Dynamic Thresholding Technique for Detection of Hemorrhages in Retinal Images

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***Abstract*—The paper proposes a dynamic thresholding based image processing technique for the detection of hemorrhages in retinal images. The algorithm uses the information about color and size of hemorrhages as a tool for classifying hemorrhages from other dark lesions present in the retinal images. The algorithm uses the concepts of contrast enhancement, background estimation and intensity variation at edges that is gradient magnitude information supported by some morphological operations. The algorithm follows a simple approach of step by step removal of unwanted features from targeted images using concepts of thresholding and morphology without compromising with accuracy and time of execution. The experimental results indicate that hemorrhages are detected with good accuracy in the retinal images.**

Keywords—Medical image processing, Fundus Image, Diabetic Retinopathy, Hemorrhages, Thresholding, Binarization

I. Introduction

Diabetic Retinopathy (DR) is a disease associated with Diabetes that causes loss of vision in diabetic patient. The chances of patient possessing Diabetic Retinopathy are more than 80% in those patients who have been suffering from diabetes for more than 10 years. DR has been identified as main and leading cause of vision loss in patients within age group 25 to 75 years. DR is curable in early stages only and can lead to permanent vision loss if not treated properly. According to a survey conducted over whole the world 382 million people were identified with DR in 2013 and the count is expected to reach up to 592 million till 2035.DR is identified from many symptoms which start appearing as the disease progresses. All the symptoms start appearing in retina of patient's eye with passage of time. DR starts affecting the patient's sight by disturbing the functioning of blood vessels in retina. On the basis of appearance of symptoms DR is divided into two types: First one is Non Proliferative Diabetic Retinopathy (NPDR) and second is Proliferative Diabetic Retinopathy (PDR). NPDR is earlier stage and is identified by the presence of Micro aneurysms, retinal hemorrhages, hard exudates and macular edema and macular ischemia. PDR is later stage of DR and is characterized by the presence of revascularization i.e. formation of new abnormal blood vessels. Micro aneurysms are small protrusions in blood vessels of retina. Retinal hemorrhages are blood patches that are formed due to leakage of blood from blood vessels and are dark red in appearance. Exudates appear by the leakage of fat or cholesterol from blood vessels and are of bright yellow color. Sometimes leaked blood from blood vessels enter into gel present in the center of eyes, called vitreous, forming vitreous hemorrhages. In clinics the identification of DR symptoms is done mainly by ophthalmologists and is quite time consuming as well as expensive process.

Image processing techniques applied in the Fundus image seems to be a great help for detection of symptoms of DR. Image processing tools can act as diagnostic tools for detection of abnormalities in Fundus retinal images. Many algorithms for the detection of DR symptoms have been developed by the researchers all over the world. Vidyasari et al**.** used the method of micro-aneurysm filter based on the concept of enhancement of vessels for the extraction of micro-aneurysm structure in retina images [1]. Verma et al. detected hemorrhages and blood vessels using the concepts of bounding box and contrast difference respectively and further classified disease using random forest classifier [2]. Ning and Yafen identified stages of DR in retinal images using SVM classifier with features such as area of blood vessels, exudates and contrast, homogeneity. They used techniques of texture analysis, morphological processing and other image processing techniques for extracting features [3]. Tjandrasa et al. [4] classified DR NPDR images into Moderate and Severe using soft margin SVM. They obtained their features from Hard exudates which was extracted from retinal images using morphological processing methods. Pootstchi et al. [5] generated several methods for preprocessing retinal images for the detection of dark lesions in. Kumari et al. [6] detected blood vessels and exudates in retinal images using a robust technique based on morphological operations. Sreng et al. [7] extracted optic disk and exudates from retinal images by estimating histogram of background, blob boundary measurement, Morphological reconstruction and entropy Thresholding. Hatanaka et al. **[8]** detected microaneurysms in retinal images by extracting candidate blobs using double ring filter and then classified them into true positive and false negative candidates by using rule based classifier.

