EFFICIENT TECHNIQUE TO UNRAVEL BLOOD VESSEL ON DIGITAL FUNDUS IMAGES

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Abstract —**The main objective of this project is to detect and segment the blood vessels from the digital fundus images. Diabetic Retinopathy is one of the leading causes of visual impairment. It is characterized by the development of abnormal new retinal vessels. This project uses a gray level based features method for segmenting the blood vessels from the optic disk. Fifteen feature parameters associated with shape, position, orientation, brightness, contrast and line density are calculated for each candidate segment. Based on these features each segment is categorized as normal or abnormal using a support vector machine (SVM) classifier. This methodology uses morphological operation to obtain blood vessel.**

Index Terms — **Diabetic Retinopathy, gray based invariants, fundus images, blood vessel (BV) segmentation.**

I. INTRODUCTION

Eyes are organs that detect light. Different kinds of light-sensitive organs are found in a variety of animals. The simplest eyes do nothing but detect whether the surroundings are light or dark, which is sufficient for the entrainment of circadian rhythms but can hardly be called vision. More complex eyes can distinguish shapes and colors. The visual fields of some such complex eyes largely overlap, to allow better depth perception (binocular vision), as in humans; and others are placed so as to minimize the overlap, such as in rabbits and chameleons.

In the human eye, light enters the pupil and is focused on the retina by the lens. Light-sensitive nerve cells called rods (for brightness) and cones (for color) react to the light. They interact with each other and send messages to the brain that indicate brightness, color, and contour.

Dimensions vary only 1-2 mm among individuals. The vertical diameter is 24 mm; the transverse being larger. At birth is it generally 16-17 mm, enlarging to 22.5-23 mm by three years of age, between then and age 13 the eye attains its mature size. It weighs 7.5 grams and its volume 6.5 millilitres. Each animal exhibits a different anatomy of the eye when compared to the humans.

Diabetic Retinopathy (DR) is the leading ophthalmic pathological cause of blindness among people of working age in developed countries. The first manifestations of DR are tiny capillary dilations known as microaneurysms. DR progression also cause neovascularization, hemorrhages, macular edema and, in later stages, retinal detachment. Although DR is not a curable disease, laser photocoagulation can prevent major vision loss if detected in early stages. However, DR patients perceive no symptoms until visual loss develops, usually in the later disease stages, when the treatment is less effective. So, to ensure the treatment, diabetic patients need annual eye - fundus examination. However, this preventive action involves a huge challenge for Health Systems due to the huge number of patients needing ophthalmologic revision, thus preventing many patients from receiving adequate treatment.

Glaucoma is the second most common cause of blindness worldwide. Glaucoma is identified by recognizing the change in shape, color, or depth that it produces in the optic disk. Thus, its segmentation and analysis can be used to detect of Glaucoma automatically. Its size may vary significantly and different estimations have been made. The optic disk size varies from one person to another, occupying about one - tenth to one - fifth of the image. In color fundus images, the optic disk usually appears as a bright yellowish region, although this feature may also experience significant variations.

Contrast all around the optic disk boundary is usually not constant or high enough piecewise due to outgoing vessels that partially obscures portions of the rim producing "shadows". Another distractor is produced when peripapillary atrophy is present, as this produces bright area just outside the optic disk rim which distorts its shape. On the other hand, eye movement at the moment of retinography capture may also lead to slightly blurred images, making their automated analysis even more difficult. This problem can be avoided by simply discarding these images and retaking new ones. However, this method

is not usually applied as their quality good enough for human visual inspection.

II. LITERATURE REVIEW

Marc *et al.,* reported about the design and test of an image processing algorithm for the localization of the optic disk in low – resolution color fundus images. An important approach of this is its fast computational time. But the computation time for the Hausdorff stage is dependent upon image content. From this, the observations are, the pyramid based stage has a quite good success when a priori knowledge about the optic disk position is used but the position found in sometimes quite far from the true optic disk center and the pyramid approach is of no help in identifying the contour. The Hausdorff – based approach has very good success in finding the optic disk contour, thus the optic disk centre, fast and reliability. However, it fails on images where optic disk contour is very diffuse. The optic disk is a bright region located either in the left corner or right corner of the fundus images. This assumption is also not always true in practice.

