Detection of Exudates in Color Fundus Image

S.Bibiana Vincy[1], Dr. C. Chitra[2]
[1] *Pg-Scholar, VLSI Design, PSNA CET, Dindigul, Tamilnadu, India*
[2] *professor, ECE, PSNA CET, Dindigul, Tamilnadu, India*

Abstract

A new method for the detection of blood vessels that improves the detection of exudates in fundus photographs. The pre-processing method is used to enhance the input image and also for noise removal. The initial estimation of exudates is obtained by segmenting the optic disc and blood vessels from the fundus image. In order to segment the optic disc and blood vessel separate algorithms are used. First, circular Hough transform is used for segmenting the optic disc inorder to find the circular object from an image. Then vessel detection algorithm is used to detect the blood vessel in the image. The extracted blood vessel tree and optic disc could be subtracted from the over segmented image to get an initial estimate of exudates. The final estimation of exudates can then be obtained by morphological reconstruction based on the appearance of exudates.

Keywords - *Pre-processing, Optic disc, Blood vessel, Exudates.*

I. INTRODUCTION

Diabetic-related eye diseases are the commonest cause of vision defects and blindness in the world. Monitoring the health of the retina is important for those people with signs of Diabetic retinopathy (DR). Exudates are lipid leaks from blood vessels of abnormal retinas and are one of the most prevalent lesions at the early stages of DR [1]. Colour fundus images are used to detect exudates in retinal images. Fig.1 shows a fundus image of an unhealthy retina with its main features and exudates.

Several techniques for exudates detection have been proposed. Notable amongst these are those who utilised fuzzy C-means for segmentation in the different classification methods, such as Sopharak et al. [2]. They employed morphological techniques for fine-tuning after the segmentation step and reported results of 87.28% sensitivity, 99.2% specificity.. Xiaohui et al. [3] applied a hierarchical support vector machine to classify bright non-lesion areas. Kande et al. [4] incorporated spatial neighbourhood information into the standard FCM clustering for exudates classification. Osareh et al. [5] used an artificial neural network to classify segmented regions in term of lesion based classification with 93% sensitivity and 94.1% specificity.

The multi-structure morphological process and segmentation technique can effectively be used for exudates detection. The modules that are used (1) retinal blood vessel detection in which plane separation, contrast enhancement, morphological process are done; (2) exudates detection in which segmentation technique is used. The segmentation technique is performed using clustering algorithm [6]. Unsupervised clustering algorithm is used to classify the

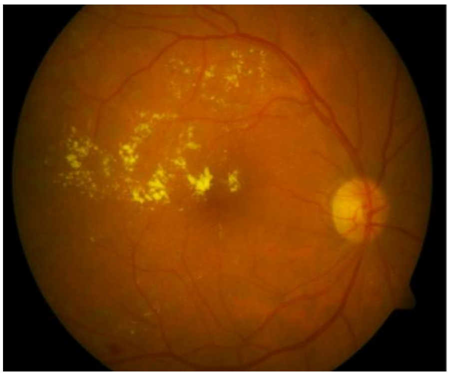


Fig. 1 – Retinal Image With the Main Features and Exudates.

input data that points into multiple classes based on their inherent distance from each other. This method will extract the exudates from the retina fundus effectively.

Exudates, being a major indicator of diabetic retinopathy should be quantified at the early stage. Patients having the symptoms of type1 stage of diabetic retinopathy are called as non-proliferative diabetic retinopathy (NPDR). Atul Kumar et al proposed a method that helps in identifying the features of exudates from the image using segment based feature extraction [11]. The classification into various stages of NPDR is based on their pixel intensity and frequency from the retinal fundus image. To get feature values from the fundus retinal image various techniques like morphological pre-processing, image boundary tracing, adaptive threshold using Otsu methodology and optic disc localization is implemented [8].