All these algorithms seems to work nicely on their respective purpose but still there is a requirement of improvements to be done on the existing techniques in this field for reduced complexity, increased accuracy, fast execution for making

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useful and cost effective real time applications of hemorrhage detection from Fundus images for identification of DR.

The main contribution of the paper is a method based on the dynamic thresholding for extraction of hemorrhages in retinal images. The method works on the fact that hemorrhages and blood vessels are darker than rest of background in the DR retinal images. The algorithm utilizes the information that the magnitude of gradient at separation of hemorrhages and blood vessels from background is quite high. So an efficient gradient based thresholding algorithm separates the blood vessels and hemorrhages from rest of background. Then removal of vasculature and fovea results into hemorrhages as desired output. This algorithm follows a very simple step by step approach and utilizes simple concepts of thresholding and morphological operations which take quite a less time for execution in comparison to other available methods, proving algorithm suitable for fast real time applications for detection of hemorrhages from Fundus image.

The rest of paper is organized as follows: The proposed methodology for detection of hemorrhages from the Fundus image is explained in Section II. The proposed methods provide output as blood vessel and hemorrhage detection, blood vessels removal and fovea removal giving only hemorrhages in the output. Results have been explained in Section III and conclusion and future work have been described in section IV.

II. PROPOSED METHODOLOGY

The proposed method of hemorrhage detection from Fundus image is divided into four main subsections:

1. First section explains preprocessing of images including Noise removal, Contrast enhancement and Shade Correction and binarization of image using Dynamic Thresholding.
2. Second section describes extraction of vascular architecture from output.
3. The third part explains technique used for extraction of fovea from retinal images.
4. Fourth and the last part describe subtraction of fovea and blood vessels from output of first part. The complete method is demonstrated in the given flowchart represented by Fig. 1.

A. *Detection of Hemorrhages and Blood Vessels :*

Green channel of input colored RGB image is extracted for processing because contrast of image is better in green channel component. The Green channel image is further converted to grayscale image so that the intensity values of each pixel get lie in range between 0 to 255. Generally very few high frequency components in form of noise appear in rough image. These noise particles are removed from images using two dimensional median filter of size [3 x 3] window. Median filter is used because it has characteristics of removing salt and pepper noise while preserving the edges. The image is inverted so that the blood vessels and hemorrhages become brighter than rest of background. Then for further enhancing contrast of our images we apply Contrast Limited Adaptive Histogram Equalization (CLAHE). CLAHE increases the contrast of image by dividing image into multiple sub windows and increasing the contrast of each window using

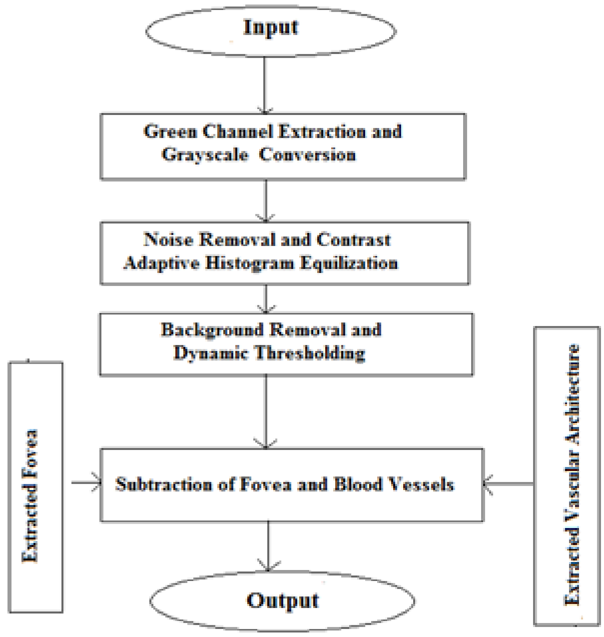


Fig. 1. : Block Diagram of proposed method

histogram equalization. Background comprises of low frequencies and unnecessary information. Background removal was done by shade correction method. A two dimensional median filter of size 33 x33 was used to estimate background and then subtract from CLAHE output to make background pixels 0. Hence we will be left with image containing blood vessels and hemorrhages only. Further contrast of image was enhanced by making maximum intensity 255 and minimum intensity as 0.

