Retinal Images Classification using Graph-Based approach for Disease Identification

Divya.K.S[1] Kamala Malar.M[2]
PG Scholar, Department of IT , Dr.Sivanthi Aditanar College of Engineering, Tiruchendur, India[1]
Asst. Professor, Department of IT, Dr.Sivanthi Aditanar College of Engineering, Tiruchendur, India[2]

Abstract-- **Retinal images play vital role in several applications such as disease diagnosis and human recognition. They also play a major role in early detection of diabetics by comparing the states of the retinal blood vessels. This paper presents an automatic approach for Artery/Vein classification based on the analysis of a graph extracted from the retinal vasculature. The graph extracted from the segmented retinal vasculature is analyzed to decide on the type of intersection points (graph nodes), and afterwards one of two labels is assigned to each vessel segment (graph links). Final classification of a vessel segment as A/V is performed through the combination of the graph-based labeling results with a set of intensity features.**

Keywords—**Retinal images, artery/vein classification, graph, diagnosis.**

I. INTRODUCTION

One of the most important internal components in eye is called retina, covering all posterior compartment, on which all optic receptors are distributed. Disorders in retina resulted from special diseases are diagnosed by special images from retina, which are obtained by using optic imaging called fundus. Blood vessel is one of the most important features in retina consisting of arteries and arterioles for detecting retinal vein occlusion, grading the tortuosity for hypertension and early diagnosis of glaucoma [1]-[2]. Checking the obtained changes in retinal images in an especial period can help the physician to diagnose the disease. Applications of retinal images are diagnosing the progress of some cardiovascular diseases, diagnosing the region with no blood vessels (Macula), using such images in helping automatic laser surgery on eye, and using such images in biometric applications, etc.

Several characteristic signs associated with vascular changes are measured, aiming at assessing the stage and severity of some retinal conditions. Generalized arteriolar narrowing, which is inversely related to higher blood pressure levels [5], [6], is usually expressed by the Arteriolar-to-Venular diameter Ratio (AVR). The Atherosclerosis Risk in Communities (ARIC) study previously showed that a smaller retinal AVR might be an independent predictor of incident stroke in middle aged individuals [7]. The AVR value can also be an indicator of other diseases, like diabetic retinopathy and retinopathy of prematurity [8]. Among other image processing operations, the estimation of AVR requires vessel segmentation, accurate vessel width measurement, and

artery/vein (A/V) classification [9], [10]. Therefore, any automatic AVR measurement system must accurately identify which vessels are arteries and which are veins, since slight classification errors can have a large influence on the final value.

Several works on vessel classification have been proposed [11]–[17], but automated classification of retinal vessels into arteries and veins has received limited attention, and is still an open task in the retinal image analysis field. In recent years, graphs have emerged as a unified representation for image analysis, and graph-based methods have been used for retinal vessel segmentation [18], retinal image registration [19], and retinal vessel classification [12]. In this paper we propose a graph-based method for automatic A/V classification. The graph extracted from the segmented retinal vasculature is analyzed to decide on the type of intersection points (graph nodes), and afterwards one of two labels is assigned to each vessel segment (graph links). Finally, intensity features of the vessel segments are measured for assigning the final artery/vein class.

II. METHODS FOR A/V CLASSIFICATION

There are visual and geometrical features that enable discrimination between veins and arteries; several methods have explored these properties for A/V classification [11]–[17]. Arteries are bright red while veins are darker, and in general artery calibers are smaller than vein calibers. Vessel calibers can be affected by diseases; therefore this is not a reliable feature for A/V classification. Arteries also have thicker walls, which reflect the light as a shiny central reflex strip [20]. Another characteristic of the retinal vessel tree is that, at least in the region near the optic disc (OD), veins rarely cross veins and arteries rarely cross arteries, but both types can

bifurcate to narrower vessels, and veins and arteries can cross each other [20]. For this reason, tracking
of arteries and veins in the vascular tree is possible, and has been used in some methods to analyze the vessel tree and classify the vessels [11], [12].

