DETECTION OF MICROANEURYSM USING LOCAL RANK TRANSFORM IN COLOR FUNDUS IMAGES

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ABSTRACT

Accurate detection of microaneurysm (MA) plays a very important role in early diagnosis of diabetic retinopathy. This paper presents a novel method based on the variation of local intensity for microaneurysms detection in retinal images. In contribution, proposed method use local rank transform effectively for separation of MAs in the retinal images. Secondly, a novel blood vessels extraction method using a gradient of guided filter is proposed. Finally, selecting MA candidates by excluding vessels and post-processing techniques. Experiments were carried out on a three publicly available datasets E-Ophtha, Diaretdb1, and Messidor. The proposed method is effective regarding fast and accurately detecting MAs compared with the other state-of-the-art methods.

Index Terms— Diabetic retinopathy, Microaneurysm, Local Rank Transform, Blood vessel segmentation.

1. INTRODUCTION

1.1. Motivation

Diabetic retinopathy (DR) is a new cause of blindness and severe eye disease that originates from diabetes mellitus [1]. In India alone, 70 million people are suffered from diabetes mellitus, and this number is projected to increase in the future [2]. DR produces a variety of lesions on the retina such as microaneurysms (MAs), hemorrhages, exudates, etc. Among these MAs are the only lesion present at the earliest stage of the disease and continue to be present at the later stages. Early detection of DR is depends upon the accurate identification of microaneurysms [3]. Therefore, much effort has been taken in creating automated decision support system by grading the severity of pathologies present in DR.

Many researchers had developed several methods for the automatic detection of microaneurysms. Antal et al. [1] proposed ensemble based framework to detect microaneurysm. They provide a framework to select the best combination of MA candidate extractors. In [4] Quellec used optimal wavelet filter bank for MA detection. In [3] uses the watershed transform to catch MA and non- MA candidates in their catchment basin region. Keerthi Ram et al. [5] detect MA based on clutter by comparing the probability of occurrence of target. In [6] Seoud et al. used a set of dynamic shape features for MA detection. Their method does not require precise segmentation of the candidates for detection. Niemeijer et al. [7] proposed a red lesion candidate detection system based on pixel classification. They used both the morphological method as well as a pixel classification technique to detect MAs. Adal et al. [8] proposed a method based on finding blobs like region from an image to automatic selection of MA. Wu et al. [9] used 27 characteristic features which contain local features and profile features, extracted for KNN classifier to distinguish true MAs from spurious candidates. In [10] Walter et al. also detect MA, based on automatic classification technique. Many of the published methods still suffers with obtaining acceptable performance, which can be used in real world application. Hence there is a need in improvement for accurate detection of MAs.

1.2. Summary of Contribution

In this paper, we propose an efficient MA detection method based on the combination of non-parametric transform and preprocessing methods. This paper makes three key contributions. Firstly, application of local rank transform for detection of MAs. Secondly, for noise reduction in fundus images and vessel extraction used edge preserving guided filter. Finally, the proposed method is faster than any other method in the literature by minimizing computational complexity drastically.

The remaining paper is organized as follows: In section II we provide the proposed method for MA candidate detection. The experimental results and discussion are provided in Sections III respectively. In Section IV, we summarize the conclusions.

2. PROPOSED METHOD

The overall framework of the proposed MA detection method is shown in Fig. 1. Since, our method particularly depends on

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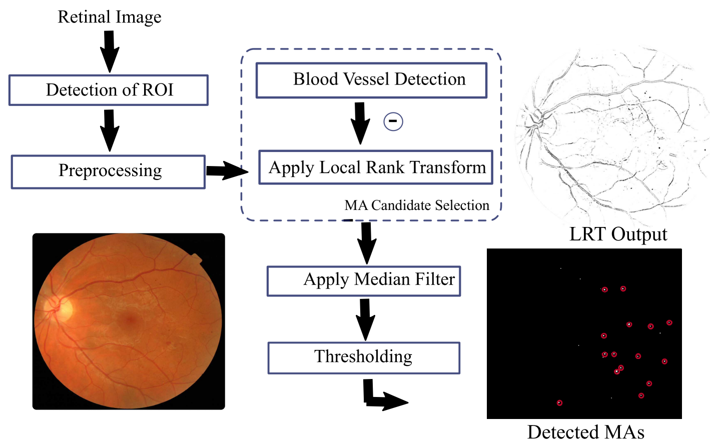

Fig. 1. Overall framework of microaneurysm detection from fundus image.

the local intensity variation, it is important to reduce the effect of noise present in image. We apply preprocessing techniques which fulfils the basic criteria of our MA detection method.

