AutomaticDetection of Microaneurysmsin Retinal Images

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ABSTRACT
Early stage symptom of the diabetic retinopathy is Microaneurysms (MAs). Diabetic retinopathy is graded with the help of number of MAs in fundus image. Detection of MAs in initial stage of diabetic retinopathy may prevent the vision loss.In this work a new approach is proposed for findingtheMAs in fundus image. This method follows the three steps for detection of MAs. Enhancement of local contrast of the fundus image and removal of blood vessels arecompleted in first two steps. In the last step,MAs are detected based on the size and shape features. The proposed method is tested on DIARETDB1 database. The proposed method achieved sensitivity of 87.5% for recognizing MAs in fundus images.

CCSConcepts
Computingmethodologies → Imagesegmentation

Keywords
Top Hat Transform;VesselExtraction;Detection;Microaneurysms

1. INTRODUCTION
Rupturing of blood vessels in retinal image occurs due to the diabetic retinopathy which leads to visual loss of the human eyes.Diagnosis and treatment in early stages of diabetic retinopathy helps to avoid from causing blindness. The formation of tiny red dots called MAs in retinal image is the only early symptom of the diabetic retinopathy.These tiny red dots are circular in shape with diameters between 10 and 100 μm [1].Detection of MAs is very challenging task in low contrast poor quality retinal image. Optic disc, Blood vessels and Fovea are the features of the retina [2]. Microaneurysms,Hard Exudates and Hemorrhages are abnormalities formed in retinal image due to the diabetic retinopathy [2].The MAs and blood vessels have similarcolor as shown in Figure 1.

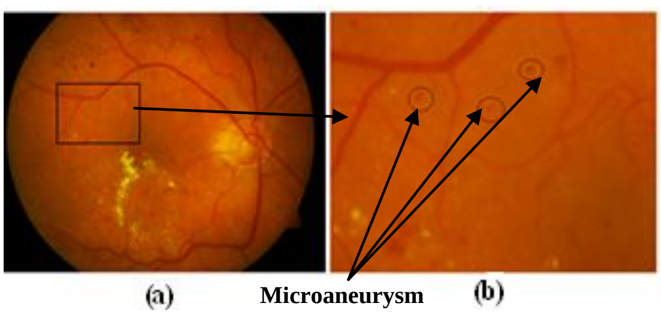

Figure 1. (a) Color fundus image (b) Microaneurysms in black square portion of Fig. (a)

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2. RELATEDWORK
The detection of MAs in fundus image is very tough task. There are several algorithms available in the literature for detection of MAs in fundus image. Bhalerao et al. [3] introduced a new technique for findingtheMAs in fundus images. In this method, the low contrast regions are improved by multiplying median filtered output image with a local-mean filtered image.Undersized dots are enhanced by applying aLaplacian of Gaussians filter followingthe preprocessing step. The complex valued, circular symmetry operator is used to distinguish the dark spots (MAs) and bright spots (hard exudates). The output of the Laplacian of Gaussians filter and complex valued, circular symmetry operator are merged. Lesion regions are positioned by thresholding the merged image.

Sopharket. al. [4] introduced a simple hybrid method for detection of MAs. They used median filtering operation to suppress the effect of noise in fundus image. Local contrast enhancement and shade corrections are applied for further improvement of the quality of fundus image. Mathematical morphology is adopted for extraction of exudates and blood vessels. A group of eighteen features is given to naive Bayes classifier for true MAsdetection.

An innovative algorithm is designed by Habib et al. [5] after grouping of different methods for automated MA detection. They extracted 70 regular features available in the state of the art.These features are organized based on the ranking to find out the features which are essential to distinguish true MA from counterfeit entities.Tavakoli et al. [6]introduced a novel and differentapproach for findingMAsin retinal images. In this approach, optic disk is removed from the retinal image and masked. Background elimination is completed with help of top-hat transform and average filter. They divided the preprocessed image into sub images and segmentation is performed on these images. Masking of blood vessels is done using radon transform. After masking of blood vessels and optic disk, true MAs are detected with the help of radon transform and thresholding.

