TECH-CHRONICLE
AN INTERNATIONAL E-JOURNAL ON
EMERGING TRENDS IN SCIENCE, TECHNOLOGY AND MANAGEMENT

Efficient Artery/Vein classification in Retinal Images using Discrete Curvelet Transform Algorithm

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***Abstract-* The classification of retinal vessels into artery/vein is an important phase for speeding up the detection of vascular changes, and for the calculation of characteristic signs associated with several systemic diseases for example diabetes, hypertension, blood pressure and other cardiovascular diseases. This paper presents an automatic approach for A/V classification based on the critical analysis of a graph extracted from the retinal vasculature. The proposed scheme classifies the whole vascular tree deciding on the type of each intersection point (graph nodes) and assigning one of two labels to each vessel segment (graph links).**

Proposed Artery vein classification method on the images of three different databases demonstrate the independence of this method in Artery vein 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 Artery vein classification method is reliable for the calculation of many characteristic signs associated with vascular alterations. In this paper we planned using the graph that represents the vessel tree and the artery vein classification method for Artery vein ratio 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 finding and follow up of diseases, namely diabetes, hypertension, and cardiovascular diseases.

Keywords: component; Artery/vein classification, graph, retinal images, vessel segmentation.

INTRODUCTION

There are two types of vessels, arteries and veins. Arteries are bright in color, since they transport blood rich in oxygen to the organs of the body. The veins then transport the blood, which is at low oxygen level and thus darker, to the lungs and the liver. For many medico applications it would be of great benefit, if the vessels could be distinguished into arteries and veins, since many diseases with one symptom being an abnormal ratio of the size of arteries to veins. Like in diabetic patients the veins are abnormally wide, while diseases of the pancreas lead to narrow arteries and high blood pressure results in thickening of arteries. To detect these diseases the retina is routinely examined.

As a basis for classification a proper segmentation of blood vessels is of course needed.

There are mainly four different features that can be used to classify arteries from veins in general:

• arteries are bright in color than veins

• arteries are thinner than neighboring veins

• the central reflex (the light reflex of the inner parts of the vessels shown in Figure 1) is wide in arteries and smaller in veins.

• arteries and veins usually alternate near the optic disk before they branching out; that means near the optic disk one artery is usually next to two veins and the other way round one important representative of each arteries and veins can be seen in Figure 2.

The mentioned features often provide ample information to successfully classify a vessel as artery or vein. However, in many cases they do not suffice for the following reasons:

• If the image quality is not good enough - which is especially in the outer regions of the image, the central reflex often disappears.

• Vessels in the outer regions of the image are very dark due to the shading effect (in-homogeneous lighting of the image). Here arteries and veins look very much similar, which necessarily leads to the wrong classification of some vessels.

• The width of the vessel is also not very useful for classification, since it is largest near the optic disk and smallest on the outer side of the image.

• The alternation of arteries and veins only found true for the vessels very near to the optic disk. When they start branching out, it is found that two branches of the same vessel go next to each other. So none of the typical features of arteries and veins is globally valid.

Figure 1. One of the most important features for the discrimination of arteries and veins is the central reflex in the red channel; left: original image containing two large veins and an artery in the center, right: red channel

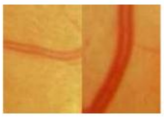

Figure 2. Typical representative of arteries (left) and veins (right), they can be discriminated by color, size, central reflex size and topological properties

To give an overall impression of the difficulty of this classification task, ten cropped veins and ten cropped arteries taken from four different retinal images. The quality of the images, the background and the small size of the vessels and the delicacy of the features themselves make it very hard to distinguish between the two classes. These examples clears that a classification method based only on local features may not be able to achieve good results. We compile these features in a learning based approach, which – with the help of global meta-knowledge - is able to classify arteries from veins with a very high classification rate.

LITERATURE SURVEY

Many characteristic signs associated with vascular changes are measured, aiming at finding the stage and severity of some retinal conditions. Generalized arteriolar narrowing, which is inversely related to higher blood pressure levels [5], [6], is expressed by the Arteriolar-to-Venular diameter Ratio. The Atherosclerosis Risk in Communities (ARIC) study previously showed that a smaller retinal Arteriolar-to-Venular diameter ratio might be an independent predictor of incident stroke in middle aged individuals [7].

