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Ratinal Microaneurysms Detection Using shape based features and Local Convergence Index Features

Suraj Suryakar, Dept. of E&TC,
Dr. DY Patil College Of Engineering, Ambi, Pune, India.

Abstract— Detection of microa-neurysms is too crucial for early detection of sugar patient retinopathy with prevention of the low vision and blindness. Within this work, a novel, reliable method for automatic detection of the microaneurysm in retinal photos is proposed. In first stage of the proposed way, several primary microaneurysm candidates are extracted us-ing a gradient weighting method and using iterative thresholding approach. In next level, and adding intensity, shape descriptors, a new set of index feature based on the local convergence index filter is taken out for each candidate. Finally, collective set of features are fed to the hybrid sampling or boosting classifiers to discriminate MA's from non-MA's candidate. The technique is evaluated on image with the different resolutions also modalities like RGB and SLO which are done by using six openly available data sets including Retinopathy Online Challenge data set (ROC). Proposed technique achieves medium sensitivity score like 0.471 on ROC data set performing state of the art approach in large-scale comparison. Experimental results on other five data sets explain the productiveness and robust-ness of proposed microaneurysm detection way regard-less of different images resolutions with the modalities.

Keywords: Computer-aided diagnosis, diabetic retinopathy, local convergence filter, microaneurysm detection, retina.

I. INTRODUCTION

DIABETIC retinopathy (DR) is the most common cause of vision loss among people with diabetes and the leading cause of vision impairment and blindness among middle-aged population in the world [1]. However, due to the limited number of ophthalmologists and the large number of people that require screening, an auto-mated computer-aided diagnosis tool can significantly improve the efficiency and reduce the costs in a large-scale screening setting [5]. In this work, we propose a novel method for the detection of MAs using local convergence index filters (LCF) and a random undersampling boosting classifier (RUSBoost). In the first stage, the MA candidates are extracted using multi-scale multi-orientation gradient weighting and iterative thresholding. The gradient weighting technique is particularly useful for the detection of small objects with weak boundaries and in low contrast regions. Compared to other techniques, the multi-orientation and multi-scale gradient weighting technique enhances the boundary of gradient structures that is very char-acteristic of local shape, and it provides local representations which have an easily controllable degree of invariance to local geometric transformations such as translations and rotations. Afterwards, the method generates a set of features for each candidate depending upon their intensity, shape and LCF responses. The LCF filters are based on gradient convergence but not intensity and as such can represent low contrast MAs which otherwise would be easily lost in the background noise. The true MA candidates are then selected using a hybrid sampling/boosting classifier to avoid the drawback of imbalanced data learning and to improve the performance of MA detection. The RUSBoost (with decision trees as the weak learners) is a suitable classifier since we deal with a skewed set with the minority of MA candidates and the majority of non-MA candidates.

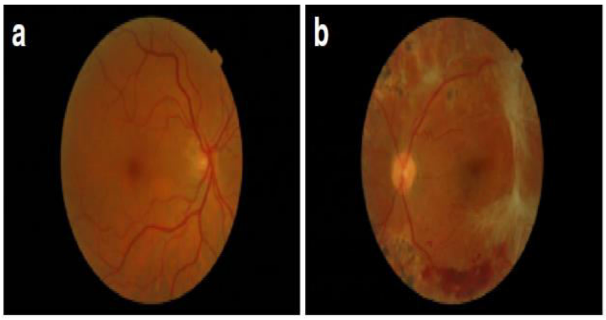

Figure 1. Normal and diabetic retinal image

The paper is organized with five sections: The first section is an introduction including previous research on diabetic retinopathy. The second section narrates the system methodology including various feature extraction methods and classification. The third section provides experimental results. Last section concludes the work.

II SYSTEM METHODOLOGY

Extracting suitable features and descriptors for the candidate regions is an important step for the final classification stage. Since the MAs appear in different colors and sizes, several shape and intensity features are extracted. The feature set is completed by including the responses and the estimated radii of different local convergence index filters (LCF). The rest of this subsection describes the 29 proposed features which we have defined to characterize and classify MAs as shown in figure. Table II contains the description of the features which we use in the proposed system.