Then SVM classifier uses the features extracted by combined 2DPCA (2D principal component analysis) instead of explicit image features. For acquiring higher accuracy of classification we can use virtual SVM. Supervised vector machine (SVM) is a supervised learning methodology that classifies input data by analyzing and recognizing the patterns. In case of linear boundary being inappropriate, the SVM can map the input vector into a high dimensional feature space by choosing a non-linear mapping kernel [9].

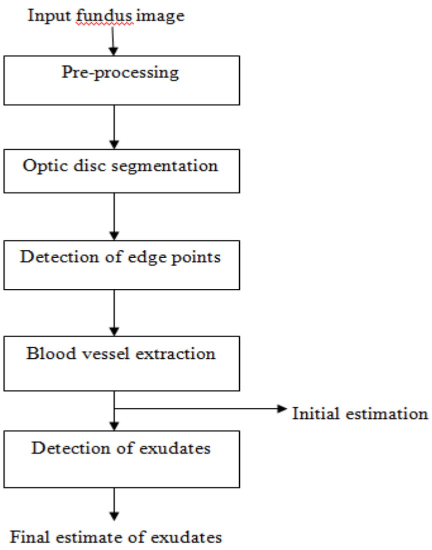
In [11] some computer methods for examining blood vessel networks and for detecting and analyzing peculiar regions in color ocular fundus images such as haemorrhages, exudates, optic discs and arterio-venous crossings are proposed. For the recognition of line segments of arteries/veins in the vessel networks shows an initial labelling scheme. For the detection of haemorrhages and exudates define loop-composable sets of edge segments which are selected from region boundaries. In order to locate optic discs, a parent- child relationship between blood vessel segments is defined and an automatic method of analyzing arterio-venous crossings is suggested.

Akita.K, et al, proposed a convergence of the blood vessel network as the primary feature for detection [12], in conjunction with the brightness of the nerve as a secondary feature. It is tested with various methods on 31 images of healthy retinas and 50 images of diseased retinas, exhibiting a wide variety of lesions and confusing manifestations. On this difficult data set, some methods successfully detect the nerve in 89% of the cases, and in 100% of the healthy cases.

From the proposed methodology the convergence of the blood vessel networks are found. The extraction of blood vessels and segmentation of optic disc can be done by an automated technique that helps in finding out the lesions with good accuracy.

II. PROPOSED METHODOLGY

The aim of this work is to accurately detect the presence of exudates in fundus images as an early symptom of some diseases that may lead to blindness. Most of the promising techniques of exudates detection are based on edge detection. Unfortunately, edge detection algorithms detect all points having some contrast to their background. Thus, the edges of all the anatomic structures and lesions would be detected to some extent. Of these, are the edges of the blood vessels which have great influence on the detection of the edges of exudates. Hence applying separate algorithm for optic disc and blood vessel to get the initial estimation of the exudates. The final estimation of the exudates is obtained by applying morphological reconstruction algorithm after the removal of blood vessels and optic disc from the image. This increases the accuracy of exudates detection as described in the following sections.



Overall Flow Diagram

A. *Pre-Processing*

Generally the retinal image is to be pre-processed to correct the problems arise from non uniform illumination. The low contrast of retinal images and the presence of noise are among these problems. The fundus image is a colour image containing three different bands; red, green and blue. It is observed that the red and blue bands do not have significant information for exudates detection and thus it is sufficient to use the green band only. The input retinal image is a three layer image containing red, green and blue layers. In the green layer, exudates appear brightest as compared to the other two layers thus the green layer is chosen for exudates detection. Median filter is used to remove the noise in the input image. Then morphological operations are applied to get the contrast enhanced image.

