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A SUPERVISED TECHNIQUE FOR IMPROVED SEGMENTATION OF FUNDUS VESSELS USING NEURAL NETWORK CLASSIFICATION

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ABSTRACT

The fundus vessel structure malformations such as variation in length, width, branching angles etc are one of the manifestations of the eye disease, Diabetic Retinopathy (DR) which is prevalent in diabetics' patients. For assessment of eye blood vessels and for early detection of DR an automated blood vessel segmentation method is necessary. This research work presents a supervised vessel segmentation method using gray level based features and neural network classifier. The fundus images present variations in pixel intensity, noise, etc. A preprocessing method employs steps to reduce these imperfections and generate images more suitable for extracting the pixel features.

The feature extraction from the preprocessed image is using the two gray level features based on differences in pixel intensities. A neural network classifier is used for pixel classification as vessel or nonvessel and generates a vessel segmented image. A post processing scheme is used to improve the segmentation result. The proposed method is implemented using MATLAB and evaluated over publically available DRIVE database in terms of sensitivity, specificity, positive predictive value, negative predictive value and accuracy. The comparison with a method using seven features based on average accuracy shows performance improvement.

KEYWORDS: Diabetic Retinopathy, Feature Extraction, Image Preprocessing, Neural Networks, Segmentation

INTRODUCTION

Diabetic retinopathy (DR) is one of the foremost causes of blindness among people suffering from diabetes. About 2% of the diabetic patients affected are blind and almost 10% after 15 year of diabetics have vision problems. [1]. Medical images provide useful information which can be effectively used in collaboration with the current technology for diagnosis. The computerised systems relieve physicians of repetitive work. These systems improve work efficiency, moreover such kinds of systems have lower costs [2]. The fundus vessels have malformations such as variation in length, width, branching angles etc as a result of an eye disease. An automated segmentation method can be an useful component for incorporating into a screening system for early DR detection. The other applications are vessel width determination for treatment of cardiovascular diseases, registration of multimodal images etc. Varied research efforts have been done in [3][4]. In this paper a technique based on a supervised classification is presented.

The method incorporates pixel classification based on pixel features extracted from preprocessed images, given as input to a classifier. Classification procedure differentiates every pixel as vessel or nonvessel to generate a vessel segmented image. Firstly preprocessing steps are carried out for improving image quality. Then the feature extraction for pixel representation is proposed using gray level based features. The classification is done using a neural network as a classifier. The paper is organised as, Section 2 is Related Work, Section 3 is the Proposed Method, Section 4 gives Results and Discussion and finally Section 5 gives Conclusion and Future scope.

RELATED WORK

The methods in literature are rule-based methods and supervised methods. The tracking based methods start from an initial set of points established automatically; the vessels are traced by deciding most appropriate candidate pixel close to the pixels under evaluation. A fuzzy approach [5] terminates when the 1D matched filter response falls below a given threshold. A recursive dual edge tracking and connectivity technique [7] uses edge map determined by the canny edge operator to check connectivity of its twin border. The morphological methods use information of shape features and apply morphological operators, for filtering vessel from background for segmentation. The top-hat-transform [9] causes vessel pixels to darken; border pixels take the value of the closing. There are other structures which have same morphology. So the cross curvature is determined using Laplacian filter [10] as curvature is linearly coherent. The matched filter method uses a 2-D linear structuring element with a Gaussian cross section for vessel detection. In [12] piecewise linear segments of vessel are detected in the gray level profile of cross section of vessel approximated by a Gaussian shaped curve. 12 kernels are determined using 12 directions and for each pixel maximum response is selected. Post processing is required to eliminate false edges detected due to bright objects.

The response is increased by optimising parameters [14]. The deformable or snake models [15],[17], model-based locally adaptive thresholding [16], multiscale feature extraction method [18] are some of other methods. The supervised methods are based on pixel classification as vessel pixels or non-vessel pixels. Manually-labelled images along with suitable learning algorithm are used for classifier training. The classifiers in literature are kNN method [21], Bayesian classifier [22], support vector machines [23] and neural networks [24]. The segmentation methods vary depending on the imaging modality, application domain, method being automatic or semi-automatic, and other specific factors. The review shows that work done by supervised approach methods have improved performance accuracy over rule based methods. Most rule based segmentation methods require user interaction. It is observed that every method discussed above has some or the other limitation based on the techniques used in preprocessing, feature extraction or classification steps. Within the retinal imaging, variability is observed in image acquisition and hence it is reported in the appearance of images. The method must be robust for different kinds of images. The NN classifier is observed to have better performance with respect to previous classifiers. The training is computationally demanding based on type and number of features. Also accuracy of outcome of classifier is dependent on training set. This paper gives a supervised technique for vessel segmentation from eye images.