Sekhar *et al.,* proposed the retinal fundus photograph is widely used in the diagnosis and treatment of various eye diseases such as diabetic retinopathy and glaucoma. The basic idea behind the Hough Transform is to transform the image into a parameter space that is constructed specifically to describe the desired shape analytically. This method failed to localize the optic disk due to the ineptness of the shade correction operator and the automatic thresholding. The number of edge pixels and the number of radii used is reduced by applying Hough Transform only to the gradient image, since the computational complexity of the Hough Transformation is highly dependent on the number of edge pixels and the number of radii to be matched. This method can be further improved by making a robust shade correction operator and automatic thresholding. And also improves by identifying the optic disk shape properly by adjusting the Hough Transform to identify both circular and elliptical shapes.

Adam *et al.,* described an automated method to located the optic nerve in images of the ocular fundus. Here using a novel algorithm called fuzzy convergence to determine the origination of the blood vessel network. If the nerve is completely obscured by hemorrhaging, then it was difficulty in optic nerve detection. The success of multiple vessel segmentation method was to detect the optic nerve using fuzzy convergence alone, and in conjunction with using brightness as a salient features. But the problem is identifying a starting point for blood vessel segmentation. They used blood vessel convergence as the primary feature for detection. In fuzzy convergence, the problem of finding the convergence of the vessel network may then be modeled as a line intersection problem. Subsets of data that do not meet this criterion are termed outliers, and cause wrong solutions. In Illumination equation, the retinal image is uneven. Because of vignetting (result of an improper focusing of light through an optional system) the nerve may appear darker than areas central to the image. To undo the vignetting, the Illumination equation was applied to an image. In hypothesis generation, the regions are sorted by size, and repeatedly partitioned into two sets, the largest value indicates the best partition. From this the nerve detection is considered unsuccessful if either the hypothesized location is wrong or if this method doesn't produced the hypothesis. The results for fuzzy convergence at multiple scales in combination with equalized brightness shows the highest performance overall and complete success on all our healthy retina test cases but the result from the fuzzy convergence at a single scale show that the convergence of the vessel network is a more stable feature of the nerve than the brightness. And also the result from the fuzzy convergence at the multiple scales shows that the persistence of this feature at multiple scales of vessels improves the detection of the nerve. Unlike Least – Squares and Hough Space based solutions, fuzzy convergence used the endpoints of the linear shapes here the blood vessel segments to find the solution.

Juan *et al.,* detailed a deformable – model based approach for robust detection of optic disk and cup boundaries. It improved and extended the original snake, which is essentially a deforming – only technique in two aspects: 1) knowledge – based clustering and smoothing updated by the combination of both local and global information. This modifications enable the algorithm to became more accurate and robust to blood vessel occlusions, noises, ill – defined edges and fuzzy contour shapes. Optic disk with bright – white region inside called pallor is one of the main components on the fundus image and it is the entrance of the optic nerve and blood vessels to the retina. The method of optic disk boundary detection can be separated into two steps: optic disk localization and disk boundary detection. Correctly locating the optic disk is the first and essential step for optic disk segmentation. Subsequently the disk centre is estimated and used to initialize the disk boundary. Interference of blood vessels was one of the main difficulties to segment the optic disk reliably and accurately. However, in optic disk boundary detection, pathological changes may arbitrarily deform the shape of optic disk and also distort the course of blood vessels. Hence deformable templates may not be able to sufficiently encode various shapes of optic disk from different pathological changes. Cup is the depressed area inside the optic disk, hence the 3 – D depth is the primary feature of the cup boundary, for which the automated detection is a reliably new task and challenging work in fundus image processing. Currently, the bending of small blood vessels at the cup edge is used as a clue to measure the cup boundary. Nevertheless, this method can only provide several points of cup boundary in the area where there are small blood vessels: for the area without small blood vessels, the cup boundary is not easy to be estimated. A novel approach for automated detection of cup and disk boundaries is based on free – form deformable model technique (snake). This algorithm extends the original snake technique further in two aspects to directly solve the influence of blood vessels without affecting the accuracy. Snake process is modified in two further extensions: 1) after