A semi-automatic method for analyzing retinal vascular trees was proposed by Martinez-Perez *et al.* in [11]. In this method geometrical and topological properties of single vessel segments and subtrees are calculated. First, the skeleton is extracted from the segmentation result, and significant points are detected. For the labeling, the user should point to the root segment of the tree to be tracked, and the algorithm will search for its unique terminal points and in the end, decide if the segment is artery or vein. Another method similar to this was proposed by Rothaus *et al.* [12], which describes a rule-based algorithm to propagate the vessel labels as either artery or vein throughout the vascular tree. This method uses existing vessel segmentation results, and some manually labeled starting vessel segments.

Grisan *et al.* [13] developed a tracking A/V classification technique that classifies the vessels only in a well-defined concentric zone around the optic disc. Then, by using the vessel structure reconstructed by tracking, the classification is propagated outside this zone, where little or no information is available to discriminate arteries from veins. This algorithm is not designed to consider the vessels in the zone all together, but rather partitions the zone into four quadrants, and works separately and locally on each of them. Vazquez *et al.* [14] described a method which combines a color-based clustering algorithm with a vessel tracking method. First the clustering approach divides the retinal image into four quadrants, then it classifies separately the vessels detected in each quadrant, and finally it combines the results. Then, a tracking strategy based on a minimal path approach is applied to join the vessel segments located at different radii in order to support the classification by voting.

A piecewise Gaussian model to describe the intensity distribution of vessel profiles has been proposed by Li *et al.* [15]. In this model, the central reflex has been considered. A minimum distance classifier based on the Mahalanobis distance was used to differentiate between the vessel-types using features derived from the estimated parameters. Kondermann *et al.* [16] described two feature extraction methods and two classification methods, based on support vector machines and neural networks, to classify retinal vessels. One of the feature extraction methods is profile-based, while the other is based on the definition of a region of interest (ROI) around each centerline point. To reduce the dimensionality of the feature vectors, they used a multiclass principal component analysis (PCA).

Niemeijer *et al.* [17] proposed an automatic method for classifying retinal vessels into arteries and veins using image features and a classifier. A set of centerline features is extracted and a soft label is assigned to each centerline, indicating the likelihood of its being a vein pixel. Then the average of the soft labels of connected centerline pixels is assigned to each centerline pixel. They tested different classifiers and found that the *k*-nearest neighbor (kNN) classifier provides the best overall performance. In [12], the classification method was enhanced as a step in calculating the AVR value.
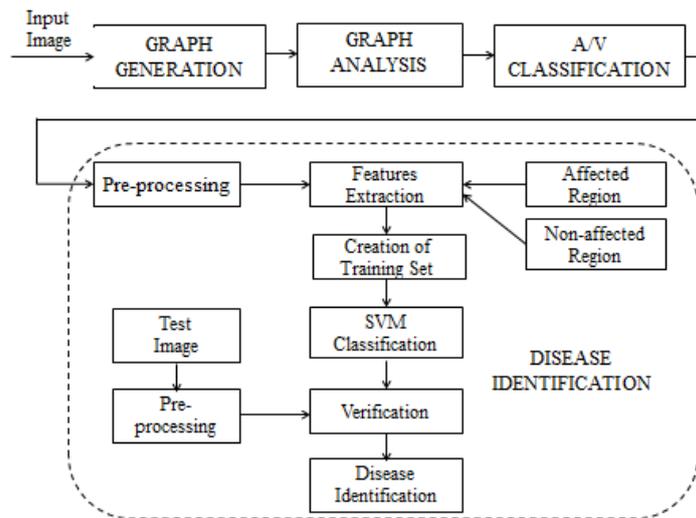

Fig 1: Block diagram of A/V Classification for Disease Identification

Most of these methods use intensity features to discriminate between arteries and veins. Due to the acquisition process, very often the retinal images are non-uniformly illuminated and exhibit local luminosity and contrast variability, which can affect the performance of intensity-based A/V classification methods. For this reason, we propose a method which uses additional structural information extracted from a graph representation of the vascular network. The results of the proposed method show improvements in overcoming the common variations in contrast inherent to retinal images.