2.1. Preprocessing of Retinal Image

Almost every retinal imaging technique considers some form of image preprocessing step, which usually consider region of interest (ROI) extraction, filtering or normalization. Here, we also extract binary ROI for reducing computational complexity. For noise reduction we used guided filter effectively which perform smoothing of retinal image by preserving fine edges [11]. The filter performs neighborhood pixel operation by considering statistics of a corresponding reference image while computing the value of the output pixel. Filter output at a pixel is a weighted average of neighbourhood pixels by using Eq. (1).

$$Y_i = \sum_j W_{ij}(X) p_i \tag{1}$$

where, i and j are pixel indexes. The filter kernel W_{ij} is a function of reference image *X* from Eq. (2).

$$W_{ij} = \frac{1}{|w|^2} \sum_{k:(i,j)\in w_k} \left(1 + \frac{(X_i - \mu_k)(X_j - \mu_k)}{\sigma_k^2 + \varepsilon}\right) \tag{2}$$

Here, μ_k and σ_k^2 are mean and variance of reference image X in w_k window, $|w|$ is the number of pixels in w_k. After getting smooth image Y for all windows w_k, the noise can be reduced for better MA detection.

$$Vessels = (Y - X) * 10 \tag{3}$$

We extract blood vessels by subtracting original image from guided filter output image using Eq. (3) as shown in Fig 2. The factor 10 is identify in Eq. (3) empirically after performing series of experiments for vessel extraction.

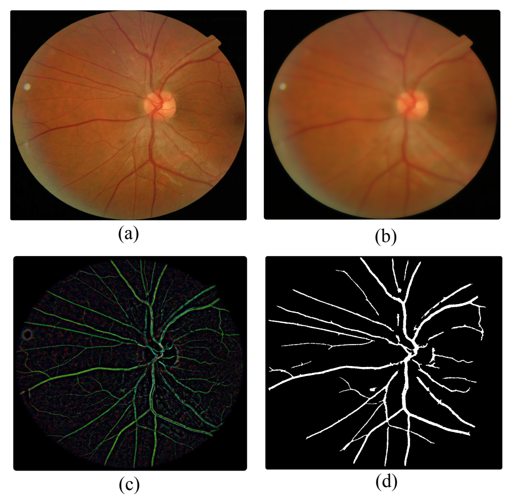

Fig. 2. Result of preprocessing (a) Original color fundus image. (b) Guided filter smoothing output. (c) Extracted blood vessels. (d) Final segmented vessels.

2.2. Microaneurysm Detection using LRT

In retinal imaging lesion are always represented in high frequencies. We take advantage of this property and capture pixels with their local ranks. In [12] gives some possible applications of these transforms to capture higher frequencies from images. People used rank transform for some application like object recognition [13], video coding [14]. Rank transform gives the number of pixels in the local region whose intensity values is less than the center pixel. LRT is defined in [12], is as follows : Let S be a total ordered set and x is an element of S. The rank of x with respect to S is defined as the number of elements less than x and it is denoted as $r(x;S)$. The local rank transform (LRT) of S is defined as,