PROPOSED METHOD

Architectural Block Diagram of Proposed System

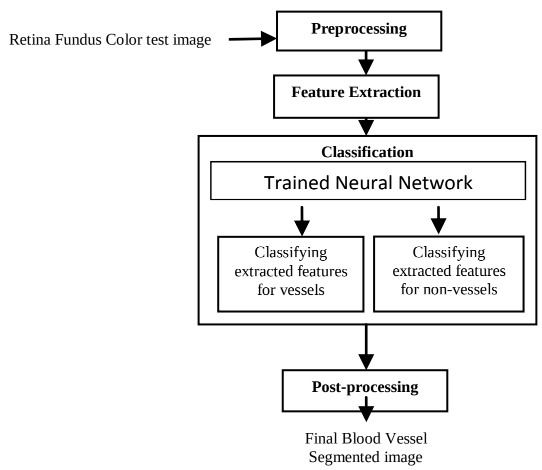

Figure 1

Preprocessing

Color fundus images often show important lighting variations, poor contrast and are noisy. In order to reduce these imperfections, a preprocessing comprising the following steps is applied:

- **Green Channel Image**

It is observed that blood carrying components of retina like the vessels are best shown in the green plane. Also, they have higher contrast in green channel. The input images used are grayscale green channel images.

- **Removing Middle Brighter Intensity Line (CLR) from Blood Vessel**

It is observed that blood vessels have lower reflectance when compared to other retinal surfaces. Some blood vessels include a brighter intensity line along the middle part of vessel called the central light reflex (CLR). To equally distribute gray levels on vessels this needs to be eliminated. The green plane image Ig is filtered by a morphological opening using structuring element 3 pixel diameter disc, using eight-connectivity. The structuring element size is taken least to avoid overlap of vessels which are near to each other.

- **Removing Background Image Illumination Variations (Homogenisation*)***

In the green channel image even though background gray-levels are higher than those of vessel pixels, the intensity values of some background pixels are comparable to that of brighter vessel pixels. Since features used to represent a pixel use gray-scale values, this effect may worsen the performance. For removing the varied illumination, the background is processed to obtain intensities corrected. Image Iv is filtered through a number of filters. The salt-and-pepper noise is smoothened by a 3 x 3 mean filter and a 9 x 9 Gaussian filter, m=0 and v= 1.8^2. A large 69 x 69 filter is applied for getting background image. In the FOV pixels at border, a 3 x 3 mean filter is applied out-of-the FOV [25] to eliminate blurring effects.

The shade/intensity-correction method uses subtractive approach. So, intensities of pixels of background image are subtracted from intensities of corresponding pixels of vessel CLR removed image to form a difference image A shade-corrected image is obtained by transforming real data values into integers. The algorithm reduces background intensity variations and enhances contrast. The histogram of shade corrected image is plotted and shifted along graylevels by altering pixel intensities according to the transformation to get homogenised image:

$Ihomo(x,y) = 0 \; if \; d < 0,$

$255 \; if \; d > 255,$

d otherwise

where, d=Isc(x, y)+128-di_m (1)

Isc(x,y) and Ihomo(x,y) are the gray-level variables of input difference Isc and output homogenised Ihomo images respectively. The variable di_m describes gray-level with the highest number of pixels in Id. By the transformation function, pixels with gray-level di_m, which correspond to background of retina, attain intensity value 128. The output at this stage is the background homogenised image Ihomo.

- **Blood Vessel Enhancement**

It is observed that the structures like the optic disc, possible presence of exudates etc need to be removed and darker artefacts as blood vessels need to be enhanced. The complementary image Ihomoc of the homogenized image Ihomo is computed as, in eq 2. Then, Top-Hat transformation is applied to the complementary image by carrying out opening using 8 pixel radius disc as structuring element.

