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Automatic Graph-Based Method for Classification of Retinal Vascular Bifurcations and Crossovers

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***Abstract*— Implementing an automatic algorithm for classification of retinal vessel landmarks as bifurcation and crossovers will help the experts to analyze retinal images and detect the abnormalities of vascular topology in less time. It also can be used as the initial step of an automatic vessel classification system which is worthwhile in automatic screening programs. In this paper, we proposed a graph based method for automatic classification of vessel landmarks which consist of three steps: generating vasculature graph from centerline image, modifying the extracted graph to reduce the errors and finally classifying vessel landmarks as bifurcations and crossovers. We evaluated the proposed method by comparing the results with manually labeled images from DRIVE dataset. The average accuracy for detection of bifurcations and crossovers are 86.5% and 58.7% respectively.**

Keywords—Retinal Vessel Landmarks; Crossover; Bifurcation; Automatic Classification; Graph

I. INTRODUCTION

Changes in blood vessel features such as caliber and tortuosity, is one of the preliminary signs of a wide range of systemic diseases, e.g. diabetes, hypertension and other cardiovascular conditions. Thus, regular examination of human vascular system will be very helpful in early diagnosis of such diseases. Retinal blood vessels, as the only part of vascular system that can be observed directly with noninvasive techniques, is of great importance.

Accordingly, many advanced researches are focused on automatic processing of retinal images to obtain beneficial information for automatic screening and diagnosis systems. The most predominant field of study is the separation and classification of blood vessels into arteries and veins. A prior step to this task, is vessel landmark detection and classification into bifurcations and crossovers which is subjected in this paper.

Several methods have been proposed in the literature for retinal vessel landmark analysis. Tsai et al. [1] proposed a model-based algorithm for estimating the location of vascular bifurcations and crossovers in retinal images but did not classify them. Bevilacqua et al. [2] puts a 3×3 window on centerline pixels and uses the number of color changes within the window's border for landmark classification. Three color changes indicates a bifurcation and four shows a crossover. The main problem of using a small fixed size window is misclassification of crossover points which are split into two close bifurcations. This situation happens when two vessels cross at an acute angle. Aibinu et al. [3] improved the previous work by adding a 5×5 window for detection of crossovers turned into two bifurcations. Bhuiyan et al. [4] addressed this problem by analyzing geometrical and topological properties of potential landmarks extracted from vessel centerline to identify true bifurcations and crossovers. In this paper, it is assumed that the acute angle between the opposite line segments, which has the closest slope values, should be greater than 120° for the same vessel. Therefore, nearby landmarks that do not satisfy this assumption, will be considered as a single crossover point. Hamad et al. [5] also described this issue and proposed more accurate criteria based on relations between widths and directions of vessel segments involved in a bifurcation, direct crossover and nondirect crossings (crossovers divided into two bifurcations). Calvo et al. [6] used a vote system with three windows with different radius sizes to make the points classification better. Subsequently, further checking is done to merge two connected nearby bifurcations or crossovers as a single crossover point. Reference [7] extends the method proposed in [4] by adding a SVM classifier to indicate whether two close points should or should not be combined as a single crossover. Fathi et al. [8] introduced a local vessel pattern operator with circular structure for detection and classification of vessel landmarks. This operator is applied to the centerline pixels and each point is classified based on the number of vessels which are intersected with the perimeter of the corresponding circle. Additional structural analysis is also included to increase the accuracy of classification. In this step if the distance between two vessel landmarks is less than a threshold, which is defined locally based on vessel diameters and crossing angles, they will be merged as a single crossover. Dashtbozorg et al. [9] also described new equations to estimate a proper distance threshold for detection of such crossovers. Sánchez et al. [10] uses a fixed size circular window on the interest points and mark the intersection points of vessel segments with the border of the window as cutoff points. Then finds connected segments by calculating the minimal path between each cutoff and interest point. Finally the interest point is classified as bifurcation or crossover after further analysis is done on the connected cutoff points based on their position relative to the interest point.

Most of the above-mentioned methods suffer from the disadvantage of using a fixed size window. Although [8] and [9] tried to improve the accuracy by utilizing adaptive thresholds dependent on local vessels caliber and branching angle, they are not as accurate as needed for vessel classification yet. In this paper, we propose a new method for vessel landmarks classification which benefits from other structural features of retinal vessels, e.g. vessel growth direction, to increase system efficiency. These properties are gained by modeling the vasculature as a directed graph.

