

AN IMPROVED APPROACH FOR RETINAL VASCULAR SKELETON EXTRACTION IN FUNDUS IMAGES

¹JIANJUN SUN, ²LIANFEN HUANG ³✉ YUE HUANG

¹Assoc. Prof., Department of Radiology, the 476th clinic section of FUZHOU general Hospital of the PLA, Fuzhou, Fujian, China

² Assoc. Prof., School of Information Science and Engineering, Xiamen University, Xiamen, Fujian, China

³Asstt. Prof., School of Information Science and Engineering, Xiamen University, Xiamen, Fujian, China

E-mail: ✉ yhuang2010@xmu.edu.cn

ABSTRACT

Retinal vascular imaging system offers a noninvasive research tool to probe the pathophysiology of the microvasculature. Retinal vascular skeleton extraction from fundus images is an essential step to analyze the retinal vascular branching pattern. An improved tracing based approach is presented in this work to extract the centerlines for retinal vasculatures in the fundus images automatically. Compared with existing work, the major contribution of the proposed algorithm is that it incorporates geometrical information and intensity distribution of the retinal vessels to define a new tracking updated direction scheme. In addition, the scale value in defining Hessian matrix is also dynamic and self-adaptive, as well as the size of searching window in identifying the boundary positions during the tracing process. Experiments results and validations have demonstrated that proposed approach has satisfied accuracy in vessel skeleton tracking.

Keywords: *Retinal Vessel Image; Image Processing; Skeleton Extraction; Direct Exploratory; Hessian Matrix Analysis*

1. INTRODUCTION

Retinal vessels are the only parts of the central circulation that can be observed and studied in vivo (1). Retinal vessel imaging systems, which take photographs of the back of the eyes, have significant potential as a noninvasive method for assessing retinal function (2). It has been reported that the studies on the morphology of retinal vascular play important roles in analyzing and diagnosing diseases such as hypertension, arteriosclerosis and diabetes, which affect the morphological pattern and functional characteristics of blood vessels (3, 4). Considered that manual labeling and analyzing are strongly time-consuming, fully automated image processing for retinal vessel image, especially vascular skeleton extraction is a prerequisite step in subsequent automatic vessel branching pattern analysis and automatic diagnosis systems(5).

Stacks of literatures have been devoted to the study on retinal vessel segmentation and extraction. Techniques such as matched filters, piece-wise threshold probing, region growing, probabilistic approach, scale multiplication, Gabor filters, wavelets, morphology edge operator and other supervised methods have been reported in the

existing work (6-12). Major purposes of these algorithms are segmenting retinal vessels from noisy and low contrast fundus images, and other processing steps such as skeleton extraction is always considered as a post-processing step. Another category of computational-aided medical research for retinal vessel images focuses on the extraction the vessel skeletons which are connected by centerline segments directly. The contribution of the latter category is that they can extract the skeleton line-structure vessel only while avoiding the challenges of dealing with other structure like optic disc and pathologies in the image. Skeleton extraction is very useful in assisting researchers in studying the tree structure of retinal vessel efficiently and effectively. Also, it has been reported as the first step in retinal vessel segmentation by reconstructing vessels from extracted centerlines (13).

Retinal vessels are always assumed to have a lower reflectance compared to the local background. In addition, their edges are well defined and the intensity within the vessels varies smoothly. Existing methods in retinal vessel centerline processing can be roughly categorized into two groups. The first one is always referred to as direct exploratory tracing, or vector tracing based

approaches. The tracing algorithm models line-like structure, such as retinal vessel in this work, as piecewise linear generalized cylinder segments (3, 14). Seed points are automatically selected by rough grid searching at the beginning of tracing, and then the tracking process starts from the initial points and the tracking is updated recursively until certain pre-defined stop criteria are satisfied(15, 16). The coordinates and orientation of each

centerline point is determined by the corresponding boundary identification, which can be derived by applying templates and calculating correlation between patterns and original image(17). Approaches in this category are efficient since only pixels close to the ideal centerlines are processed; in addition, no linking step is required as post-processing.