1) Top-hat Morphological Operation

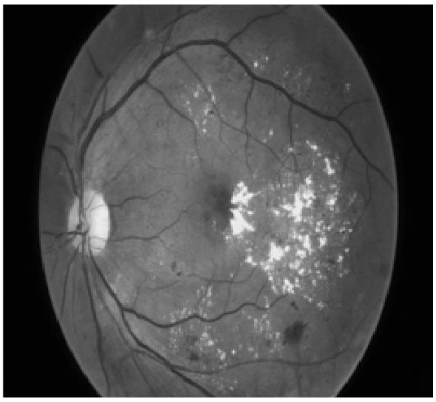
The existing dilation and erosion operators have been extended to work with gray scale images [8 10]. New functions range from additional basic operators (morphological opening and closing) to advanced tools useful for segmentation (distance transforms, reconstruction-based operators, and the watershed transform). The functions use advanced techniques for high performance, including automatic-structuring element decomposition. The operation has been described in the following steps:

Step1: Applied top-hat by opening results in an image of bright regions only.

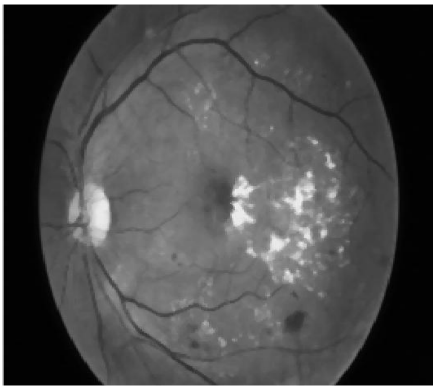
Step2: Top-hat by closing was applied and results in image of dark regions.

Step3: By subtracting these results the contrast enhanced image was obtained which is shown in the fig 2.d

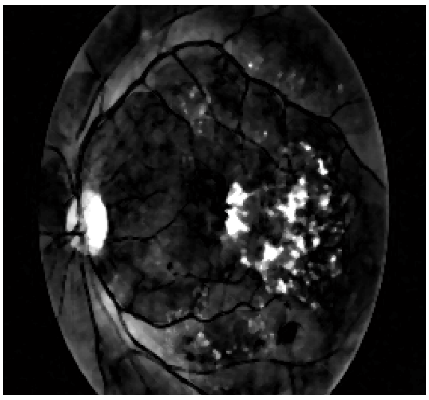
Fig.2. a) Original Image



b) Green Plane of Image



c) Filtered Image



d) Contrast Enhanced Image

B. Optic Disc Segmentation

The optic disc is a circular structure in retinal fundus images. So, Hough transform is used which is well known for its robustness in detecting circular objects in digital images [10]. The Canny edge detector is used to detect pixels to be candidates of the required circle. The optic disc appears brighter in the red component of the input image. The optic disc shares the colour features with the exudates as both of them appear as yellow-colored structures in fundus images. The values of the pixels composing the optic disc are set to zero in the colored image in order to differentiate the optic disc and exudates. The optic disc is segmented by way of setting the pixels composing of optic disc to one and others are set to zero which is shown in the fig 3.c

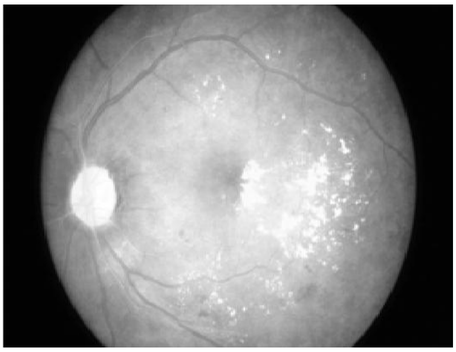


Fig.3. a) Red plane of the image

b) Optic Disc Removal

c) Segmented Optic Disc

C. Detection of Edge Points

Edge detection is the name for a set of mathematical methods which aims at identifying points in a digital image at which the image brightness changes sharply or, more formally, has discontinuities. The Sobel operator [9] is based on convolving the image with a small, separable, and integer valued filter in horizontal and vertical direction which is shown in the fig 4.a. The points at which image brightness changes sharply are typically organized into a set of curved line segments termed edges. Here contour detection algorithm is applied to detect the edge points without discontinuities. In this algorithm, a contour represented by a discrete set of points $\{v_1, v_2, . . ., v_n\}$ with $v_i = (x_i, y_i)$ is to be initialized close to the contour of interest. Then, the algorithm checks the energies of a point on the initial contour and its 8-neighbors and replaces this point by the point of minimum energy among the nine points. The check and replacement process is done for all points on the contour. So, the shape of the contour will change accordingly. The process can be repeated until no changes in the shape of the contour occur and the final contour will rest at the shape of minimum energies.