Ihomoc (x,y)=255-Ihomo(x,y) (2)

Ive= Ic-γ(Ic) (3)

where, Ic-complementary image, γ - morphological opening, Ive- enhanced image. While preprocessing images for training the classifier, size is diminished to reduce dimensionality of input feature vector created in feature extraction. Also, it is observed that, the intensities at border pixels are diffused. The use of such pixel may cause classifier to give incorrect classification. For this, border removal is done by reducing FOV mask dimension. The new mask is applied to homogenised and vessel enhanced image to generate images with border removed and size diminished.

- **Intensity Adjustment**

The intensities in the vessel enhanced image are adjusted to reach a higher contrast to generate an intensity adjusted image.For training the classifier a target vector is required which is the known representation of the pixels. In this work, while preprocessing images for generating training set, the images are thresholded by using a threshold of 80 which is determined by trial and error method. The thresholded images are used as target vector.

Feature Extraction

The feature extraction is used to obtain a pixel representation in terms of some measure which can be used in the classification stage to decide whether a pixel belong to a blood vessel or not. Retinal blood vessels are always darker than their surroundings. The features which consider the intensity variation in the surroundings of current pixel can be used to describe the candidate pixel. The gray level features are derived from preprocessed image considering a 3 x 3 pixel region centred on the described pixel (x,y). The feature values are calculated over the intensity adjusted image as,

$$F1(x,y) = I(x,y) \quad (4)$$

$$F2(x,y) = mean\ \{I(s,t)\} \quad (5)$$

where, $(s,t)\epsilon S3(x,y)$

$S^{3}_{x,y}$ stands for the set of coordinates in a 3 x 3 sized square window centred on point (x,y). In the feature extraction stage, each pixel from a fundus image is characterized by a vector in a 2-D feature space given as,

$$F(x,y) = (F1(x,y), F2(x,y)) \quad (6)$$

Classification

Supervised classification has been applied to obtain the vessel structure segmentation. The classification procedure assigns one of the classes, vessel or non vessel to a candidate pixel when its representation is known. The Artificial Neural Network classifier is proposed in this paper. The classification is subdivided into 3 steps:

- **Training Dataset**

The training set are candidates for which the feature vector F(x,y) and the result (vessel or nonvessel) are known. The preprocessing steps are carried out over different fundus images and then the 2 features are calculated over every pixel in each image. Due to the computational cost of training the classifier and the large number of samples, a subset of the available pixel samples from three images is selected. All pixel samples belonging to vessels are taken and equal number of non-vessels samples is taken. The input vector consists of the feature vectors for a number of pixel samples for both vessel and nonvessel pixels. The thresholded images generated in the preprocessing step are used to obtain target vector for the corresponding pixel samples.

- **Deciding the NN Configuration and Training the NN**

A multilayer feed forward network, consisting of an input layer, two hidden layers and an output layer is used. The input layer consists of 2 neurons corresponding to the two features. For deciding the number of hidden layers trial and error method was used. The first hidden layer consists of 6 neurons. The second hidden layer consists of 3 neurons. The output layer contains a single neuron which gives output as vessel or nonvessel. The training set is used for training the NN. The NN is trained by using the Back propagation algorithm. The Logistic Sigmoid function is used as the activation function. The mean square error is taken as error function. The training of NN is continued until the minimum error goal is met.

- **Applying the Trained NN to Classify Each Pixel to Obtain a Vessel Structure Binary Image**

At this stage, the trained NN is applied to an unknown test fundus image to generate an image in which blood vessels are identified from retinal background. The unknown image is preprocessed and feature vector for each pixel is computed. The feature vectors given as input to trained NN. The NN classification procedure assigns one of vessel or nonvessel to each candidate pixel and generates as output the final vessel segmentation image. The resultant image has pixels with intensity values 1 as vessel pixels and remaining pixels are nonvessel pixels. The pixels with intensity values 1 are multiplied by 255 so they are bright and clearly visible.

Postprocessing

From visual inspection of the NN output, vessels may have a few gaps (i.e., pixels completely surrounded by vessel points, but not labeled as vessel pixels). A window is centered on pixel under consideration. The average of intensities of all pixels in the window is calculated. If the average intensity comes above 128, the center pixel is more likely to be a vessel pixel. This is achieved by using the inpaint_nans method [26] and improves the vessel segmentation result.

