Artery/Vein Classification in Retinal Images using Automatic Graph Method

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ABSTRACT---- ***The classification of retinal vessels into artery/vein (A/V) is an important phase for automating the detection of vascular changes, and for the calculation of characteristic signs associated with several systemic diseases such as diabetes, hypertension, and other cardiovascular conditions. This paper presents an automatic approach for A/V classification based on the analysis of a graph extracted from the retinal vasculature. The proposed method classifies the entire vascular tree deciding on the type of each intersection point (graph nodes) and assigning one of two labels to each vessel segment (graph links). Final classification of a vessel segment as A/V is performed through the combination of the graph-based labelling results with a set of intensity features.***

Keywords--- retinal images, graph method, graph nodes, artery/vein

1. INTRODUCTION

Automated detection of retinopathy in eye Fundus images using digital image analysis methods have hugepotential benefits, allowing the examination of a large number of images in less time, with lower cost and reduced subjectivity than current observer-based techniques. Another advantage is the possibility to perform automated screening for pathological conditions, such as diabetic retinopathy, in order to reduce the workload required of trained manual graders. Retinal vessels are affected by several systemic diseases, namely diabetes, hypertension, and vascular disorders. In diabetic retinopathy [2], the blood vessels often show abnormalities at early stages, as well as vessel diameter alterations [7]. Changes in retinal blood vessels, such as significant dilatation and elongation of main arteries, veins, and their branches, are also frequently associated with hypertension [6] and other cardiovascular pathologies.

Several characteristic signs associated with vascular changes are measured, aiming at assessing the stage and severity of some retinal conditions [5]. Generalized arteriolar narrowing, which is inversely related to higher blood pressure levels, is usually expressed by the Arteriolar-to-Venular diameter Ratio (AVR) [4] [10]. 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. The AVR value can also be an indicator of other diseases, like diabetic retinopathy and retinopathy of prematurity. Among other image processing operations, the estimation of AVR requires vessel segmentation, accurate vessel width measurement, and artery/vein (A/V) classification. 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.

2. SEGMENTATION

In computer vision, image segmentationis the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyse.Image segmentation is typically used to locate objects and boundaries in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image.

2.1. THRESHOLDING

The simplest method of image segmentation is called the thresholding method. This method is based on a clip-level (or a threshold value) to turn a gray-scale image into a binary image. There is also a balanced histogram thresholding. The key of this method is to select the threshold value (or values when multiple-levels are selected). Several popular methods are used in industry including the maximum entropy method, Otsu's method (maximum variance), and k-means clustering. Recently, methods have been developed for thresholding computed tomography (CT)

images. The key idea is that, unlike Otsu's method, the thresholds are derived from the radiographs instead of the (reconstructed) image.

2.2.MATHEMATICAL MORPHOLOGY:

Mathematical morphology (MM) is a theory and technique for the analysis and processing of geometrical structures, based on set theory, lattice theory, topology, and random functions. MM is most commonly applied to digital images, but it can be employed as well on graphs, surface meshes, solids, and many other spatial structures. Topological and geometrical continuous-space concepts such as size, shape, convexity, connectivity, and geodesic distance, were introduced by MM on both continuous and discrete spaces.

2.3. RETINAL IMAGE

Fig.2. shows the system architecture of a generic retinal image analysis system [1], which consists of five components, 1) Sensors, 2) Extractors, 3) Classifiers, 4) Threshold and 5) Decision. After the retina is captured, it is processed to facilitate feature extraction. Once the features are mined a feature vector can be built and used for classification by a classifier. The result of classification will be some matching score. A threshold can then be subsequently applied to this score in order to arrive at a decision of match or non-match.

