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Supervised Blood Vessel Segmentation in Retinal Images Using Gray level and Moment Invariant Features.

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Abstract:
The segmentation of retinal blood vessels in the retina is a critical step in diagnosis of diabetic retinopathy. In this paper, present a new method for automatically segmenting blood vessels in retinal images. Two techniques for segmenting retinal blood vessels, based on different image processing techniques, are described and their strengths and weaknesses are compared. This method uses a neural network (NN) scheme for pixel classification and gray-level and moment invariants-based features for pixel representation. The performance of each algorithm was tested on the STARE and DRIVE dataset. widely used for this purpose, since they contain retinal images and the vascular structures. Performance on both sets of test images is better than other existing images. The method proves especially accurate for vessel detection in STARE images. This effectiveness and robustness with different image conditions, is used for simplicity and fast implementation. This method used for early detection of Diabetic Retinopathy (DR),

Index Terms: Diabetic retinopathy, Retinal images ,Neural network ,Gray level and Moment invariant.

I . INTRODUCTION:

Diabetic retinopathy is the leading cause of blindness among adults aged 20-74 years in the United States [1]. According to the World Health Organization (WHO), screening retina for diabetic retinopathy is essential for diabetic patients and will reduce the burden of disease [3]. However, retinal images can be difficult to interpret, and computational image analysis offers the potential to increase efficiency and diagnostic accuracy of the screening process. Automatic blood vessel segmentation in the images can help speed diagnosis and improve the diagnostic performance of less specialized physicians. An essential step in feature extraction is blood vessel segmentation of the original image. Many algorithms have been developed to accurately segment blood vessels from images with a variety of underlying pathologies and across a variety of ophthalmic imaging systems [9]. This work focuses on developing existing retinal blood vessel segmentation algorithms, comparing their performances, and combining them to achieve superior performance. For this project, the Digital Retinal Images for Vessel Extraction STARE and DRIVE database of retinal images was used [6], [7]. This database contains 40 images, 20 for training and 20 for testing. These images were manually segmented by two trained researchers. The algorithms were implemented on the original images and the hand segmentations were used to evaluate the performance of the developed algorithms. The next section of this report explains five distinct vessel segmentation algorithms developed and applied to the STARE and DRIVE database. This section is followed by the pipeline developed for combining these algorithms for superior performance. The performance results of all these algorithms are then presented and compared.

II. LITERATURE SURVEY:

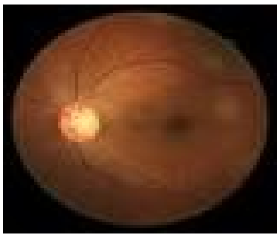
Retinal vessel segmentation algorithms have been heavily researched. There are several approaches to the segmentation. Among these approaches, two of them were chosen for implementation in this project. These methods utilize different image processing techniques and each offer different advantages and disadvantages in vessel segmentation [9]. These are Gray level and Moment invariant features.

III. PROPOSED SEGMENTATION METHOD:

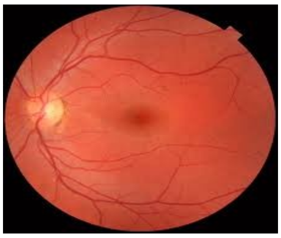
Supervised methods have been shown to perform well on the problem of blood vessel segmentation [18], [19], [20], [21], [22]. These methods vary widely in their choice of features and type of classifier used, but all perform pixel-based classification. The disadvantage of any supervised method that ground truth classes from a training set are required. Though these may not always be available or convenient to obtain in practice, for our application this data is available to researchers in the STARE and DRIVE [6], [7].data base.

A. Preprocessing the Image:

In following with [22], three preprocessing steps are applied to the images before the features are extracted.The Pre processing method mainly used for detect the fundus image of the retina. The algorithm uses only the green color channel in the RGB colorspace. The first preprocessing step is morphological opening with a three-pixel diameter disk structuring element to reduce the effect of the central vessel light reflex, a brighter section along the vessel ridges.and detection of fundus image shown in figure.



(a)



(b)

Figure 1:Fundus Image

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2. Homogenize the Background:

The second preprocessing step, called background homogenization, produces uniform background gray levels across the entire set of images. The local background gray level is computed by applying a 69_69 mean filter to the image. The background is then subtracted and the resulting gray levels are scaled from 0 to 1. Finally, a constant is added to the image gray levels so the mode gray level value in image is set to 0:5. The final preprocessing step is a top-hat transformation on the complement of the image using an eight-pixel radius disk as the structuring element. This final preprocessing step enhances the dark regions in the original image, including the blood vessels, while removing brighter regions such as the optic disk.

