DETECTION OF MICROANEURYSM USING LOCAL RANK TRANSFORM IN COLOR FUNDUS IMAGES

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Outline

- Introduction
- Previous Work
- Proposed Method
- Experimental Results
- Conclusions
- References

Introduction: Need of accurate detection of Mas

- Diabetic retinopathy (DR) is a new cause of blindness and severe eye disease that originates from diabetes mellitus

- 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].

➢ Previous work

- 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.
- Quellec [4] used optimal wavelet filter bank for MA detection.
- Keerthi Ram et al. [5] detect MA based on clutter by comparing the probability of occurrence of target.
- 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.

➢ Previous work

- 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.
- Seoud et al. [6] used a set of dynamic shape features for MA detection. Their method does not require precise segmentation of the candidates for detection.
- Fleming et al.[2] uses the watershed transform to catch MA and non-MA candidates in their catchment basin region.
- Walter et al. [10] 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.

Proposed method: Detection of microaneurysms.

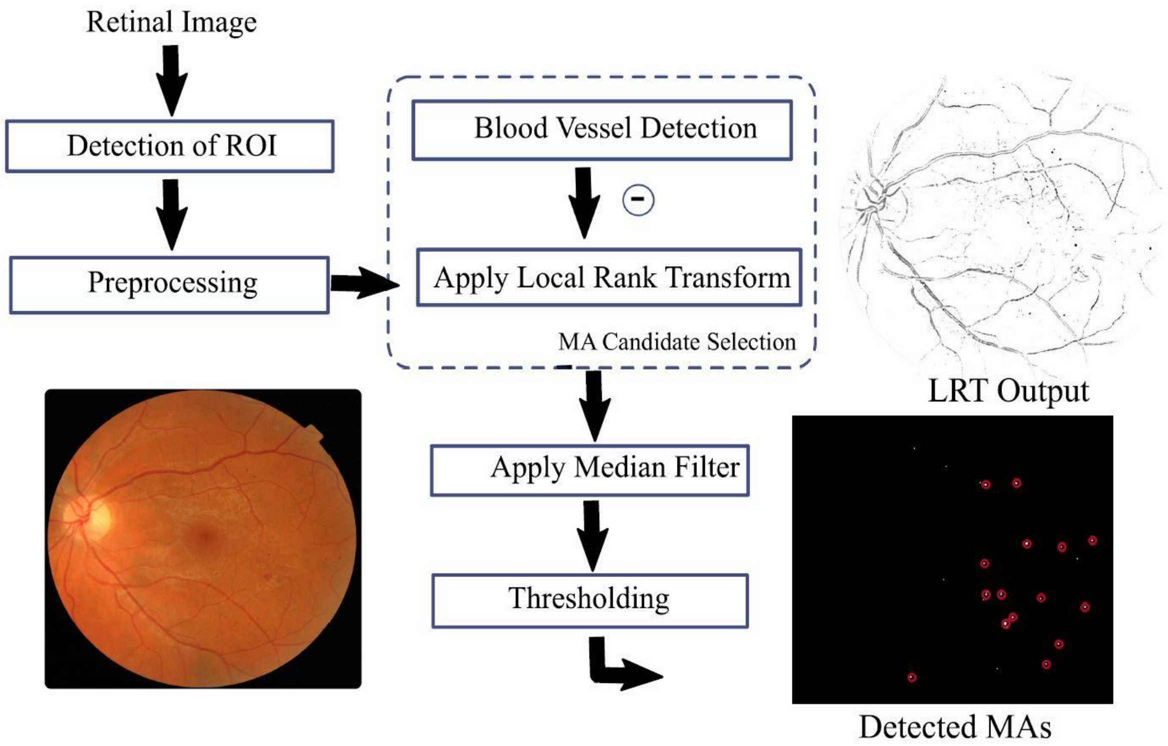

Figure: Overall framework of microaneurysms detection.