each deformation, the contour points are classified into the edge point cluster or uncertain point cluster by knowledge based unsupervised learning, 2) the contour is updated through variable sample numbers. The updating is self – adjusted using both global and local information so that the balance on contour stability and accuracy can be achieved. The available 3- D optic disk image and disk boundary are the preconditions to estimate the cup boundary. The automated detection of cup boundary is a challenging task in fundus image processing, the free – form deformation may give uncertain shape if the cup features are not obvious. Therefore, shape model is introduced in the energy function to constrain the deformation to be close to certain predefined shape. This method correctly located the disk boundary while both the GVF snake and modified ASM method failed. This method achieved more successful number of results; and also obtained more accurate boundaries in the successful cases than the other two methods. Clustering operation can perform self – grouping of contour points into uncertain – point cluster and edge – point group based on the knowledge in the extended area of the contour. The estimated C/D ratios based on the detected cup and disk boundaries show good consistency and compatability when compared with the results from HRT (Heidelberg Retina Tomography).

III. METHODOLOGIES

We are addressing the problem of automatic detection of diabetic retinopathy. Further our aim is to emphasize the significance of our work by putting an algorithm which is relatively easy for implementation and hence the viability of a realizable and repeatable step. In Blood vessel segmentation, we are having four main modules as preprocessing, feature descriptors, classification and post processing.
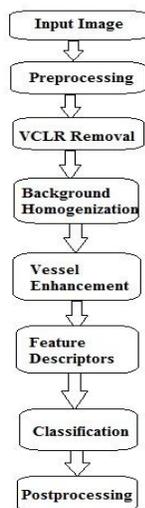
FLOW DIAGRAM OF BV SEGMENTATION:

Figure 1: Flow Diagram of BV Segmentation

3.1 PREPROCESSING:

Before that, an input image is splitted into R,G,B components. Because the light is reflected in green plane than the red and blue plane. Hence the green plane of the image is extracted initially.
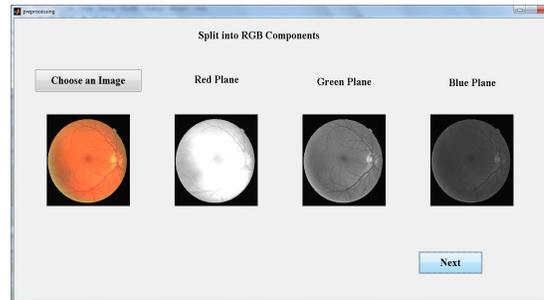

Figure 2: Splitting of RGB Components

This preprocessing also contains three sub modules as,

1)   Vessel Central Light Reflex (VCLR) Removal

2)   Background Homogenization

3)   Vessel Enhancement

3.1.1 VCLR REMOVAL:

Since retinal blood vessels have lower reflectance than other retinal surfaces they appear darker than the background. Some blood vessels include a light streak which runs down the central length of the blood vessel. Hence to remove this brighter strip the extracted green plane of the image is filtered by applying morphological opening as structuring element.
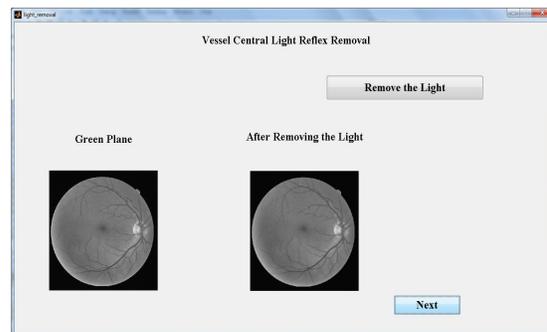

Figure 3: VCLR Removal

3.1.2 BACKGROUND HOMOGENIZATION:

Background pixels may have different intensity for the same image and although their gray levels are usually higher than those of vessel pixels, the intensity value of some background pixels is comparable to that of brighter vessel pixels. With the purpose of removing these background lightening variations, the shade – correction

algorithm is observed to reduce the background intensity variations and enhance contrast in relation to the original green plane image.

