Detection and Classification of Microaneurysms for Diabetic Retinopathy

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Abstract

Detection of Microaneurysm at an early stage is the first step in preventing Diabetic Retinopathy. Diabetic Retinopathy is caused by the complications of diabetes which can eventually lead to blindness. This paper proposes Support Vector Machine classifier to impove the detection of the microaneurysm in digital fundus images so that the detections are not faulty. Support Vector Machines are supervised learning models with associated algorithms that analyse data and recognise patterns used for classification and regression analysis.The proposed algorithm classifies the images using Support Vector Machine Classifier. Pre-processing methods are used to enhance the image. The candidates are then extracted from the pre-processed image using the methods described. These extracted candidates is the problem domain for the Support Vector Machine classifier. The Support Vector Machine classifier classifies the images to correctly determine the findings of candidate extraction to be microaneursym or not. The simulations of the algorithms are done and the results are shown.

Keywords— *Diabetic Retinopathy, Microaneurysm, Support Vector Machine*

I. INTRODUCTION

Diabetic retinopathy is a condition occurring in persons with diabetes, which causes progressive damage to the retina, the light sensitive lining at the back of the eye. It is a serious sight-threatening complication of diabetes. Diabetic retinopathy is the result of damage to the tiny blood vessels that nourish the retina. They leak blood and other fluids that cause swelling of retinal tissue and clouding of vision. The condition usually affects both eyes. The longer a person has diabetes, the more likely they will develop diabetic retinopathy. If left untreated, diabetic retinopathy can cause blindness.

The four stages of Diabetic Retinopathy are

1. Mild Non-Proliferative Retinopathy
2. Moderate Non-Proliferative Retinopathy
3. Severe Non-Proliferative Retinopathy
4. Proliferative Retinopathy

Mild Non-proliferative Retinopathy is the earliest stage of Diabetic Retinopathy. It is characterized by the presence of “dot” and “blot” hemorrhages and “microaneurysms” in the retina. Microaneurysms are areas of balloon like swelling of the tiny blood vessels in the retina caused by the weakening of their structure. Moderate Non- proliferative Retinopathy is the second and slightly more severe stage of Diabetic Retinopathy. During this stage, some of the small blood vessels in the retina may actually become blocked. The blockage of these tiny blood vessels causes a decrease in the supply of nutrients and oxygen to certain areas of the retina. Severe Non-proliferative Retinopathy is the next stage of Diabetic Retinopathy. Severe Non-proliferative Retinopathy is characterized by a significant number of small blood vessels in the retina actually becoming blocked. As more blood vessels become blocked, it results in areas of the retina being deprived of nourishment and oxygen. Proliferative Retinopathy is the most severe stage of Diabetic Retinopathy and carries a significant risk of vision loss. The retina grows abnormal blood vessels which are fragile and tend to break easily leading to bleeding and profound vision loss.

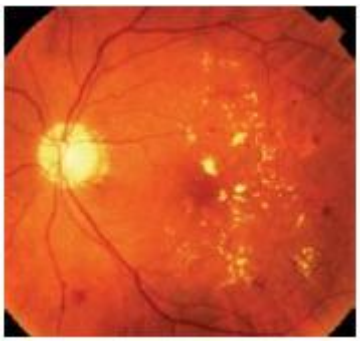

Fig. 1. Sample digital fundus image with Diabetic Retinopathy

Detection of Microaneurysms is the first step in the prevention of Diabetic Retinopathy. Antal *et al.* [1] has proposed an ensemble-based framework to improve microaneurysm detection which combines the internal components of microaneurysm detectors, namely preprocessing methods and candidate extractors. High reliability can be ensured and accuracy can be raised in a detector by considering ensemble-based systems,

which have been proven to be efficient in several fields. However, the usual ensemble techniques aim to combine class labels or real values that cannot be adopted in this case. In MA detection, detectors provide spatial coordinates as centers of potential MA candidates. The use of well-known ensemble techniques would require a classification of each pixel, which can be misleading in this context, since different algorithms extract MAs with different approaches and the MA centers may not coincide exactly. To overcome this difficulty, close MA candidates of the individual detectors are gathered and a voting scheme is applied on them.

Zuiderveld *et al*. [2] has discussed the Contrast Limited Adaptive Histogram Equalization, a preprocessing method used to improve the overall contrast of the image by splitting the image into regions and applying equalization individually. In this paper, a system level realization of CLAHE is proposed, which is suitable for VLSI or FPGA implementation. The goal for this realization is to minimize the latency without sacrificing precision.