- We propose an efficient MA detection method based on the combination of non-parametric transform and preprocessing methods.
- Firstly, utilize the local rank transform for the detection of MAs.
- Secondly, for noise reduction and vessel extraction used edge preserving guided filter for color fundus images .

Pre-procesing

Blood vessel detection.

- Use of guided filter for pre-processing (smoothing) and vessel segmentation step.
- 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.

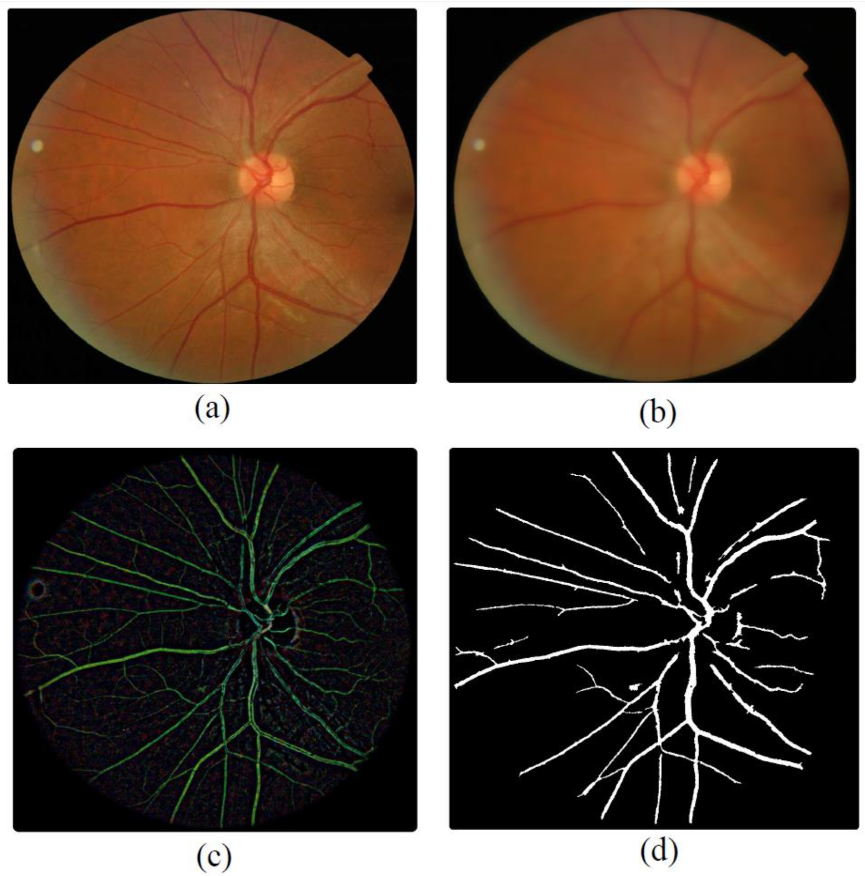

Figure: Result of preprocessing (a) Original color fundus image. (b) Guided filter smoothing output. (c) Extracted blood vessels. (d) Final vessel segmentation.

➢ Blood vessel detection results.

- Guided filter output at a pixel is a weighted average of nearby pixels in local window ω [11].

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

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

$$D = (Y - X) * 8 \qquad (3)$$

- Usign eq.(3) the vessels are detected shown in fig.

