Identifying All True Vessels From Segmented Retinal Images

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***Abstract*—Measurements of retinal blood vessel morphology have been shown to be related to the risk of cardiovascular diseases. The wrong identification of vessels may result in a large variation of these measurements, leading to a wrong clinical diagnosis Both the arteries and veins of the retina are generally binary trees, whose properties can be considered either locally or globally. Measurable geometrical changes in diameter, branching angle, length, or tortuosity, as a result of disease, have been described in retinal blood vessels. The detection and measurement of retinal blood vessels can be used to quantify the severity of disease such as hypertension, stroke and arteriosclerosis, as part of the process of automated diagnosis of disease or in the assessment of the progression of therapy. Thus, a reliable method of vessel detection and quantification would be valuable. In this paper, we address the problem of identifying true vessels as a postprocessing step to vascular structure segmentation. We model the segmented vascular structure as a vessel segment graph and formulate the problem of identifying vessels as one of finding the optimal forest in the graph given a set of constraints.**

***Index Terms*—Ophthalmology, optimal vessel forest, retinal image analysis, simultaneous vessel identification, vascular structure.**

I. INTRODUCTION

A retinal image provides a snapshot of what is happening inside the human body. In particular, the state of the retinal vessels has been shown to reflect the cardiovascular condition of the body. Measurements to quantify retinal vascular structure and properties have shown to provide good diagnostic capabilities for the risk of cardiovascular diseases. For example, the central retinal artery equivalent (CRAE) and the central retinal vein equivalent (CRVE) are measurements of the diameters of the six largest arteries and veins in the retinal image, respectively. These measurements are found to have good correlation with hypertension, coronary heart disease, and stroke. However, they require the accurate extraction of distinct vessels from a retinal image. This is a challenging problem due to ambiguities caused by vessel bifurcations and crossovers. In order to disambiguate between vessels at bifurcations and crossovers, we need to figure out if linking a vessel segment to one vessel will lead to an adjacent vessel being wrongly identified.

By considering multiple vessels simultaneously, information from other vessels can be used to better decide on the linking of vessel segments. In this paper, we describe a novel technique that utilizes the global information of the segmented vascular structure to correctly identify true vessels in a retinal image. We model the segmented vascular structure as a vessel segment graph and transform the problem of identifying true vessels to that of finding an optimal forest in the graph. An objective function to score forests is designed based on directional information. Our proposed solution employs candidate generation and expert knowledge to prune the search space.

II. LITERATURE SURVEY

Image processing involves changing the nature of an image in order to either improve its pictorial information for human interpretation and also for autonomous machine perception**.** Image processing is the perception of several algorithm that take an image as input and proceeds an image as output. Retinal vessel extraction involves segmentation of vascular structure and identification of distinct vessels by linking up segments in the vascular structure to give complete vessels. The work in [9] required the user to resolve the connectivity of bifurcation and crossover points before vessels were individually identified. For [10], a graph formulation was used with Dijkstra's shortest path algorithm to identify the central vein. Similarly, Joshi *et al.* [11] used Dijkstra's algorithm to identify vessels one at-a-time. Al-Diri *et al.* [12] used expert rules to resolve vessel crossovers and locally linked up segments at these crossovers to give a vascular network . Our work is focused on vessel identification as a postprocessing step to segmentation. Our approach differs from existing works in that we identify multiple vessels simultaneously and use global structural information to figure out if linking a vessel

segment to one vessel will lead to an overlapping or adjacent vessel being wrongly identified.

III. VESSEL SEGMENTATION

A. Preprocessing

Color fundus images often show important lighting variations, poor contrast and noise. In order to reduce these imperfections and generate images more suitable for extracting the pixel features demanded in the classification step, a preprocessing comprising the following steps is applied:

1) *Vessel Central Light Reflex Removal:* Since retinal blood vessels have lower reflectance when compared to other retinal surfaces, they appear darker than the background. To remove this brighter strip, the green plane of the image is filtered by applying a morphological opening using a three-pixel diameter disc, defined in a square grid by using eight-connexity , as structuring element.

2) *Background Homogenization:* Fundus images often contain background intensity variation due to non uniform illumination. Consequently, background pixels may have different intensity for the same image and, although their gray-levels are usually higher than those of vessel pixels (in relation to green channel images), the intensity values of some background pixels is comparable to that of brighter vessel pixels. Since the feature vector used to represent a pixel in the classification stage is formed by gray-scale values, this effect may worsen the performance of the vessel segmentation methodology. With the purpose of removing these background lightening variations, a shade-corrected image is accomplished from a background estimate.

3) *Vessel Enhancement:* The final preprocessing step consists on generating a new vessel-enhanced image , which proves more suitable for further extraction of moment invariants-based features Vessel enhancement is performed by estimating the complementary image of the homogenized image and subsequently applying the morphological *Top-Hat transformation* where a morphological opening operation is done by using a disc of eight pixels in radius.

