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A WIDE-RANGING STUDY OF RETINAL VESSEL CLASSIFICATION METHODS IN FUNDUS IMAGES

D. Rama Krishna[1], C. Vishnupriya[2], A. Shirisha[3], CH. Ruchitha[4]

[1]Assistant Professor, Department of ECE, Malla Reddy Engineering College For Women, Hyderabad.

[2,3&4] UG Scholar, Department of ECE, Malla Reddy Engineering College For Women, Hyderabad

ABSTRACT

Nowadays, it is obvious that there is a relationship between changes in the retinal vessel structure and diseases such as diabetic, hypertension, stroke, and the other cardiovascular diseases in adults as well as retinopathy of prematurity in infants. Retinal fundus images provide non-invasive visualization of the retinal vessel structure. Applying image processing techniques in the study of digital color fundus photographs and analyzing their vasculature is a reliable approach for early diagnosis of the aforementioned diseases. Reduction in the arteriolar–venular ratio of retina is one of the primary signs of hypertension, diabetic, and cardiovascular diseases which can be calculated by analyzing the fundus images. To achieve a precise measuring of this parameter and meaningful diagnostic results, accurate classification of arteries and veins is necessary. Classification of vessels in fundus images faces with some challenges that make it difficult. In this paper, a comprehensive study of the proposed methods for classification of arteries and veins in fundus images is presented. Considering that these methods are evaluated on different datasets and use different evaluation criteria, it is not possible to conduct a fair comparison of their performance. Therefore, we evaluate the classification methods from modeling perspective. This analysis reveals that most of the proposed approaches have focused on statistics, and geometric models in spatial domain and transform domain models have received less attention. This could suggest the possibility of using transform models, especially data adaptive ones, for modeling of the fundus images in future classification approaches.

Keywords: Arteries and veins, computer-aided diagnosis, medical image processing, retinal fundus images, retinal vessel classification

INTRODUCTION

The retina is a multi-layered tissue of light-sensitive cells which has surrounded the posterior cavity of the eye, where light rays are converted into neural signals for interpretation by the brain. One of the most important retina associated diseases is diabetes. Diabetes affects a patient's body from various aspects such as changes in the retinal blood vessels. Diabetic retinopathy refers to a common complication of diabetes which affects the retinal vascular area, and it is increasingly becoming a major cause of blindness throughout the world.[1,2,3,4] Diabetic retinopathy is broadly divided into nonproliferative and proliferative types. The earliest form of diabetic retinopathy is nonproliferative, in which damaged blood vessels in the retina begin to leak extra fluid and small amount of blood spreads into the eye. In proliferative

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retinopathy, new fragile blood vessels grow in the retina, which can result in significant visual impairment.[2,5,6] Laser therapy in the earliest stages of diabetic retinopathy can prevent from progression of the eye damages, and the risk of blindness may even be reduced to a great extent. Success of the treatment depends on early detection and regular check up/follow up by ophthalmologist. Various methods have been proposed for early diagnosis of this disease. Fundus imaging has been known as one of the primary methods of screening for retinopathy.[2] Recent advances in digital imaging and image processing have been resulted in widespread use of image modeling and analysis techniques in all areas of medical sciences, especially in ophthalmology. Retinal blood vessel network is the only blood vessel network of the body that is visible in a non-invasive imaging method.[7] Retinal fundus color imaging is a common procedure for both manual and automatic evaluation of this vessel structure. Structural analysis of retinal vessel network is used as a reliable tool for early detection of retinopathies.[8,9,10,11] Researchers started this analysis with the development of vessel segmentation methods and expanded it for the evaluation of morphological features of the vessel network.[12,13] There are many parameters that can be measured from the retinal vessels structure such as changes in the thickness of the vessels, curvature of the vessel structure, and arteriolar–venular ratio (AVR). AVR has been found useful for early diagnosis of diseases such as hypertension, diabetes, stroke, and the other cardiovascular diseases in adults, and retinopathy of prematurity in infants.[14,15,16] Therefore, to achieve meaningful diagnostic results, accurate measurement of this parameter is necessary. Various protocols have been defined for measuring the AVR. In Japan, it is often measured using the largest adjacent pair vessels in macula-centered images and in a certain distance from the optic disc margin, usually 0.25–1 of the optic disc diameter. However, in the U.S., six largest vessels in the area within 0.5–1 of the optic disc diameter from its margin in optic disc-centered images are generally considered to AVR calculation.[17] AVR calculation problem comprises several smaller problems including: optic disc localization, vessel segmentation, accurate vessel diameter measurement, vessel network analysis, and classification of arteries and veins. Optic disc localization is required to determine region of interest (ROI), where the measurements are performed according to the protocol. Vessel segmentation is necessary for finding the exact location of the vessels and also for thickness calculation. Vessel network analysis is required because the location of bifurcations and cross over points should be determined for successful implementation of medical protocols. Classification of arteries and veins is a fundamental step in measuring the AVR. Separation of arteries and veins with high accuracy is important because small errors in classification may lead to relatively large errors in the final AVR. Therefore, providing an effective and efficient method for vessel classification seems necessary. The structure of this paper is as follows: first, the problem of the retinal vessel classification and its challenges are expressed. Then, in third section, a comprehensive review of the state-of-the art methods for arteries and veins classification in fundus images is provided and finally, in fourth and fifth sections, discussion and conclusions are presented, respectively.

