Detection of Glaucoma and Hypertension using Artery or Vein Classification

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Abstract

This paper recognizes the detection of vascular changes in retinal vessels. From the retinal vasculature, artery/vein classification is done. It classifies the types of graph nodes and assigns graph links for one of two labels. Finally for the classification of artery/vein (A/V), graph based labeling results with a set of intensity features are performed. For doing this, list of 30 features are to be extracted. To measure the distance between nodes, a biometric graph matching algorithm (BGM) is used. In this diseases like glaucoma, hypertension is detected by using feed forward neural network (FFN).A gray level co-occurrence matrix (GLCM) is used for feature extraction. Here STARE, DRIVE, MESSIDOR databases are used.

Keywords: Arteries and Veins, BGM, FFN, Retinal vessel classification, Vessel segmentation

I. INTRODUCTION

In retina, blood vessels are divided into arteries and veins. Bright colored arteries transport blood rich in oxygen to organs of the body and dark colored veins transport blood low in oxygen level. To detect the diseases, it is essential to classify arteries and veins. For high blood pressure an abnormal artery or vein ratio is one of important symptom. Digital image analysis has large benefits forexamining many number of images in less time and low cost.In diabetic retinopathy,vessel diameter alterations [12] as well as blood vessels show abnormalities at early stages [13]. Dilatation and elongation of main arteries, veins, and their branches are also related with hypertension [12].Diabetes, hypertension and vascular disorders occur in retinal vessels.Higher blood pressure levels, [15] are inversely related to Arteriolar-to-Venular diameter Ratio (AVR). Also arteries and veins are identified by using AVR measurement system. Graph based methods have been used for retinal image registration and retinal vessel classification [9], retinal vessel segmentation [6].In this paper for A/V classification a graph based method is used. Graphs extracted from vasculature of retina decide on the type of graph nodes and assign graph links for one of two labels. Finally for classification of A/V graph based labeling results with a set of intensity features.Here STARE, DRIVE, MESSIDOR databases are used and its threshold value 0.5 are used. To measure the distance between nodes a biometric graph matching algorithm is used. Diseases like glaucoma, hypertension are detected by using feed forward neural network (FFN).

This paper is organized as follows. In section II, describes previously presented methods for retinal vessel classification, Section III presents the proposed graph based method for A/V classification.

II. RELATED WORKS

There are many geometric and visual features that discriminate between arteries and veins. Bright colored arteries have thicker walls than dark colored veins and artery calibers are smaller than vein calibers. Another important characteristic of retinal vessel is that at least in the region of optic disc, arteries rarely cross arteries and veins rarely cross veins but artery and vein bifurcate to narrower vessels and can cross each other.

Vazquez *et.al.*[2], describeda vessel tracking method with a color-based clustering algorithm .First the clustering approach divides the retinal image into four quadrants, then it separately classifies, and finally it combines the results. Then a tracking method based on a minimal path approach is applied to join the vessel segments .Kondermann*et.al.*[3]described two classification methods and two feature extraction methods .Classification methods are based on neural networks and support vector machines. For analyzing retinal vascular trees, a semi-automatic method was proposed by Martinez-Perez *et.al.in* [5.]From the segmentation result,skeleton is extracted and points are detected.For labeling, root segment of the tree to be tracked by the user and algorithm will search for terminal points.Dijkstra's shortest-pathalgorithm[6] is extracting the vascular

network.In [11] ,based on a model of the observed image a new method to normalize both luminosity and contrast in retinal images.

III. PROPOSED APPROACH

Another important characteristic of retinal vessel is that at least in the region of optic disc, arteries rarely cross arteries and veins rarely cross veins. There are different types of intersection points: meeting, bifurcation, crossing, and connecting points.A bifurcation point, where a vessel bifurcates to narrower parts.In a crossing point anarteryand avein cross each other.In a meeting point the artery and vein meet each other without crossing.Connecting point connects different parts of thesamevessel.Fig.1 depicts the block diagram ofthe proposed approach.The main phases are: 1) graph generation; 2) graph analysis; 3) A/V classification; and 4)detection of glaucoma, hypertension.