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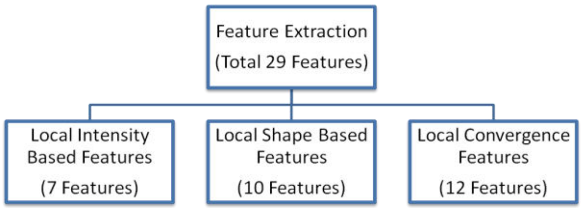

Figure 2 : Total Feature extraction

A. *Intensity based feature*

Total 7 intensity based features are extracted for the MA region as shown in figure 3 which consists of maximum, minimum, mean intensity of local and neighboring MA region and green intensity of local region.

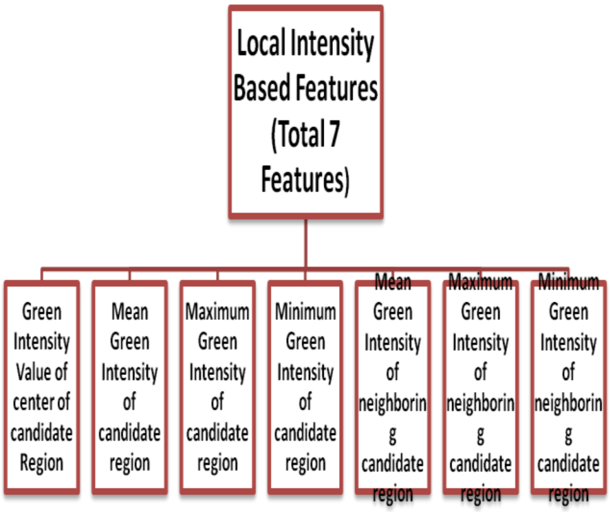

Figure 3. Intensity based feature

B. *Shape based Feature*

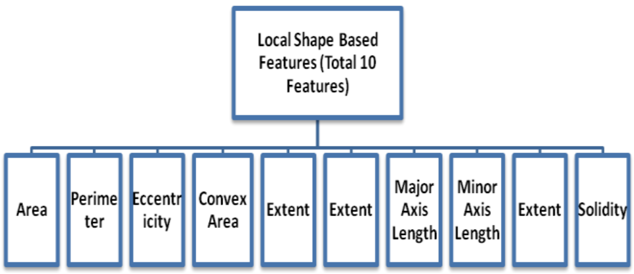

Figure 4. Shape based feature

Since MAs are small and they appear as round structures with a diameter less than 125 m, the following shape-based features are extracted for each candidate region:
Area (S_{Area}): area of candidate region specified by the actual number of pixels (white pixels in Fig. 6a).
Convex area (S_{ConA}): area of candidate convex region specified by the actual number of pixels.
Solidity (S_{Sol}): ratio of the area of candidate (S_{Area}) over the convex area (S_{ConA}).
Extent (S_{Ext}): ratio of S_{Area} to the pixels in the bounding box.
Perimeter ($S_{P\ er}$): distance around the boundary of the region by calculating the distance between each adjoining pair of pixels.
Circularity (S_{CirD}): diameter of a circle with the same p area as the region which is equal to S_{Area}.
Ellipticity (S_{AxiA}; S_{AxiB}): lengths of the major and minor axes of the ellipse that has the same normalized second central moments as the candidate region. The major and minor axes are depicted by red lines.
Eccentricity (S_{Ecc}): ratio of distance between the foci (blue stars in Fig. 6c) and the major axis length (S_{AxiA}) of the ellipse with a same 2nd moment as the region.
Euler number (S_{Eul}): number of objects in the region minus the number of holes in those objects.