PROBLEM STATEMENT

Many research works have been conducted for retinal vessel segmentation,[12] but automatic classification of the segmented vessels has received less attention. Classification of vessels in retinal fundus images faces some challenges which make it difficult. Two challenging factors are low contrast of the fundus images and inhomogeneous lighting of the background. Inhomogeneous lighting is caused by imaging process, while low contrast is the result of this fact that different blood vessels have different contrast with the background. In other words, thicker vessels have higher contrast in comparison to thinner ones. In addition, changes in color of retina for different subjects which emanate from biological characteristics raise another problem. Retinal vessel classification approaches are often based on visual and geometric features which discriminate arteries and veins. Generally, arteries and veins are different in four features: veins are thicker than arteries, veins are darker (redder), and central reflex is more recognizable for arteries. Moreover, arteries and veins usually alternate near the optic disc and before branching off. However, in many cases, these differences are not sufficient to distinguish arteries from veins. For example, in low quality images, central reflex in the outer areas often will be removed. In addition, the vessels in the outer regions of the image are very dark because of shading effect resulted from inhomogeneous lighting of the image. In these cases, arteries and veins look very similar that leads to misclassification of some vessels. Furthermore, thickness does not account an appropriate feature for classification, because this feature is variable from the highest value near the optic disc to the smallest value in outer parts. Moreover, if major arteries or veins are branched off inside the optic disc, it is possible that there are two adjacent arteries or veins just out of the optic disc.

LITERATURE REVIEW

Estrada et al. developed a semi-automatic approach which combines graph-theoretic methods with domain-specific knowledge and is capable of analyzing the entire vasculature. This classification framework which relies on estimating the vascular topology is indeed the extension of previously proposed tree topology estimation framework that incorporates expert, domain-specific features to construct a likelihood model. In the next step, this model is maximized by iteratively exploring the space of possible solutions consistent with the projected vessels. The proposed method was tested on four retinal datasets namely WIDE AV-DRIVE,CT-DRIVE, and AV-INSPIRE and achieved classification accuracies of 91.0, 93.5, 91.7, and 90.9%, respectively.

Most of the conducted efforts for retinal vessel classification tend to be fully automatic methods which can be utilized for clinical purposes. In the following section, a comprehensive review of this kind of classifiers is presented.