2) Neural Network classifier:
A neural network is used to classify each pixel in the test images as vessel or non-vessel. The feature vector associated with each pixel includes seven features, five based on local gray-level information and two based on moment invariants. moment invariants were selected for their scale and rotational invariance. The gray-level features are computed for a pixel, (x; y) , using the pixel gray-level value,and the gray-level statistics in a 9 _ 9 window, W_9(x; y) centered at (x; y).

The five features include the center pixel gray-level value, the graylevel standard deviation within the window, and the absolute differences between the center pixel gray-level and the minimum, maximum and mean gray-level values in the window. Additionally, for each pixel, the 1st and 2nd Hu moments, I_1 and I_2 are computed for a 17 _ 17 neighborhood window multiplied point-wise by a zero-mean Gaussian of the same size.

The absolute value of the logarithm of the Hu moments (j log(I_1)j and j log(I_2)j) are used as the final two features associated with the pixel. The features are scaled so that each has zero mean and unit variance. The training set included 27503 pixels (8096 vessel, 19407 non-vessel), representing a relatively small percentage (0:61%) of pixels in the training images. The structure of the neural network used is a multi-layer feed-forward back propagation neural network, with seven input nodes, three hidden layers with 15 nodes each and one output node.

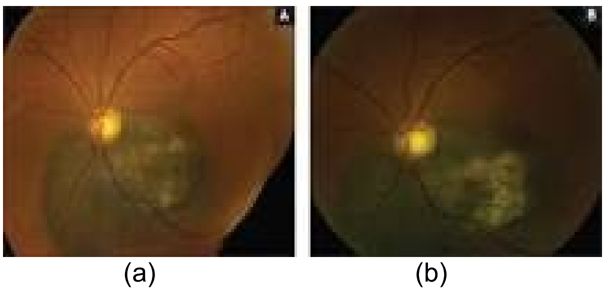
The transfer functions for the hidden layers are linear, and the transfer function for the output layer is the logsigmoid function, logsig(x) = 1 1+expf□xg . 70% of the training set was used for training and the other 30% for cross-validation to prevent over-fitting of the classifier. No post-processing was applied to the results of the neural network classifier besides binarization. The output of them classifier was nearly binary (the exception being a small number of pixels along the edges of vessels with values very close to 1), so a threshold of _ = 0:75 was used for all images.

A disadvantage of this method is that because the classification is pixel-by-pixel, the result often has many smaller disconnected segments. Therefore, post-processing methods designed to reduce noise by removing small connected components will also remove these disconnected segments.

B. Feature Extraction
Transforming the input data into the set of features is called feature extraction. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input. The main aim of the feature extraction stage is pixel characterization by means of a feature vector, a pixel represented in some quantifiable measurements to classify whether the pixel belong to a real blood vessel or not. Features may be extracted using Gray-level-based or moment invariants-based. In this paper gray-level based feature is selected. Since blood vessels are always darker than their surroundings, gray-level features helps to extract more information. These features are extracted from the homogenized image IH by considering only a small pixel region centered on the described pixel (x,y). (s,t) stands for the set of coordinates in a 8 x 8 square window centered on point (x,y). Before the statistical operation the image is smoothed around 5 pixels width and then the features are extracted using the following equations.

I_y = I(x; y) _ sG_y (1)
Ixx = I(x; y) _ s2Gxx (2)
Ixy = I(x; y) _ s2Gxy (3)
Ixy = I(x; y) _ s2Gyy (4)

When analyzing these five features f2 image shows the complement of blood vessels. So the remaining four features are used for the final image. The histogram of each of these five images are analysed. Of these the histogram of f4 image is selected for further processing. By using a local threshold value in f4 image, a minimum and maximum value is chosen with the help of manual image in the test database set. This histogram image is used to calculate the membership of each pixel in the f4 image. By setting a threshold of 0.025, the pixels having membership value greater than or equal to this threshold value is taken for the f4 image. The final image is then obtained by combining the features of f1 image,f3 image, f4 membership image, and f5 image. The result is thresholded to a value greater than or equal to two.