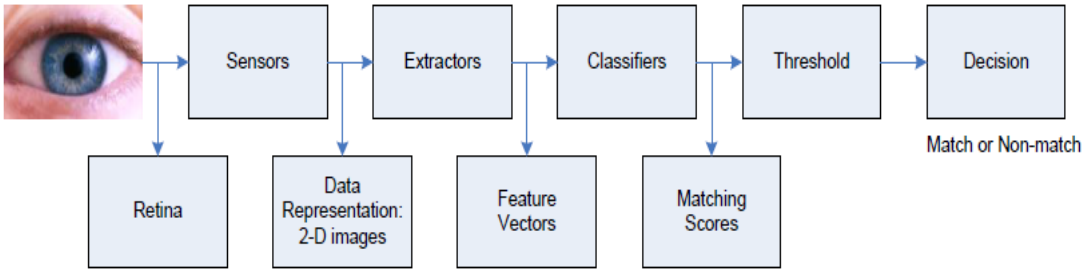

Fig.2Architecture of a generic retinal image analysis system

2.4. ABNORMALITIES ASSOCIATED WITH THE EYE

Abnormalities associated with the eye can be divided into two main classes, the first being disease of the eye, such as cataract, conjunctivitis, blepharitis and glaucoma. The second group is categorized as life style related disease such as hypertension [6], arteriosclerosis and diabetes.When the retina is been affected as a result of diabetes, this type of disease is called Diabetic Retinopathy (DR), if not properly treated it might eventually lead to loss of vision. Ophthalmologists have come to agree that early detection and treatment is the best treatment for this disease. DR occurrence have been generally categorise into three main form viz, BDR, PDR, SDR.

3. METHODOLOGY

The method proposed in this paper follows a graph-based approach, where we mostly 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 [3].

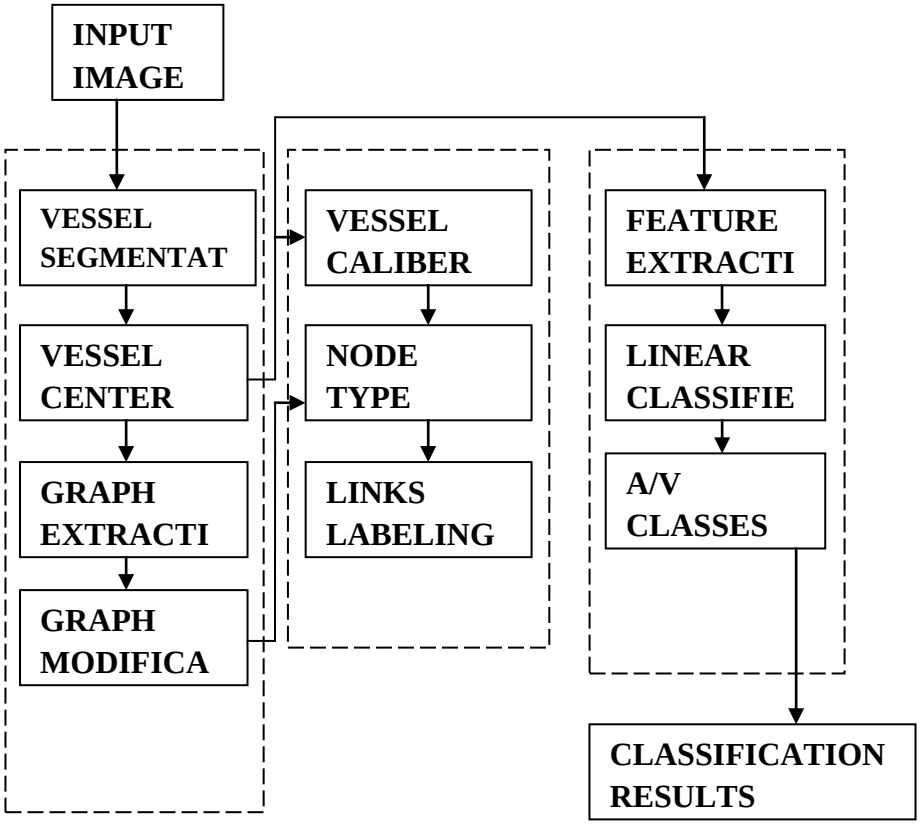

Fig.3.Block diagram of the proposed system

3.1. AUTOMATIC GRAPH GENERATION ALGORITHM

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.

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. 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. 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.

Algorithm 1 graph modification

For i=1 to N do

For j=1 to N , j≠I do

If $Dn_i=1 \wedge d_{ij}<T_{ml}$ then

make a new link (l_{i2}) between n_i, n_j

else if n_i, n_j are adjacent $\wedge$ $Dn_i=3 \wedge Dn_j=3$ then

if $d_{ij}< T_{sn} \wedge (\angle l_{i1}l_{i3} + \angle l_{j2}l_{j3} = 180^o \pm 10^o) \wedge (\angle l_{i2}l_{i3} + \angle l_{j1}l_{j3} = 180^o \pm 10^o)$ then

mergen_i and n_j.

