A Novel Approach for the Detection of New Vessels in the Retinal Images for screening Diabetic Retinopathy

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***Abstract*— Diabetic Retinopathy is a major cause of blindness. It is mainly due to the development of abnormal new blood vessels in the retina. In this approach, we proposed an efficient method to detect the abnormal new blood vessels. The retinal images are pre-processed using Adaptive Histogram Equalization (AHE) and the blood vessels are enhanced by applying Top-hat and Bottom-hat transforms. The enhanced image is segmented using Fuzzy C Means Clustering (FCM) technique. Features based on shape, brightness, position and contrast are extracted from the segmented image and classified as normal or abnormal using K Nearest Neighbour (KNN) Classifier. The performance was evaluated on DRIVE and MESSIDOR database and an accuracy of 96.5% was obtained.**

***Index Terms*— Diabetic Retinopathy (DR), Fuzzy C Means Clustering(FCM), K Nearest Neighbour (KNN), Moment Invariants.**

I. INTRODUCTION

Diabetic retinopathy is one of the major causes of legal blindness in the working age population around the world. It is a disorder of retinal vasculature that eventually develops to some degree in nearly all the patients with long standing diabetes mellitus [6]. In [5], it is estimated that the number of people with diabetes is likely to increase to 366 million by the year 2030 from 171 million at the turn of century. In India, there will be 79 million people with diabetes by 2030 making it the diabetic capital of the world. Although DR is not a curable disease, Laser photocoagulation can prevent major vision loss. Therefore the timely diagnosis and referral for management of diabetic retinopathy can prevent 98% of severe visual loss.

Diabetic Retinopathy is mainly caused by the changes in the blood vessels of the retina due to increased blood glucose level. People with diabetic retinopathy, blood vessels may swell, leak fluid, abnormal new blood vessels grow on the surface of the retina. Digital Colour fundus images are widely used by ophthalmologists for diagnosing Diabetic Retinopathy. DR also causes numerous abnormalities like microaneurysm, hemorrhages, cotton wool spot,, neo-vascularization and in later stages, retinal detachment.

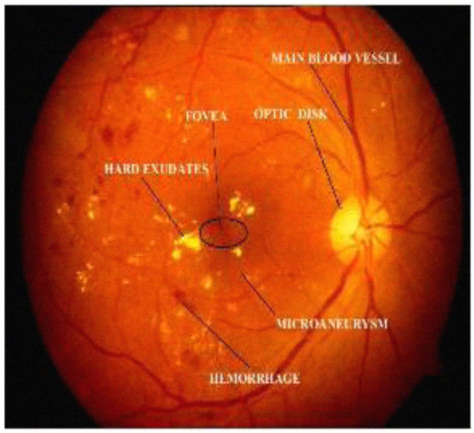

Fig. 1. A typical retinopathy image

Fig.1 shows a typical retinal image labelled with feature components of Diabetic Retinopathy. Microaneurysms are small saccular pouches caused by local distension of capillary walls and appear as small red dots. This may also lead to big blood clots called haemorrhages. Hard exudates are yellow lipid deposits which appear as bright yellow lesions. The bright circular region from the blood vessels emanate is called the optic disk. Macula is the centre portion of the retina and has photoreceptors called cons that are highly sensitive to color and responsible for perceiving fine details. It is situated at the posterior pole temporal to the optic disk. The fovea defines the centre of the macula and is the region of highest visual acuity.

II.STATE OF ART

M.Mendonca *et al*.[9] proposed a method to extract vessel centerlines, which are used as guidelines for the subsequent vessel filling phase. The outputs of four directional differential operators are processed in order to select connected sets of candidate points to be further classified as centerline pixels using vessel derived features. The final segmentation is obtained using an iterative region growing

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method that integrates the contents of several binary images resulting from vessel width dependent morphological filters.

E.Ricci *et al.* [3], evaluated the average grey level along lines of fixed length passing through the target pixel at different orientations. Two segmentation methods, first uses the basic line detector whose response thresholded to obtain unsupervised pixel classification. As a further development, it employs two orthogonal line detectors along with the grey level of the target pixel to construct a feature vector for supervised classification using a support vector machine.

In the method presented in [13], blood vessel-like objects were extracted by using Laplacian operator and noisy objects were pruned according to centerlines, detected by means of the normalized gradient vector field.