Automatic methods

Artery and vein classification problem in retinal fundus images is complicated because of the similarity between descriptive features of these two structures and also variability in contrast and illumination of fundus images. Retinal images suffer from inhomogeneous contrast and illumination which arises from inter-image and intra-images changes. Some sample fundus images are shown , which depict high color and illumination variations inter and intra images. To achieve meaningful color information, these changes must be eliminated. For this purpose,

in the works of Grisan and Ruggeri image background is analyzed to detect changes in contrast and illumination, then these changes are corrected by statistical estimation of their characteristics.
One of the first automatic retinal vessel classification methods proposed by Grisan and Ruggeriin 2003. Vessel network extraction is a primary stage in fundus image analysis which is often performed by a vessel tracking process and a set of vessel segments are provided. Grisan and Ruggeri used sparse tracking algorithm for automatic extraction of the vessel network. To take advantages of local features and vessel network symmetry, retinal image is divided into some zones with the equal number of arteries and veins. It is assumed that two vessel types in these zones have considerable differences in their local features. In this method, an area around the optic disc (within 0.5–2 of the optic disc diameter from its center) is divided into four zones, in which each one contains one of the major arches.

Among various features, variance of the red channel and mean of the hue channel in each vessel segment are considered as the most discriminative features for classification. Clinically, in two adjacent vessels, the darker (more reddish) vessel is considered as vein, and if there is not considerable difference in red values, the vessel that has more color uniformity is considered as vein. After feature extraction, vessels have been classified using a fuzzy clustering algorithm. The Euclidean distance of each pixel from the mean value of features in each class is considered as classification criterion. Finally, labels of pixels in each segment are combined based on major voting and the whole segment is classified. After vessel classification in the specified zone, this classification can spread out of this zone (where little information is available from texture and color to discriminate arteries and veins) by vessel tracking. Thirty-five fundus images have been analyzed in this study, in which 11 images were used to develop the algorithm, and 24 images were used for validation. Reported results on 24 validation images show the overall error of 12.4%. Considering that this classification procedure is performed around the optic disc and the underlying assumption is that all four quadrants have similar number of arteries and veins, this method is more suitable for optic disc-centered images.
Ruggeri et al. developed this method in 2007 by AVR assessment in the area from 0.5 to 1 disc diameter from the optic disc margin. In this paper, a correlation with a manual reference standard on 14 images is provided which varies between 0.73 and 0.83, depending on the protocol which is used for AVR calculation. Afterward, Tramontan et al. further developed this method in 2008 by improving the vessel-tracking algorithm which led to an increase in correlation with the reference standard up to 0.88 for 20 images acquired from DCCT study. In this method, red contrast parameter is used which is defined as the ratio between the peak of the central line intensity value and the largest intensity value of two vessel edges. Arteries and veins have been classified based on the average value of the red contrast along the vessel which determines the probability of belonging to the vein class.
A piecewise Gaussian model is proposed by Li et al. to capture central reflex in the green channel for separating arteries from veins. The minimum Mahalanobis distance classifier is