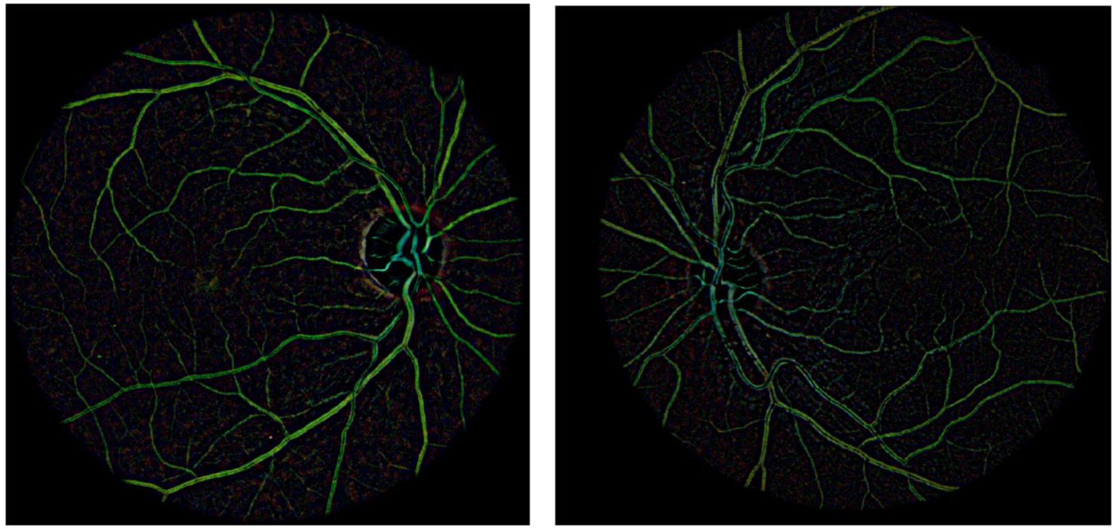

Figure: Blood vessel detection Result of Eq. (3).

Proposed method: Detection of microaneurysms.

- Apply local rank transform

- The severity of DR is usually identified through the features like border information, colour information of different lesions.

- Rank transform gives the number of pixels in the local region whose intensity values is less than the center pixel [11].

- 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).*

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

Where, N(x) is neighbourhood of x, is subset of *S*.

Using delta-local rank transform

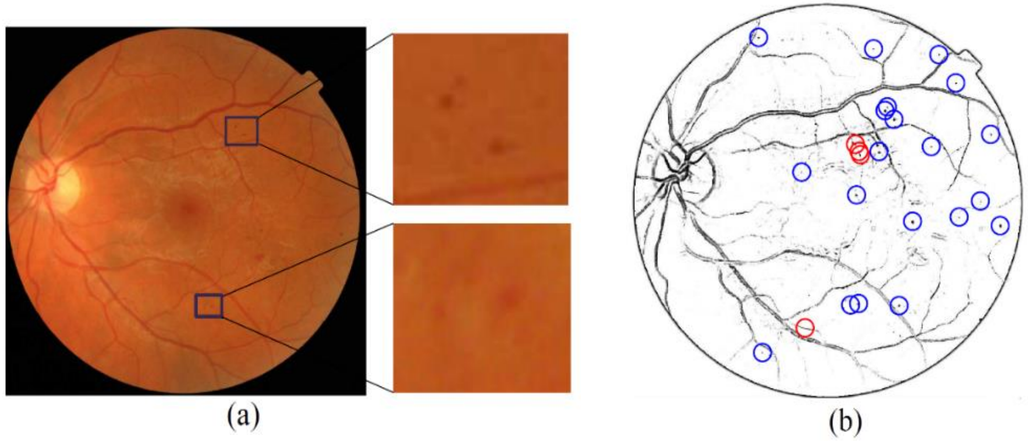

Figure: Result of LRT output. (a) Original Image with Zoom MAs from E-ophtha database. (b) LRT image with detected MA in blue colour and non-MA in red circular region.

- Finally, *delta* - rank of x with respect to S is nothing but the number of pixels less than x by at least *delta* amount, and it is denoted as *r(x; S)*.
- *delta*-LRT produces zeros (or low values) for smooth region where MA is not presents, and produces high values associated to MAs.

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

- Finally, thresholding and considering only small circular dots creates binary image mask of an accurately detected Mas.