Then the difference between green image and homogenized image for every pixel is stored in D. Besides the intensity can reveal significant variations between images due to different illumination conditions in the acquisition process. In order to reduce this influence, a homogenized image I_H is produced as the histogram of I_{SC} is displaced toward the middle of the gray scale by modifying pixel intensities according to the global transformation function:

$$g_{output} = \begin{cases} 0, & \text{if } g<0 \\ 255, & \text{if } g>255 \\ g & \text{otherwise} \end{cases}$$

where $g = g_{input} + 128 - g_{input\_max}$

Firstly, a 3x3 mean filter is applied to smooth occasional salt-and-pepper noise. Further noise smoothing is performed by convolving the resultant image with a Gaussian kernel of dimensions m x m = 9 x 9. Then 69 x 69 mean filter is applied later.
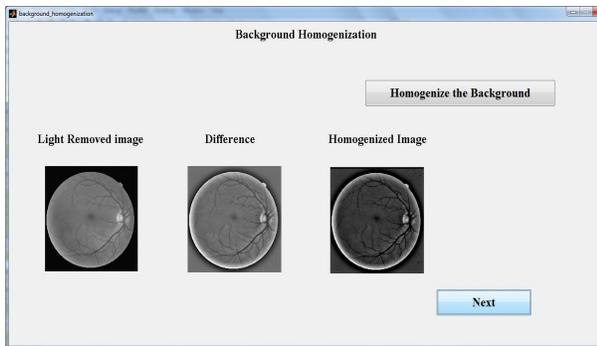

Figure 4: Background Homogenization

3.1.3 VESSEL ENHANCEMENT:

It is performed by estimating the complementary image of the homogenized image I_H, I^C_H and subsequently applying the morphological operation. Thus the bright retinal structures are removed and the darker structures remaining after the opening operation become enhanced.
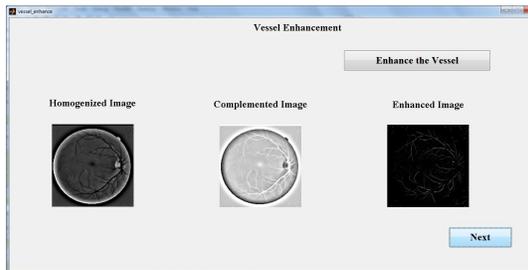

Figure 5: Vessel Enhancement

3.2 FEATURE DESCRIPTORS:

These feature descriptors stage is for pixel characterization by means of a feature vector, a pixel representation in terms of some quantifiable measurements which may be easily used in the classification stage to decide, whether the pixels belong to a real blood vessel or not. For this the gray level based feature is used.
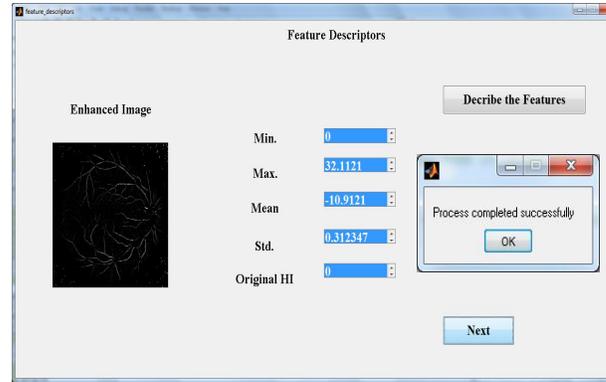

Figure 6: Feature Descriptors

A set of gray level based descriptors such as minimum, maximum, mean, standard deviation and the homogenized image value is taking from homogenized images I_H considering only a small pixel region centered on the described pixel(x,y). Then, these descriptors can be expressed as,

$$f_1(x,y) = I_H(x,y) - \min_{(s,t)\in S^9_{x,y}} \{I_H(s,t)\}$$
$$f_2(x,y) = \max_{(s,t)\in S^9_{x,y}} \{I_H(s,t)\} - I_H(x,y)$$
$$f_3(x,y) = I_H(x,y) - \text{mean}_{(s,t)\in S^9_{x,y}} \{I_H(s,t)\}$$
$$f_4(x,y) = \text{std}_{(s,t)\in S^9_{x,y}} \{I_H(s,t)\}$$
$$f_5(x,y) = I_H(x,y).$$

