this paper, a fully automated trackingbased method is described. This approach takes into account vessel edges detection on the whole retinal image, which was not the case in our previous work, and handles different vessel structures such as vessel bifurcation and crossing.

2. METHOD

2.1. General description

Our method is based on an iterative tracking algorithm. First, a number of seed points are selected automatically on the retinal image. Each seed point provides the initial vessel parameters, including initial vessel edge points, center point and tracking direction. The tracking process starts from each of the seed points and detects vessel edge points iteratively using the proposed Bayesian method. The tracking process from one seed point stops when current vessel ends or encounters detected vessel segments. When all seed points are processed, the proposed algorithm ends.

2.2. Selection of seed points

At the initialization, several seed points are selected automatically by a method combining the grid lines and matched filter. First, the grid lines are drawn on a retinal image and seed points candidates are selected on these lines [4]. Here, we choose local grey level minima as candidates. We build a set of Gaussian kernels [1] with different orientations (12 different orientations spaced in 15 degrees from each other). Then, we convolve the 12 oriented filters with the given retinal image. If the highest response for a point candidate is above a given threshold, it is considered as a seed point, and corresponding filter direction is regarded parallel to local vessel direction. A retial image and its selected seed points are shown in Fig.1.

2.3. Statistical sampling

Our tracking method starts from each of the seed points. Now, we consider a tracking process which is initialized by one of the seed points. At iteration k, vessel edge points \hat{U}_k , \hat{V}_k , center point O_k , direction \overrightarrow{D}_k and diameter d_k are known parameters. O_k is the middle point of $[\hat{U}_k, \hat{V}_k]$, \overrightarrow{D}_k heads towards $\overrightarrow{O_{k-1}O_k}$ and $d_k = |\hat{U}_k\hat{V}_k|$. As shown in Fig.2, a semi-ellipse



(a) retinal image

(b) grid lines and seed points

Fig. 1. Selection of seed points

(c) initial vessel directions

 C_k is defined to be centered on O_k and heading towards \overrightarrow{D}_k . C_k is considered as a dynamic search window restricting the possible locations of new vessel edge points. Its major axis a_k is perpendicular to \overrightarrow{D}_k while the minor axis b_k is parallel to it. In this study, $a_k = 2d_k$ and $b_k = 1.5d_k$.



Fig. 2. Dynamic search window

 N_k edge points candidates which are numbered from 1 to N_k are selected on C_k . In order to choose new edge points among these candidates, we define configuration models by a set of points candidates. There are three types of models: normal, bifurcation and crossing, which combine points candidates on C_k with possible vessel's structures at iteration k+1 (see Fig.3). Any Two points selected from the N_k ones are called a normal configuration, which means a single vessel is assumed to exist at iteration k+1. For a bifurcation configuration, four points are selected to describe the edge points of two supposed new branches. Six points are needed for a crossing configuration.

During the tracking process, local vessel structures and edge points are estimated based on different configurations.

2.4. Vessel detection

At iteration k, $Y_k = \{y_s, s = 1, 2..., N_k\}$ is the discrete grey level profile corresponding to the N_k points on semi-



Fig. 3. Three types of configurations

ellipse C_k . In our study, the probability of a configuration χ is described by $P(\chi|Y_k)$ [11]. Based on the Maximum *a posteriori* (MAP) criterion, the best configuration $\hat{\chi}$ is the one which has the maximum probability among all the configurations, $\hat{\chi} = \arg \max\{P(\chi|Y_k)\}$. Selected points candidates used to define $\hat{\chi}$ are considered as new vessel edge points. With Bayes' rule we obtain $P(\chi|Y_k) = \frac{P(Y_k|\chi) \cdot P(\chi)}{P(Y_k)}$. Because $P(Y_k)$ does not depend on the configuration, it will be disregarded. The best configuration is:

$$\hat{\chi} = \underset{\chi}{\arg\max} \{ P(Y_k|\chi) \cdot P(\chi) \}$$
(1)

Assuming that the discrete grey levels on the semi-ellipse are independent,

$$P(Y_k|\chi) = \prod_{i=1}^{N_k} P(y_i|\chi)$$
⁽²⁾

We suppose the conditional probability model $P(y_i|\chi)$ describes the variability of the i^{th} point on C_k belonging either to the background or to the blood vessel. We consider first the case of a normal configuration χ_n . Two corresponding points M_{m_1} and M_{m_2} are the m_1^{th} and m_2^{th} points on C_k . Likelihood function is expressed as:

$$P(Y_k|\chi_n) = \prod_{i=1}^{m_1-1} P(y_i|b) \prod_{m_1}^{m_2} P(y_i|v) \prod_{m_2+1}^{N_k} P(y_i|b) \quad (3)$$

where b and v denote background and vessel respectively.

In our method, Local vessel's sectional intensity profile is approximated by a Gaussian model, and local background is assumed to have a constant intensity. For the given normal configuration χ_n , true grey level of M_i , the i^{th} point on C_k , is estimated as:

$$\mu_{i} = \begin{cases} G(M_{i}) & if \ i \in [m_{1}, m_{2}] \\ B_{k} & if \ i \in [1, m_{1}[\bigcup]m_{2}, N_{k}] \end{cases}$$
(4)