➢ Experimental results

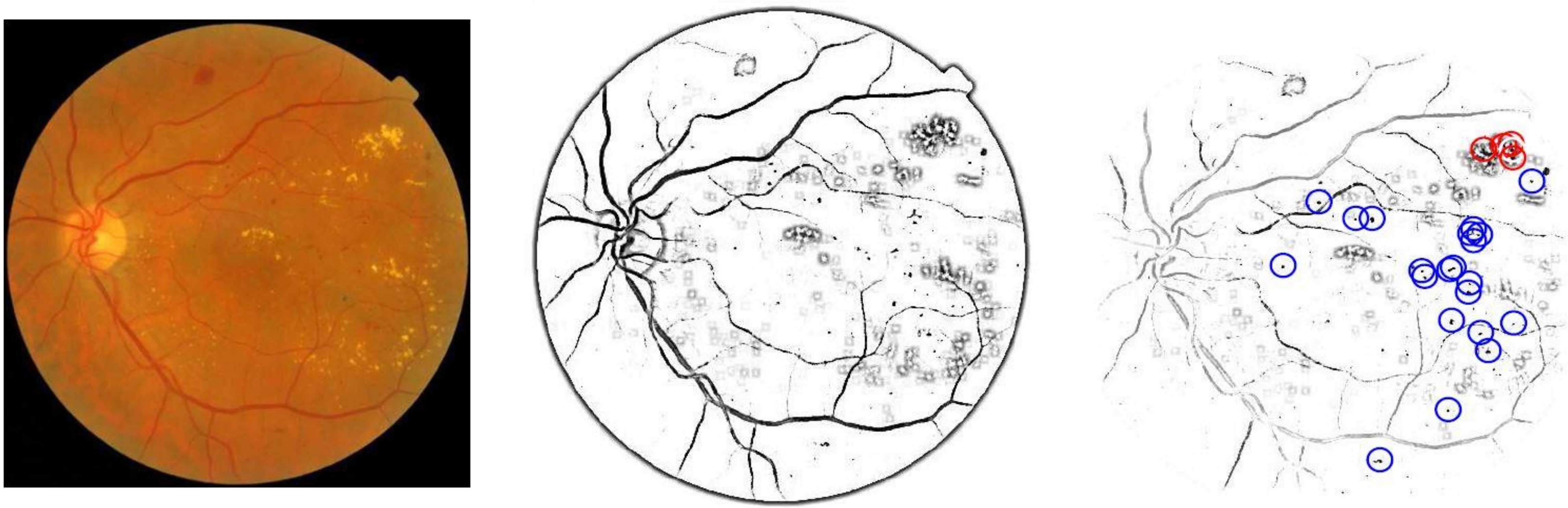

Figure : Result of MA detection on messidor database. Left: Original color images. Center: LRT output images. Right: Final detected MA candidates.

