Segmentation and Classification of Anomaly in Fundus Images

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***Abstract*—Automatic detection of microaneurysms (MAs) is proposed in this paper. The detection of MAs is essential step in the diagnosis and grading of diabetic retinopathy. Microaneurysms appear as a small round shaped dots on the retina. Here MA is detected by the method of cross-sectional profile analysis. Naive baye's and KNN classifiers are used for classifying detected components as microaneurysm(MAs) and non-microaneurysm components. Performance of this method is calculated by using microaneurysm score calculation.**

Key Words: Diabetic Retinopathy (DR), Naïve Bayes Classifier (NB), K Nearest Neighbor Classifier (kNN), Biomedical image processing.

I. INTRODUCTION

Retinal image processing is an interesting and demanding field, having a lot of practical applications, such as the development of applications for massive medical revision and the research in pharmacology effectiveness. The retina is the only location where blood vessels can be directly visualized non-invasively in vivo. Increasing technology leading to the development of digital imaging systems over the past two decades has revolutionized fundal imaging. Digital imaging has the advantage of easier storage on media that do not deteriorate in quality with time, can be transmitted overshot distances throughout a clinic or over large distances via electronic transfer can be processed to improve image quality, and subjected to image analysis to perform objective quantitative analysis of fundus images and the potential for automated diagnosis.

Microneurysm is the first symptom of diabetic retinopathy. Microaneurysm appears as small structures whose diameter is usually considered to be less than the diameter of the optic veins. The figure.1 shows the microaneurysms in a fundus image. Some parts of the blood vessel may appear as microaneurysm component, so the detection of blood vessel is important for the detection of MAs. MA detection steps consist of noise removal, segmentation and classification. Abnormalities are more visible in the inverted green channel, so the green channel is selected for the segmentation process. There are several methods for the detection of the microaneurysm. The first computerized approaches for the segmentation of retinal MAs were described by Laÿ[1]and Baudoin[2].These method is based on the calculation of morphological opening in different orientations.This step results in an image from which the structures that are smaller than the structuring element are missing. Therefore, the difference of this image and the original image (top-hat transformation) is calculated and thresholded to obtain MA candidates. These approaches have constituted the basis for several later algorithms.

Fig.1. Fundus image showing Microaneurysm

Zana [3] applied the same morphological approach for the segmentation of retinal blood vessels. Spencer [4] applied a illumination and shade correction steps to improve the quality of the fluorescein angiography images before the actual segmentation and detection steps. A Gaussian match filter was used after the bilinear top-hat transformation to enhance MA like objects, and a recursive region growing method produced the segmented MA candidates. This was the first method that applied an additional classification step, that is, supervised learning based methods are used to filter out spurious candidates. A set of features are calculated for each candidate. These features are intended to capture those characteristics that help to distinguish true candidates from false ones, since the first step usually results in a high number of possible candidates.

In [5], the authors considered an additional pixel wise classification based candidate extraction method, and merged the output. Other morphology based methods include the one proposed by Walter [6], in which criteria based morphology operators [7] are applied in the candidate extraction phase followed by the candidate classification.

Mizutani. [8] utilized a double-ring filter for the initial detection of MAs. Quellec proposed an approach using template matching in the wavelet domain [9]. In the method proposed by Sanchez. [10]the histogram of the preprocessed image is modeled using a three-component mixture model, assuming normal distribution of the gray level of each class. The microaneurysm candidatesare extracted by thresholding the obtained model, and classified by a logistic regression classifier.

The Microaneurysm detection method proposed by Giancardo in [11] is based on Radon transformation with a similar theoretical background. A similar cross-sectional approach for vessel segmentation and the 2D "tramline" filter proposed by Lowell [12] is also concluded that it is suitable for vessel center line detection. The proposed method is based on the profile calculation. The microaneurysm is detected by the analysis of cross-sectional profiles. Performance of this method is analysed by microaneurysm score.

II. PROPOSED METHOD

The input of the proposed method is inverted green channel image. The abnormalities are more visible and appear as bright structures in inverted green channel image. The microaneurysm region contains the highest pixel values. The region containing the local maxima is calculated by using the breadth first search algorithm. Next step is the cross-sectional scanning. It is used to examine the surrounding of a maximum pixel. After cross-sectional scanning, microaneurysm profile is calculated and features are extracted. Features are classified by using Naïve baye's (NB) and k nearest neighbor (kNN) classifiers. Finally MAs score is calculated by using proposed score equation. The flow diagram of the proposed method is shown in figure 2.

A. Image Preprocessing

The image preprocessing is the first step of the MA detection. The fundus images are in the form of lossy and compressed format. Preprocessing is used to remove the noises present in the fundus images. There are several filters for the noise removal. The proposed method uses the Gaussian filter of variance 1.0. In terms of signal to noise ratio Median filter is the best filter, but it will change the pixel value. Here microaneurysm detection is based on the pixel value calculation, so median filter is not suitable for image preprocessing.