When $i \in [m_1, m_2]$, M_i is assumed to belong to the blood vessel. Its grey level is estimated by the Gaussian intensity model: $G(M_i) = (A_k - B_k) \exp(-\frac{l_i^2}{2\sigma_{\chi_n}^2}) + B_k$. A_k and B_k are local intensity parameters for vessel and background respectively. A_k is the mean grey level of the region surrounding local vessel center line. B_k is the mean grey level of region in local background. l_i is the distance between M_i and the straight line which passes through the middle point of $[M_{m_1}, M_{m_2}]$ and is perpendicular to $\overline{M_{m_1}M_{m_2}}$. Spread parameter $\sigma_{\chi_n} = \frac{1}{4}|M_{m_1}M_{m_2}|$. If we assume the retinal image affected only by additive white Gaussian noise ξ , the observed grey level of M_i is supposed:

$$y_{i} = \mu_{i} + \xi = \begin{cases} G(M_{i}) + \xi_{v} & if \ i \in [m_{1}, m_{2}] \\ B_{k} + \xi_{b} & if \ i \in [1, m_{1}[\bigcup]m_{2}, N_{k}] \end{cases}$$
(5)

where $\xi_v \sim N(0, \sigma_v^2)$ and $\xi_b \sim N(0, \sigma_b^2)$ are the Gaussian noise in local blood vessel and background respectively. So conditional probability model of χ_n is:

$$\begin{cases} P(y_i|v) = \frac{1}{\sqrt{2\pi\sigma_v}} \exp(-\frac{(y_i - G(M_i))^2}{2\sigma_v^2}) \\ P(y_i|b) = \frac{1}{\sqrt{2\pi\sigma_b}} \exp(-\frac{(y_i - B_k)^2}{2\sigma_b^2}) \end{cases}$$
(6)

And the likelihood function $P(Y_k|\chi_n)$ is obtained by Eq.3.

For the case of bifurcation or crossing, sectional intensity profile of new vessel branches are also estimated by the proposed Gaussian intensity model. Likelihood functions are computed similarly based on the four selected points and six selected points respectively.

The *a priori* distribution of the vessel's contour can be modeled by means of a uni-dimensional Markov Chain. At each iteration k, new edge points are assumed to be detected based on the previous four iterations. The *a priori* probability of a configuration χ is described as:

$$P(\chi) = P(\chi | \hat{\chi}(k-1), \hat{\chi}(k-2), \hat{\chi}(k-3), \hat{\chi}(k-4)) \times P(\hat{\chi}(k-1), \hat{\chi}(k-2), \hat{\chi}(k-3), \hat{\chi}(k-4))$$
(7)

where $\hat{\chi}(k-j)$, j = 1, 2, 3, 4 stands for the best configuration at iteration k-j. At iteration k, $P(\hat{\chi}(k-1), \hat{\chi}(k-2), \hat{\chi}(k-3), \hat{\chi}(k-4))$ is a constant. The way of computing $P(\chi|\hat{\chi}(k-1), \hat{\chi}(k-2), \hat{\chi}(k-3), \hat{\chi}(k-4))$ does not depend on the nature of the configuration. Therefore, $P(\chi)$ will be disregarded, and based on Eq.1 the best configuration at iteration k is:

$$\hat{\chi} = \underset{\chi}{\arg\max} \{ P(Y_k|\chi) \}$$
(8)

If $\hat{\chi}$ is a normal configuration, the local blood vessel is considered to be linear and two candidate points used to define $\hat{\chi}$ are regarded as new vessel edge points. If $\hat{\chi}$ is a bifurcation or crossing configuration, new vessel branches are found. In this case, four or six selected candidate points according to $\hat{\chi}$ are considered as initial edge points of new branches, from which the tracking of vessel branches starts.

3. EXPERIMENTAL RESULTS

The proposed method is evaluated on the public STARE database [2]. It contains twenty retinal fundus images captured by a TopCon TRV-50 fundus camera at 35° field of view (FOV). These retinal images are segmented manually by two independent specialists. In experiments, segmentation results of the first observer is used as ground truth.

We tested our algorithm on 20 images of STARE database [2]. In this study, we join detected edge points and fill regions inside these obtained edge lines to get the segmented blood vessels. Hoover's [2] filter-based method is also applied for comparison purpose. We performed a ROC analysis to assess the accuracy. If a pixel in detected blood vessel belongs to true blood vessel, it is called true positive pixel. Otherwise, it is a false positive if it does not belong to true blood vessel. True positive rate (TPR) is defined as the ratio between the number of true positive pixels and the total number of pixels in true blood vessel. False positive rate (FPR) is the ratio between the number of false positive pixels and the total number of pixels in the true background. The evaluation accuracy is defined as the ratio of the total number of correctly classified pixels to the number of pixels in the FOV. Test results of the proposed method, Hoover's method and the manual segmentations of the second observer are shown in Table.1. We can

Table 1. Evaluation results of different methods on 20 retinal images of STARE database.

Method	TPR	FPR	Accuracy
2nd observer	0.8949	0.0610	0.9354
Hoover [2]	0.6751	0.0433	0.9267
Proposed	0.6887	0.0438	0.9290

see that both the TPR and accuracy of the proposed method are higher than Hoover's. Besides, the FPR of our method is even lower than manual segmentation results. An example is given in Fig.4, which presents a retinal image from the



Fig. 4. Segmentation results on retinal image (im0077) from the STARE database.

STARE database, the corresponding ground truth, and segmentation results of two different methods. Initial seed points of our method on this retinal image are shown in Fig.1(b). The proposed method detected most of the vascular tree and performed better than Hoover's method.

4. CONCLUSION

We have introduced an automatic tracking method for vessel detection in retinal images. The tracking algorithm starts from a number of seed points selected all over the image. It managed to segment main vascular trees and detect different vessel structures. Tests of the proposed method on STARE database show promising results. The necessary work in the future includes improvements of the vessel sectional intensity model and a deeper evaluation on more retinal images.

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