Walter *et al.* [3] has proposed a polynomial contrast enhancement operator which is a simple grey level transformation. It assigns to each pixel a grey level independently of the neighbor grey level distribution.

Walter *et al*. [4] has proposed diameter closing which finds the connected components in the image and extracts the candidates based on the properties of microaneurysm. In this paper, the automatic detection of microaneurysms in color fundus images, which plays a key role in computer assisted diagnosis of diabetic retinopathy using a new algorithm, is presented. The algorithm can be divided into four steps. The first step consists in image enhancement, shade correction and image normalization of the green channel. The second step aims at detecting candidates, i.e. all patterns possibly corresponding to MA, which is achieved by diameter closing and an automatic threshold scheme. Then, features are extracted, which are used in the last step to automatically classify candidates into real MA and other objects; the classification relies on kernel density estimation with variable bandwidth.

Zhang *et* al. [5] has proposed a method that finds the correlation co-efficient between microaneurysm and Gaussian filter and thereby extracts the microaneurysms. In this paper, an approach to the computer aided diagnosis (CAD) of diabetic retinopathy (DR) is presented. Since red lesions are regarded as the first signs of DR, there has been extensive research on effective detection and localization of these abnormalities in retinal images. In contrast to existing algorithms, a new approach based on Multiscale Correlation Filtering (MSCF) and dynamic thresholding is developed. This consists of two levels, Red Lesion Candidate Detection (coarse level) and True Red Lesion Detection (fine level).

II. METHODS OF DETECTION AND CLASSIFICATION

The microaneurysm in digital fundus images is detected by creating an ensemble of preprocessing and candidate extraction methods. The preprocessing improves the contrast of the image or enhances salient objects present in the image. Another preprocessing method removes the vessels for better detection of microaneurysm. Then microaneurysm is detected in the preprocessed image by extracting the candidates. Candidate extraction is a process that aims to spot any objects in the image showing microaneurysm-like characteristics. Individual microaneurysm detectors consider different principles to extract microaneurysm candidates.

To eliminate wrong detection of microaneurysm candidates, the image is subjected to classification using Support Vector Machine Classifier. The support vector classification approach is a relatively recent development in statistical pattern recognition with earlier origins. In this approach, optimal classification of a separable two-class problem is achieved by maximizing the width of the empty area (margin) between the two classes. The margin width is defined as the distance between the discrimination hyper surface in n-dimensional feature space and the closest training patterns: these are called support vectors. The support vectors thus specify the discrimination function. The general flow diagram is shown in Fig 2.

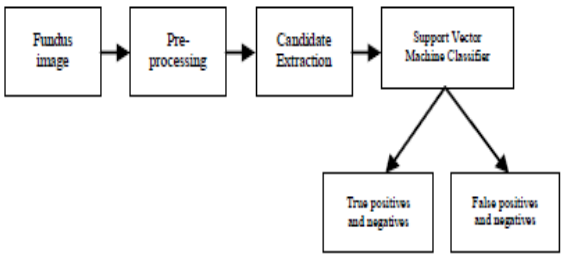

Fig. 2. General Flow Diagram

III. PRE-PROCESSING

Preprocessing is among the simplest and most appealing areas of digital image processing and is mainly composed for image filtering and enhancement. Basically, the idea behind enhancement techniques is to bring out detail that is obscured, or simply to highlight certain features of interest in an image. A familiar example of enhancement is when the contrast of an image is increased the image "looks better". It is important to keep in mind that enhancement is a very subjective area of image processing. There is no general theory of image enhancement. When an

image is processed for visual interpretation, the viewer is the ultimate judge of how well a particular method works.

A. Contrast Limited Adaptive Histogram Equalization (CLAHE)

CLAHE differs from ordinary adaptive histogram equalization in its contrast limiting as proposed by Zuiderveld [2]. This feature can also be applied to global histogram equalization, giving rise to contrast-limited histogram equalization (CLHE), which is rarely used in practice. In the case of CLAHE, the contrast limiting procedure has to be applied for each neighborhood from which a transformation function is derived. CLAHE was developed to prevent the over-amplification of noise that adaptive histogram equalization can give rise to.

The image is divided into Corner regions (CR), Border regions (BR) and Inner regions (IR) as shown in Figure 4.