This paper is organized as follows: Section II describes the components of the proposed system and results of test are presented in section III. Finally section IV summarizes the conclusions of the research.

II. Proposed Method

In this section, a new method for detection and classification of retinal blood vessel landmarks, i.e. bifurcations and crossovers, is proposed. This method contains three stages. First, a directed graph is extracted from vessel centerlines. Then, some vertices and edges are modified to enhance the graph. Finally, each node's type is determined based on its indegree and outdegree in the modified directed graph.

A. Graph Generation

In the graph representation of the retinal vessels network, each node corresponds to an intersection point and each link stands for a vessel segment between two adjacent intersection points. For generating the directed graph, first vessel centerline is extracted from vessel segmented image. Then, an undirected graph is created using the centerline and finally, the most appropriate direction is estimated for each graph link.

1) Vessel Centerline Extraction: The centerline image is extracted from vessel segmented image using a morphological thinning algorithm, which removes pixels on the vessel bounfries until it shrinks to a single-pixel-wide connected object. The centerline network obtained from the binary image of Fig.

As the vessel network in optic disk area is so complex and unreliable, the information acquired from this part may be inaccurate. So, before constructing the graph, all the centerline pixels in this part are deleted.

2) Undirected graph extraction: In this step, all centerline pixels with more than two neighbors, i.e. intersection points, and pixels with only one neighbore, i.e. endpoints, are marked as initial landmarks. These points are represented by graph nodes in the vasculature model. In this model, every adjacent landmarks, i.e. points which are connected by a vessel segment in the centerline image, are related to each other by a graph link.

3) Link Direction Estimation: Prior to estimating the most proper direction for each link, we introduce a topological ordering for graph nodes. This ordering is based on the nodes distances from optic disk area, where all vessels are originated from. For this purpose, we consider graph nodes on the optic