III. GRAPH-BASED A/V CLASSIFICATION

The method proposed in this paper follows a graph-based approach, where it focus on a characteristic of the retinal vessel tree that, at least in the region near the optic disc, veins rarely cross veins and arteries rarely cross arteries. Based on this assumption we may define different types of intersection points: bifurcation, crossing, meeting and connecting points. A bifurcation point is an intersection point where a vessel bifurcates to narrower parts. In a crossing point a vein and an artery cross each other. In a meeting point the two types of vessels meet each other without crossing, while a connecting point connects different parts of the same vessel. The decision on the type of the intersection points are made based on the geometrical analysis of the graph representation of the vascular structure. Fig. 1 depicts the block diagram of the proposed method for A/V classification. The main phases are: 1) graph generation; 2) graph analysis; and 3) vessel classification. The method fi t extracts a graph from the vascular tree, and afterwards makes a decision on the type of each intersection point (graph node). Based on the node types in each separate subgraph, all vessel segments (graph links) that belong to a particular vessel are identified and then labeled using two distinct labels. Finally, the A/V classes are assigned to the subgraph labels by extracting a set of features and using a linear classification.

A. Graph Generation

A graph is a representation of the vascular network, where each node denotes an intersection point in the vascular tree, and each link corresponds to a vessel

segment between two intersection points. For generating the graph, we have used a three-step algorithm. First we use the segmented image to obtain the vessel centerlines, then the graph is generated from the centerline image, and finally some additional modifications are applied to the graph.

1) Vessel Segmentation: The vessel segmentation result is used for extracting the graph and also for estimating vessel calibers. The method proposed by Mendonça *et al.* was used for segmenting the retinal vasculature, after being adapted for the segmentation of high resolution images.

This method follows a pixel processing-based approach with three phases. The first one is the pre-processing phase, where the intensity is normalized by subtracting an estimation of the image background, obtained by filtering with a large arithmetic mean kernel. In the next phase, centerline candidates are detected using information provided from a set of four directional Difference of Offset Gaussian filters, then connected into segments by a region growing process, and finally these segments are validated based on their intensity and length characteristics. The third phase is vessel segmentation, where multi-scale morphological vessel enhancement and reconstruction approaches are followed to generate binary maps of the vessels at four scales. The final image with the segmented vessels is obtained by iteratively combining the centerline image with the set of images that resulted from the vessel reconstruction. Fig. 2(b) illustrates the result of vessel segmentation.

This method achieved an accuracy of 94.66% for the images of the DRIVE database, with an overall sensitivity and specificity of 0.75 and 0.98, respectively.

2) Vessel Centerline Extraction: The centerline image is obtained by applying an iterative thinning algorithm to the vessel segmentation result. This algorithm removes border pixels until the object shrinks to a minimally connected stroke. The vessel centerlines from the segmented image of Fig. 2(b) are shown in Fig. 2(c).

3) Graph Extraction: In the next step, the graph nodes are extracted from the centerline image by finding the intersection points (pixels with more than two neighbors) and the endpoints or terminal points (pixels with just one neighbor). In order to find the links between nodes (vessel segments), all the intersection points and their neighbors are removed from the centerline image and as result we get an image with separate components which are the vessel segments.

Next, each vessel segment is represented by a link between two nodes. Fig. 2(d) shows the graph obtained from the centerline image of Fig. 2(c).
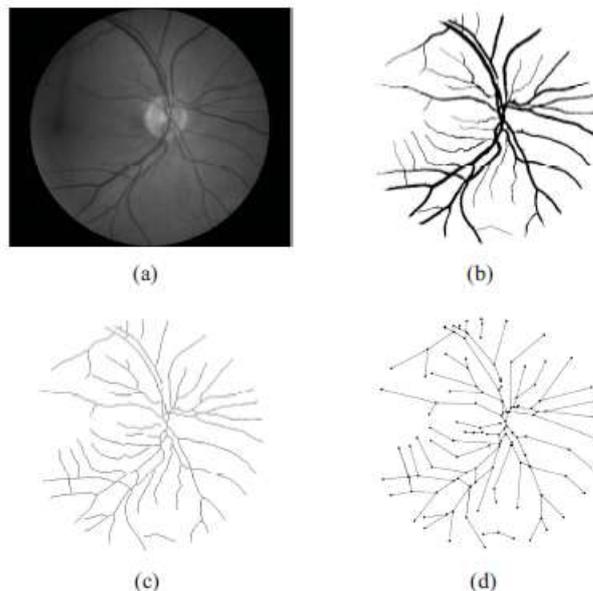

Fig 2: Graph Generation. (a) Original Image; (b) Vessel Segmentation Image (c) Centerline Image (d) Extracted Graph

The graph contains nodes, and at each node several links can be connected. On the other hand, any given link can only connect two nodes. Table I shows the graph notations for nodes and links which will be used in the rest of this document. The degree of a node is the number of adjacent nodes. Two nodes in a graph are called adjacent if they are connected by one link. The angle between links is defined as the magnitude of the smallest rotation that projects one of the links onto the other by considering the common node between them as the vertex. A vessel caliber is assigned to each link, as the average of the calibers along the corresponding vessel segment.