else if $d_{ij}<T_{fl} \wedge ((\angle l_{i1}l_{i3} = 90^o \pm 5^o \wedge \angle l_{i2}l_{i3} = 90^o \pm 5^o) \vee (\angle l_{j1}l_{j3} = 90^o \pm 5^o \wedge \angle l_{j2}l_{j3} = 90^o \pm 5^o))$ then

remove the link between n_i, $n_j(l_{i3}, l_{j3})$

end if

end if

end for

end for

3.2.A/V CLASSIFICATION

The trained classifier is used for assigning the A/V classes to each one of the sub graph labels. First, each centerline pixel is classified into A or V classes, then for each label (Ci j , j = 1, 2) in sub graph i , the probability of its being an artery is calculated based on the number of associated centerline pixels classified by LDA to be an artery or a vein. The probability of label Ci j to be an artery is Pa(Ci j) = naCi j /(naCi j + nvCi) where naCi j is the number of centerline pixels of a label classified as an artery and nvCi j is the number of centerline pixels classified as a vein. For each pair of labels in each sub graph, the label with higher artery probability will be assigned as an artery class, and the other as a vein class.

Finally, to prevent a wrong classification as a result of a wrong graph analysis, we calculate the probability of being an artery or a vein for each link individually. The probability of a link (li) being an artery (Pa (li)) is computed as Pv (li) = nv li / _ na li + nv li _ , and the probability of being a vein ((Pv (li)) is computed as Pv (li) = nv li / _ na li + nv li _ , here na li is the number of centerline pixels of link (li) classified as an artery and nv li is the number of centerline pixels classified as a vein. If the probability of being an artery is higher than 0.9 (Pa (li)≥ 0.9) then the link will be assigned as an artery, and if Pv (li) ≥ 0.9 then it will be assigned as a vein, without considering the result of the graph analysis.

4. RESULTS AND DISCUSSION

The primary objective of the project is to take a retinal coloured image, and generate an image using thinning algorithm which enable the removal of the optical disc from the input image which is essential for subsequent steps. The output image at this stage is our primary demonstration. In subsequent steps we remove the optical disc and using this new image as the input, arteries and veins are classified. The output of this operation is our final image which can be used for medical examination and are shown in Fig.1 to Fig.14.

Fig-1.input image

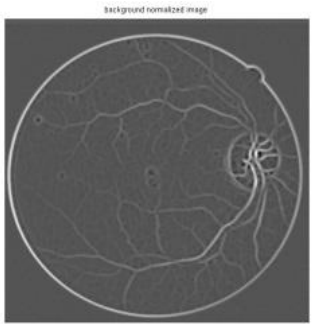

Fig-2.Background normalized image

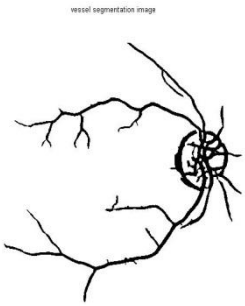

Fig-3.vessel segmentation image

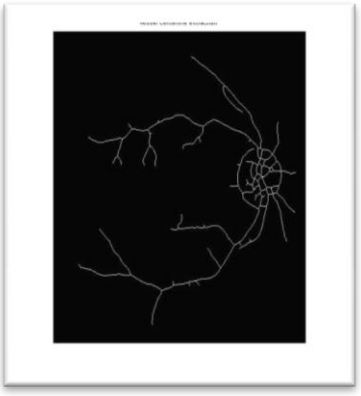

Fig-4.vessel centreline extraction

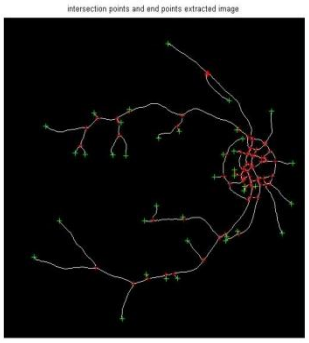

Fig-5.Intersection and end points

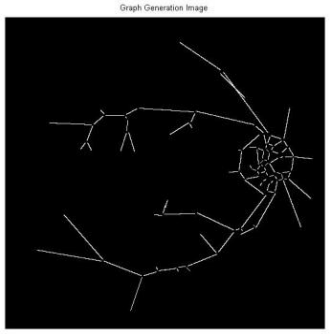

Fig-6.graph generation Image

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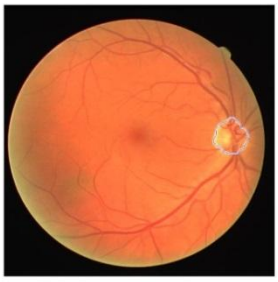