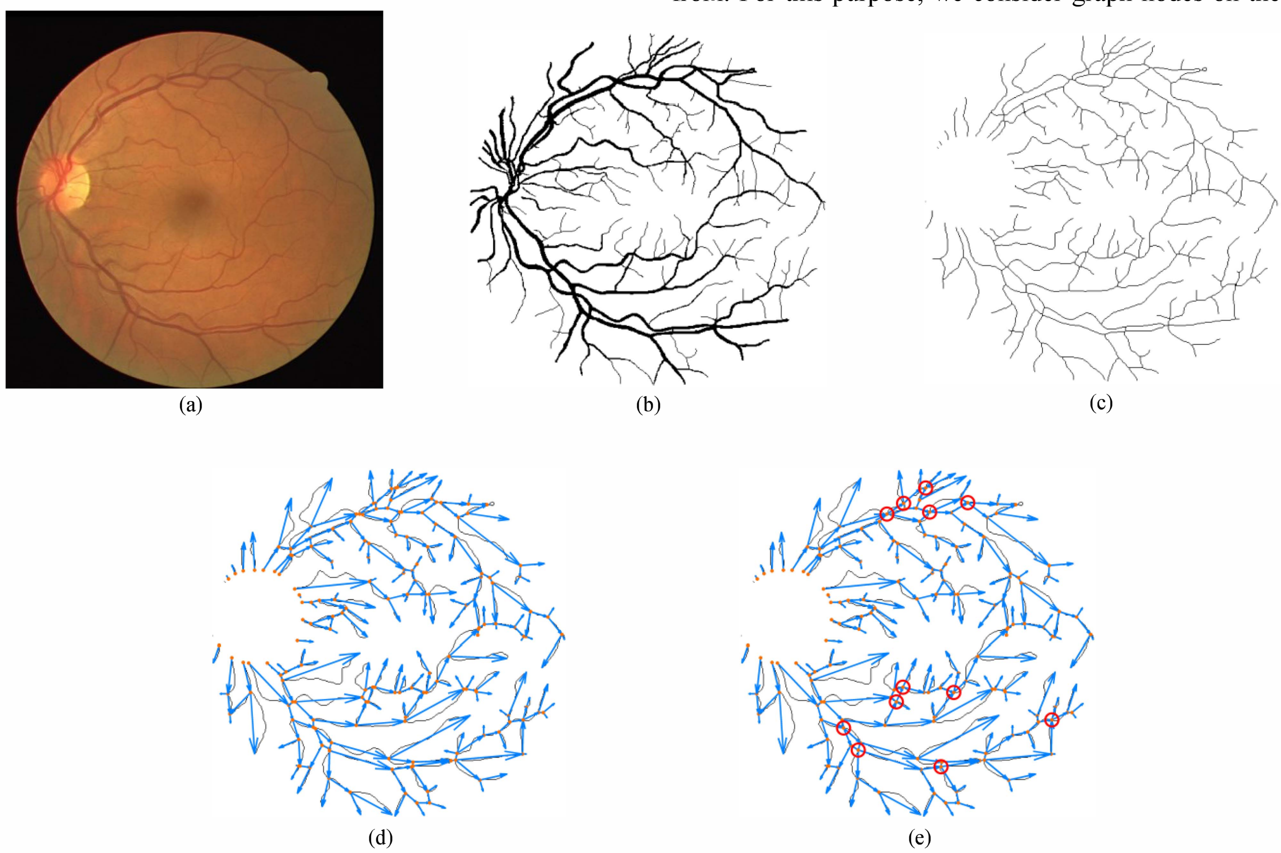


Fig. 1. Graph generation and modification, (a) RGB image; (b), vessel segmented image; (c) vessel centerline image; (d) initial graph; (e) modified graph.

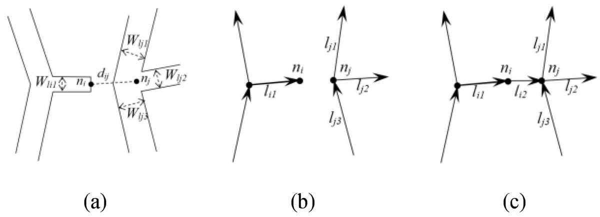


Fig. 2. Missing link error, (a) vessel representation; (b) initial graph; (c) modified graph.

disk border as start points and find the shortest-path spanning tree of the undirected graph using Dijkstra's algorithm. The cost of each link is the Euclidean distance between its two endpoints. Next, Each link direction is determined according to this ordering; the node with lower distance to start points is the head and the other one is the tail of that link. Fig. 1(d) shows the initial graph for centerline network of Fig. 1(c).

B. Graph Modification

The initial graph obtained from the centerline may have some mistakes due to segmentation and centerline extraction errors. As described in [11] the most common mistakes are missing a link between two near nodes and the splitting of one node into two which occurs at the place of crossovers. In this section, we try to detect these conditions and modify the graph in these parts to improve the graph structure.

1) Missing Link: This situation may happen at the endpoints which are too close to another graph node. The threshold for nodes distance is calculated by (1) which is proposed in [9]. This equation estimates T_{ml} based on the widthes of local vessels. For solving this problem, the distance between an endpoint and other graph nodes is calculated and if it is less than the threshold T_{ml}, the nodes will be connected with a new link. The link direction is set based on the nodes distances from the optic disk center. This situation and the modified graph is depicted in Fig. 2(a) and Fig. 2(c).

$$T_{ml} = W_{l_{i1}} + \max_{p\in\{1,2,3\}} W_{l_{jp}} \tag{1}$$

2) Node Splitting: Using the centerline network may provide two nodes instead of one at the crossovers. This error occurs in two manners in the directed graph which are illlustrated in Fig. 3. In the first type, Fig. 3(b), a node having an indegree of two and an outdegree of one is adjacent with a node having an indegree of one and an outdegree of two. The second type is vice versa, i.e. a node having an indegree of one and an outdegree of two is adjacent with a node having an indegree of two and an outdegree of one, Fig. 3(d). After one of the above circumstances is detected, the distance between two adjacent nodes is measured. If the distance is smaller than the thresohld calculated by (2) to (5), which are proposed in [9], the two corresponding nodes will be merged as shown in Fig. 3(c) and Fig. 3(e).The graph modification algorithm is applied on the graph of Fig. 1(d) and the result is illustrated in Fig. 1(e) where red circles show the modified nodes.

$$T_{ns} = \frac{1}{\sin\alpha}\left({d_1}^2 + {d_2}^2 + 2d_1 d_2\cos\alpha\right)^{1/2} \tag{2}$$

$$\alpha = \min(\angle l_{i1} l_{i2}, \angle l_{j1} l_{j2}) \tag{3}$$

$$d_1 = \max(W_{l_{i1}}, W_{l_{j2}}) \tag{4}$$

$$d_2 = \max(W_{l_{i2}}, W_{l_{j1}}) \tag{5}$$

C. Landmark Classification

Since constructing the directed graph for the vessel network, classifying vessel landmarks into bifurcations and crossovers will be almost obvious. All graph nodes with more than one input links are crossovers and the nodes with more than one output and only one input link are bifurcations.