An energy function is formulated to provide an estimate of the quality of the model in terms of its internal shape and external forces. The energy function E of is given by:

$E=E_{int} + E_{ext}$

Where E_{int} and E_{ext} are the internal and external energies of a point on the contour. The internal energy determines the shape of the contour. The external energies are those not from the contour shape but from the image characteristics. The most common external energy represents the intensity difference or the presence of an edge at this point.

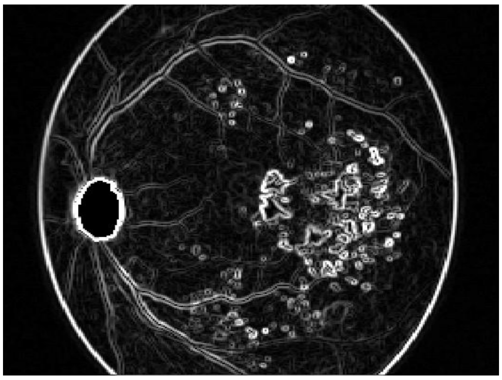
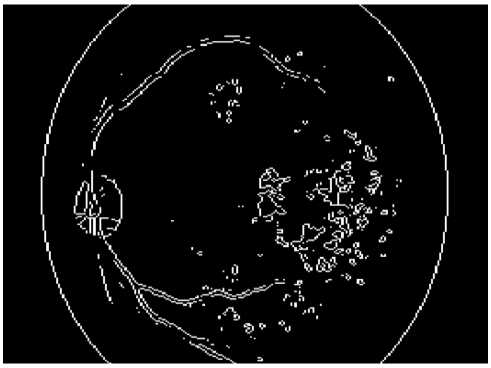


Fig.4. a) Sobel Gradient



b) Edge Detected Image

D. Blood Vessel Detection

The green component of the RGB image is extracted to detect the blood vessels because the vessels have higher contrast in this component. Since the blood vessels appear as dark regions in brighter background, it is narrow them by morphological dilation. If the dilated image is then eroded using the same structuring element, the very small dark region should be eliminated from the image while the larger area returns to their initial size. Vessel detection algorithm is applied to extract the blood vessels from the input image. This algorithm is based on closing the image with two linear structuring elements of different sizes which is describe in the following steps

Step i: Closing by the bigger element would make the vessels to disappear while closing by the smaller one leaves the cores of the vessels.

Step ii: Subtracting the two closed images would result in brighter areas of blood vessels in a darker background with a contrast higher than that of the original image.

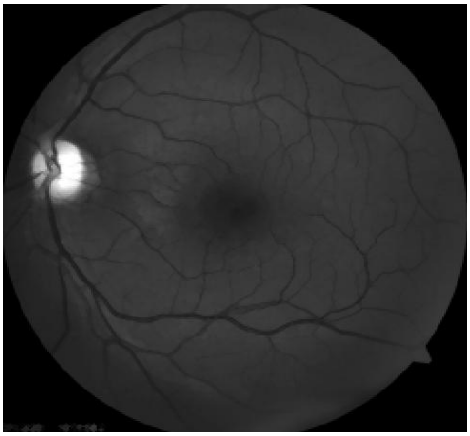
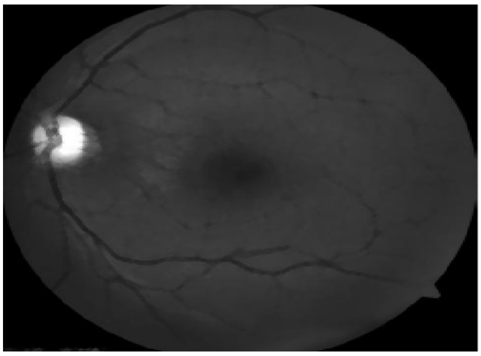
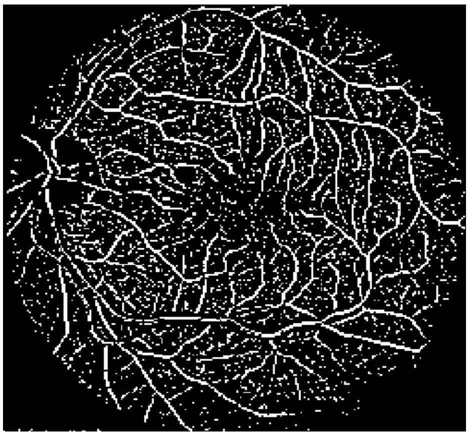