B. Maximum Region Extraction

Abnormality region contains the maximum pixel value. So the maximum region extraction is important in the detection of microaneurysm. The proposed method uses breadth first search algorithm [13] for the calculation of the maximum region. In this method the preprocessed image is divided in to different regions. This will reduce execution time of the process. Here the image is divided in to sixteen equal regions. Pixels of the images are processed sequentially, and compared to 8-neighbors. Pixel is a local maximum region if all neighbors have a lower intensity. If there is a neighboring pixel with higher intensity, then the current pixel may not be a maximum. A pixel is considered to be a possible maximum if all neighboring pixels have lower or the same intensity, in which case pixels with the same intensity are stored in a queue, and tested in the same way. The output of the maximum region extraction is shown in figure 3.

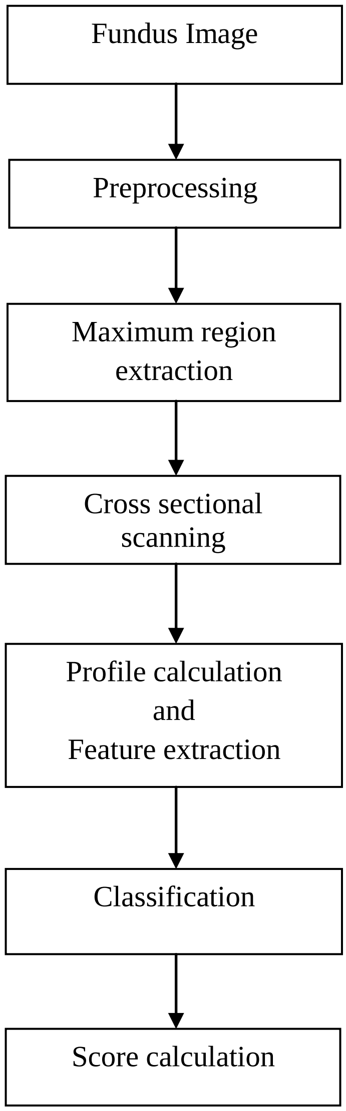

Fig.2. Flow diagram of the proposed method

C. Cross-sectionl Scanning

Cross sectional scanning is used to examine the surrounding of a single maximum pixel in a MA candidate region. The image is scanned for different orientation. The intensity values along discrete line segments of different orientations, whose central pixel is the candidate pixel, are recorded [14]. In this way, a set of cross-sectional intensity profiles are obtained. The line operators of the same length are used as structuring elements for vessel segmentation. In that case the average intensity along the line is considered, resulting intensity profiles used to detect and measure the properties of a central peak on it, if present.

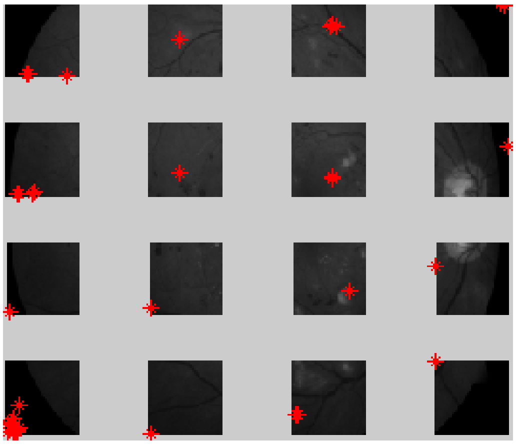

Fig.3. Maximum region extraction of preprocessed image

D. Profile Calculation

Profile calculation[15] is important in the detection of microaneurysm. The profile is calculated and features are extracted for classification. The profile contains many properties like width, height, ramp slope, ramp height. These profile properties are used as features for the classification. Microaneurysm score is calculated after classification. The profile parametes which is used for the feature extraction are shown in figure 4. The properties of profile is expressed as follows,

(1) The peak width is the difference between the start and end indices of the peak: $W_p = D_e - I_s$
(2) The top width is the size of the gap between the increasing and decreasing ramp: $W_t = D_s - I_e$
(3) The increasing ramp height: $H_i = P[I_e] - P[I_s]$
(4) The decreasing ramp height: $P[D_s] - P[D_e]$
(5) The increasing ramp slope: $s_i = H_i / (I_e - I_s)$
(6) The decreasing ramp slope: $S_d = H_d / (D_e - D_s)$
(7) The peak height is calculated as the difference between intensity of the central of pixel and a baseline that connects the start and end of the profile.

$$Hp=P[center]-(P[De]-P[Is]) / W_p.(center-Is)+P[Is]$$

where,

W_p = Peak Width
W_t = Top Width
H_i = Increasing Height
H_d = Decreasing Height
I_s = Starting Point of the Peak
D_e = Ending Point of the Peak
H_p = Peak Height
D_e = Ending Point of the Peak
H_p = Peak Height

The value of peak width corresponds to the extension of the structure in the considered direction. The top width measure show large the maximum area in the structure is. The heights and slopes of the increasing and decreasing ramps provides the information about the distinction from