Despite all advantages of graph representation, there might be some errors because of wrong direction estimation for some links. For this reason, we perform an extra step to revise node labels. In this level, we first use a window with radius 5 to assign a new label to each node. The center of the window is placed on each centerline pixels *(p)* and number of intersections between window's border and centerline network *(N_p)* is counted. Type of each point can be determined by one of the cases below:

- If $N_p = 1$, pixel p is the vessel endpoint.
- If $N_p = 2$, pixel p is a vessel point.
- If $N_p = 3$, pixel p is bifurcation point.
- If N_p>3, pixel p is crossover point.

Then, we compare nodes labels obtained from two methods and nodes with different labels are marked as uncertain ones. If only one endpoint of a link is in the list, we can not decide which method tells the correct label. But if both endpoints are marked,

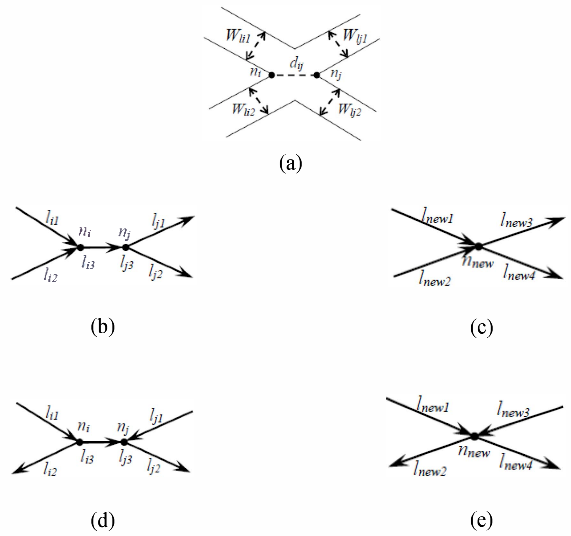


Fig. 3. Node splitting error, (a) vessel representation; (b), (d) initial graph; (c), (e) modified graph.

it is more than likely that the link direction is wrong and we should trust second method results.

III. Experimental Results

A. Database

The automatic method proposed in previous sections was tested on the images of DRIVE database [12]. This database contains 40 images randomly selected from 400 photographs of diabetic subjects between 25-90 years of age where 33 of them do not show any signs of diabetic retinopathy and the others have early symptoms. Each image is captured using 8 bits per color plane at 768 by 584 pixels. A binary vessel map which is manually segmented by ophthalmologists is also available for all 40 images.

To generate the ground truth for vessel landmark classification, we first extracted the centerline network using morphological thinning algorithm. Then manually determined real position of vessel landmarks, i.e. bifurcations, crossovers and endpoints.

B. Results

To evaluate the proposed method we applied our algorithm on the manually segmented images to eliminate segmentation errors. For this purpose, system's capability to detect bifurcations and crossovers is measured separately using the metrics defined below:

TP: number of bifurcations (or crossovers) that are correctly classified as bifurcations (or crossovers).

FP: number of points that are wrongly classified as bifurcations (or crossovers) by automatic algorithm.

FN: number of bifurcations (or crossovers) that are not detected by automatic algorithm.

We have also calculated sensitivity, precision and accuracy according to (6) to (8) for better comparison of results with other works. The results are summarized in Table I. Sample results are also depicted in Fig. 4.

$$Sensitivity = \frac{TP}{TP + FN} \tag{6}$$

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

$$Accuracy = \frac{Sensitivity + Precision}{2} \tag{8}$$

Generally, the proposed method performs at a higher standard than other methods in detecting and classifying bifurcations. Although higher rate of true positive bifurcation detection in [3] results in higher sensitivity, the large number of false positives declines the overall performance in bifurcation detection.