(a) (b)

Figure 2. a) Shade corrected image b) Final segmented image

1) Gray-Level-Based Features:
The blood vessels are always darker than their surroundings, features based on describing gray-level variation in the surroundings of candidate pixels seem a good choice. A set of gray-level-based descriptors were derived from homogenized images considering only a small pixel regions. centered on the described pixel stands for the set of coordinates in a sized

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square window centered on point . Then, these descriptors can be expressed as

$$f_1(x,y) = I_H(x,y) - \min_{(s,t)\in S^9_{x,y}} \{I_H(s,t)\} \qquad (5)$$

$$f_2(x,y) = \max_{(s,t)\in S^9_{x,y}} \{I_H(s,t)\} - I_H(x,y) \qquad (6)$$

$$f_3(x,y) = I_H(x,y) - \operatorname*{mean}_{(s,t)\in S^9_{x,y}} \{I_H(s,t)\} \qquad (7)$$

$$f_4(x,y) = \operatorname*{std}_{(s,t)\in S^9_{x,y}} \{I_H(s,t)\} \qquad (8)$$

$$f_5(x,y) = I_H(x,y). \qquad (9)$$

2) Moment Invariants-Based Features:

The retinal images is known to be piecewise linear and can be approximated by many connected line segments. For detecting these quasi-linear shapes, which are not all equally wide and may be oriented at any angle, shape descriptors invariant to translation, rotation and scale change may play an important role.

They are computed as follows. Given a pixel of the vessel-enhanced image ,a sub image is generated by taking the region defined by . The size of this region was fixed to 17 so that, considering that the region is centered on the middle of a "wide" vessel (8-9-pixel wide and referred to retinas of approximately 540 pixels in diameter), the sub image includes an approximately equal number of vessel and non vessel pixels.

3) Multi-scale Line-detection:

This method is based on the work of Nguyen et. al. [23]. The idea behind this approach is that the blood vessel structures can be approximated as piecewise linear, so line detection on multiple scales can be used to separate the blood vessel structure from the background. By using lines of multiple lengths, vessels of different sizes and scales can be detected; problematic features, such as the small-scale vessel central light reflex (described above) have limited impact on the result at larger scales.

1) Preprocessing: Background homogenization (described in Neural Network preprocessing) without denoising was applied to the inverted green channel of each RGB image. To limit the impact of the optical disk, bright regions (grayl evel values exceeding a fixed threshold) are replaced with a local average gray-level calculated with a 69 _69 mean filter.

2) Line Detection: A total of seven scales are used for line detection, with the line detectors of lengths 3; 5; : : : ; 15.For each scale, the following procedure was carried out. For each pixel, the mean gray-level in a local 15 _ 15 window, I (x; y), is computed. For scale s, line detection is performed by computing the weighted average of graylevel values along lines of length S for each of 18 different angles. The largest response, I (x; y) over all directions is calculated for each pixel. The line response for scale s is the difference between the maximum line detection response and the average gray-level, R . The line response is rescaled, to have zero mean and unit variance. The multi-scale line response is obtained by computing a linear combination of the line responses for each scale and the original gray values in the image, I. The weighting used for each line response is proportional to the scale of the response:

$$R = \frac{1}{64}\left(\sum_s s\tilde{R}^s + I\right).$$

The final output is scaled so that the values range from a 0 to 1.

C. Post Processing

The final image now contains pixels of the vessel as well some smaller disconnected regions are found in this image. In order to remove these smaller disconnected regions the final image needs to be processed. This is done in the post processing stage. First the outer circle of the final image is to be removed. For this morphological operation is performed on the final image. Erode the FOV image using a structuring element. Then dilate the final image using the structuring element and then perform AND operation between these images. Finally erode the resultant image. Now the outer circle is cleared. Next to remove the smaller disconnected region, the pixels in each connected region is calculated. Then region connected to an area below 50 is reclassified as non vessel. The final vessel segmented image after postprocessing is shown in figure 3.(b)

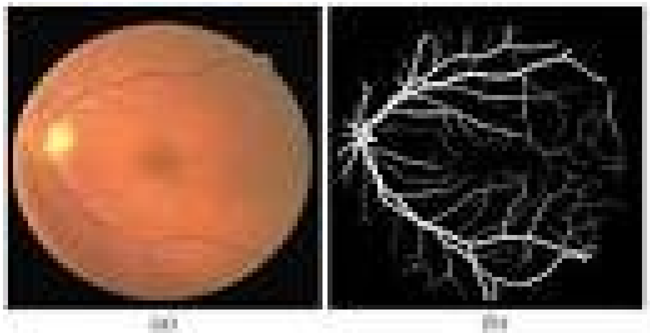

Figure 3: (a) Color retinal image, (b) Blood vessels segmentation.

D. COMPARISON TO OTHER METHODS:

Matched filtering for blood vessel segmentation has first been developed in 1989 [11]. Since then, several different algorithms were developed based on this approach. All of these algorithms are based one the following observations from the retinal blood vessels [11]:

1) Blood vessels usually have limited curvature. Therefore, the anti-parallel pairs can be approximated by piecewise linear segments.