J.J.Staal *et al.*[1], described that the system is based on extraction of image ridges, which coincide approximately with vessel centerlines. The ridges are used to compose primitives in the form of line elements. With the line elements an image is partitioned into patches by assigning each image pixel to the closest line element. Martinez *et al*. [12], proposed a method based upon multiscale feature extraction. The local maxima over scales of the gradient magnitude and the maximum principal curvature of the Hessian tensor were used in a multiple pass region growing procedure. Perfetti and Ricci [3]used a support vector machine (SVM) for pixel classification as vessel or non-vessel. They used two orthogonal line detectors along with the y-level of the target pixel to construct the feature vector.

III. MATERIALS AND METHODS

A. Image Acquisition

To evaluate the performance of this method, the digital retinal images were acquired using Topcon TRC-50 EX non-mydriatic camera with a 50˚ field of view at Aravind Eye hospital, Coimbatore. Also, the proposed algorithm were tested and evaluated on DRIVE and MESSIDOR databases. The image set contains both normal and abnormal (pathological) cases.

B. Pre-processing

Pre-processing stage equalizes the uneven illumination associated with fundus images and also removes the noise present in the image. Color fundus images often show important lighting variations, poor contrast and noise. In order to detect the abnormalities associated with fundus images, a pre-processing comprising the following steps is applied: 1) Green Component Extraction. 2) Median Filtering 3) Contrast Enhancement. 4) Blood Vessel Enhancement

1) Green Component Extraction: The blood vessels usually have lower reflectance compared with the background retina, the green color plane was used in the analysis and it shows the best contrast between the vessels and the background retina.

2) M*edian Filtering*: To reduce the distortions due to media decay (e.g. astigmatic blur, defocusing, color shift, uneven magnification, scratches) the image of fig was pre-processed by 5x5 median filter. The pre-processed image is shown in Fig. 2(a).

3) Contrast enhancement: Fundus images often contain background intensity variation due to non-uniform illumination. Consequently, background pixels may have different intensity for the same image. To normalize and to enhance the contrast of an image, Adaptive Histogram Equalization is used. The contrast enhanced image is shown in Fig. 2(b).

4) Blood Vessel enhancement: The final pre-processing step generates a blood vessel enhanced image using Top-hat and Bottom-hat transforms, which proves to be more suitable for further extraction of Blood vessels. Top-hat and Bottom-hat transform [7] is an operation that extracts small elements and details from given images. To enhance the blood vessels, the original image is added with the top-hat transformed image and the result is subtracted with the bottom-hat transformed image. The Blood Vessel Enhanced image is shown in Fig. 2(c).

C. Segmentation based on Fuzzy C-Means Clustering

The Blood Vessels Enhanced image obtained from the above step is segmented using Fuzzy C-Means Clustering (FCM) techniques.

FCM clustering is an overlapping clustering algorithm, where each point in an image may belong to two or more clusters with different degrees of membership. The features with close similarity in an image are grouped into the same cluster. The similarity is defined by the distance of the feature vector to the cluster centers. Euclidean distance is used to measure this distance and data will be associated to an appropriate membership value [11]. The cluster center is updated until the difference between adjacent objective function , as displayed in equation 1 is close to zero or practically less than a predefined small constant:

$$J_m = \sum_{i=1}^{M}\sum_{j=1}^{C} U_{ij}^{m}\left\|x_i - c_j\right\|^2 \qquad (1)$$

where m is an exponential weighting function that controls the fuzziness of the membership function, it is set to 2 by Bezdek [20]. M is number of features. C is number of clusters. u_{ij} is the degree of membership of xi in the cluster j, x_i is the i^{th} of d-dimensional measured data, c_j is the d-dimension center of the cluster, and $\|*\|$ is any norm expressing the similarity between any measured feature and the center.

Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the

update of membership u_{ij} and the cluster centers c_j by

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\frac{2}{m-1}}} \quad (2)$$

$$c_j = \frac{\sum_{i=1}^{M} u_{ij}^{m} x_i}{\sum_{i=1}^{M} u_{ij}^{m}} \quad (3)$$

The iteration will stop when equation 4 is satisfied

$$max_{ij} = \left\{\left|u_{ij}^{(k+1)} - u_{ij}^{(k)}\right|\right\} < \epsilon \quad (4)$$

where ϵ is a termination criterion, 0.00001 for our case. *k* is the iteration number, it is set to a maximum of 200 for our case. This procedure converges to a local minimum or a saddle point of *Jm*.

The algorithm is composed of the following steps:

Step 1: Initialize the fuzzy partition matrix $U = [u_{ij}]$ $(U(0))$ by generating random numbers in the range 0 to 1 subject to Equation 5:

$$\sum_{i=1}^{M}\sum_{j=1}^{C} u_{ij} = 1 \quad (5)$$

Step 2: At *k*-step: calculate the centers vectors $C(K)=[c_j]$ with $U(K)$ according to Equation 3.