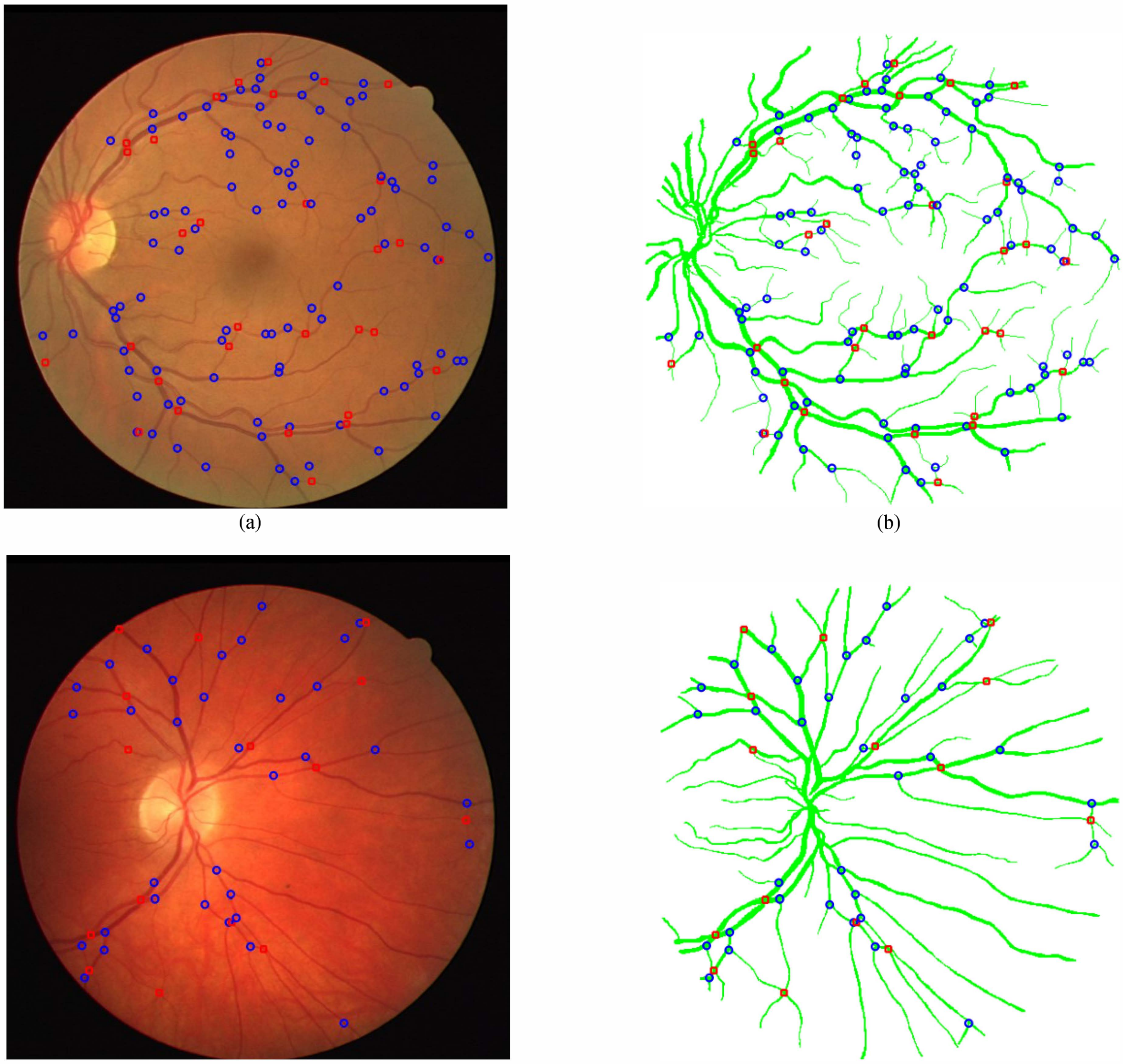
The proposed method also excels Aibinu et al. [3] in crossover detection by distinguishing crossovers which are split into two bifurcations. The poor performance of [3] in these situations can be noticed in low sensitivity of crossover detection as well as low precision of bifurcation detection. Fathi et al. [8] has somewhat solved this problem by introducing additional analysis on the vessel landmarks, but it is still incapable of detecting the crossovers wherein a vessel ends exactly on the other one. This situation becomes more prevalent when we take into consideration all vessels, particularly small ones, while analyzing vessel network. Our method overcomes this problem

TABLE I. Results of the proposed method in comparison to the other methods in the literature.

Method	Bifurcations			Crossovers		
	Sensitivity	Precision	Accuracy	Sensitivity	Precision	Accuracy
Fathi et al. [8]	80.8%	88.4%	84.6%	85.9%	78.9%	82.4%
Aibinu et al. [3]	94.8%	51.9%	73.3%	4.6%	85.3%	44.9%
Proposed method	88.13%	84.93%	86.53%	56.04%	61.43%	58.73%

TABLE II. Results of the proposed method before and after revising node labels.