Fig-7.Optic disc removal .in graph generation

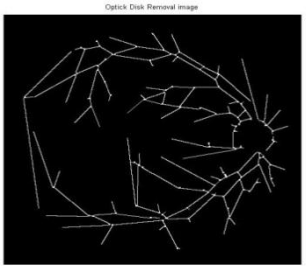

Fig-8.optic disc removal generation image

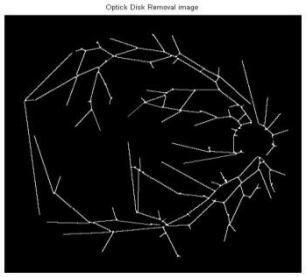

Fig-9.Graph analysis from graph

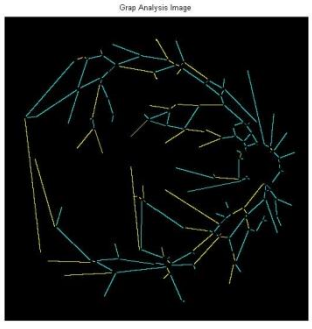

Fig-10.Graph generationimage

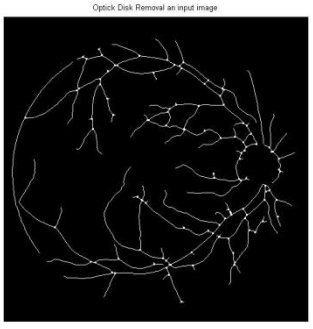

Fig-11.Optic disk removal

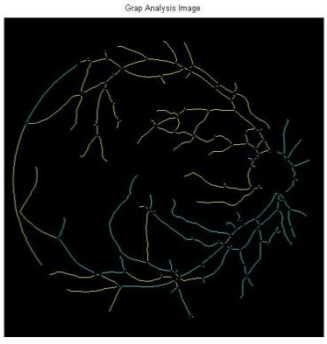

Fig-12.Graph analysis image

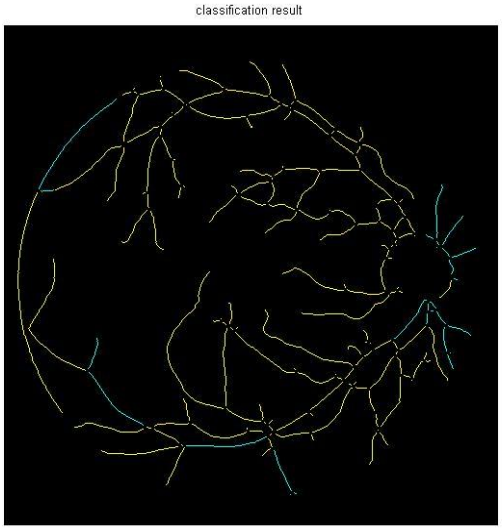

Fig-13.Outputwhen input is normal image

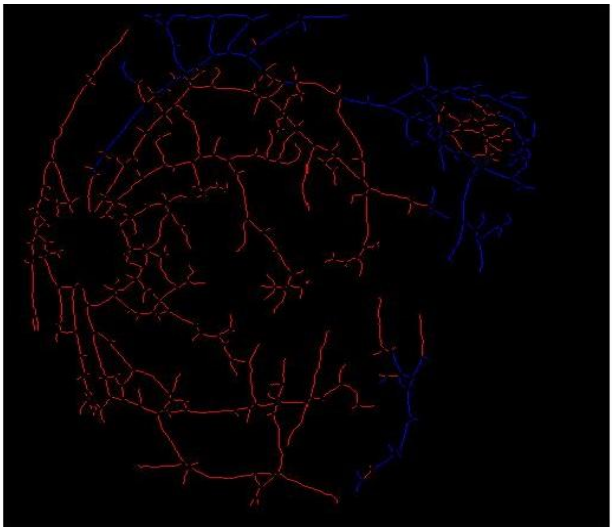

Fig-14. Glaucoma diseased image

The accuracy for all vessel pixels in entire image and inside ROI using LDA only are 98.99% and 98.62% ,using combination of graph based method with LDA are 99.17% and 99.65% and the results are tabulated in Table 1.

METHODS	All vessel pixels in entire image	All vessel pixels inside ROI
LDA alone	**98.99%**	**98.62%**
Combination of graph based method with LDA	**99.17%**	**99.65%**

5. CONCLUSION

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 andthe 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.

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7. REFERENCES

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