CR	BR	BR	CR
BR	IR	IR	BR
BR	IR	IR	BR
CR	BR	BR	CR

Fig. 4. Splitting the image into regions

After calculating the histogram of each region, based on the desired limit of contrast expansion, a clip limit β for clipping histograms is obtained as follows

$$\beta = \frac{M}{N}\left(1 + \frac{\alpha}{100}(s_{max} - 1)\right)$$

where M is the number of pixels, N is the number of grayscales, α is the clip factor and smax is the maximum possible slope.

Each histogram is redistributed in such a way its height does not go beyond the clip limit. The cumulative distribution functions (CDF) of the resultant contrast limited histograms are determined for gray scale mapping as shown below

$$f_{i,j}(n) = \frac{N-1}{M} \cdot \sum_{k=0}^{n} h_{i,j}(k);\ n = 1,2,3 \ldots . N-1$$

Pixels in the inner region are bilinearly interpolated (IR), pixels in the boundary region (BR) are linearly interpolated, and pixels near corners (CR) are transformed with the transformation function of the corner tile

B. Shade Correction

The non-uniform illumination in the image has to be corrected if the microaneurysm in these areas has to be detected correctly. The non-uniform illumination is corrected by shade correction. The shade correction is done by estimating the background and subtracting it from the preprocessed image as shown below.

$Is\ adeCorrected = ICLAHE - IbackgorundEstimate$

The background estimation is done by using a polynomial fitting algorithm.

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IV. CANDIDATE EXTRACTION

Candidate extraction is a process that aims to spot any objects in the image showing Microaneurysm-like characteristics. Individual Microaneurysm(MA) detectors consider different principles to extract Microaneurysm candidates. In this section, a brief overview of the candidate extractors is provided. Again, just as for pre-processing methods, adding new Microaneurysm candidate extractors may lead to further improvement in the future.

The candidate extraction is done after preprocessing as shown in Figure 4.1. The candidate extraction will extract microaneurysms form the preprocessed image. But the microaneurysms obtained will may contain true or false positives and negatives. So, they have to be classified using Support Vector Machine Classifier which will classify the extracted microaneurysms to to correct or wrong.

A. Top hat transformation

The objective of this step is to find "candidates", i.e. regions possibly corresponding to MA as proposed by Spencer et al. [4]. The image is inverted and a white top hat transformation is applied. The white top hat transformation works as follows.

A linear structuring element of 11 pixels is created and the inverted shade corrected image is opened

using this structuring element. The structuring element is rotated at angles from 0 to 165 in 15 degrees increment and then the maximum value from all the openings is taken and a new image is formed. This is subtracted from the complemented shade corrected image which will give the possible candidates.

$IwiteTopHat=IcompSadeCorr-$ max{$Iopen$ 0:15:165 }

B. Matching Multiple Gaussian Masks

Microaneurysm exhibit a Gaussian shape. Therefore, a Gaussian function can be used to detect microaneurysm according to the similarity between the distributions of its grayscale. The Gaussian function is defined as

$$G(x,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-x^2+y^2/2\sigma^2}$$

As proposed by Zhang et al. [5], the correlation coefficient is a good way to measure the resemblance between the Gaussian function and grayscale distribution of microaneurysm. If the two match, the correlation coefficient will be high and if they don"t, the value will be low. The range of the coefficient is from 0 to 1.

The correlation co-efficient of each pixel is calculated as shown below

$$r = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{[\sum_m \sum_n (A_{mn} - \bar{A})^2][\sum_m \sum_n (B_{mn} - \bar{B})^2]}}$$

where A and B are the mean of the input and the Gaussian filtered image.

The maximum coefficient from each of the five responses is combined to get the final response.

C. Vessel Segmentation There are some vessels that still appear as candidates. To remove them the vessels are extracted from the shade corrected image using a morphological operation. The image is closed using a disc shaped structuring element of 5 pixels. The shade corrected image is filled to eliminate holes in the vessels. Then the filled image is subtracted from the closed image to give a vessel difference image. This image is thresholded to get the binary images containing the vessels. $IvesselDiff=Iclose- Ifill IbinaryVessel=T\ res\ old(IvesselDiff)$ This binary image is subtracted from the Gaussian filtered image so the the final image has vessel free candidates.