applied for identification of vessel type. Experiments on 505 vessel segments from different fundus images were resulted in true positive rate of 82.46% for arteries and 89.03% for veins.
Jelinek et al. tested different classifiers and features to discrimination of arteries and veins. They used eight features including mean and standard deviation of red, blue, green and hue channels as well as 13 classifiers available through the Weka toolbox. The three best features were the mean of green, and the mean and standard deviation of hue. Best classification result obtained from Naive-Bayes which led to a mean accuracy of 70% over eight images.
Four different classifiers namely nearest neighbor (NN), 5-NN, Fisher linear discriminant, and support vector machine (SVM) are investigated by Narasimha-Iyer et al. to retinal vessel classification and the best result has obtained by the SVM. Structural and functional features are utilized for separating arteries and veins. Central reflex as a structural indicator and the ratio of the vessel optical densities from images at oxygen-sensitive and oxygen-insensitive as a functional feature have been used. The classifier is applied to a set of 251 vessel segments from 25 dual wavelength images and has achieved to true positive rate of 97% for arteries and 90% for veins.
In 2007, Kondermann et al. examined two profile-based and ROI-based feature extraction methods, as well as two classification methods based on SVM and neural networks for the separation of arteries and veins in retinal fundus images. Profile-based features are RGB color space values by subtracting their mean values that have been determined for each centerline pixel and also pixels belonged to its profile. ROI-based features are obtained in a square region around each centerline pixel (that is rotated in such a way that its horizontal axis is aligned with the main axis of the vessel). Multiclass principle component analysis is used to reduce the size of the feature vector before applying it to the classifier.
The methodologies have been assessed on four 1024 × 1280 retina images containing 10,132 centerline pixels. Four kernels including: linear, polynomial, radial basis function (RBF), and sigmoidal with different values of the parameters were examined for SVM classification which RBF kernel yielded the best result. Both classifiers show good performance on manually segmented data, but for automatic segmented images, their performance is deteriorated about 10%. The best reported results indicate that 95.32% of the pixels belong to the major vessels in the area within three diameters of the optic disc are properly classified using ROI-based feature extraction method combining with multi-layer perceptron (MLP) classifier. Adding meta-knowledge (all pixels of a vessel section, between two intersections, must belong in a same class) has contributed to classification rate by 6.44%. It is worth mentioning that these experiments have been conducted on high-quality images, and optic disc is in the center of the images which reduces destructive effects of the inhomogeneous illumination.
In the works of Muramatsu et al., two major pair vessels in upper and lower temporal regions which come out from the optic disc are selected manually for AVR calculation. First, retinal vessels are extracted using top-hat transformation and double-ring filter techniques. Subsequently, the position and diameter of the optic disc are obtained to determine the desired ROI for measuring the AVR. Once the vessels were segmented, RGB color information is extracted from the vessel segments in quarter-disc to one disc diameter from the edge of the

optic disc. Centerline pixels are classified using linear discriminant analysis (LDA) classifier, and the label of each segment is determined by majority voting. Classification accuracy of the centerline pixels that were classified correctly was 88.2% which resulted correctly in the classification of 30 pairs out of 40 pairs of the major arteries and veins in 20 test images from DRIVE dataset.

In 2011, Muramatsu et al. further improved their approach and proposed a method, in which vessels are classified using LDA classifier that utilizes features including RGB color and contrast values. Contrast value is defined as the difference between the average of intensity values in a 5 × 5 window around the intended pixel (centerline pixel) within the vessel, and the average of intensity values in a 10 × 10 window around that. By applying a feature selection, contrast value of the blue channel was removed, and the other five features have been used to train the classifier. Finally, each vessel segment is classified by majority voting using obtained labels for centerline pixels which has led to the accuracy of 92.8%.

In the works of Váazquez and co-authors,a color-based clustering procedure is combined with a vessel tracking method based on the minimal path approach. Considering AVR measurement protocols, the ROI is defined by several circumferences centered at the optic disc. Five feature vectors from RGB, HSI, and gray level color spaces were selected including red values, green values, red and green values, hue values, and gray level values. Another feature vector was also defined that contains a mean of the hue and variance of the red values in each profile. Furthermore, to minimize the effect of outliers, the mean and the median of each profile in each color channel were also considered. Finally, of all these features, median of the green values was selected as the most discriminant feature.

After defining feature vectors in each circumference, optic disc-centered retinal image is divided into four quadrants, in which coordinates axes are rotated by 20° steps between 0° and 180°. Then, k-means clustering is applied to extracted feature vectors in each quadrant and classify them. In the next step, vessel segments are classified by majority voting based on the classification results of the feature vectors extracted from their profiles. Final label of each vessel segment is obtained by combining the local classification results in the quadrants in which the vessel is found. Finally, vessel tracking strategy tracks vessel segments along the vessel, in different circumferences, to obtain the final label of the vessel. Reported results in the works of Vázquez et al.show the classification rate of 87.68% in 100 retinal images from VICAVR-2 dataset.One disadvantage of the k-means clustering method is that this method is sensitive to initialization, and it is possible to get stuck in local minima.