4) Graph Modification: The extracted graph may include some misrepresentation of the vascular structure as a result of the segmentation and centerline extraction processes. The typical errors include the splitting of one node into two nodes; (2) missing a link on one side of a node; false link. The extracted graph should be modified when one of these errors is identified.

B. Graph Analysis

The output of the graph analysis phase is a decision on the type of the nodes. The links in each subgraph (i) are labelled with one of two distinct labels ($Ci1$ and $Ci2$). In this phase we are not yet able to determine whether each label corresponds to an artery class or to a vein class. The A/V classes will be assigned to these subgraphs only in the last classification phase.

We have considered four different types of nodes:
1. Connecting point: most of the nodes with two links belong to this type; these nodes, where vessels never cross or bifurcate, are continuation nodes connecting different segments of the same vessel.
2. Crossing point: two different types of vessels cross each other.
3. Bifurcation point: a vessel bifurcates into narrower vessels.

4. Meeting point: two different types of vessels meet each other without crossing; the two vessels are very close to each other or one vessel ends exactly on the other vessel.
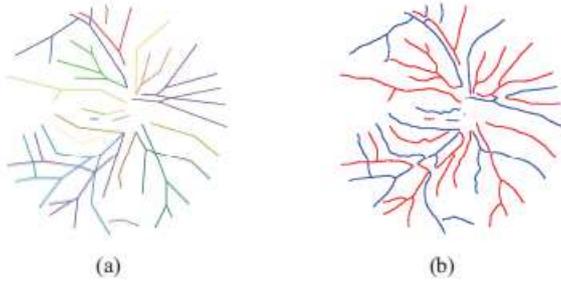

Fig 3: (a) Graph analysis result; (b) A/V Classification result (Red: Correctly Classified Arteries, Blue: Correctly Classified Veins).

The node classification algorithm starts by extracting the following node information: the number of links connected to each node (node degree), the orientation of each link, the angles between the links, the vessel caliber at each link, and the degree of adjacent nodes.

C. A/V Classification

The above described labeling phase used the vessel structural information embedded in the graph representation. Based on these labels, the final goal is now to assign the artery class (A) to one of the labels, and the vein class (V) to the other. For this purpose we add to the structural information, vessel intensity information in order to allow the final discrimination between A/V classes.

As a result of the acquisition process, very often the retinal images are non-uniformly illuminated and exhibit local luminosity and contrast variability. In order to make the classifier more robust, each image is processed using the method proposed by M. Foracchia *et al.* [26], which normalizes both luminosity and contrast based on a model of the observed image. Luminosity and contrast variability in the background are estimated and then used for normalizing the whole image. For each centerline pixel, the 30 features listed in Table III are measured and normalized to zero mean and unit standard deviation. Some of these features were used previously in [13], [21]. We have tested the most commonly used classifiers, namely linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), and *k*-nearest neighbor (kNN), on the INSPIRE-AVR dataset. For feature selection, we have used sequential forward floating selection, which starts with an empty feature set and adds or removes features when this improves the performance of the classifier.

D. Disease Identification

For disease identification, the retinal images are pre-processed and the features such as affected and non-affected regions are extracted from the retinal images. The features are trained and the training set is created. The classification whether the region is affected or not can be done using SVM (Support Vector Machine). The image to be tested is pre- processed and the verification is done with the trained retinal image to identify the diseases.

