Methodology for Identification and Detection of Diabetic Retinopathy using the Retinal area and Exudates of SLO Images

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ABSTRACT

Scanning Laser Ophthalmoscopes (SLOs) are used for early detection of retinal diseases. In this, we propose a new method to automatically extract out true retinal area from an SLO image based on image processing. To reduce the complication of image processing tasks and provide a suitable primary image pattern, we have grouped pixels into regions based on the territorial size and compactness, called super pixels. Diabetic retinopathy (DR) is one of the major causes of blindness in the world among patients suffering with diabetes. It is an eye disease and happens by nature. It is identified by many types, namely micro-aneurysms, hard exudates, soft exudates, haemorrhages, etc., among them presence of exudates is the important sign of non-proliferative DR. Both hard and soft exudates play a main role in grading DR into various stages. This is an efficient new method to identify and classify the exudates as hard and soft exudates. The retinal image in CIELAB color space is processed before to delete noise. Next, blood vessels network is deleted to facilitate detection and deletion of optic disc. Optic disc is deleted using Hough transform method. The patient exudates are then detected using k-means Segmentation technique. At last, the exudates are classified as hard and soft exudates based on edge energy and threshold.

KEYWORDS: *Image, Diabetic Retinopathy, Exudates, Hough Transform, K-means Segmentation*

I. Introduction

Optometrists and ophthalmologists frequently depends on image operations such as change of contrast and zooming to explain these images and diagnose results based on their own experience and territory knowledge. These diagnosing techniques are time taking. Automated analysis of retinal images has the possibility to reduce the time, which doctors need to look at the images, who can expect more patients to be conceal and more consistent diagnoses can be given in a time good manner. In a retinal scan, irrelative objects such as the eyelashes, eyelids, and dust on optical surfaces may appear bright and in focus. So therefore, automatic segmentation of these artefacts from an imaged retina is not a minor task. The purpose of performing this study is to evolve a method that can delete artefacts from retinal scans so as to make better automatic detection of disease features from the retinal scans. Due to the broad field of view (FOV) of SLO images, shapes such as eyelashes and eyelids are also included along with the retina. If these structures are deleted, this will not only make easy the effective analysis of retinal area, but also make it possible to listing multi view images into a montage, resulting in a completely visible retina for disease identification.

Diabetic retinopathy is an issue of diabetes and a leads to cause of blindness. It occurs when diabetes damages the small blood vessels inside the retina which is in the back of the eye. Diabetic retinopathy advances from mild non proliferative abnormality, describes by increased vascular permeability results in forming of micro aneurysms, to new and critical non-proliferative diabetic retinopathy (NPDR), characterized by vascular closure-results in formation of exudates, to proliferative diabetic retinopathy (PDR), distinguish by the growth of new blood vessels on the retina. According to ophthalmologists, both hard and soft exudate plays an important role in grading the DR and tracks the progress of treatment. A computer aided detection of exudates could give fast and precise diagnosis and then shows the ophthalmologist to treat the proposed for differentiating the exudates as hard and soft exudates automatically. Most of the work presented in this literature processes the color retinal image in RGB space to achieve exudates detection. In this, the colored retinal image shown in CIELAB color space is processed to identify and classify the exudates for getting good results.

II. Previous Method

In Previous, there are different methods for detection and segmentation of eyelids and eyelashes applied on images of the eye from front, which has the pupil, eyelids, and eyelashes. On that image, the eyelashes are usually in the form of lines or cluster of lines are grouped together. Therefore, the starting step of detecting them was the application of edge detecting techniques such as Sobel, Prewitt, Canny, Hough Transform, and Wavelet transform. The eyelashes on the iris were then deleted by applying nonlinear filtering on the mistrust eyelash areas. Since eyelashes can be in either separated form or in the form of many eyelashes grouped together, Gaussian and Variance filter were applied in order to differentiate among both forms of eyelashes. This experiment showed that separable forms of eyelashes were most equally detected by testing Gaussian filter, whereas Variance filters are more advantageous for multiple eyelash segmentation. The image obtained from SLO, the eyelashes shows either dark or bright region compared to retinal area depending upon how laser beam is concentrated as it passes the eyelashes. The eyelids show as reflectance region with greater reflectance response when compared to retinal area. So therefore, we need to find out the features, which can distinguish among true retinal area and the artefacts in SLO. Our methodology is based on examining the SLO image-based features, which are calculated for a tiny region in the retinal image called superpixels. The determination of quality vector for each superpixel is conditionally efficient as compared to quality vector determination for each pixel. The superpixels from the images in the training set are given the class of either retinal area or artefacts depending upon the majority of pixels belonging to the particular class. The Difference is performed after ranking and selection of qualities in terms of effectiveness in classification.