In the works of Niemeijer et al., an automatic supervised method is provided for arteries and veins classification in DRIVE dataset images. First, centerline pixels of the vessels are extracted, and bifurcations and cross over points are removed by omitting pixels with more than two neighbors. In this way, vascular network is divided into some segments. In the next step, width (ωi) and angle (θi) of each pixel are calculated. After performing preprocessing on all 20 training images, 24 features have been extracted (for each centerline pixel and along its profile) which are including intensity values and derivative information. All features are normalized to have zero mean and unit standard deviation. In the next stage, dimension of the feature space has been reduced by sequential forward floating selection (SFFS) method and the most prominent features

EXISTING SYSTEM Blood Vessels is one of the most significant causes of mortality in the world today. Prediction of cardiovascular disease is a critical challenge in the area of clinical data analysis. Blood Vessels is very dangerous if not immediately treated on time. The existing system doesn't effectively classify and predict the disease in human body. Practical use oh healthcare database systems and knowledge discovery is difficult in Blood Vessels .

Disadvantages

- Doesn't Efficient for handling large volume of data.
- Theoretical Limits
- Incorrect Classification Results.
- Less Prediction Accuracy.

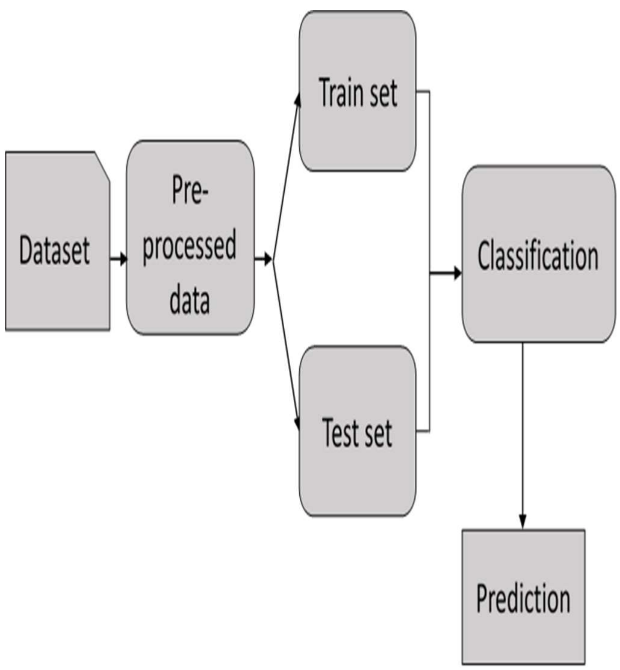
PROPOSED SYSTEM

The proposed model is introduced to overcome all the disadvantages that arises in the existing system. It is based on UNET

Advantages

- High performance.
- Provide accurate prediction results.
- It avoid sparsity problems.

ARCHITECTURE DIAGRAM



Modules

- Data Selection and Loading
- Data Preprocessing
- UNET
- Classification

Prediction
Result Generation

RESULT GENERATION

The Final Result will get generated based on the overall classification and prediction. The performance of this proposed approach is evaluated using some measures like,

Accuracy

Accuracy of classifier refers to the ability of classifier. It predicts the class label correctly and the accuracy of the predictor refers to how well a given predictor can guess the value of predicted attribute for a new data.

$$AC = \frac{TP+TN}{TP+TN+FP+FN}$$

Precision

Precision is defined as the number of true positives divided by the number of true positives plus the number of false positives.

$$Precision = \frac{TP}{TP+}$$

Recall

Recall is the number of correct results divided by the number of results that should have been returned. In binary classification, recall is called sensitivity. It can be viewed as the probability that a relevant document is retrieved by the query.

$$Recall = \frac{TP}{TP+}$$

F-Measure

F measure (F1 score or F score) is a measure of a test's accuracy and is defined as the weighted harmonic mean of the precision and recall of the test.

$$F\text{-measure} = \frac{2TP}{2TP+FP+FN}$$

CONCLUSION

In this process, we present the hybrid predictive models by UNET Segmentation In this paper, a new convolutional network architecture was proposed for retinal image vessel segmentation. It achieved a better outcome in the DRIVE database and performed better than a skilled ophthalmologist. From Table 2 and comparing to the different methods for image vessel segmentation, the accuracy of the proposed method in this paper on DRIVE is 0.9790. That is to say that our method is on the top of these compared methods

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