MAsdetection based on gradient vector analysis and class imbalance classification is proposed by Dai et al. [7]. In this paper, gradient field of the image is used for calculating the log condition number map at different scales.The secondorder directional derivatives were computed in various directions for localization of the MAs.

Shah et al. [8] computed statistical features based on curvelet coefficients for findingtheMAs in color fundus images. They removed the blood vessels from green channel image and MAs were located by local thresholding method. A rule-based classifier is introduced which utilizes a group of features for separation of MAs.In this work, they reported 48.21% sensitivity.Sophark et al. [9] explored most advantageous and fine tune morphological operators for recognizing MAs in poor retinal images. Michael et al. [10] used shade correction and median filtering in preprocessing of fundus images. Withdrawal of vessel structure is done with the help of top-hat transform.Promising MAs are recognized by applying a matchedfilter to the image.

Shade rectification, enrichment of the contrast of an image and removing of noise, these preprocessing steps are used bySeoudet al. [11] to enhance the quality of fundus image.They used all regionalminima with sufficient contrast for consideration of candidates.Dynamic shape features which are based on the intensity of an image are estimated and a Random Forest classifier is used for segregation of the candidatesinto lesions and non lesions. Soares et al.[12] established an innovative scale-space based approach for theMAsdetection. After segmentation of blood vessel sturtcure,they used coarser and finer scales to define the overall set of MAs candidates. Finer scale is used to form a set of MAs candidates based on shape and size. They reported 47% Sensitivity.Adal et al. [13] used robust blob descriptors to locate the MAs in retinal image.

Though many researchers have worked to tackle the challenges in MAs detection of fundus images, still detection of MAs in low contrast retinal image with anomalies is a challenge. In this work a simple method is proposed for detectionof MAs. This approach locates the MAs in retinal images. In this method, only five features are used to define the MA structure. Hence this approach is computationally simple as compared to the methods available in the literature. Also this method achieved a good sensitivity on DIARETDB1 database.

Rest of the paper is organized as follows. Section 3 explains the proposed algorithm for detection of MAs in fundus image. Experimental results are presented in Section 4. Section 5 states the conclusions.

3. PROPOSEDMETHOD

Figure2shows the flow diagram of the proposed algorithm for detection of MAs in retinal images. It consists of three main functional blocks namely color retinal image database, preprocessing, removal of blood vessels and detection of MAs in retinal image.

3.1 Color Retinal Image Database

Collection of color fundus images form color retinal image database. In this paper DIARETDB1 database is used for experimentation of proposed method.

3.2 Preprocessing

Three components (Red, Green and Blue) together form Color retinal image.Instead of using information in three channels of color retinal image, for further processing green channel image is selected. Because green channelimage presents more contrast as compared to the remaining two channel images. Hence the features (Blood vessels, Optic disk and Fovea) and anomalies(Hemorrhages, Exudates and MAs) are more vivid in green channel image.Pixel intensity of blood vessels and MAs is similar. Blood vessels and MAs have low brightness in original green channel image as compared to optic disc. Therefore complement of the original green channel image is taken to increase the brightness of blood vessels and MAs.Local contrast of the complement of the original green channel image is further enhanced by applying contrast limited adaptive histogram equalization.

3.3 Removal of Blood Vessels

Top-hat transform is one of the morphological operation which plays a vital role in eliminationof insignificant elements from image [14]. Blood vessels are captured with the help of morphological top-hat transform. Bright objects of interest in a gloomy backgroundare augmented by white top hat filter. So white top hat transform is chosen for capturing the directional information of vessel structure.Equation (1) gives the white top hat transform of a contrast limited histogram equalized image.

$$THT_w(f_{CL}) = f_{CL} - f_{CL} \circ b \quad (1)$$

Where f_{CL} , b, $\circ$ and THT_w are the contrast limited histogram equalized image,structuring element,opening operation andwhite top hat transform respectively.