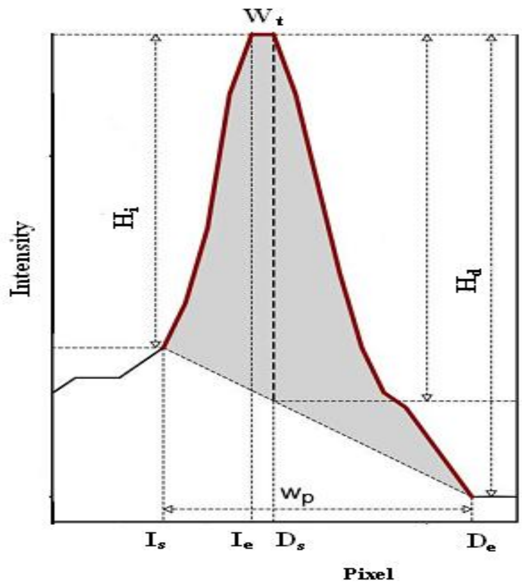

Fig.4. Profile Properties

the surroundings, and the sharpness of the intensity transition. Slope is considered to be positive for decreasing ramps, too. The peak height value combines the heights of the increasing and decreasing gramps by fitting a baseline to the peak, and calculating the central pixels distance from it.

E. Feature Extraction and Classification

The extracted features contain width, height, ramp slope etc. These parameters are extracted from the peak properties. The features are kept in a five sets. The ramp height values are stored in RHEIGHT, likewise ramp slope values are stored in RSLOPE. The topwidth , peak width and peak height are represented by TWIDTH, PWIDTH PHEIGHT. Naive Bayes and kNN classifier are used for classification.

E.1. Naïve Bayes Classifier

The Bayes classifier is based on the Bayes decision rule and will minimise the probability of the total number of errors. Bayes theorem is expressed in Eq. (1)

$$P(w_i \mid X) = \frac{p(X \mid w_i)\, P(w_i)}{p(X)} \quad (1)$$

where

$$p(X) = \sum_{i=1}^{n} p(X|w_i)\, P(w_i) \quad (2)$$

where $P(w_i|X)$ is the posterior probability that the sample **X** belongs to the class i. **X** is a vector representing all features calculated for each sample. $p(X|w_i)$ is the state-conditional probability density function for **X**. $P(w_i)$ is the a priori probability denoting the probability that an abnormality occurs in the entire set of retinal images used in this study. n is the number of classes. The output of the kNN classifier is shown in figure.6

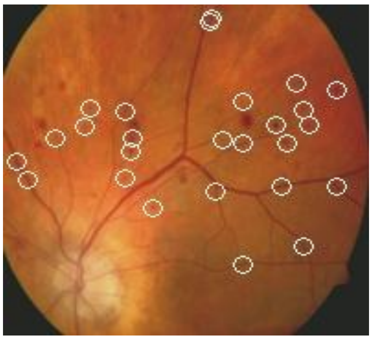

Fig.6. Naïve Bayes Classifier Output

E.2. K Nearest Neighbor Classifier

The k nearest neighbor classifier has no assumptions regarding the distribution of the data. A sample is classified to class i if, of the K nearest neighbors [16] in the feature space, a majority of them belong to class i. The distance measure used is chosen to be the Euclidean measure. The features have to be comparable in value for this classifier to operate reliable and therefore each feature scaled to fit into the range from 0 to 1. The output of the kNN classifier is shown in figure.7

Fig.7. kNN classifier output

Advantage Naive Bayes is that it only requires a small amount of training data to estimate the parameters (means and variances of the variables) necessary for classification. In kNN classifier features like width, height, ramp slope etc are used. False positives are reduced in kNN classifier .

F. MA Score Calculation.

Microaneurysm score is calculated for the performance analysis. Microaneurysm score indicates the shape, symmetry, sharpness and contrast of the microaneurysm candidate.The stronger, more visible MAs achieve higher score than faint ones. The score is calculated depending upon the features calculated from the peak properties. Mean and standard deviation values are taken from the training set. The microaneurysms score is calculated for different set of images. The Microanerysm score equation can be expressed as follows.

$$\text{Score} = \frac{\min_{PH} \cdot \mu_{RS}}{1 + \sigma_{PW} + \sigma_{TW} + \sigma_{RS} + \sigma_{RH} + \sigma_{PH}}$$

where,

$\min_{PH}$ = Minimum Peak Height
μ_{RS} = Mean of the Ramp Slope
σ_{PW} = Standard Deviation of the Peak Width
σ_{TW} = Standard Deviation of the Top Width
σ_{RS} = Standard Deviation of the Ramp Slope
σ_{RH} = Standard Deviation of the Ramp Height
σ_{PH} = Standard Deviation of the Peak Height

The microaneurysm score is calculated different set of images. Table.1.shows the microaneurysm scores

Table.1.Microaneurysm score calculation

Images	**Score**
Image 1	0.151
Image 2	0.138
Image 3	0.144
Image 4	0.148

III. CONCLUSION

The microaneurysm is detected by the method of cross-sectional profile analysis.The parameters are calculated from the profile. The parameters include peak height, peak width, ramp height, increasing and decreasing ramps etc. The naive Bayes and kNN classifier is used for classification . The microaneurysm score is calculated based on the obtained feature values. The score is constructed in such a way that stronger and more visible MAs achieve higher score than faint ones. Here, by using naive Bayes and kNN classifier a score of 0.150 is obtained.

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