B. *Dynamic Thresholding :*

Thresholding technique is used for discriminating foreground pixels (object pixels) from background pixels. Thresholding operations employ difference in intensities of foreground and background for segmentation purpose. Generally the intensity of foreground or object pixels lie in one group and intensity of background in other. So by using a suitable threshold grayscale image can be converted to binary image by employing one value to foreground pixels and other value to background pixels. Most employed technique for threshold selection is by observing the histogram of images.

Here the foreground pixels are pixels of blood vessels and hemorrhages and all other pixels are background. To binarize shade corrected image the 'Dynamic Thresholding' technique [9], [10] was used. Dynamic Thresholding works on the fact that intensity of edges in objects remains higher than other background. So gradient information can be employed for obtaining appropriate threshold parameter. The threshold value is computed by implementing an equation on each pixel and its neighborhood pixels. The required equation can be easily computed with two mask operators and then threshold value is computed in each detail subband. Then binary image, B(x,y) is computed by comparing each detail subband 'eds' with threshold 'Th'.Following equation is utilized for calculation of threshold 'Th'.

$$Th = \frac{\sum(|eds(x,y)|, s(x,y))}{\sum s(x,y)} \qquad (1)$$

where s(x,y) = max(|m1 ** s(x,y) | , |m2 ** s(x,y)|) , m1 = [-1,0,1] and m2 =[-1,0,1]^T . ' ** ' represents two dimensional linear convolution. The values of x =1,2,3…..P and y =1,2,3…. Q for P x Q subband. Then the binary image can be obtained from following equation.

$$B(x,y) = \begin{cases} 1 \text{ if } eds(x,y) \geq Th \\ 0 \text{ if } eds(x,y) < Th \end{cases} \qquad (2)$$

Hence formed binary image contains hemorrhages and blood vessels that will be used in further steps.

C. Blood vasculature Extraction:

Blood vessel architecture is extracted using Morphological white top hat transform. White top Hat transform is use to detect those objects that are brighter than the background and in which structuring element gets fit, As blood vessels are of small width in comparison to hemorrhage particles so a ball type structuring element with small size is used on CLAHE image extracted in previous step for blood vessel architecture estimation. White top hat transform 'W' on image 'I' with structuring element 'S' is implemented through following equation :

$$W = I - (I \circ S) \qquad (3)$$

Where "o" symbol indicates Morphological opening.

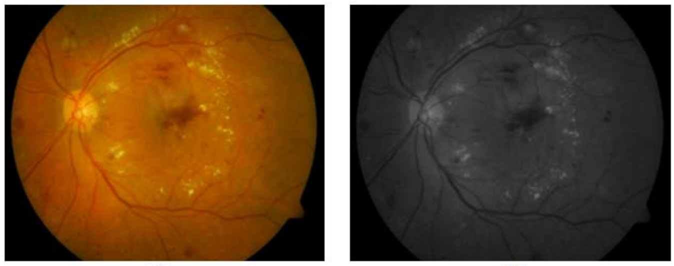
Above equation explains subtraction of morphologically opened image from original image. Then binarization of image is done by Dynamic Thresholding algorithm explained earlier. Now our output contains some artifacts and blood vessel. To extract only vasculature we will employ Morphological opening technique. Morphological opening retains those objects which are fit in used structuring element and removes those which do not fit. So as blood vessel possess linear structure ,so for opening the image, a linear structuring element of size 15 is used and rotated it at angles of 10^o for covering entire image. Then maximum of all the 18 opened images will result blood vessel architecture as final output.

D. Extraction of Fovea :

For extracting fovea, we have followed method described by Kovacs et. al. [11]. First of all, shade corrected image is generated from green channel image using median filter. Further image is converted to binary by assigning all zero pixels to background and non zero pixels to foreground. Finally using label connectivity and area thresholding, fovea is detected as largest size object. This image is subtracted from previous output resulting fovea removed image. Some small vessels are removed by using morphological opening with structuring element of small size leaving us with only hemorrhage candidates.