III. Proposed Method

For Obtaining Retinal area, this work has been divided into three stages. The first stage is related with building of classification model based on training images and the notations reflecting the partition around retinal area. In the second and third stages, the automated notations are performed on the “test set” of images and the classifier performance is evaluated against the manual notations for the determination of exactness. Finally, the third stage performs the automatic extraction of retinal area. The images for training and testing have been obtained and are obtained using their ultra wide field SLO. Then each image has a FOV of up to 200of the retina in a resolution of 14μm. The device apprehends the retinal image without dilation, through a tiny pupil of 2 mm. The image hastwo channels. The green channel (wavelength:532 nm) gives data about the sensory retina to retinalpigment epithelium, whereas the red channel (wavelength:633 nm) shows very deep structures of the retina toward the choroid. Each image has a size of 3900 ×3072 and each pixel is entitled by 8-bit on both red and green channels.

The Exudates detection method is outlined in the below figure.

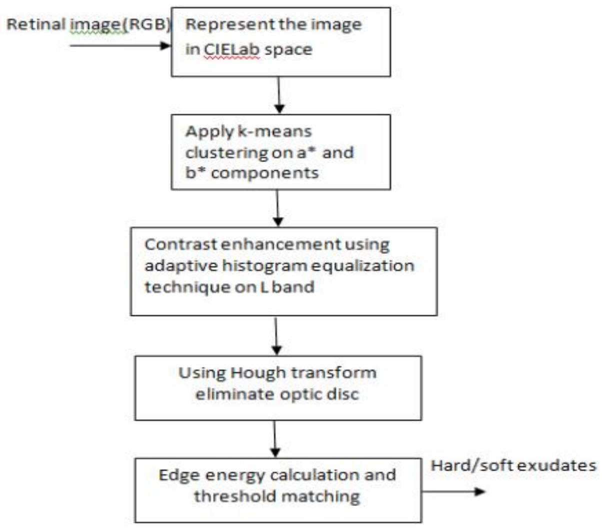
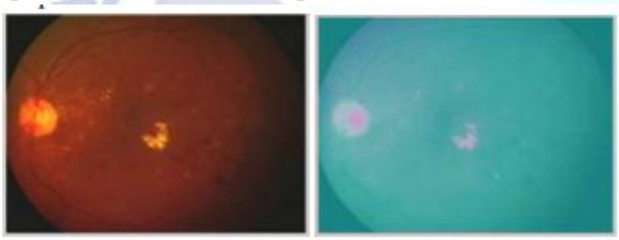


Figure 1. Block Diagram of Proposed work

A. Transformation from RGB color space to CIELAB color Space

LAB color space is a new model of human vision and an absolute reference space for color. Working in LAB is counter instinctive at best. All the brightness information is in the L* channel while color is encoded in a* and b* channels. Pre-processing methods work more efficiently and explicitly in LAB space. For example, noise removal from the image can be achieved by applying filters to both either a* channel or b* channel not affecting the contrast which is stored in L* channel. So therefore, in this method we choose LAB color space over RGB color space.



a *b*

Figure 2. a. Original RGB Fundus Image b. CIELAB image

B. K-means Segmentation

Due to the computational simplicity of the k-means algorithm over other clustering processes, we have decided to use the k-mean segmentation in the proposed work. The k-mean segmentation algorithm is a particular case of the generalized hard clustering algorithms. It is applied when point indicatives are used and the squared Euclidean Distance is adopted to measure the dissimilarities between vectors xiand cluster representatives Ɵj. The k-means algorithm isgiven below.

Algorithm:

Step1: Choose arbitrary initial estimates Ɵj (0) for the Ɵj's,j=1,…,m.