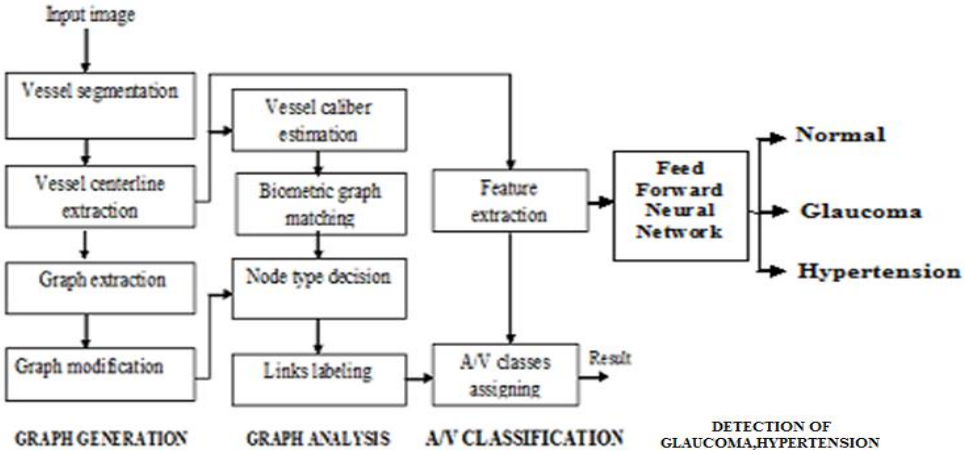


Fig. 1: Proposed system architecture

A. Graph Generation:

For generating the graph, we first used the segmented image to get the vessel centerlines. The second graph is generated from the centerline image and later some additional modifications are given to the graph.

1) *Vessel Segmentation:*

The result of vessel segmentation is used for estimating vessel calibers and extracting the graph. In this method there are three phases for pixel processing method. First is pre-processing phase, where the normalization of intensity is done by subtracting the image background. In second phase, centerline candidates are detected using Difference of Offset Gaussian filters. The third phase is vessel segmentation, whereareconstructionare followed to generate binary maps of the vessels.

2) *Vessel Centerline Extraction:*

Border pixels are removed by using this extraction.

3) *Graph Extraction:*

For finding endpointsandintersection points,graph nodes are extracted from the centerline image.To find the links between nodes,pixels with more than two neighbors and their neighbors are removed. Then separate components of vessel segments are obtained. Graph nodes are connected by several lines. At each node several links are connected. So two nodes are adjacent in a graph.

4) *Graph Modification:*

There are many errors like node splitting, missing link and false link. Node splitting means split the nodes into two instead of one.
In missing link cases can be avoided by adding with a new link by calculating the distance from degree 1 node to other nodes and then comparing distance with threshold. If it is less, connect with a new link. False link means that there is an incorrect finding of a link between nodes.

B. Graph Analysis:

The output of the graph analysis depends upon the node types. Links in each subgraph (i) are labeled with one of the two distinct labels. There are four different types of nodes and with four node cases these are differentiated. Nodes of degree's(2,3,4,5) are the cases. The degrees of numbers 2,3,4,5 represent their number of links with each node. The possible node types are based on the relation of endpoints of the adjacent nodes or the angle between the links. A biometric graph matching algorithm (BGM) is used in graph analysis section. Graph matching means determining the similarity of graphs. That is measure the distance between arteries and veins. In this there are three concepts 1)Graph isomorphism; 2) Subgraph isomorphism;3)Maximum common subgraph.When two objects are same, it is graph isomorphism. One object is part of another object ,it is Subgraph isomorphism.If there exists no graph or subgraph isomorphism then measure the similarity of objects called Maximum common subgraph.

C. A/V Classification:

There are 30 features to be extracted in feature extraction. These 30 features are measured then normalized to zero mean and unit standard deviation. The features are red, green, blue, hue, saturation and value intensities of centerline pixels and also take mean, standard deviation of these pixels. Take maximum and minimum of red, green and blue intensities in the vessel. Finally takes centerline features of red and green plane.

D. Detection of Glaucoma, Hypertension:

Feed forward neural network (FFN) is used to detect diseases like hypertension and glaucoma.Detection of glaucoma, hypertension are based on feature extraction. So Gray Level Co-occurrence Matrix is used. It calculates pairs of pixel with specific values and in a specified spatial relationship occur in a image. For feature extraction, the features of GLCM are Contrast, Correlation, Energy and Homogeneity.Additionally the other features are Mean and Standard deviation of Red, Green , Blue ,Hue, Saturation and Intensities in the vessel. A FFN is an artificial neural network where information moves only in one direction i.e. forward from input node .There are hidden nodes in between input nodes and output nodes. The reason for hypertension is due to high blood pressure. High blood pressure can damage the vessels in retina. Their Symptoms are Double vision, vision loss, Headaches. Glaucoma is a type of eye disorder that creates damage in optic nerve. It isassociated with increased fluid pressure in the eye known as intraocular pressure.

IV. EXPERIMENTAL RESULTS

The experiment was conducted by using DRIVE, STARE and MESSIDOR databases. The threshold value used here is 0.5. Here biometric graph matching algorithm and feed forward neural network are used. By biometric graph matching algorithm, the arteries and veins are classified and to detect diseases like glaucoma and hypertension, FFN method is used. First the image is filtered by using difference of offset Gaussian kernel and then the image is enhanced. Next vasculature is found for the graph analysis. So vasculature is taken from input image and then a vasculature boundary is created for vasculture. The intersection points are the obtained from the output of graph analysis. Finally artery/vein classification is assigned.