B. Segmentation

Retinal vessel extraction involves segmentation of vascular structure and identification of distinct vessels by linking up segments in the vascular structure to give complete vessels. One branch of works, termed vessel tracking, performs vessel segmentation and identification at the same time [5]–[8]. These methods require the start points of vessels to be predetermined. Each vessel is tracked individually by repeatedly finding the next vessel point with a scoring function that considers the pixel intensity and orientation in the vicinity of the current point in the image. Bifurcations and crossovers are detected using some intensity profile. Tracking for the same vessel then continues along the most likely path. This approach of tracking vessels one-at-a-time does not provide sufficient information for disambiguating vessels at bifurcations and crossovers. Another branch of works treat vessel identification as a postprocessing step to segmentation [9]–[11].The Kirsch operator or Kirsch compass kernel is a non-linear edge detector that finds the maximum edge strength in a few predetermined directions. The operator takes a single kernel mask and rotates it in 45 degree. The edge magnitude of the Kirsch operator is calculated as the maximum magnitude across all directions.

The Kirsch operator is made up of a number of templates. Each template focuses on the edge strength in one direction. For each voxel, the Kirsch algorithm cycles through the desired number of directions and assigns an attribute (as specified by the parameter ``function'') of the best direction to the voxel. The best direction is the direction indicating the largest edge strength (gradient magnitude). The masks of this Kirsch technique are defined by considering a single mask and rotating it to eight main compass directions: North, Northwest, West, Southwest, South, Southeast, East and Northeast. It perform segmentation at various image resolutions. The main advantage of this technique is its high processing speed. Major structures(larger vessels in our application domain)are extracted from low resolution images while fine structures are extracted at high resolution. Another advantage is the high robustness. The edges in the image depict the topological connectivity of the vessel structures.

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IV. GRAPH TRACER

To identify vessels and represent them in the form of binary trees for subsequent vessel measurements. It has two main steps: 1) identify crossovers, and 2) search for the optimal forest (set of vessel trees).The details of tracing algorithm, Graph Tracer. The input is the segment graph GP with n root segments given in Sroot . Initialize the global variables and call the recursive procedure Trace. F[1. .n] corresponds to the initial forest of n vessels. R[1. .n] denotes a fringe stack for each

vessel. Fmin and cmin record the minimum cost forest and its corresponding cost. In Trace, if F satisfies all constraints and cannot be grown further, update Fmin if cost(F) < cmin.

Otherwise, it may prune descendant forests grown from F with the lower bound LBcost(F) . The outer loop orders each vessel T ∈ [1, n] for growth. T ranges from the current index i to n, ensuring that Trace does not enumerate duplicate forests. Each vessel's fringe stack, R[T], stores its current leaf nodes to be grown. R[T] is used in conjunction with the loop to enumerate vessels in a depth-first traversal order. A subprocedure FindChildren returns pairs (sl, sr) of possible children for the current fringe node sT . If only one child is to be added, we set sr = 0. FindChildren eliminates many combinations using the constraints presented.

A set of such binary trees is called a *forest* A binary tree is a natural representation of an actual blood vessel as it only bifurcates. Segment end points near the inner circle of the zone of interest are automatically identified as root pixels. The root of each tree corresponds to the root segment that contains a unique root pixel.

Given a segment graph $G_P = (S_P, E_P)$, and a set of root segments S_{root}, let F_P be the set of al possible forests from G_P for each root segment in S_{root} . The optimal forest, $F^* \in F_P$ that corresponds to vessels in G_P is given by $F^* = \text{argmin}_{F \in F_P} cost(F)$.

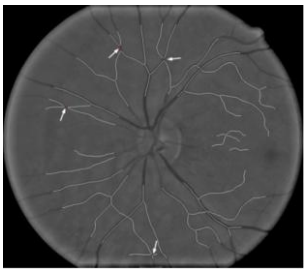
The constraints are 1) Roots are unique to each tree. 2) Directional change between parent and child segments are within the threshold.3) Any segment appearing in more than one tree must be a crossover segment. 4) A parent segment at crossover junction must connect to the child with minimum directional change.5) Crossover segment is the only child and have only one child that has the minimum directional change.6) Leaf segments cannot be crossovers segments.

V. EXPERIMENT RESULTS

We evaluate our proposed method on DRIVE database. For each image, the edges of the retinal vessels is obtained using the semi automated retinal Kirsch Edge Detection. Trained human graders then follow a protocol to verify the correctness of the vascular structure obtained, e.g., arteries, veins, crossover locations, and branch points. We use these verified vascular structures as the *gold* standard and call the corresponding vessel center lines as *clean* line images. The vessel measurements CRAE and CRVE, and average curvature tortuosity of arteries (*CTa*) and veins (*CTv*) have been found to be correlated with risk factors of cardiovascular diseases and are positive real numbers. CRAE and CRVE are computed by iteratively combining the mean widths of consecutive pairs of vessels in the Big6 arteries and veins [19], respectively, as follows:

Arteries: $\hat{} w = 0.88 \cdot (w21 + w22)12$
Veins: $\hat{} w = 0.95 \cdot (w21 + w22)12$

where$w1$, $w2$ is a pair of width values and $\hat{} w$ is the new combined width value for the next iteration. Iteration stops when one width value remains.



Identified crossover segments indicated by the white arrows

VI. CONCLUSION

We have presented a novel technique to identify true vessels from retinal images. The accurate identification of vessels is key to obtaining reliable vascular morphology measurements for clinical studies. The proposed method is a postprocessing step to vessel segmentation. The problem is modeled as finding the optimal vessel forest from a graph with constraints on the vessel trees. All vessel trees are taken into account when finding the optimal forest; therefore, this global approach is acutely aware of the mislinking of vessels. Experiment results on a large real world population study show that the proposed approach leads to accurate identification of vessels and is scalable.

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