2) It is observed that the vessel diameters (observed in 2D retinal images as widths) decrease as they move radially outward from the optic disk and range from 2 to 10 pixels in the resulting images from DRIVE database.

3) The cross section gray level pixel intensity of blood vessels has a Gaussian profile. Their profile can be approximated by a Gaussian curve. where d is the perpendicular distance between the point (x; y) and the straight line passing through the center of the blood vessel in a direction along its length, _ is the spread of the intensity profile, A is the gray-level

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intensity of the local background and k is a measure of reflectance of the blood vessel relative to its neighborhood. For the implementation of this algorithm, a 2D matched filter of Gaussian profile is used. 12 different kernel filters are implemented in 15_ increments to cover all directions. The kernels have a _ of 2, and are truncated at a neighbourhood of N = f(u; v) j juj _ 3_; jvj _ L 2 g, where L = 9. The mean value of each kernel is then subtracted from it. These kernels are then used as convolution masks across the image. All 12 kernels are convolved with the image and at each neighborhood, the filter that generates the maximum result is considered the correct vessel orientation. and then now introduced 7-D vector (NN) classifier. These used for pixel classification .Pixel representation denoted by the Gray - level and moment invariant features.

RESULT:

The algorithmic performance of the proposed method on a fundus image, the resulting segmentation is compared to its corresponding dataset images. This image is obtained by manual creation of a vessel mask in which all vessel pixels are set to one and all non vessel pixels are set to zero. Thus, automated vessel segmentation performance can be assessed. In our algorithm was evaluated in terms of sensitivity, specificity , positive predictive value , negative predictive value , and accuracy. Taking Table I into account, these metrics are defined as and metrics are the ratio of well-classified vessel and non vessel pixels, respectively. is the ratio of pixels classified as background pixel that are correctly classified. Finally,is a global measure providing the ratio of total well-classified pixels. In addition, algorithm performance was also measured with receiver operating characteristic (ROC) curves. A ROC curve is a plot of true positive fractions versus false positive fractions by varying the threshold on the probability map. The closer a curve approaches the top left corner, the better the performance of the system. The area under the curve , which is 1 for a perfect system, is a single measure to quantify this behavior.

TABLE - I
NEURAL NETWORK PERFORMANCE RESULTS

Image	Accuracy	Sensitivity	Precision	Specificity
01	94.40	76.16	80.11	97.15
02	94.58	73.46	88.44	98.31
03	93.34	69.20	82.26	97.45
04	94.20	63.49	90.08	98.92
05	93.99	67.73	84.97	98.12
06	93.71	67.14	85.11	98.07
07	93.35	65.73	80.48	97.57
08	92.93	63.30	76.41	97.19
09	94.19	68.86	79.01	97.57
10	94.36	71.13	79.47	97.51
11	93.76	65.50	82.78	97.97
12	94.17	72.43	79.22	97.28
13	93.63	66.70	85.15	98.08
14	94.21	75.80	75.26	96.67
15	94.21	74.03	71.33	96.55
16	93.97	68.44	82.45	97.81
17	93.80	70.15	77.44	97.13
18	94.02	72.56	74.68	96.81
19	95.51	80.70	81.74	97.53
20	94.49	76.97	72.92	96.59
Mean	**94.04**	**70.47**	**80.47**	**97.51**

IV. DISCUSSION:

This project focuses on blood vessel segmentation in retinal fundus images for the potential application of automatic diabetic retinopathy diagnosis. In this project, two algorithms were implemented based on methods from relevant literature. These algorithms were then combined using two different approaches in order to take advantage of their individual advantages. Several performance measures were computed in order to evaluate the performance of each of the developed methods. These measures include accuracy, precision, sensitivity, and specificity. Each of the developed algorithms offer trade-offs between these performance metrics.

V. CONCLUSION:

Blood vessel detection in retinal images can be classified into rule-base and supervised method. In this method NN scheme for pixel classification is applied. To find out a vessel pixel or any type of classification, a well classified training set is required, since machine learning needs sufficient examples to capture the basic structure so that it can be generalized to new cases. This method uses membership classification of pixels and the feature vector of each pixel using gray level features. Since many of the blood vessel pixels have gray level values similar to that of the background pixel, membership classification gives better result than other type of classification. This proposed method uses only the DRIVE database images and it can be further tested with the STARE database also. Using proposed method, image with varying sizes can also be tested

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