A. A/V Classification-Glaucoma:

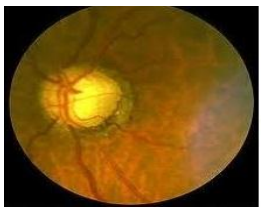


Fig. 2: (a) Input Image

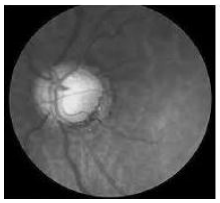


Fig. 3: (a) Difference of Offset Gaussian kernel

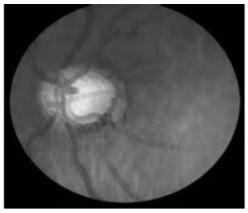
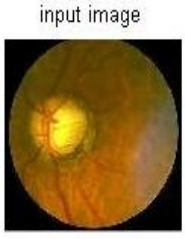


Fig. 4: (a) Vessel enhancement



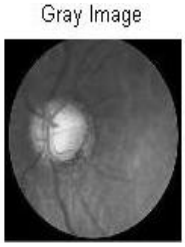
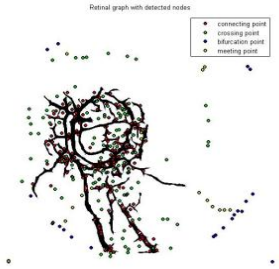


Fig. 5: (a) Input image to vasculature

Fig. 6: (a) vascular boundary



. Fig. 7: (a) Retinal graph with detected nodes

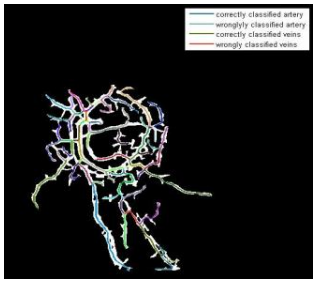


Fig. 8: (a) A/V classification

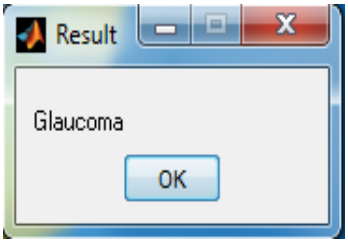


Fig. 9: (a) Retina of glaucoma

B. A/V Classification-Hypertension:

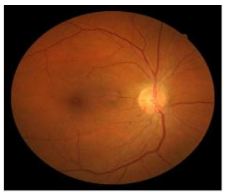


Fig. 2: (b) Input Image

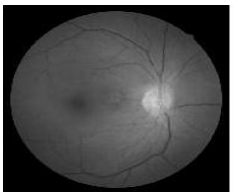


Fig. 3: (b) Difference of Offset Gaussian kernel

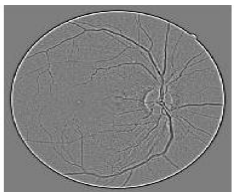
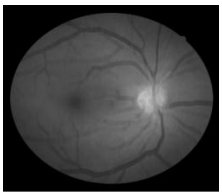


Fig. 4: (b) Vessel enhancement



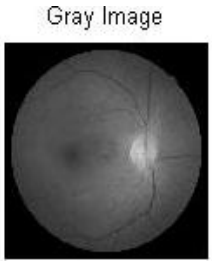


Fig. 5: (b) Input image to vasculature

Fig. 6: (b) vascular boundary

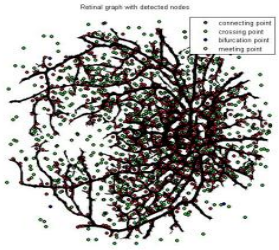


Fig. 7: (b) Retinal graph with detected nodes

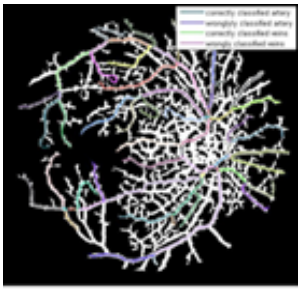


Fig. 8: (b) A/V classification

Fig. 9: (b) Retina of hypertension

V. CONCLUSION

This paper proposes a system for detectingA/V classification and diseases like glaucoma and hypertension .The main advantage is to classify the whole vascular tree but in other methods it can classify only upto specific region of interest. It has better accuracy ,speed and good performance when compared to other methods.Decision on the type of crossing, metting, connecting and bifurcation points are made to detect links. Then A/V classes are assigned. Feed forward neural network is used to detect diseases like glaucoma and hypertension.

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