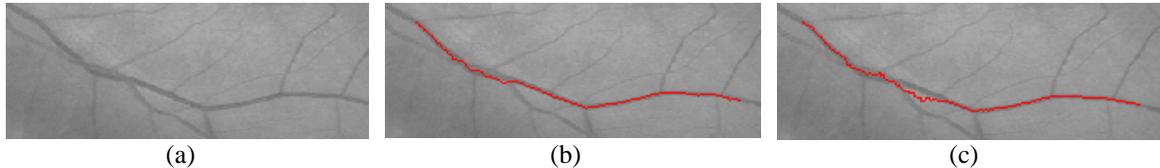


Figure 1 Performances Comparison Between Proposed Approach And Traditional Exploratory Method In Vessel Overlapping. Original Image Is Shown In (A), Tracking Results With (B) The Proposed Method, And (C) Direct Exploratory Approach.



Figure 2 Performances Comparison Between (A) Direct Exploratory Approach And (B) Proposed Method With Vessel Bifurcation. (C) And (D) Are Close Observation Of A Crop In (A) And (C) Respectively.

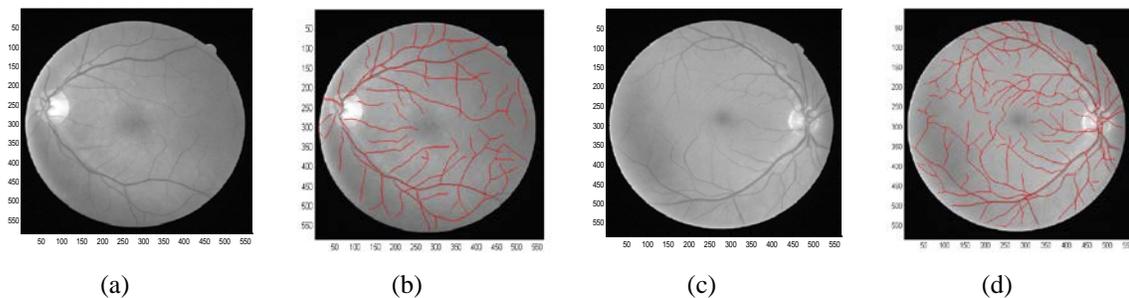


Figure 3 Tracking Results From Proposed Method In Retinal Vessel Images From DRIVE Database.

Algorithms in the second group are often called curvilinear structure detector, or ridge based approaches, which consider intensity image as 3D elevation maps in which intensity ridges or valleys approximating the skeleton of the line-structure.(18, 19) Eigen-analysis of Hessian matrix is always applied to estimate the orientation of each pixel in the image (20). The line structure skeletons can be derived by modeling the profile of the line-structure and examining its first and second derivatives with Gaussian kernel along the profiles (21). Hysteresis linking phrase is usually necessary in the post-processing to connect all the centerline points and detect the bifurcation markers (22). It has been

discussed that curvilinear structure detector always achieve high accuracy in centerline extraction; however, its performances are still limited especially on low contrast objects since the image is smoothen by the Gaussian filter(23). It also suffers from the limitation of high computational cost since it exams every pixel in the image.

The main purpose of the work is to improve the accuracy of current exploratory approach in tracing the skeleton network of retinal vasculature and try to minimum the user interactions. The framework of the paper is organized as follows: data description and methodology are detailed proposed in section 2 and section 3; Results of proposed

approach is presented in section 4; finally we make a discussion and conclude the work.

2. DATABASE DESCRIPTIONS

All the images in this work come from the popular public retinal vessel image database DRIVE, which has been established in Utrecht University. DRIVE consists of 40 images (7 with pathologies) captured by a Canon CR5 3CCD camera with 45 FOV. The slides were digitized to 700×605 pixels with 8 bits per color channel. The FOV in the images is approximately 650×550 pixels (18). Detailed description is available in <http://www.isi.uu.nl/Research/Databases/DRIVE/>.

3. METHODOLOGY

Seed points, which are the original points for tracking, are labeled manually with the positions and their directions.

The core step of the direct exploratory approach is the tracking process, which is based on the adaptive tracking processing of the image(24). Traditional exploratory procedure sequentially detects the incremental sections along a retinal vessel segment.

Starting from a detected seed point p_i on or near the centerline, and an initial estimate of the direction u_i , the line structure is traced recursively, estimating and refining successive points p_{i+1}, p_{i+2}, \dots , along the centerline. The processing is repeated until a stopping criterion is satisfied. Typical edge based exploratory approach will be introduced at first, followed by description of proposal improved method.

As discussed above, the basic idea of exploratory algorithm contains two steps, estimation and correction. Before processing, it should be mentioned at first that all the directions in a two dimension digital image are quantized into 16 directions, each indicated by an index number from the set u_i , where $i = 0, 1, 2, \dots, 15$.