RESULTS AND DISCUSSIONS

To evaluate the proposed methodology a publicly available database containing retinal images, the DRIVE[27] is used. The corresponding manual segmentations for each image is given for segmentation methodology performance evaluation. In order to quantify the performance of the proposed method, the resulting segmentation is compared to its corresponding manual segmented image. The proposed method is evaluated in terms of sensitivity (S_e), specificity (S_p), positive predictive value (P_{pv}), negative predictive value (N_{pv}) and accuracy (A_{cc}). These metrics are defined as,

$\mathrm{S_e} = \dfrac{\mathrm{TP}}{\mathrm{TP+FN}}$	(7)
$\mathrm{S_P} = \dfrac{\mathrm{TN}}{\mathrm{TN+FP}}$	(8)
$\mathrm{P_{Pv}} = \dfrac{\mathrm{TP}}{\mathrm{TN+FP}}$	(9)
$\mathrm{N_{Pv}} = \dfrac{\mathrm{TP}}{\mathrm{TN+FP}}$	(10)
$\mathrm{A_{cc}} = \dfrac{\mathrm{TP+TN}}{\mathrm{TP+FN+FN+FP}}$	(11)

The method is implemented in MATLAB 2010 on INTEL(R) CORE(TM) i3 CPU 2.53GHz with 4GB RAM. The experiments are carried out over a number of images available in the DRIVE database. The preprocessing stage results for an image are shown in Figure 2.

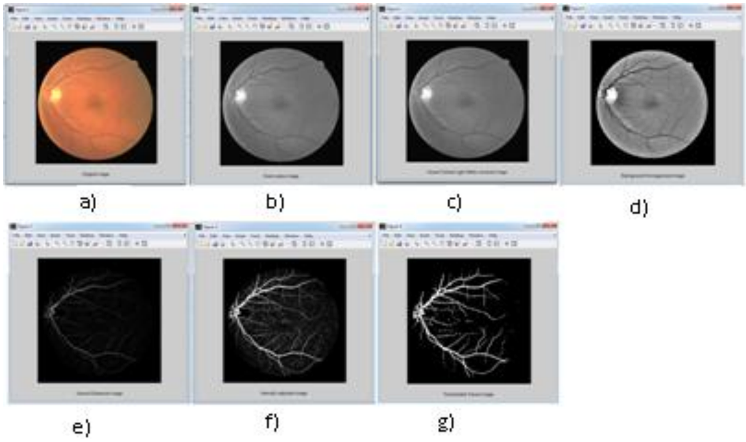

Figure 1: a) Original Image, b) Green Plane Image, c) Vessel Central Light Reflex Removed Image, d) Background Homogenised Image, e) Vessel Enhanced Image, f) Intensity Adjusted Image, g) Thresholded Image

The experimental results for two images are shown in Figure 3 and Figure 4. The image a) is the input color fundus image and the image b) is the vessel segmentation obtained by proposed method. The corresponding performance measures are also shown.

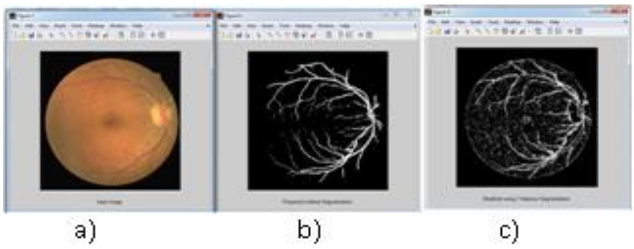

Figure 2: a) Original Image, b) Proposed Method Segmentation, c) Method Using 7 Features Segmentation

Proposed method: sensitivity:0.6495 ; specificity:0.9846 ; positive predictive value:0.8784 ; negative predictive value:0.9425 ; accuracy:0.9356

Method using 7 features: sensitivity: 0.509; specificity: 0.9082; positive predictive value:0.487; negative predictive value: 0.9153 ; accuracy: 0.8498

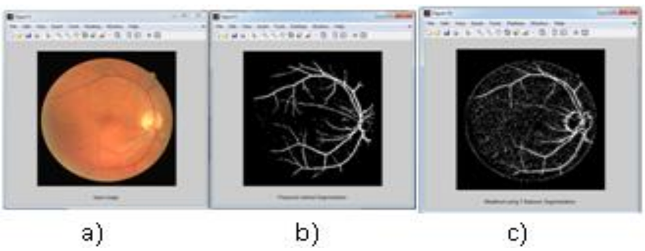

Figure 3: a) Original Image, b) Proposed Method Segmentation, c) Method Using 7 Features Segmentation