C. *LCF based feature*

The LCF filters are based on gra-dient convergence and not intensity and as such can detect low contrast MAs which otherwise would be easily lost in the background noise. Additionally, the convergence evaluation in a regional band allows the reduction of uncertainty caused by noise. We first give explanations about the local convergence index filters and then introduce the set of LCF-based features extracted for each candidate. The convergence index (CI) filters are suitable for the detection of convex shapes and objects with a limited range of sizes regardless of their contrast with respect to the background. The CI filters evaluate the convergence degree of gradient vectors within a local area (support region) towards a pixel of interest [32].

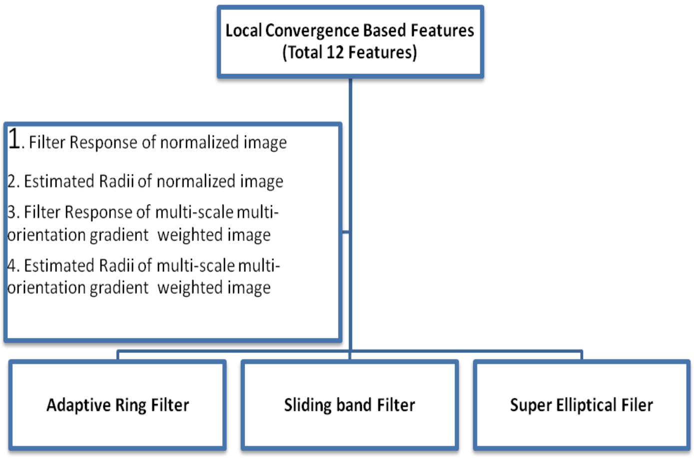

Figure 5. Local convergence filters feature

D. Classification

The Neural Network Classifier is used to classify the rheumatoid arthritis and non-rheumatoid arthritis person[12]. A neural network consists of units (neurons), arranged in layers, which convert an input vector into some output. Each unit takes an input, applies a (often nonlinear) function to it and then passes the output on to the next layer. But there is no feedback to the previous layer.

III EXPERIMENTAL RESULTS

We have implemented the method on the personal computer with core I3 processor with 1.7 GHz and 4GB RAM and MATLAB R2013b in windows environment. We have used DiaretDB1database images containing 500 normal and 500 abnormal images with resolution of 300x 400 pixels.
Some sample images are shown in figure:

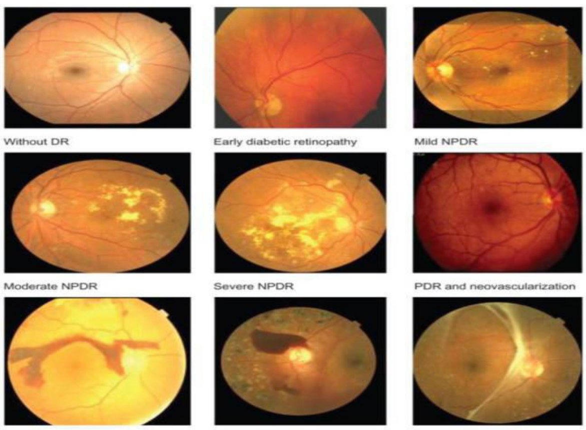

Fig. 6 Sample of DiaretDB1 database images

The following result is obtained after preprocessing steps applied to original image.

IV CONCLUSION

In this work, we have proposed a new method for detecting MAs in retinal images using a gradient weighting technique, a new set of features based on local convergence filters (LCF) and a random undersamping boosting classifier. Feature importance analysis demonstrates that LCF-based descriptors can well characterize the low contrast MAs since the LCF filters are based on gradient convergence and not intensity. The performance of the proposed method on the ROC, DiaretDB1 and e-ophtha-MA datasets shows the competitiveness of the introduced approach against state-of-the-art techniques. More-over, the evaluation results on six public datasets demonstrate that the proposed MAs detection method is insensitive to the characteristics of the imaging device, image resolution and image modality. Future work will involve exploiting the introduced LCS-based features for the detection of dot hemorrhages and bright lesions namely exudates.

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