(1) Given the coordinate and orientation of current centerline point p_i , the next centerline point along the process p_{i+1} can be predicted by the following update equation of the form:

$$p_{k+1} = p_k + du_k, \quad (1)$$

Where p_k is the x-y coordinate of current centerline point, p_{k+1} is the position of next vessel skeleton point from prediction, \sim indicates approximation, d is the forward step size, and u_k is the orientation of the current point p_k .

(2) Fine-turning step is applied to p_{k+1} for extracting the precise direction and coordinate of centerline point p_{k+1} derived from prediction in Eq.(1). p_{k+1} can be achieved by Eq.(1), however, it may not exist exactly on the centerline. Therefore, the core issue in direct exploratory is the correction step. With the direction u_k , it is possible to define two direction vector perpendiculars to u_k , which can be assigned as u_{Rk} and u_{Lk} respectively. The edge points corresponding to p_{k+1} , both in left side and right side can be determined by scanning along the direction u_{Rk} and u_{Lk} from p_{k+1} . The two dimension 5×6 kernels are considered as a 'template' in searching the vessel boundary approximated positions. For convenience of exposition, the templates are grouped as left and right templates, which can be denoted as T_{Li} , and T_{Ri} , with subscripts L, R, i , indicating the left side, right side and i th direction respectively. The algorithm motives an exhaustive search by scanning all the pixels within a pre-defined searching window along the direction u_{Rk} and u_{Lk} , with the templates rotated in different directions. The template response at a location p_{k+1} with coordinate (x, y) along the direction u_{Rk} and u_{Lk} is expressed as:

$$R_i(x, y, u_{Rk}) = \sum_{x,y} I(x+n, y+m)T_{Ri} \quad (2)$$

$$L_i(x, y, u_{Lk}) = \sum_{x,y} I(x+n, y+m)T_{Li} \quad (3)$$

Where R_i and L_i denote the correlation between the neighborhoods of p_{k+1} in the image data I , and the right, left template T_{Li} , and T_{Ri} , by scanning

through the direction u_{Rk} and u_{Lk} . The subscription i indicates the i th direction in the orientation set u_i . Location and orientations of boundary points are then estimated as those resulting in maximum template responses. Finally, \tilde{p}_{k+1} is updated to p_{k+1} by averaging the left and right boundary locations where the template response on each boundary is locally a maximum.

(3) Return to step (2) to obtain the subsequent skeleton chain until some stop criterions are satisfied.

As discussed in the introduction, direct exploratory approach and curvilinear structure detector are two major categories in detecting line-structure objects. Direct exploratory approach focuses on the geometrical topological feature of retinal vessels in the image only. Curvilinear structure detector always treats grayscale images as 3D elevation maps, in which the intensity ridges approximate the medial axes of the tubular objects such as vessels. The proposed method follows the basic idea of vector tracing, and then employs combination of two kinds of approaches in order to incorporate geometrical topological information and intensity distribution at the same time in order to achieve a better performance in the centerline point direction update scheme. A brief introduction of curvilinear structure detector will be introduced first, and then the contribution of proposal approach will be discussed later.

One of the key steps in curvilinear structure approaches is the construction and eigen-analysis of the Hessian matrix, which can be defined as follows:

$$H = \begin{bmatrix} I_{xx}(\sigma), I_{xy}(\sigma) \\ I_{yx}(\sigma), I_{yy}(\sigma) \end{bmatrix} \quad (4)$$

Where I_{xx}, I_{xy}, I_{yx} and I_{yy} are the normalized second order derivatives along the x, y directions from the intensity image, which can be generated by convolving the image with a derivative of the Gaussian kernel,

$$I_{uv}''(\sigma) = I * G_{uv}''(\sigma) \quad (5)$$

where G denotes a Gaussian kernel, subscripts u and v represents x or y direction, σ is the scale of Gaussian kernel(27, 28).

A key parameter in the Hessian matrix construction is how to select the appropriate scale of Gaussian filter, the σ in Eq.(4) and (5). According to the literatures, the scale proportional to the width of current centerline point in retinal vessel. Existing methods determine σ from an ordered list of scale, in which the largest and smallest elements of the list are pre-defined by the users, as well as the step size in the ranges(22). Different scales generate different Hessian matrixes and then lead to different eigenvalues, therefore, the appropriate scale is the one which leads to the maximum absolute value among all the eigenvalues. However, in retinal vessels, vessel width varies from images in the stacks, so it is time-consuming for the users to measure and determine maximum and minimum value of the list for each image. As mentioned above, the proposal approach follows the basic idea of direct exploratory to trace the vessels and obtain the skeletons, so it is possible to derive the width of a given local point from a pair of boundary points. Based on the discussion, we utilize the width corresponding to centerline

point P_k , called w_k , to simulate the scale value in constructing Hessian matrix for the next centerline point P_{k+1} , which avoids facing the difficulty in defining the scale range for each individual image.