Step2: Repeat

1. For i=1 to N

o Determine the closest representative, say Ɵj for xi.

o Set b(i)=j;

End {for}

2. For j=1 to m

o Parameter updating: Determine Ɵj as the mean of the vectors xi X with b(i)=j.

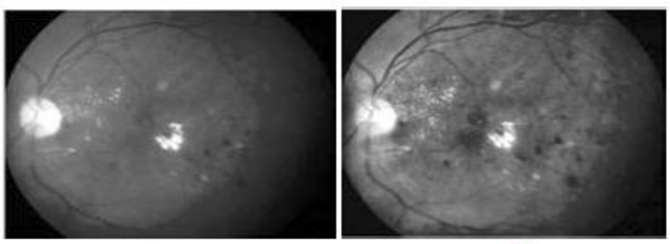
End {for}

Until no change in js occurs between two successive iterations.

Figure 3. Cluster labelled image

C. Contrast Enhancement

This leads to enhancement of separation between exudates (foreground) and background. As CIELAB color space is been used in this method, we have known that L* channel has all the information related to brightness. Adaptive histogram equalization technique is performed to this channel to facilitate enhancement of feature extraction.



a *b*

Figure 4. a. L Channel Image b. Contrast enhanced image

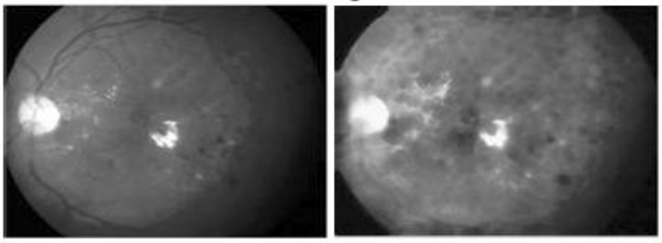
D. Blood vessel detection

To make easier the exudates extraction from the pre-processed image, blood vessel network is observed and then removed from it using morphological operations.

Morphological operations can willingly be used in medical image analysis as it holds powerful tools to extract pathologies based on shape. The morphological operations used in this work are given below.

1. Dilation, 2.Erosion, 3.Closing

The main part of applying morphological operations is to decide on the shape and size of structuring element. In this work, a ball shaped structuring element of size 8,was found to be optimal for deleting the blood vessel network from the retinal images of local data base.



a b

Figure 5. a. L channel image b. image after morphological operation

E. Hough Transform for circle

This transform is used as mathematical morphology and image reconstruction for eliminating the optic disk(OD).The technique empirically deletes the OD but does no tensure that the right part of the image is deleted. Hence, we used Hough transform technique to fit acircle to OD and protects that the area located in the image isO D. The Circular Hough Transform (CHT) depends on equations for circles. The equation of the circle is, Here a and b be elected by the coordinates for the centre, and ris the radius of the circle. The representation of this circle is Circular Hough Transform.

Step by Step procedure is presentedbelow.

Step 1: Transform color retinal image into grayscale

Step 2: Generate a 3D Hough array (accumulator) with the two dimensions representing the coordinatesof the circle origin and the third dimensionrepresents the radii.

Step 3: Do edge detection using the canny edgedetector.

For each edge pixel, increment the analogous Elements in the Hough array.

Step4: Collect candidate circles, and then delete similarcircles.

Step5: Draw circles throughout the object.

In this work, to assign the values for a and b,we first have extract the portion of image that contain the optic disk. This is achieved by performing optic disk localization using correlation coefficient. Then, the size of the sub-image is allocated to a and b and radius is fixed to range around 45 to 55 pixels.