Vessel structure is extracted by usingline structuring element of length 19. Line structuring element is oriented at 0°, 60° and 120°respectively toobtainthe vessel structure [14]. In these three images the dominance of vessel structure is more as compared to small circular dots called MAs. Hence the dominance of vessel structure is eliminated by keepingminimumgray level intensity pixels among the three images f_0, f_{60} and f_{120} respectively. The resulting image is represented by f_R and it is obtained using equation (2).After taking minimum response among three orientations, vessel structure is removed.

$$f_R = min_{(0^\circ,60^\circ,120^\circ)}(f_0, f_{60}, f_{120}) \quad (2)$$

Where f_0, f_{60}, f_{120} are the images obtained after computing top hat transformat orientations 0°, 60° and 120° respectively. f_R is the resultant minimum response of three orientations.

3.4 Detection of MAs

The contrast of the resultant image is improved by using the gray level contrast adjustment algorithm. After extracting the blood vessels, the contrast enhanced resultant image f_R is thresholded using following equation (3).

$$f_B = \begin{cases} 1 & if f_R(x,y) = max(f_R) \\ 0 & otherwise \end{cases} \quad (3)$$

After thesholdingresultant image f_R, binary image $f_B$is obtained. In this binary imagef_B along with MAs some noise elements are there. These noise elements are minimized by applying median filter to binaryimage f_B . The size of the median filter is kept small to remove the noise from the binary image f_B. In fundus image, MAs appear as small round shape dots. So in this work the features of MAs are computed using the information of size and shape. Following set of features are used to locate the true MAs.

a. Area of the each element can be computed as follows $B_A = \sum_{r=0}^{R-1}\sum_{c=0}^{C-1} B(r,c)$, where B_A is the area of B^{th} element having size $R \times C$

b. Elongation: $B_E = 1 - \frac{P}{Q}$, Where P and Q are the width and length of the bounding box of the B^{th}element oriented along its major axis.For circular element the value of elongation is zero.

c. Eccentricity: $B_{EC} = \frac{\sqrt{Q^2-P^2}}{Q}$, A circular element has an eccentricity of zero.

d.Solidity:Ratio of the area of element over the area of its convex hull.

e. Circularity: $B_C = \frac{4\pi B_A}{B_P}$, Where B_P is the perimeter of the B^{th} element. A circular element has circularity of one.

Above mentioned features of each component of binary image are computed and based on these features each element is classified as MA or non MA.