IV. RESULTS

The automatic methods described were tested on the images of three databases, DRIVE, INSPIRE-AVR, and VICAVR. The images in the DRIVE dataset were captured with 768×584

pixels, with 8 bits per color plane. The 40 high resolution images of the INSPIRE-AVR database have resolution of 2392×2048 pixels and are optic disc-centered. Finally, the 58 images of the VICAVR database were acquired using a TopCon nonmydriatic camera NW-100 model with a spatial resolution of 768×584, and are also optic disc-centered. Results of automatic vessel segmentation were available for the three datasets, and a manual artery/vein labeling was performed by an expert on the 20 images of the DRIVE test set and for the 40 images of the INSPIRE database. The accuracy values are obtained for centerline and vessel pixels in the entire image, as well as for the pixels inside the region of interest (ROI) that is usually defined for the calculation of the arteriolar-to-venular ratio.

V. CONCLUSION

The classification of arteries and veins in retinal images is essential for the automated assessment of vascular changes. In previous sections, we have described a new automatic methodology to classify retinal vessels into arteries and veins which is distinct from prior solutions. One major difference is the fact that our method is able to classify the whole vascular tree and does not restrict the classification to specific regions of interest, normally around the optic disc. While most of the previous methods mainly use intensity features for discriminating between arteries and veins, our method uses additional information extracted from a graph which represents the vascular network. The information about node degree, the orientation of each link, the angles between links, and the vessel caliber related to each link are used for analyzing the graph, and then decisions on type of nodes are made (bifurcation, crossing, or meeting points). Next, based on the node types, the links that belong to a particular vessel are detected, and finally A/V classes are assigned to each one of these vessels using a classifier supported by a set of intensity features. The graph-based method with LDA outperforms the accuracy of the LDA classifier using intensity features, which shows the relevance of using structural information for A/V classification. Furthermore, we compared the performance of our approach with other recently proposed methods, and we conclude that we are achieving better results. The promising results of the proposed A/V classification method on the images of three different databases demonstrate the independence of this method in A/V classification of retinal images with different properties, such as differences in size, quality, and camera angle. On the other hand, the high accuracy achieved by our method, especially for the largest arteries and veins, confirm that this A/V classification methodology is reliable for the calculation of several characteristic signs associated with vascular alterations. Further research is planned using the graph that represents the vessel tree and the A/V classification method for AVR calculation, as well as identifying other vascular signs, such as vascular bifurcation angles, branching patterns, and fractal-based features, which can have significant impact on the early detection and follow up of diseases, namely diabetes, hypertension, and cardiovascular diseases.

REFERENCES

[1] N. Patton, T. M. Aslam, T. MacGillivray, I. J. Deary, B. Dhillon, R. H. Eikelboom, K. Yogesa, and I. J. Constable, "Retinal image analysis: Concepts, applications and potential," Progr. Retinal Eye Res., vol. 25, p. 99–127, Jan. 2006.

[2] T. T. Nguyen and T. Y. Wong, "Retinal vascular changes and diabetic retinopathy," Current Diabetes Rep., vol. 9, pp. 277–283, Aug. 2009.

[3] K. Guan, C. Hudson, T. Wong, M. Kisilevsky, R. K. Nrusimhadevara, W. C. Lam, M. Mandelcorn, R. G. Devenyi, and J. G. Flanagan, "Retinal hemodynamics in early diabetic macular edema," Diabetes, vol. 55, pp. 813–818, Mar. 2006.

[4] A. S. Neubauer, M. Ludtke, C. Haritoglou, S. Priglinger, and A. Kampik, "Retinal vessel analysis reproducibility in assessing cardiovascular dis- ease," Optometry Vis. Sci., vol. 85, p. 247–254, Apr. 2008.

[5] N. Cheung and T. Y. Wong, "The retinal arteriole to venule ratio: Infor- mative or deceptive?" Graefe's Archive Clinical Experim. Ophthalmol., vol. 245, no. 8, pp. 1245–1246, 2007.

[6] G. Liew, P. Mitchell, J. Wang, and T. Wong, "Effect of axial length on retinal vascular network geometry," Amer. J. Ophthalmol., vol. 141, pp. 597–598, Mar. 2006.

[7] S. R. Lesage, T. H. Mosley, T. Y. Wong, M. Szklo, D. Knopman, D. J. Catellier, S. R. Cole, R. Klein, J. Coresh, L. H. Coker, and A. R. Sharrett, "Retinal microvascular abnormalities and cognitive decline: The ARIC 14-year follow-up study," Neurology, vol. 73, no. 11, pp. 862–868, 2009.