Step 3: Update the fuzzy partition matrix $U(K)$, $U(K+1)$ by the new computed u_{ij} according to Equation 2.

Step4: Compute the objective function according to Equation 1. If the difference between adjacent values of the objective function is less than termination criterion (ϵ), then stop the iteration; otherwise return to step 2.

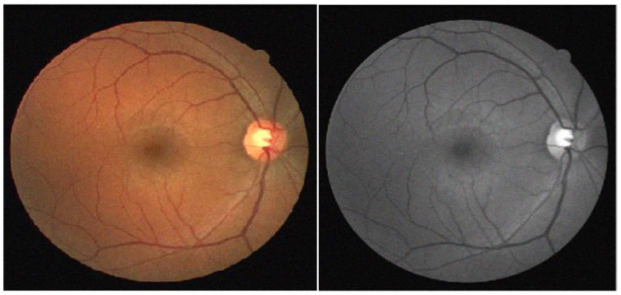
The output from FCM clustering is a list of cluster centers and *n* membership-grades for each pixel, where *n* is a number of desired clusters. A pixel will be assigned to the cluster with highest membership-grade.

D.*Feature Extraction*

The process of defining a set of features, or image characteristics, which will most efficiently or more meaningfully represent the information that is important for analysis and classification. In our approach, features based on shape, position, contrast and brightness are calculated.

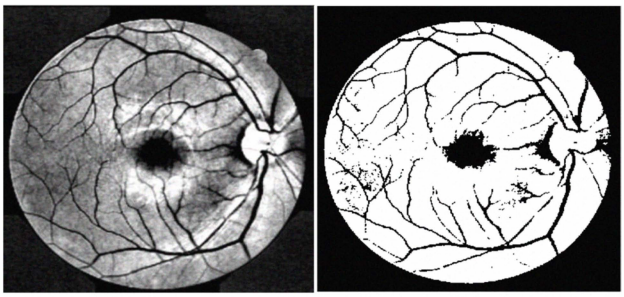
The features are discussed below:

1) Gradient: The mean gradient magnitude along the segment is calculated using Gauss Gradient Operator.



(a) (b)

Fig. 2.(a)Input image (b) Green component image



(c) (d)

Fig. 2. (c) Contrast Enhanced image (d) Result of FCM

2) Gradient variation: The standard deviation of the Gauss gradient along the segment. This feature is based on the observation that abnormal vessels are less homogeneous with more contrast variation than normal vessels.

3) Gray Level: The normalized mean segment grey level

$$g_{norm} = \frac{1}{G_{max} - G_{min}}\left[\left(\frac{1}{n}\sum_{i=1}^{n} g_i\right)\right] - G_{min} \quad (6)$$

where g_i is the grey level of the i^{th} segment pixel. G_{max} and G_{min} are the maximum and minimum grey level values in the original image, respectively.

4) Gray level coefficient of variation: This measure was based on the observation that new vessels appear less homogeneous than normal vessels. It is calculated as the ratio of the mean to the standard deviation of the segment grey level values.

5) Moment invariants- based features: The vasculature in 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 equally wide and may be oriented at any angle, shape descriptors invariant to translation, rotation may play an important role. Moment invariants proposed by Hu provide an attractive solution and are included in the feature vector. They are computed as follows.

Given a pixel (x,y) of vessel enhanced image, a sub-image is generated by taking the region defined by $S^{17}_{x,y..}$

where $S^{17}_{x,y}$ stands for the set of co-ordinates in a 17x17 sized square window centered on the middle of a wide vessels. The subimage includes an approximately equal number of vessels and nonvessels. The 2-D moment of order (p+q) is defined as

$$m_{pq} = \sum_i \sum_j i^p j^q I_{VE}^{S^{17}_{x,y}}(i,j) \quad p,q = 0,1,2,\ldots. \tag{7}$$

Where summations are over the values of the spatial coordinates i and j spanning the subimage. The corresponding central moment is defined as

$$\mu_{pq} = \sum_i \sum_j (i-\bar{i})^p (j-\bar{j})^q I_{VE}^{S^{17}_{x,y}}(i,j) \tag{8}$$

Where

$$\bar{i} = \frac{m_{10}}{m_{00}}, \quad \bar{j} = \frac{m_{01}}{m_{00}} \tag{9}$$

are the coordinates of the centre of gravity of the subimage. The normalized central moment of order (p+q) is defined as

$$\eta_{pq} = \frac{\mu_{pq}}{(\mu_{00})^{\gamma}} \quad p,q = 0,1,2,\ldots.. \tag{10}$$