Method	Bifurcations			Crossovers		
	Sensitivity	Precision	Accuracy	Sensitivity	Precision	Accuracy
Before node revising	**89.33%**	78.61%	83.97%	49.96%	52.94%	51.45%
After node revising	88.13%	**84.93%**	**86.53%**	**56.04%**	**61.43%**	**58.73%**



(a) (b) (d) (e)

Fig. 4. Result of the proposed method on DRIVE database images. Bifurcations and crossovers are depicted by blue circles and red squares respectively.

by extracting structural information from vessel directed graph. The main drawback of this algorithm is the link direction errors which significantly reduces the performance. We dealt with this issue by including an extra step to revise some nodes labels but more effective procedure is needed to resolve this problem adequately. Table II shows the results of the proposed method before and after revising node labels.

IV. Conclusion

In this paper, we have introduced a new automatic system for classification of retinal blood vessel landmarks into bifurcations and crossovers. In this method, we first extract blood vessel centerline from vessel segmented images. Then the centerline network is modeled as a directed graph. Finally each node is analyzed and labeled as a bifurcation or crossover based on its input and output links. The proposed algorithm has been tested on DRIVE database images and shows reasonable performance in comparison to other works on the literature. The information provided by this method can be used in automatic systems for detecting vessel abnormalities in retinal images as well as human identification and biometric security systems.

Acknowledgment

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References

[1] Chia-Ling Tsai, C. V. Stewart, H. L. Tanenbaum and B. Roysam, "Model-based method for improving the accuracy and repeatability of estimating vascular bifurcations and crossovers from retinal fundus images," IEEE Transactions on Information Technology in Biomedicine, vol. 8, no. 2, pp. 122-130, 2004.

[2] V. Bevilacqua, S. Cambo, L. Cariello, and G. Mastronardi, "A combined method to detect retinal fundus features," Proceedings of IEEE European Conference on Emergent Aspects in Clinical Data Analysis, pp. 1-6, 2005.

[3] A. M. Aibinu, M. I. Iqbal, A. A. Shafie, M. J. E. Salami, and M. Nilsson, "Vascular intersection detection in retina fundus images using a new hybrid approach," Computers in Biology and Medicine, vol. 40, no. 1, pp. 81–89, 2010.

[4] A. Bhuiyan, B. Nath, J. Chua and K. Ramamohanarao, "Automatic detection of vascular bifurcations and crossovers from color retinal fundus images," Third International IEEE Conference on Signal-Image Technologies and Internet-Based System (SITIS '07), Shanghai, China, pp. 711-718, 2007.

[5] H. Hamad, D. Tegolo, and C. Valenti, "Automatic detection and classification of retinal vascular landmarks," Image Analysis & Stereology, 2014.

[6] D. Calvo, M. Ortega, M. G. Penedo, and J. Rouco, "Automatic detection and characterisation of retinal vessel tree bifurcations and crossovers in eye fundus images," Computer Methods and Programs in Biomedicine, vol. 103, no. 1, pp. 28–38, 2011.

[7] A. Bhuiyan, B. Nath, and K. Ramamohanarao, "Detection and classification of Bifurcation and branch points on retinal vascular network," 2012 International Conference on Digital Image Computing Techniques and Applications (DICTA), Fremantle, Australia, pp. 1–8, 2012.

[8] A. Fathi, A. R. Naghsh-Nilchi, and F. A. Mohammadi, "Automatic vessel network features quantification using local vessel pattern operator," Computers in Biology and Medicine, vol. 43, no. 5, pp. 587–593, 2013.

[9] B. Dashtbozorg, A. M. Mendonça, and A. Campilho, "An automatic graph-based approach for artery/vein classification in retinal images," IEEE Transactions on Image Processing, vol. 23, no. 3, pp. 1073–1083, 2014.

[10] L. Sánchez, N. Barreira, M. G. Penedo, and B. Cancela, "Automatic identification of vessel crossovers in retinal images," Proc. SPIE 9445, Seventh International Conference on Machine Vision (ICMV 2014), 2015.

[11] K. Rothaus, X. Jiang, and P. Rhiem, "Separation of the retinal vascular graph in arteries and veins based upon structural knowledge," Image and Vision Computing, vol. 27, no. 7, pp. 864–875, 2009.

[12] "DRIVE: Digital retinal images for vessel extraction,". [Online]. Available: http://www.isi.uu.nl/Research/Databases/DRIVE/.