Proposed method: sensitivity: 0.6778; specificity: 0.9842; positive predictive value: 0.8592; negative predictive value: 0.9555; accuracy: 0.9461

Method using 7 features: sensitivity: 0.4772; specificity: 0.9175; positive predictive value: 0.4512; negative predictive value: 0.9251; accuracy: 0.8627

The proposed method is compared with another method which employees a feature extraction strategy with feature vector composed of seven features and a neural network classifier[24]. The method is implemented and the results of segmentation are obtained for the same images in DRIVE. The results of segmentation produced by method using seven features for the same two images as above are shown in image c). The values of the above five performance measures are determined for the method using seven features in Table 1a) and proposed method in Table 1b). The average values of the performance measures over 10 images for proposed method are found to be Specificity is 0. 70472, Sensitivity is 0.97621, Positive predictive value is 0.81278, Negative predictive value is 0.95761 and Accuracy is 0.9413. The comparison of the proposed method with the method using seven features based on Average Accuracy shows performance improvement by 0.09116.

Table 1: Performance Measures for a) Method Using Seven Features, b) Proposed Method

a)

Image	Se	Sp	Ppv	Npv	Acc
1	0.3733	0.9139	0.406	0.9025	0.8403
2	0.509	0.9082	0.487	0.9153	0.8498
3	0.3818	0.9014	0.2855	0.9339	0.8528
4	0.4772	0.9175	0.4512	0.9251	0.8627
5	0.3458	0.9068	0.3251	0.9143	0.8423
6	0.4773	0.9133	0.4675	0.9164	0.8534
7	0.4709	0.9058	0.4345	0.9176	0.8478
8	0.4037	0.9176	0.4401	0.9056	0.8466
9	0.332	0.912	0.3424	0.9082	0.8416
10	0.4964	0.9189	0.4758	0.9249	0.8644
Average	**0.42674**	**0.91154**	**0.41151**	**0.91638**	**0.85017**

b)

Image	Se	Sp	Ppv	Npv	Acc
1	0.6311	0.9863	0.8788	0.9443	0.9379
2	0.6495	0.9846	0.8784	0.9425	0.9356
3	0.6702	0.964	0.6573	0.9659	0.9365
4	0.6778	0.9842	0.8592	0.9555	0.9461
5	0.7754	0.9647	0.7404	0.9707	0.9429
6	0.7571	0.9725	0.8144	0.9617	0.9429
7	0.6279	0.9849	0.8649	0.9451	0.9373
8	0.6593	0.9846	0.8729	0.9474	0.9397
9	0.747	0.9651	0.7472	0.9651	0.9386
10	0.8519	0.9712	0.8143	0.9779	0.9558
Average	**0.70472**	**0.97621**	**0.81278**	**0.95761**	**0.94133**

CONCLUSIONS & FUTURE SCOPE

An automated vessel segmentation method can be a suitable component to be inserted into a full-fledged screening system for early detection of eye diseases. This paper proposes a supervised method for fundus vessel segmentation from retina images using 2 Gray level based based features and Neural network as classifier.

The proposed method is evaluated on the images from the publically available database DRIVE. The average performance measures are given as Specificity is 0. 70472, Sensitivity is 0.97621, Positive predictive value is 0.81278, Negative predictive value is 0.95761 and Accuracy is 0.9413. The comparison of the proposed method with the method using seven features and neural network classifier based on Average Accuracy shows performance improvement by 0.09116.The neural network classifier learns a classification procedure according to the training data provided. Thus, method is simple. The training of a neural network classifier is computationally demanding based on type and number of features and number of pixel samples. The proposed method uses feature vector with only two features.

The training set is chosen such that it includes most pixel samples from each class, as accuracy of outcome of classifier is dependent on it. The proposed method employees a preprocessing stategy to eliminate noise, contrast variations, intensity variations and so method can be applied to different images. Moreover, the method generates its own FOV masks. Also, method is not dependent on availability of manual segmentations for training as it produces thresholded segmentations which are used. Once image is given as input, method generates vessel segmented image without user intervention. The fundus vessel structure has malformations as variation in length, width,etc as a result of a disease. After segmentation, measurement of vessels can be used to classify severity of disease. The removal of the vessel vasculature from retinal image gives an image from which disease manifestations such as microaneurysms, haemorrhages, etc can be accurately detected and analysed. A full system for automated detection of Diabetic Retinopathy can be developed.

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