After eigen-analysis of Hessian matrix, two eigenvalues and their corresponding eigenvectors are obtained. One eigenvector points to the direction of the vessel, while the other eigenvector corresponds to the orthogonal direction of the vessel. In retinal vessel images, vessels are dark line-structures surrounded by the brighter background; therefore, skeletons of the vessels are the valley of the image and curvilinear structure detector method in this paper becomes valley based algorithm. Let λ_1 and λ_2 denote the two eigenvalues of the Hessian matrix in Eq.(4), v_1 and v_2 represent the corresponding eigenvectors, while it is also assumed that the two eigenvalues are ordered by $|\lambda_1| < |\lambda_2|$. Based on this, the direction u for the local point in the vessel can be represented by normalized eigenvector v_1 , as shown in the expression: $\|u\|_2 = 1$.

In order to incorporate the geometrical information with the intensity information, the proposal algorithm defines the direction of each centerline point as(29):

$$u_k = \alpha u_{ke} + (1 - \alpha) u_{kc} \quad (6)$$

where α is the weighted factor which ranges from 0 to 1, subscription k denotes the k th iteration in the tracing process, u_{ke} represents the normalized direction from the average boundary orientations, which is similar in direct exploratory approach; while u_{kc} is derived from eigen-analysis of Hessian matrix(27, 29). The definition in Eq.(6) considers both geometrical information and intensity distribution, which will lead to a better orientation estimation performance.

u_{ke} in Eq.(6) is determined by the geometrical topology of vessels, and can be derived from the directions of boundary points. Before direction estimation, the location of boundary points should be identified at first. As described before, two kinds of rotated templates are utilized in the correlation calculation, as shown in Eq.(2) and (3). It is necessary to start an exhaustive scan on each pixel along the given orientation u_{Rk} and u_{Lk} respectively, until it reaches the given maximum value of fixed iteration number $M/2$. It should be noticed that, in the searching process, correlation measurement has to be performed between image data and rotated pattern at different directions pixel by pixel along the given orientation. For example, the orientation space has been discredited to 16 values, yielding an angular precision of 22.5° and a total of 32 left and right templates; in addition, the maximum step size of scanning for each side is 5 pixels, therefore, $32*5=160$ correlation calculations is processed in the searching for one centerline point. In order to accelerate the process, the proposed method employs the results of Hessian matrix to define the boundary points. While defining the Hessian matrix, second order derivatives of the image along x and y direction are calculated; in addition, temporary local orientation is given as u_k ; it is possible to derive the second order derivative of vessel profile with the direction perpendicular to u_k at local point by adopting steerable filters, as expressed as:

$$I''_{uk} = u_{xk}^2 I''_{xx} + 2u_{xk}u_{yk} I''_{xy} + u_{yk}^2 I''_{yy} \quad (7)$$

Where u_{xk} and u_{yk} indicate the normalized elements of u_k (30, 31).The partial derivatives in Eq.(7) can be treated as the likelihood of a point

belonging to the centerline, and also can be called 'strength value' or 'vessel confidence'(32). This value will change dramatically in the boundary position. In the correction step, given the orientation of centerline point P_k and the approximating position \tilde{P}_{k+1} , we will still motive the searching along the perpendicular direction of u_k from \tilde{P}_{k+1} , which are u_{Rk} and u_{Lk} . It is also possible to calculate strength value along the profile of \tilde{P}_{k+1} . In the scanning process of each side, if the detected strength value of a pixel is smaller than a predefine threshold, it will be considered as a boundary and the searching process stops. Since the scanning is applied along two perpendicular direction of u_k , there are two searching processes and the corresponding boundary position vector B_L and B_R could be identified. It is also necessary to estimate orientation of the boundaries; the proposal approach follows the idea in typical direct exploratory approaches which estimates the directions by calculating the correlation between rotated patterns and image data.

Moreover, the size of searching window is also adopted to be dynamic, which is assigned to be $1.5 W_k$, where W_k is the vessel width corresponding to previous centerline point P_k . This definition is based on the assumption that the vessel width does not change abruptly in the tracing process.