[8] C. Sun, J. J. Wang, D. A. Mackey, and T. Y. Wong, "Retinal vascular caliber: Systemic, environmental, and genetic associations," Survey Ophthalmol., vol. 54, no. 1, pp. 74–95, 2009.

[9] L. D. Hubbard, R. J. Brothers, W. N. King, L. X. Clegg, R. Klein, L. S. Cooper, A. Sharrett, M. D. Davis, and J. Cai, "Methods for evaluation of retinal microvascular abnormalities associated with hyper- tension/sclerosis in the atherosclerosis risk in communities study," Ophthalmology, vol. 106, pp. 2269–2280, Dec. 1999.

[10] M. D. Knudtson, K. E. Lee, L. D. Hubbard, T. Y. Wong, R. Klein, and B. E. K. Klein, "Revised formulas for summarizing retinal vessel diameters," Current Eye Res., vol. 27, pp. 143–149, Oct. 2003.

[11] M. E. Martinez-Perez, A. D. Hughes, A. V. Stanton, S. A. Thom,
N. Chapman, A. A. Bharath, and K. H. Parker, "Retinal vascular tree morphology: A semi-automatic quantifi " IEEE Trans. Biomed. Eng., vol. 49, no. 8, pp. 912–917, Aug. 2002.

[12] K. Rothaus, X. Jiang, and P. Rhiem, "Separation of the retinal vascular graph in arteries and veins based upon structural knowledge," Image Vis. Comput., vol. 27, pp. 864–875, Jun. 2009.

[13] E. Grisan and A. Ruggeri, "A divide et impera strategy for automatic classification of retinal vessels into arteries and veins," in Proc. 25th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., Sep. 2003, pp. 890–893.

[14] S. Vazquez, B. Cancela, N. Barreira, M. Penedo, and M. Saez, "On the automatic computation of the arterio-venous ratio in retinal images: Using minimal paths for the artery/vein classification," in Proc. Int. Conf. Digital Image Comput., Tech. Appl., 2010, pp. 599–604.

[15] H. Li, W. Hsu, M. Lee, and H. Wang, "A piecewise Gaussian model for profiling and differentiating retinal vessels," in Proc. Int. Conf. Image Process., vol. 1. Sep. 2003, pp. 1069–1072.

[16] C. Kondermann, D. Kondermann, and M. Yan, "Blood vessel classi- fication into arteries and veins in retinal images," Proc. SPIE, Progr. Biomed. Opt. Imag., vol. 6512, no. 651247, Feb. 2007.

[17] M. Niemeijer, B. van Ginneken, and M. D. Abramoff, "Automatic classification of retinal vessels into arteries and veins," Proc. SPIE, Progr. Biomed. Opt. Imag., vol. 7260, no. 72601F, Feb. 2009.

[18] R. Estrada, C. Tomasi, M. T. Cabrera, D. K. Wallace, S. F. Freedman, and S. Farsiu, "Exploratory dijkstra forest based automatic vessel segmentation: Applications in video indirect ophthalmoscopy (VIO)," Biomed. Opt. Exp., vol. 3, no. 2, pp. 327–339, 2012.

[19] K. Deng, J. Tian, J. Zheng, X. Zhang, X. Dai, and M. Xu, "Retinal fundus image registration via vascular structure graph matching," Int. J. Biomed. Imag., vol. 2010, no. 906067, Jul. 2010.

[20] R. S. Snell and M. A. Lemp, Clinical Anatomy of the Eye. New York, NY, USA: Wiley, 1998.

About Author

Divya.K.S received the B.Tech degree in Information Technology from Anna University, Chennai, in 2013. Currently, she is pursuing M.Tech degree in Information Technology from Anna University, Chennai. Her research areas of Interests include Image Processing and Networking.

Kamala Malar.M received the B.Tech degree in Information Technology from Anna University, Chennai in 2007 and M.E degree in Computer Science from Anna University, Chennai in 2012. Currently, she is working at Dr.Sivanthi Aditanar College of Engineering, Tiruchendur as the Associate Professor. Her working experience is about six years. Her research areas of Interests include Image processing, cryptography and network security.