The Arteriolar-to-Venular diameter Ratio values are also be an indicator of other diseases, like diabetic retinopathy and retinopathy of prematurity [8]. Among other image processing operations, the estimation of Arteriolar-to-Venular diameter Ratio requires vessel segmentation, accurate vessel width measurement, and artery/vein (A/V) classification [9], [10]. Therefore, any automatic Arteriolar-to-Venular diameter ratio measurement system must accurately identify which vessels are arteries and which are veins, some slight classification errors can have a large influence on the final value.

Several works on vessel classification has been proposed [11]–[17], but automated classification of retinal vessels into arteries and veins can received limited attention, and is still an open task in the retinal image analysis field. In recent years, graphs emerge as a unified representation for image analysis and graph-based methods has 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 can 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 can measured for assigning the final artery/vein class.

Grisan et al. [13] developed a tracking artery/vein (A/V) classification technique which classifies the vessels only in a well-defined concentric zone around the optic disc. Therefore, by using the vessel structure reconstructed by tracking, the classification can propagated outside this zone, where little or no information is available to discriminate arteries from veins. This algorithm cannot design 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 can combines a color-based clustering algorithm with a vessel tracking method. First the clustering approach divides the retinal image into four quadrants, therefore it can classify separately the vessels detected in each quadrant, and finally it can combine the results.

Therefore, a tracking strategy based on a minimal path approach can applied to join the vessel segments located at different radius in order to support the classification by voting.

A piece wise Gaussian model to elaborate the intensity distribution of vessels profiles has been proposed by Li et al. [15]. In this model, the central reflex is considered. A minimum distance classifier based on the Mahalanobis distance is used to differentiate between the vessels types using features obtained from the estimated parameters.

Kondermann et al. [16] describes two feature extraction methods and two classification methods, which are based on support vector machines and neural networks, to classify retinal vessels.

One of the feature extraction methods is profile based, while the other method is based on the definition of region of interest (ROI) around each center line point. To reduce the dimensionality of the feature vectors, they used the multiclass principal component analysis (MPCA).

PROPOSED SYSTEM

We tried to understand in details which are the most relevant features related to the vascular classes and how they can be used to discriminate veins and arteries on heterogeneous images. For this purpose we considered a large number of features, which includes not only color and size descriptor, but we also adding explicitly context related values like spatial position with respect to the optic disc.

In order to have detailed analysis we tried to separate features that are different in veins and arteries for different reasons, which are trying to analyze their real contribution to the classification.

Central color and within-vessel variations:

The principal features used for vessel classification are related to color. Color space components in a neighborhood of the central pixels or along a profile perpendicular to the vessel are mainly considered, usually after a color component normalization to zero mean and unitary standard deviation.

We similarly tested a large set of color features, but decided to analyze separately color features related to the internal part of the vessel and color features including the contrast with the background. We did not find necessary to consider profiles perpendicular to the vessel direction, due to the fact that we studied variations within circular regions around the central pixel. This makes the technique a more robust and thus not depending on the local estimation of the vessel direction. So to characterize the colors inside the vessel and the central reflex, we used the central pixel color components (R,G,B,H,S,V) and component derivatives, also the mean, minimum, maximum and variance of that values in a disc of diameter equal to the locally estimated vessel diameter (small region in Fig. 1).

Contrast with surrounding pixels it is then interesting to check if the contrast with the background provide relevant information for vessel classification (and to see which are the most discriminating parameters). For this purpose we computed further features averages and standard deviations of color components and color derivatives in a disc with diameter equal to twice the locally estimated vessel diameter (large region in Fig. 1).

In this case the computed features are largely dependent on the contrast between vessel color and background color.

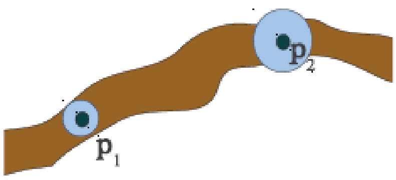

Figure 1. Small (only internal, radius equal to half vessel width) and large (radius equal to vessel width) region used to compute color features potentially characterizing the vessel type.

