Early Detection of Microaneurysms Using Retinal Fundus Images With Removed Blood Vessel Analysis

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Abstract

Detection of microaneurysms in retinal fundus images involves the proper selection of green sub-band channel of retinal fundus image illumination smoothing of retinal fundus image by bi-cubical interpolation blood vessel detection. Rotational cross-sectional profile analysis on the regional maximum pixels centered on regional maximum pixels and the peak other properties are measured. The statistical parameters like mean standard deviation, co-efficient of variation of feature set are calculated. The microaneurysm candidates are estimated by comparison of distribution from the values of mean and standard deviation with the training set obtained from various datasets. The final result obtained is MA co-ordinates

Introduction

Diabetes mellitus is a metabolic disease and a common lifestyle disorder affecting people of any age group and the retinal complications are one of the common causes for preventable blindness in adults. A retinal microaneurysm is a tiny area of blood vessel protruding from an artery or vein in the retina of the eye. They may rupture and leak blood into the retinal tissue surrounding it, which may lead to further bleeding in the retina, vitreous, progressing to detachment of retina and visual loss, if not detected and treated at an earlier stage. The earlier stages in detection of the diabetic retinopathy is thus important to prevent blindness in diabetic patients as India is the diabetic capital of the world. Currently the microaneurysm evaluation is manually performed and is subject to individual evaluation by ophthalmologists. There are various other indicators for the detection of microaneurysm namely visual field test and adaptive optics scanning laser ophthalmoscope. But the detection involves
extensive clinical examination, consuming a lot of time. Taking this into consideration, a system is developed for detection of microaneurysms.

There are three images from which microaneurysm can be detected: Fundus photograph, OCT and HRT. In this process we detected the microaneurysm from fundus images as OCT and HRT have limited depth penetration and lack true color data. The fundus of the eye reveals the surface of the retina with its blood vessels and nerve fibres. The instrument used to view the retina is called ophthalmoscope. A fundus camera or retinal camera is a specialized low power microscope with an attached camera designed to photograph the interior surface of the eye, including the retina, optic disc, macula, and posterior pole. Generally the fundus camera is used for the detection of microaneurysms and the diabetic retinopathy grading.

![Figure 1: Colour retinal fundus image having microaneurysms](image)

**Related Work**

Istvan lazar et al, 2013 [4] proposed a method for microaneurysm detection in the retinal fundus image, using MA detection through the analysis of directional cross-section profiles centered on the local maximum pixels. The statistical measures of these attribute values as the orientation of the cross-section changes constitute the feature set that is used in a naïve Bayes classification to exclude spurious candidates. Giancardo. L et al, 2011[3] proposed a method for detecting microaneurysms is based upon the Radon transformation, microaneurysms segmentation technique based on a novel application of the radon transform. This method has some detection of false positives. Ram. K et al, 2011 [9] proposed a method for MA detection as a problem of target detection from clutter, where the probability of occurrence of target is considerably smaller compared to the clutter. The true positives that remain after the final rejector are assigned a score which is based on its similarity to a true. Quellec. G, et al, 2008 [8] proposed a method to detect them by locally matching a lesion template in sub bands of wavelet transformed images. But some high intensity regions itself are taken as microaneurysms. Niemeijer. M et al, 2005 [7] proposed a new red lesion candidate detection system based on pixel classification. Using this technique, vasculature and red lesions are separated from the background of the image. Second, an extensive number of new features are added to those proposed by Spencer–Frame.
The detected candidate objects are classified using all features and a k-nearest neighbor classifier. The problem is that some of the vasculature is not separated. Mendonca et al, 1999 [6] proposed method includes initial preprocessing and enhancement steps, followed by object segmentation. In the final phase, microaneurysms are validated using two new criteria based on local intensity, contrast and shape relations. Due to the parameters of size and intensity there are some missed microaneurysms.

**Proposed Method**

The high resolution retinal image obtained from the high resolution retinal camera is alone analyzed and with certain suitable image quality images are alone chosen for the detection. Images with dimension 3857 X 2588 pixels are alone used. The inverted green channel image convolved with then Gaussian mask then local maximum regions are extracted. The cross–sectional scanning is done. Then properties of the profile are calculated. From the statistical properties the feature set. Based in naive Bayes classifier the microaneurysm candidates are extracted.

```
Input fundus image
↓
Image preprocessing
↓
Blood vessel extraction and removal
↓
Region maximum extraction
↓
On each peak region
↓
Analysis and property measurement on Profile
↓
Naive bayes classifier
↓
Microaneurysm co-ordinates
```

**Figure 2:** Work Flow of Proposed Algorithm

A. *Inverted green channel*

Color of each pixel consists of three components namely red, blue, green and intensity value of individual pixel. The red channel can enhance the blood vessel and other red structures, but it cannot distinguish between the blood vessels and adjacent structures.
The blue channel is incompetent in the fundus image. The green channel can be used to distinguish between the blood vessels and other neighboring structure, so the green channel is used for further stages in computation.