$$LRT(S) = \{r(x; N(x)) \mid x \in S\} \tag{4}$$

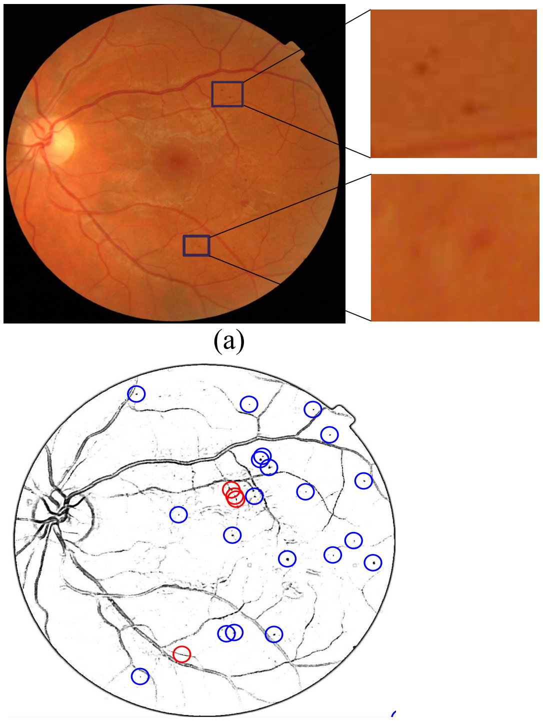

Fig. 3. Result of LRT output. (a) Original Image with Zoom MAs from E-ophtha database. (b) LRT image with detected MA in blue color and non MA in red circular region.

where, $N(x)$ is neighborhood of x, is subset of S. Finally, δ rank of x with respect to S is nothing but the number of pixels less than x by at least δ amount, and it is denoted as $r_\delta(x; S)$.

$$LRT_{\delta}^{m,n}(I) = \{r_\delta(x; N^{m,n}(x)) \mid x \in I\} \quad (5)$$

It follows that δ-LRT produces zeros (or low values) for smooth region where MA is not presents, and produces high values associated to MAs. We use this property to isolate and extract MAs from retinal images. By changing the value of δ fine MAs can be detected, here we use -13 value of δ from experimentation. The retinal image with zoom MAs and LRT output image with detected MAs in blue circles and non-MA candidate in red circles are shown in Fig. 3.

2.3. Final MA Candidate Selection

2.3.1. Blood Vessel Exclusion

As our proposed approach is based on local intensity variation, one should take care of similar intensities in images. The intensity of blood vessels and MAs are somewhat in similar range. Hence, after excluding the blood vessels select the remaining MA candidates for further post-processing.

2.3.2. Filtering and Thresholding

The final stage of the proposed method is very crucial as chances of inserting noise is more here. Noise is reduced by applying median filter operation. Each output pixel contains the median value in the 3x3 neighborhood around the corresponding pixel in the LRT image. Finally, thresholding and considering only small circular dots creates binary image mask of an accurately detected MAs from Eq.(6).

$$G(x,y) = \begin{cases} 1 & if \quad LRT_{\delta}^{x,y}(I) \geq T \\ 0 & otherwise \end{cases} \quad (6)$$

3. EXPERIMENTAL RESULTS AND DISCUSSION

3.1. Results of MAs Detection

We carried out experimentation on three publicly available fundus image database summarized in table 1. The ground truth available for all images of E-ophtha and Diaretdb1. However, we evaluate our method on 32 images from Messidor database as only their MA ground truths are available. The outcome of proposed MA detection is a pixel level classification, as given pixel identified as MA or non-MA, there are four possibilities as true positive (TP), true negative (TN), false positive (FP) and false negative (FN). From these quantities sensitivity (Se) and Specificity (Sp) performance measures are used for evaluation of proposed method. Se is also called true positive rate (TPR) given in Eq. (7) signifies actual MA regions found. The specificity is the proportion of non MA regions correctly detected. Accuracy, which is more meaningful performance measure is obtained from Eq. (8).

Table 1. Database Used For Evaluation

Database	Resolution	FOV	Images
E-ophtha [15]	1440 x 960, 2544 x 1696.	40°	148
Diaretdb1 [16]	1500 x 1152,	50°	89
Messidor [17]	1440 x 960, 2240 x 1488, 2304 x 1536.	45°	1200

$$Se = \frac{Tp}{Tp + Fn} \quad , \quad Sp = \frac{Tn}{Tn + Fp} \quad (7)$$

$$Acc = \frac{Tp + Tn}{Tp + Fn + Tn + Fp} \quad (8)$$

On messidor database out of 32 images, Ma is presents in 15 images. We achieved pixel level sensitivity of 0.384 on the selected images for messidor database. From the Diretdb1 database, we consider 89 images for measuring performance. The obtained accuracy in this experiments are 94.34 %, 96.04 % and 96.31 % for e-ophtha, Diretdb1 and Messidor database shown in table 2. The receiver operating characteristics