Experimental results

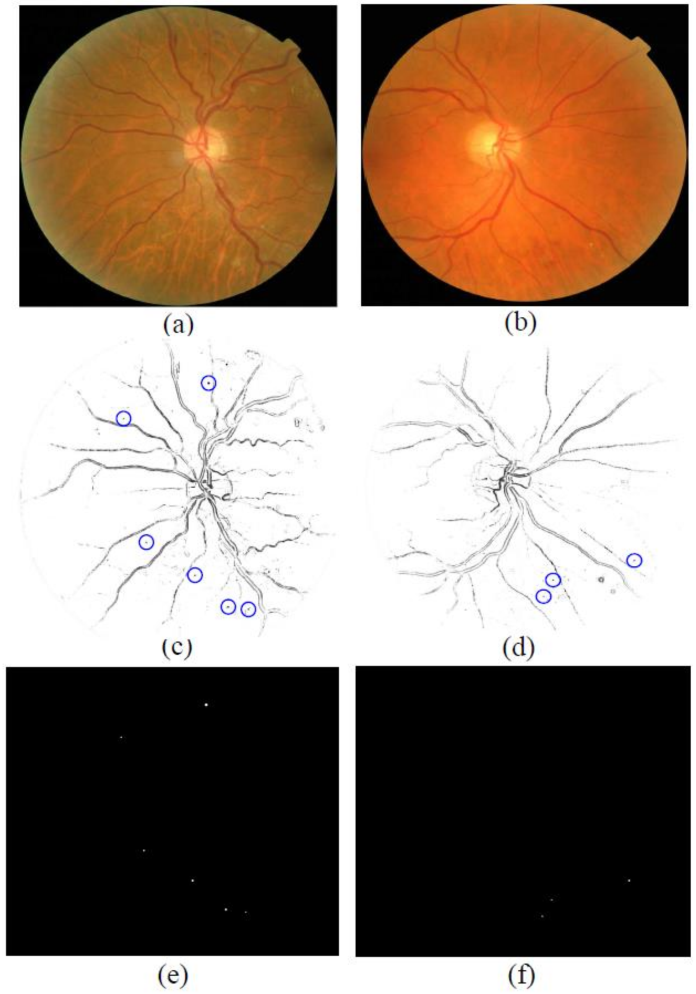

Figure : Result of MA detection on e-ophtha database (a) and (b) Original color images (c) and (d) LRT output images. (e) and (f) Final detected MA candidates.

- The obtained accuracy in this experiments are 94.34 %, 96.04 % and 96.31 % for E-ophtha, Diretdb1 and Messidor database.

Performance measures :

$$Acc = \frac{TP + TN}{TP + FN + TN + FP}$$

Table: Comparative results for Diretdb1.

Method	Accuracy
Oliveira	84.2 %
Akram	96.6 %
Rahim	90.9 %
Proposed	**96.04** %

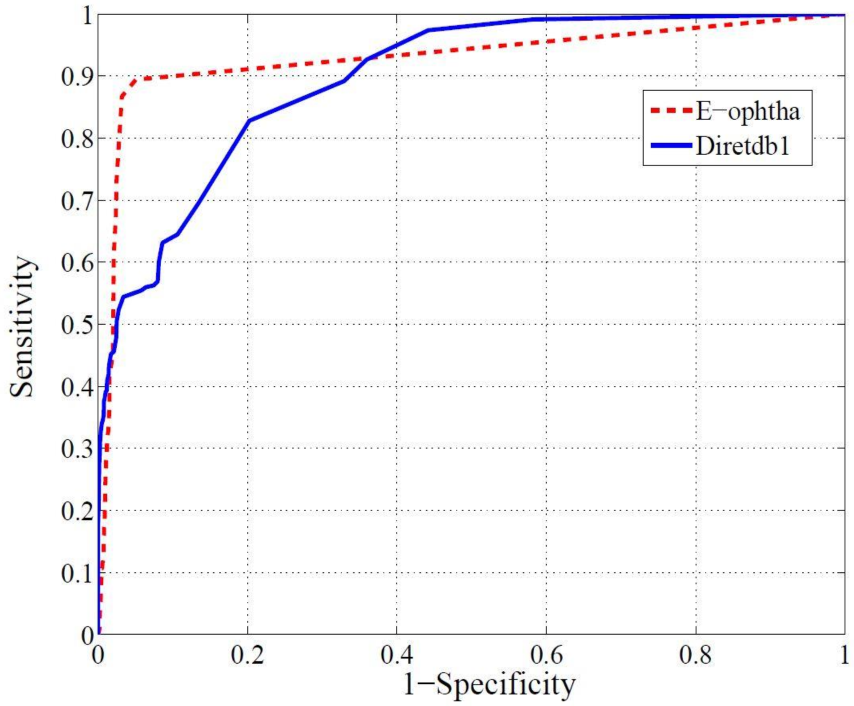

Figure : ROC curve for E-ophtha and Diretdb1 database.

➢ Database used

- MESSIDOR database is used [16].
- 1200 retinal images of sizes 1440 x 960, 2240 x 1488 and 2304 x 1536


- E-ophtha database is used [14].
- 148 retinal images of sizes 1440 x 960 and 2544 x 1696


- Diaretdb1 database is used [15].
- 89 retinal images of sizes 1500 x 1152 and 1440 x 960,


Conclusions

- This paper presents a simple and novel method for microaneurysms 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.

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Thank you.