3.3 CLASSIFICATION:

In this module, based on the feature descriptor the images are classified as whether the pixel is a blood vessel or non-blood vessel image. For this Support Vector Machine (SVM) classifier is used. Here the pixel which belongs to blood vessel are classified separately and the pixel which do not belongs to blood vessel are classified separately.
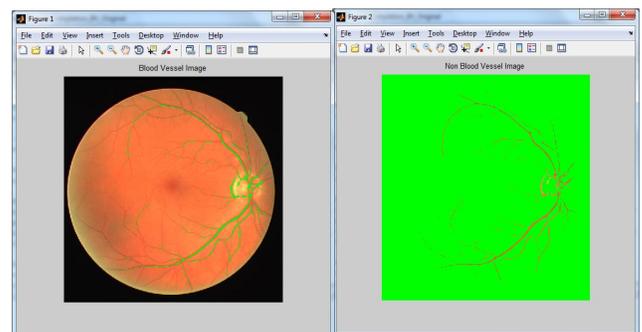
Figure 7: Classification

3.4 POSTPROCESSING:

The final step is post processing stage includes two stages,

1) Filling pixel gaps in detected blood vessels
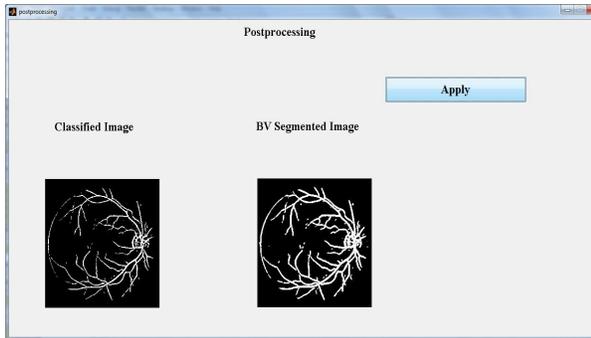
2) Removing the falsely detected isolated vessel pixels.

Figure 8: Postprocessing

The above two steps are processed by using morphological operation as structuring element.

IV.   CONCLUSION

This work presents the automated blood vessel segmentation for Diabetic Retinopathy. In this we are choosing the green plane of the image because the vessels reflect more than the red and blue plane. The final results of each plane are shown as follows:
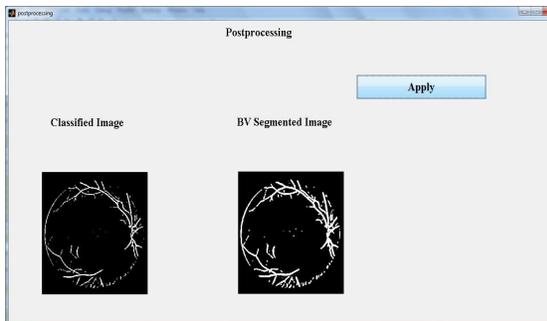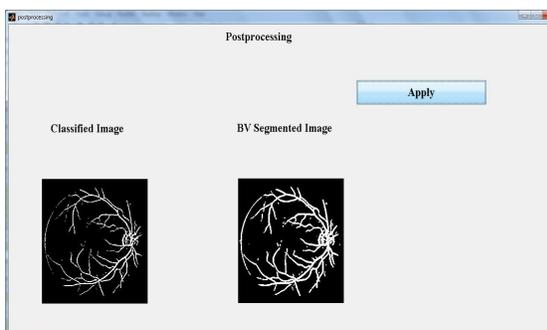

Figure 9: Result of Red Plane
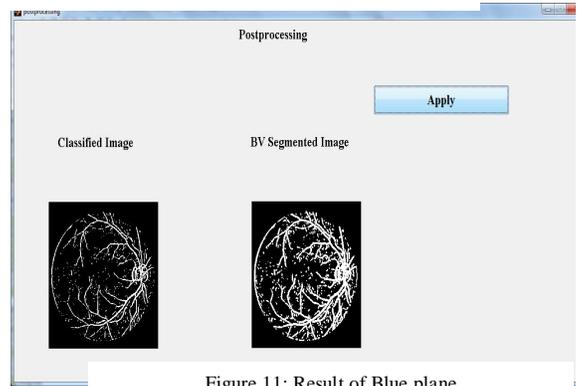

Figure 10: Result of Green Plane

Figure 11: Result of Blue plane

V.   FUTURE ENHANCEMENT

In future we will segment both Optic Disk and Blood Vessel to improve the performance of the automatic diagnosis of Diabetic Retinopathy.

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