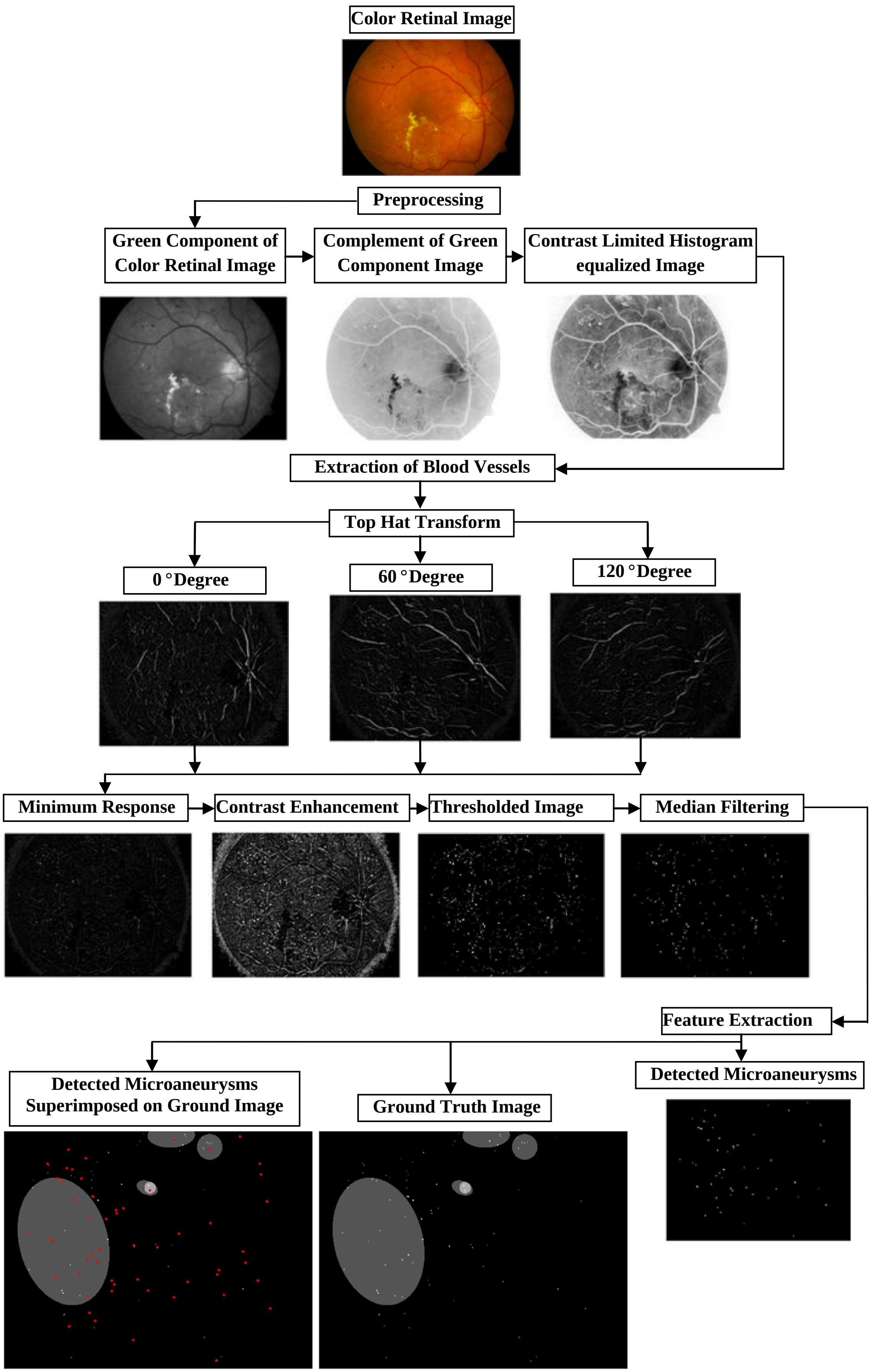

Figure 2.Flow diagram of proposed method.

4. EXPERIMENTALRESULTS

Publicly available standard database DIARETDB1 [15] is used for evaluation of proposed method. In this database fundus images are acquiredwith 50 degree field of view. Each image has size 1500×1152 pixels.For this database ground truth for MAs, hemorrhages, hard-exudates, soft exudates by four experts are available. For evaluation of the proposed method, in this work, ground truth for MAs are used.The accuracy of the proposed method is measured using sensitivity metric which is represented by equation (4). Table I shows the image based classification. This algorithm is evaluated on 40 images from DIARETDB1 database. In these 40 images, 35 images contain MAs and 05 images are normal. Sensitivity gives the percentage ofabnormal retinal images classified as abnormal by the algorithm. Higher value of sensitivity indicates the better performance of the algorithm. The proposed approach achieved 87.5% sensitivity on DIARETDB1 database.

$$Sensitivity = \frac{TP}{TP+FN} \quad (4)$$

WhereTP, $FN$are true positives , false negatives respectively.