Where

$$\gamma = \frac{p+q}{2} + 1: \quad (p+q) = 2,3,\ldots. \tag{11}$$

A set of seven moment invariants under size, translation, and rotation, known as Hu moment invariants, can be derived from combinations of regular moments. Among them, our tests have revealed that only those defined by

$$\emptyset_1 = \eta_{20} + \eta_{02} \tag{12}$$

$$\emptyset_2 = (\eta_{20} + \eta_{02})^2 + 4\eta_{11}^2 \tag{13}$$

Constitute the combination providing optimal performance in terms of average accuracy. The following descriptors were considered to be the part of the feature vector of a pixel located at (x,y).

$$f_6(x,y) = |\log(\emptyset_1)| \tag{14}$$

$$f_7(x,y) = |\log(\emptyset_2)| \tag{15}$$

6) Tortuosity: Tortuosity is the twisted part or bent of blood vessels and estimated using arc-chord ratio. It is the ratio between length of the curve to the distance between ends of it.

E. *Classification*

The dataset obtained above are classified into normal or abnormal blood vessels using K Nearest Neighbour (KNN) Classifier. KNN classifier operate on the premises that classification of unknown instances can be done by relating the unknown to the known according to some distance or similarity function. To classify an unknown pixel x_q, choose the class of the nearest example in the training set as measured by a distance metric. A common extension is to choose the most common class in the K Nearest Neighbours. Let an arbitrary pixel x be described by a feature vector

$$< a_1(x), a_2(x), \ldots\ldots a_n(x) > \tag{16}$$

Where $a_r(x)$ is used to denote the values of the *r*th attribute of the pixel x. If we consider two pixels x_i and x_j , then the distance between these pixels is defined as(x_i , x_j) which is expressed in

$$d(x_i,x_j) = \sqrt{\sum_{r=1}^{n} \left(a_r(x_i) - a_r(x_j)\right)^2} \tag{17}$$

In our experiments, a set of 50 images were selected , which includes 30 normal and 20 abnormal. For supervised classifiers, two sets are required; one for training and the other for testing. The training set contains 20 normal and 10 abnormal images. Feature parameters calculated above are given as input for KNN classifier. The testing set contains 20 images to test the performance of the classifier.

IV. RESULT AND DISCUSSION

In this approach, we proposed a method to automatically extract the blood vessels from fundus images. These images are segmented using Fuzzy C-Means Clustering Technique. Features based on shape, contrast, brightness are calculated and classified as normal or abnormal blood vessels using K Nearest Neighbour (KNN) Classifier. The proposed method performs best by segmenting even smaller blood vessels.

Performance is verified by evaluating True Positive (TP, a number of abnormal pixels correctly detected), False Positive (FP, a number of normal pixels which are detected wrongly as abnormal pixels), False Negative (FN, number of abnormal pixels that are not detected), True Negative (TN, a number of normal pixels which are correctly identified as normal pixels). From these quantities, Sensitivity, Specificity are chosen as measurement of accuracy and are calculated using the following equation.

$$Sensitivity = \frac{TP}{TP+FP} \tag{18}$$

$$Specificity = \frac{TN}{TN+FP} \tag{19}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \tag{20}$$

Table 1 gives a comparative analysis of performance of our method with our research work. Our method appears

promising as it can detect very smaller blood vessels. The method is tested on DRIVE and MESSIDOR database. Performance is also evaluated on real time fundus images obtained from Aravind Eye Hospital, Coimbatore.

Table 1
Comparision of our method with some different vessel segmentation method.

Method	Accuracy
Mendonca	0.9442
Staal	0.9442
Niemeijer	0.9417
Zana	0.9377
Xu and Luo	0.9328
Our method	0.9653

V. CONCLUSION

The image processing of color fundus images has a significant role in the early diagnosis of Diabetic Retinopathy. In this paper, a novel method is presented for the detection of abnormal new blood vessels from the color fundus images. The color fundus images are subjected to pre-processing followed by blood vessel enhancement. Subsequently with the help of Fuzzy C Means Clustering segmentation, the variation in the blood vessel are detected. Finally the images are classified as normal and abnormal by the use of K Nearest Neighbor Classifier. Accuracy and robustness of the method have been evaluated on different databases. The overall sensitivity, specificity and accuracy were 96.25%, 89.65% and 96.53% respectively.

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