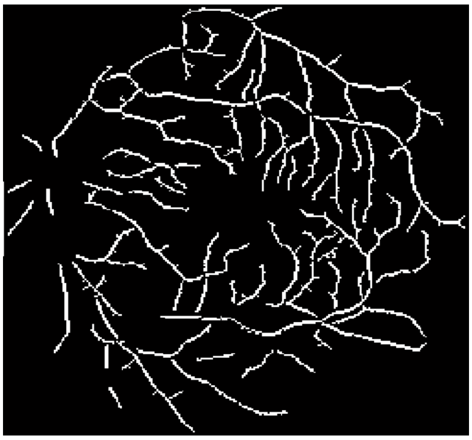
Fig.5. a) Closed Green Component



b) Image Closed by a Larger Structuring Element



c) Resulting Image



d) Extracted Blood Vessel

E. Detection of Exudates

The intensity plays important role in detection of exudates, in practices the "light" part in retina image represented with high numbers in terms of intensities, each pixel in image has intensity value ranging from 0 (darkest pixel), and 255 (light pixel). The regions with high and low intensities in image may have very important features because it marked as image objects. In an image of several objects, points of high intensity could represent the tops of the objects; these maxima can be used to identify objects in an image. After eliminating the blood vessels and the optic disc from the result of edge detection, an initial estimate of exudates is obtained. Then the morphological reconstruction algorithm [20,21] is applied to get the final estimate of exudates. This is an iterative process that should be repeated until no changes occur in h. The result of final iteration is then subtracted from the input image to get the final estimate of exudates in I_{out} as given by,

$$I_{out} = I_{in} - h_{final}$$

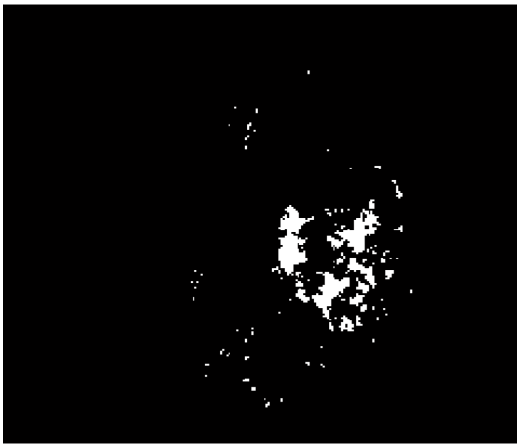


Fig.7. a) Initial Estimate of Exudates

b) Detected Exudates

III. CONCLUSION

The development of automated Diabetic Retinopathy screening system becomes a highly effective way of reducing the burden of ophthalmologists. So, early detection of exudates are useful to reduce the occurrence of vision loss. A combination of both accurate and early diagnosis as well as correct application of treatment can prevent blindness caused by DR in more than 50% of all cases. Therefore, regular screenings for DR of patients with diabetes is important. The proposed algorithm not only detects the blood vessel tree accurately but also helps to enhance the detection of exudates. Automated DR detection can reduce the severity of diseases and prevents from the faults that are available in prevailing technologies.

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