Position and Size

Vessel size is considered in some work a potentially discriminative feature, but often not considered due to the fact that it changes with the distance from the optical disc .

But this is not a reason to avoid its use, but rather a reason to use it in combination with spatial information. Actually, if we consider the results, where it is reported that color features are more discriminative if used independently in different sectors around the OD, it is reasonable to think that color features should also be combined with spatial information in order to obtain a better classification.

We decided to test the discriminative power of spatial features like angular and radial distance from the Optic disc center and distance from the image optic center. The analysis of the discriminative power of these features alone and also combined with size and color based one is surely relevant to determine how to improve the performance of classification tools. To compute angular distance from the estimated OD center we used the OD locator developed for the VAMPIRE tool, based on multi scale ellipse fitting. The angular position is computed differently in case of left or right image. In the first case we consider a clockwise orientation, and in the second case counterclockwise as shown in (Fig. 2), so that the possible effects of the variable on the image color should be the same.

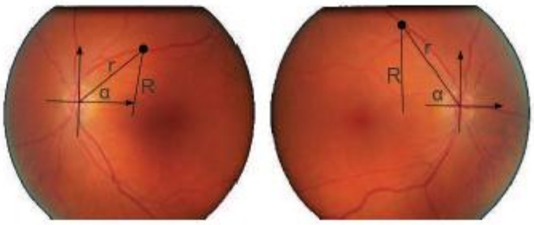

Figure 2. Measurements related to image position: linear distances from the estimated OD center and image center and angular position with respect to the OD center differentiated for left and right images.

MODULES

Image enhancements:

In image enhancements we extract the green channel of image which show the more probability of veins of retina image. Retina image is RGB (red green blue). We extract green channel. After that we enhance the extract image by using histograms adjustment algorithm to improve the image quality.

Vessel segmentation:

After getting the improve image we apply the canny edge detector to finding the edges in image for classifying feature extraction and A/V (artery vein) Classification.

Feature extraction module contain SVM (state vector machine) module which is used to train the project for detection the feature points in image.

Node and Branches descriptor:

Node and branches descriptor used to find the cross section points of edges in image to classify the vein and artery by using graph method with the help of bfs (breath first search) to transverse a graph.

Classification Result:

This module classifies the input image by basic of training of feature detection and node descriptor module and shows the calculated result.

RESULT & DISCUSSION

We will perform several tests aimed to understand which groups of features are useful to discriminate veins and arteries in digital fundus images. Results could be useful to improve the performances of existent systems for the estimation of related biomarkers such as the Artery vein ratio.

First of all, color contrast between vessels and background appear as one of the most important cue for discrimination, but there are vessels that are not well recognized so simply and thus required to add more information. This information can be related to vessel position and to the color variations inside the vessel. While the vessel width does not add much useful information.

Finally, image resolution should be taken into account. It seems that high resolution sensors introduces noise and can reduce the color based information, the same features computed on sub sampled images gave, in fact, better results even if an excessive sub sampling could remove the information about the central reflex in vessels. The dependency of performance on color confirms the importance of normalizing image resolution in studies involving different-resolution fundus cameras. to guarantee consistency.

CONCULSION

We introduced a technique for unsupervised information extraction from unstructured, ungrammatical text. Previously, unsupervised extraction used patterns that make assumptions about the regularity of the structure in the data. We relax this assumption by exploiting reference sets to aid the extraction. These reference sets are chosen by the algorithm, removing the need for any human intervention.

The main ability of neural network is to learn from its environment and to improve its performance through detailed learning. For this purpose there are two types of learning supervised or active learning – learning with an external supervisor who present a training set to the network. But another type of learning also exists : unsupervised learning . Unsupervised learning is self organized learning doesn't require an external supervisor. During training session neural network receives a number of input patterns , discovers significant features in these patterns and learns to classify input data into appropriate categories. It follows the neuro - biological organization of the brain. These algorithms aim to learn rapidly, so learn much faster than back-propagation networks and thus can be used in real time. Unsupervised neural networks are effective in dealing with unexpected and changing conditions. We have shown that as compared to Trinity Tree Algorithm Back Propagation is more accurate and less time consuming.

Acknowledgment

The authors would like to thank the authors whose reference are available in this regards.

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