Smoothing illumination The existing illumination changes in the background of the retinal images are corrected by estimating the illumination of the background and contrast distribution. The enhanced image of \( U(x, y) \) is formulated as follows

\[
U(x, y) = \frac{I(x,y) - K_1 \cdot L(x,y)}{K_2 \cdot C(x,y)}
\]

Where \( I \) is the original image, \( C(x,y) \) and \( L(x,y) \) are the contrast and illumination deviations of the pixel located in location \((x,y)\), respectively, \( k_1 \) and \( k_2 \) are constant coefficients. \( L \) and \( C \) are estimated through sampling the original image.

![Figure 3: Green Channel Retinal Fundus Image Where The Blood Vessels And Red Colour Regions Are Enhanced](image)

Owing to the circular structure of the OD region in the retinal images, we use a non-uniform sampling grid as shown in Fig. 4.3.3. Bicubic interpolation is an extension of cubic interpolation for interpolating data points on a two dimensional regular grid. The interpolated surface is smoother than corresponding surfaces obtained by bilinear interpolation or nearest-neighbor interpolation. Bicubic interpolation is often chosen over bilinear interpolation or nearest neighbor in image resampling. Images resampled with bicubic interpolation are smoother and have fewer interpolation artifacts. Bi-cubic interpolation to calculate the mean and the standard deviation of the remaining pixels in the retinal images. To recognise the pixels in the background for the threshold.
Mahalanobis distance is used as
\[ D(x, y) = \frac{I(x, y) - \mu(x, y)}{\sigma(x, y)} \]

According to above relation, the pixels whose Mahalanobis distance \( D(x, y) \) from \( \mu \) is less than the local threshold \( t \) belongs to the background.

The quantity of local threshold \( t \) in this section is defined as
\[ t = \mu - \alpha \cdot \sigma \]

Where \( \alpha \) is a constant value that controls the amount of the threshold \( t \). \( t \) is a local threshold which is variable for all pixels in the retinal image. This threshold is the deciding factor for the retinal components that have the intense illumination changes in the background.

### B. Improved morphology

The improved morphology function is proposed to extract the blood vessels from the background of the retinal images. For input image \( I \) and structuring element \( SE \).

Improved Function \( IF \) is given by
\[ IF = \{(I \circ SE) \circ SE\} \bigoplus SE - \{(I \bullet SE) \circ \} \bigodot SE \]

In output of the improved function, an image is produced in which the edges are highlighted and so the sensitivity to the noise is resolved. \( SE \) is the structural elements applied to the morphology functions. \( \circ, \bullet, \bigoplus \) and \( \bigodot \) are the ‘opening’, ‘closing’, ‘dilation’ and ‘erosion’ morphology markers, respectively.
C. Region Maximum
The local region maximum extraction is the process of extracting the pixels with higher intensity in the retinal fundus image. A region maximum (RM), of the inverted green channel image is a connected components with a given constant intensity value, such that every neighboring pixel has a strictly lower intensity value.

C. Analysis and property measurement on each profiles
The profile analysis is done iteratively over the all the candidate pixels and with two discrete line segments of different orientations corresponding to the pixel and its values are stored. The multiplication of the matrix L with the discrete line segment gives profile intensities.

From the obtained profiles middle value of the cross-sectional profile is taken as the maximum intensity. P[C] the maximum region and the discrete line were taken based upon the central maximum candidate pixel.

Let P be a profile and P[i] denote its i\textsuperscript{th} value. Once the peak analysis are located, it is tested, whether there is a full peak at the center of the profile that is the, the peak left to the central index is increasing, and the one on the right is decreasing. Only maximum regions are considered as candidates.

Figure 5: Detected Blood Vessel of Retinal Fundus Image

Figure 6: Analysis Across The Peak Candidate Pixel Locations
The figure 4.1 shows the sample peak analysis. Then final peak is represented by start of pixel locations (P[IR]), (P[HI]), and end of peak analysis by (P[DH]), (P[DR]). The central peak is taken to be central pixel P[C] the peak analysis was done only along the peak pixel. Let P be a profile and P[i] denote its i\textsuperscript{th} value. A rising peak is defined as the increase in pixel values along the peak. Then it is compared with the neighboring profile values the increasing peak P[IR] and decreasing peak P[DR]. Then the start and decrease of the peak is given by P[IH] and P[DR]. From the central value is compared with the neighboring pixel value and if the difference between the two pixels is above certain value then the pixel is considered to be the P[IR] and P[DR]. From the above measured peak properties are stored.