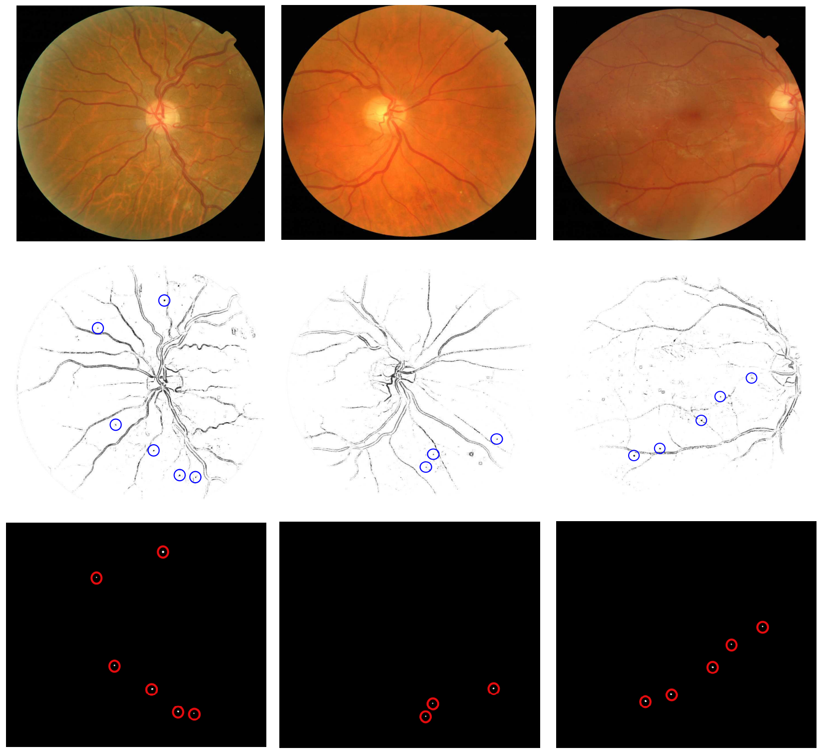

Fig. 4. Result of MA detection on e-ophtha database, First row: Original color images. Second row: LRT output images. Third row: Final detected MA candidates.

Table 2. Comparative results on Diretdb1 database.

Methods	Oliveira [18]	Akram [19]	Rahim [20]	**Proposed**
Accuracy	84.2 %	97.6 %	90.9 %	**96.04** %

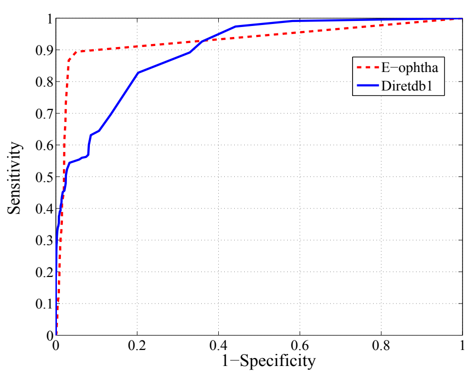

Fig. 5. ROC curve for E-Ophtha and Diaretdb1 dataset.

(ROC) curve for e-ophtha and diretdb1 database is shown in Fig. 5. The proposed method achieved an AUC of 0.82 on DB1 database.

3.2. Discussion

The computational complexity of the proposed method is less as it is based on local comparison of intensity values. The proposed method was implemented entirely in Matlab 2014 on Windows 7 with an Intel i7 2.4GHz Cpu with Ram DDR2 4GB. The method takes average 6 seconds per image with above system configuration without parallel computing. The drawback of proposed method is, it is sensitive to noise in the retinal images. Furthermore, results can be improved using other techniques which extract exactly the small isolated dark dots of LRT output image.

4. CONCLUSIONS

This paper presents a simple and novel method for micro-aneurysms detection in color fundus images. The proposed method was effectively used local rank transform to extract fine MA candidates. Experimental results are evaluated on publicly available databases namely, E-ophtha, Messidor and Diaretdb1. The method outperforms well with respective to sensitivity and accuracy compare to other state-of-the-art approaches. The proposed method identified the dark MAs accurately but there is a scope of improvement detection accuracy in future.

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