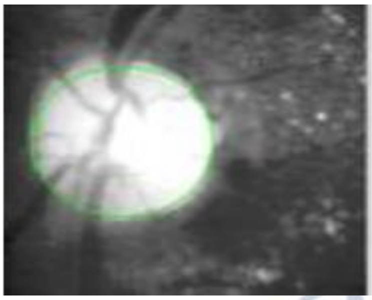
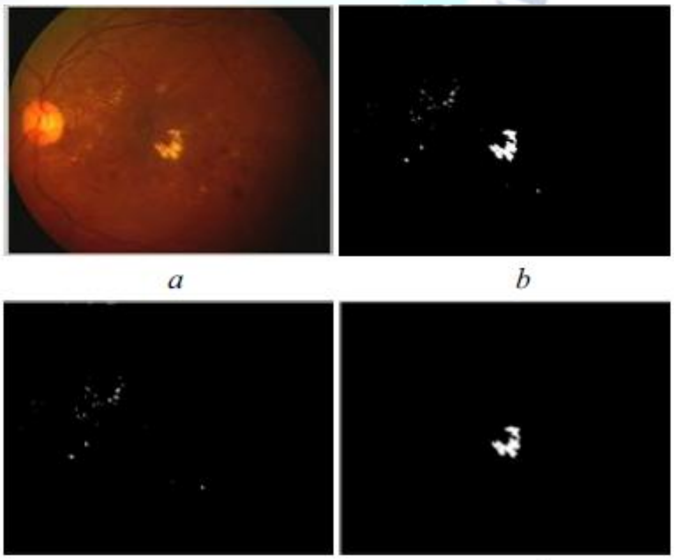


Figure 6. Optic disk marked using Hough Transform for circle

F. Classifying Hard and Soft Exudates

The last step is to classify the exudates as hard and soft based on the threshold value and edge energy. For Edge energy calculation, we have to extract the exudates with sharp edges which are a characteristic feature of hard exudates. Kirsch operator needs more computational time and the results are not better than canny operator. So, we preferredcanny operator than Kirsch operator for edge energydetection. The hard exudates are extracted by integratingthis edge energy and the threshold value. To extract the softexudates, subtract the hard exudates image from the imagethat contains both types of exudates.



a b c d

Figure 7. a. Original RGB image b. binary image with Exudates c. Binary image with only HE d. Binary image with only CWS

IV. Results

This method is experimented on different images collected from Google. All the images have a full visible optic disk. For these images, using Hough transform technique, Optic Disk has been eliminated with an accuracy of 100%. However, the method fails for the images that have only a portion of optic disk (Fig 8). The morphological operations for eliminating the blood vessel network have provided 100% results. At last, the exudates have been classified as hard and soft exudates based on edge energy and threshold value.

e

Figure 8. Partial optic Disk

Then it displays a warning dialogue as the given image is Healthy Eye or Diabetic Eye based on the threshold value.

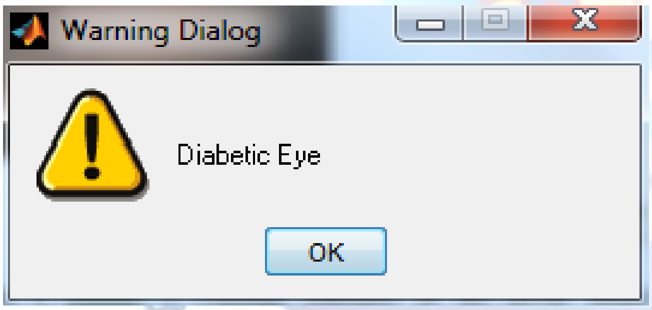


Figure 9. Diabetic Eye Warning

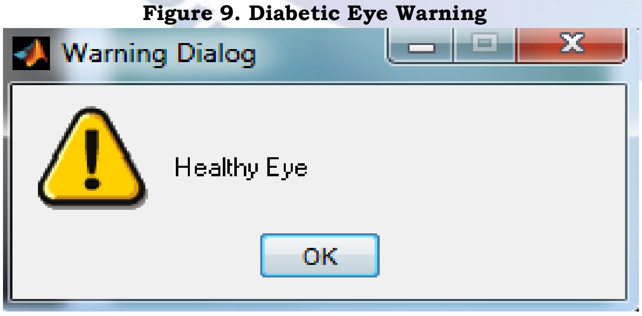


Figure 10.. Healthy Eye Warning

V. Conclusion and Future Scope

Automatic detection and classification of exudates using k-means segmentation algorithm has been presented in this paper. The method has provided encouraging result. The method has successfully classified the exudates as hard and soft exudates and successfully detects the exudates for retinal images wherein Optic Disk is visible completely. However, the method fails to identify the Optic Disk in case of retinal images where Optic Disk is partial visible. Comparing the results with the method presented in Diabetic Retinopathy, this method classifies the exudates as soft and hard as to identifying only hard exudates. Such categorization helps the ophthalmologists in diagnosing the retinal diseases. In Future, we can do this detection by using DSP Processors also.

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