Once a peak is detected the following properties are calculated.

- The peak width is the difference between the start and end pixel:
  \[ P_{w} = P[DR] - P[IR] \]
- The top width is the size of the gap between the increasing and decreasing ramp:
  \[ T_{w} = P[DH] - P[HI] \]
- The increasing peak height: \( I_{p} = P[IP][HI] - P[IR] \)
- The decreasing peak height: \( D_{p} = P[IP][DH] - P[DR] \)
- The increasing peak slope: \( S_{IP} = I_{p} / (P[IP][HI] - P[IR]) \)
- The decreasing peak slope: \( S_{DP} = D_{p} / (P[DR] - P[DH]) \)
- The peak height (PH) is calculated as the difference between the intensity of the central pixel and a baseline that connects the start and end of profile.
  \[ PH = P[C] - (P[PH] - P[IR]) / P_{w}(center-[IR]) + P[IR] \]

The value of peak width corresponds to the extension of the structure in the considered direction. The top width measures how large the maximum area of the structure. The heights and slopes of the increasing and decreasing peak analysis provide information about the distinction from the surroundings, and the sharpness of the intensity transition.

\textbf{G. Naïve bayes classifier}

From the calculated statistical measures of the peak properties, five sets of array that contain the values of the corresponding peak properties as obtained by scanning. The increasing and decreasing peak height values are stored in IPH and DPH. The increasing and decreasing peak slope values are stored in IRS AND SPS respectively. The TW, PW and PH sets contain the top width, peak width and peak height values respectively. Let mean (\( \mu \)), standard deviation (\( \sigma \)) and coefficient of variation (\( CV_{P} \)) of the values in set T, where the coefficient of variation is ratio of standard deviation and mean, that is \( CV = \mu / \sigma \). Then we consider a feature set for classification \( F = \mu_{PW}, \sigma_{PW}, \mu_{TW}, \sigma_{TW}, CV_{PH}, CV_{PH} \). The value of \( \sigma_{PW} \) gives a good measure of extension of candidate object. The value of \( \sigma_{TW} \) shows the symmetric of candidate object.

Naïve bayes classifier is a classifier based on all model parameters class priors and feature probability distributions can be approximated with relative frequencies from the training set. These are maximum likelihood estimates of the probabilities. \( \mu_{c} \) be the mean of the values in \( x \) associated with class \( c \), and let \( \sigma_{c}^{2} \) be the variance of the values in \( x \) associated with class \( c \). The probability density of some value given a
class, \( P(x=v|c) \), can be computed by plugging \( v \) into the equation for a normal distribution parameterized by \( \mu_c \) and \( \sigma_c^2 \).

![Image](image.png)

**Figure 7:** Colour Retinal Fundus Image Showing The Detected Microaneurysm Centered By Blue Colour Circles

**Experimental Results**

A. *Performance evaluation methodology*

Analysis involves the accuracy of detections in the implemented algorithm when compared with the manual detections of the physicians, which includes the missed MA candidates which are left undetected by algorithm and other false detections FD (falsely taken as microaneurysm candidates) and the true microaneurysm candidates as true detections TD of the implemented algorithm.

Sensitivity of algorithm is given by

\[
\text{Sensitivity}(S) = \frac{\text{True detection}(s)}{\text{True Positive}(s) + \text{False Positive}(s)}
\]

Higher the sensitivity of the algorithm higher is the accuracy of the algorithm.

**Table 1:** Sensitivity of The Proposed Method of Microaneurysm Detections

<table>
<thead>
<tr>
<th>Fundus Image</th>
<th>Physician Detection</th>
<th>Algorithmic detections without blood vessel removal</th>
<th>Sensitivity S</th>
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<td>False detections</td>
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Conclusion and Further Work

For the detection of microaneurysm the directional cross-sectional analysis is used. Directional cross-sectional analysis yields the best results in the computation and has significant effect on the microaneurysm candidate pixels in the retinal fundus images. The microaneurysm candidates are extracted by means of local regional maximum pixels and the cross-sectional profile analysis along the local regional maximum pixels followed by cross-sectional profile analysis for property measurement and the final feature set for the classification. There is also still some defects of the missed MA candidates and some falsely detected candidates, particularly in the cup disk region and in some vessel crossing regions.

This proposed algorithm can distinguish the microaneurysm candidates in the blood vessel, bifurcations and other regions, but it falsely detects the local maximum regions inside the optic disk cup region and considering it an microaneurysm, leading to increase in the false positives, so an algorithm must be developed such that the local maximum regions in the optic cup disk regions are neglected.

References