The fully automated proposal algorithm can be finally concluded as following:

- (1) Preprocessing is applied first to enhance the image contrast based on basic approaches, such as morphological operator and intensity adjustment.
- (2) Seed points are detected in order to be the starting point and ending points in the tracing process of following modified exploratory method.

Tracing framework in the work is similar as the traditional vector tracking, as described in 3.2.1. However, orientation updating scheme is modified by combining information from geometrical information and intensity information. Given a centerline point P_k and its orientation u_k , an approximation position of the next point \tilde{P}_{k+1} is predicted by Eq.(1). Hessian matrix is then constructed, as well as the strength value profile

along the perpendicular direction of u_k . Boundary identification can be finished by searching \tilde{p}_{k+1} in the strength value image, and their orientations are also estimated based on correlation measurement with rotated templates. After that, both of the position of p_{k+1} and its orientation are derived. Finally, the estimated direction of p_{k+1} is updated by Eq.(6).

4. RESULTS

As discussed above, each seed point is the first point of each tracing chain, and it may not exist exactly on the centerline of the retinal vessel segment. In addition, there is no prior direction estimation for a seed point; all we have is its coordinate. Therefore, traditional direct exploratory approach is applied here to refine its position and to estimate the direction. For the convenience in the implementation of Eq.(6), normalization is necessary. In the proposal algorithm, all the directions space in the image is quantized into 16 values, and then it is easy to get them normalized with $\|u_k\|_2 = 1$. After the calculating in Eq.(6), u_k is re-normalized to be an element in direction set u_i , and will be applied in the tracking process. In the proposed work, direction space is discrete into 16 values, and then the forward step in tracking is fixed 2 pixels so far. Another parameter in Eq.(6) is the weight value α is setup to be 0.5, which takes account the geometrical information and intensity information equally.

Performances comparisons are tested especially in cases with complicated vessel distribution, such as overlapping and bifurcation, as shown in Fig.1 and Fig.2. Vessel skeletons identified from different methods are overlaid over the original images with red lines. It should be mentioned that the extracted centerlines in each case start from the same given seed point and have the same tracing length. Original image with vessel overlapping is shown in Fig.1(a), and tracking results achieved from proposed method and exploratory method without Hessian matrix analysis respectively, shown in Fig.1(b) and (c). It can be observed in Fig.1(c) that the centerline of one vessel segment appears to jump to another vessel in overlapping area, and then deviates outside the vessel. Typical case of vessel bifurcation is shown in Fig.2, Fig.2(c) and Fig.2 (d) are close investigation of Fig.2 (a) and Fig.2 (b) respectively. As in Fig.2(c), extracted centerline

points to the background instead of following either vessel in the bifurcation area. Performance from the proposed approach in Fig.2 (d) is satisfied. Tracking in Fig.1 and Fig.2 have demonstrated that the tracking results from the proposed method have higher accuracy. Tracing results of four retinal vessel images in DRIVE database are shown in Fig.3.

5. DISCUSSION AND CONCLUSIONS

The method proposed in the paper has proved to be a valuable research tool for extract the retinal vascular skeleton network in retinal images. The main purpose of this work is to propose a novel approach to improve the performance of skeleton extraction of retinal vascular network, especially in some complicated situations, such as bifurcation and crossing area. Major contributions of the proposed approach can be organized into two parts: firstly, a improved seed point detection algorithm is presented to assign starting point and ending point for each tracing segment, which employs SNR measurement to remove redundant seed points from rough grid searching; secondly, a new tracking direction estimation scheme which incorporates geometrical and intensity features of the vascular structure is presented to yield higher estimation accuracy; in the application, the scale value of Gaussian model in defining Hessian matrix is self-adaptive, which is helpful to reduce the interactions from users and improve estimating performance; a dynamic searching window acknowledges the vessel width of previous traced centerline point is applied for detection of current boundary points. Quantitative analysis in validation section has demonstrated that performances from program have strong similarity with manual labeling.

We hereby conclude the work by discussing some of the possible extensions to the proposed approach. After centerline extraction, retinal vasculature can be represented by a tree skeleton and then topological properties of the retinal vascular structure can be studied after some of post-processing such as land-markers detection. Branching pattern study on retinal vasculature such as branching angle, length, and even branching order analysis, can be treated as a novel implementation of current studies on quantitative analysis on retinal vessel, which mainly focus on the diameter measurement or tortuosity measurements.

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