III. Experimental Results

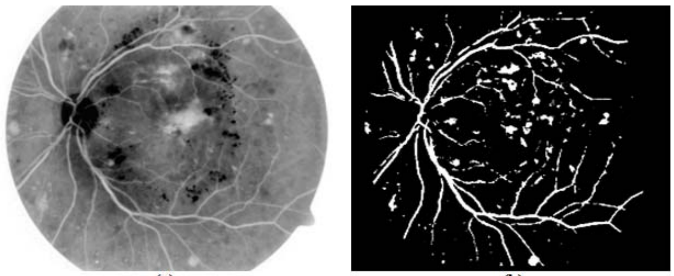
DR retinal images for experimentation have been acquired from publically available DR Retinal images database DIARETDB1. The method solely relies on the concept of dynamic thresholding as it is employed in detection of blood vessels, fovea and hemorrhages.



(a) (b)

Fig. 2: (a) Fundus Image (b) Green Channel to Grayscale converted image

Figure 2(a) and 2(b) represents input colored retinal image and grayscale converted image from green channel of input image.



(a) (b)

Fig. 3: (a) CLAHE operation on inverted image, (b) Dynamic Threshold image

Figure 3 (a) and 3 (b) represents output of applying contrast limited adaptive histogram equalization on inverted image and image after applying dynamic thresholding on image.

(a) (b)

Fig. 4: (a) Blood vasculature extracted image (b) Fovea Extracted image

Fig. 4(a) and 4(b) represents the outputs of Section C and Section D where blood vessels architecture and fovea have been extracted out from same image using technique of morphological operators and Dynamic Thresholding.

Fig. 6. : Hemorrhage extracted from the fundus image

Figure 6 represents the final output obtained as a result of subtracting blood vasculature and fovea from image containing hemorrhage, blood vessels and fovea. Hence the method accurately detects hemorrhages in DR infected retinal images with good speed.

TABLE: 1
COMPARISION OF RESULTS OF PROPOSED ALGORITHM TO THE RESULTS OF DIAGNOSIS OF MEDICAL EXPERTSs.

Retinal Image sample No.	**Detection Result and Comparison of Result with Expert Result**		
	Detection Result (Proposed Method)	***Medical Expert's Diagnostic Result***	***Compared Result***
Sample 1	Healthy	Healthy	Positive
Sample 2	Healthy	Healthy	Positive
Sample 3	Healthy	Healthy	Positive
Sample 4	Healthy	Healthy	Positive
Sample 5	Healthy	Healthy	Positive
Sample 6	Hemorrhages	Hemorrhages	Positive
Sample 7	Hemorrhages	Hemorrhages	Positive
Sample 8	Hemorrhages	Hemorrhages	Positive
Sample 9	Healthy	Hemorrhages	Negative
Sample10	Hemorrhages	Hemorrhages	Positive

The algorithm was tested over large data set. Some of the test results are tabulated in Table 1. The output result of the algorithm and comparison with the diagnosis of medical professional expert result in given in the table. The test results of the experiments performed on the Fundus images have given positive results to around 90% accuracy and hence this proposed algorithm may be considered as a significant development towards automatic detection of hemorrhages from Fundus images.

IV. CONCLUSION

The proposed method is an image processing method of detecting hemorrhages from the Fundus retinal image. This method is based on green channel extraction and grayscale conversion of image, using dynamic thresholding and blood vessels removal and fovea removal from retinal images providing hemorrhages as only left objects. The approach has followed step by step removal of unwanted objects from images. The method is fast in execution and also provides quite accurate results. This can be useful in making cost effective application to be used a diagnostic tool for identification of hemorrhages for Diabetic retinopathy detection. There is a wide scope for future expansion of this algorithm by classifying DR images into mild, severe and moderate by obtaining features from extracted hemorrhages.

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