Table 1.Image based classification

	MAs present	MAs absent
MAs detected	true positive	false positive
MAs not detected	false negative	true negative

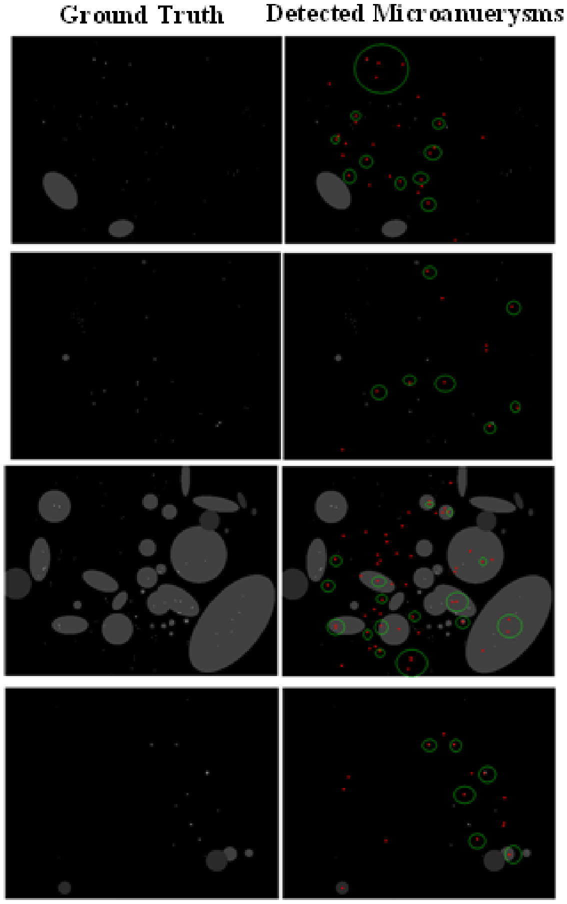

Figure 3. Results of proposed method on DIARETDB1 database (red dots inside the green circle are the true MAs detected by the algorithm and red dots outside the green circle are false MAs detected by the algorithm).

Figure 3 shows the results of the proposed method on images from DIARETDB1 database. This method detects few false MAs along with true MAs. Hence the proposed algorithm correctly recognizes the images which contain the MAs but for healthy retinal images it shows the 2-4 false MAs per image as shown in Figure 4.

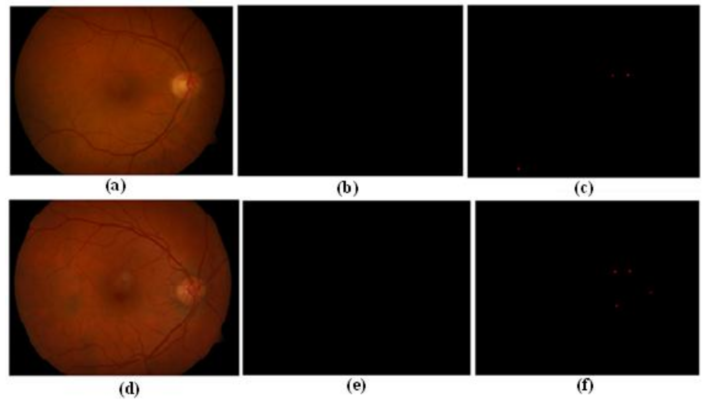

Figure 4. (a),(d) Normal fundus images from DIARETDB1 database (b),(e) Ground truth images (c),(f) False MAs detected by algorithm.

5. CONCLUSION

This work elaborates the new approach for detection of MAs in retinal images. This approach is tested on standard DIARETDB1 database. In this approach, shape and size based features are used for detection of MAs. In the first step color fundus image is enhanced using very few preprocessing steps. In the second step, blood vessels are removed using gray scale morphological top hat transform. In the final step, MAs are detected with help of shape and size based features. The proposed method achieved 87.5% sensitivity. Experimental results show the better performance of the proposed method. However proposed method detects false MAs along with true MAs. So accuracy of the proposed method can be improved by enhancing the quality of fundus image and incorporating more features for detection of MAs.

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