$Icandidate=IgaussianFilter-IbinaryVessel$

V. CLASSIFICATION OF MICROANEURYSM

The extracted candidates are subjected to classification to eliminated false detection. The Support Vector Machine classifier is used for classification. The aim of Support Vector classification is to devise a computationally efficient way of learning „good" separating hyperplanes in a high dimensional feature space.

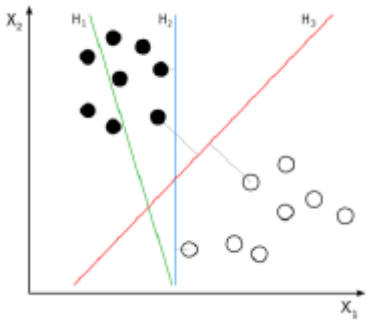

Fig. 5. Maximum margin separating hyperplane Any hyperplane can be written as the set of points x satisfying $w.x-b=0$

subject to (for any i=1,…,n)

$yi\ w.xi-b \geq 1$

By introducing Lagrange multipliers α the constraint problem can be expressed as

$$\min_{w,b} \max_{\alpha \geq 0} \left\{ \frac{1}{2}||w||^2 - \sum_{i=1}^{n} \alpha_i [y_i(w.x_i - b) - 1] \right\}$$

A kernel is used in non-linear classifiers to fit the maximum margin hyperplane in a transformed feature space. The often used kernel is

$$K(x_i, x_j) = \exp(-\frac{||x_i - x_j||^2}{2\sigma^2})$$

VI. RESULTS

Fig 6(a) and 6(b) represents the input fundus image and the grey scale image respectively. Fig 6(c) and 6(d) gives the results of pre-processing with CLAHE and Shade correction respectively.

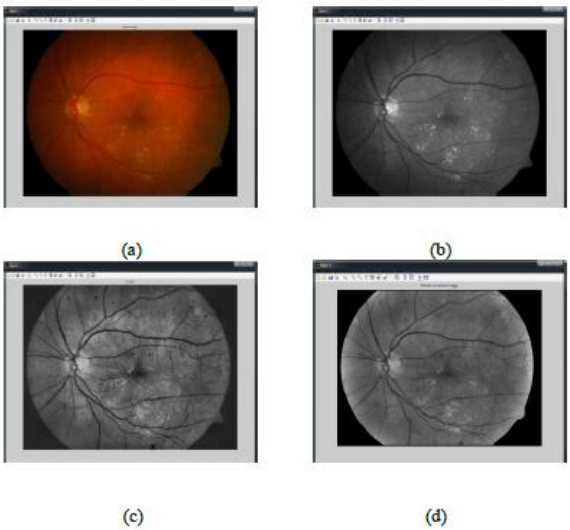

Fig. 6. Pre-processed image (a) Input image (b)RGB to Gray (c) CLAHE (d) Shade corrected image Fig 7(a) is the complemented shade corrected image. Fig 7(b) is the added open image. Fig 7(c) and 7(d) gives the result of Top hat transformation and Matching filter Gaussian mask respectively. Fig 8(a) and 8(b) is the closed image and filled image respectively. Fig 8(c) and 8(d) gives the result of Vessel segmentation and candidate extraction after subtraction of vessel. Fig 8(e) is the result of noise removed image.

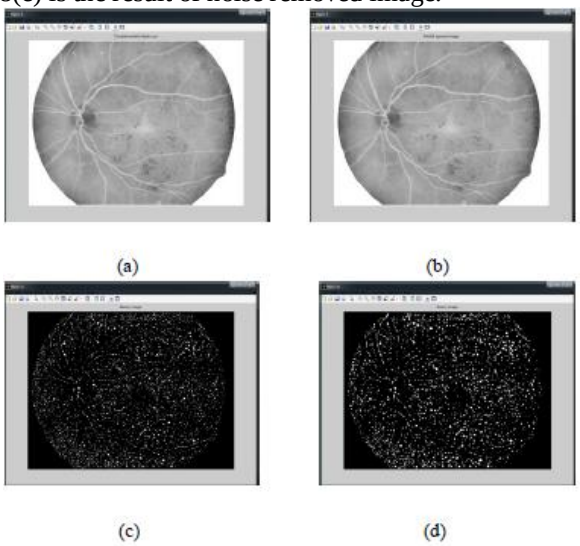

Fig. 7. Candidate Extraction after Shade Correction (a) Complemented shade corrected image (b) Added open image (c) Top hat transformed image (d) Matched filter Gaussian image

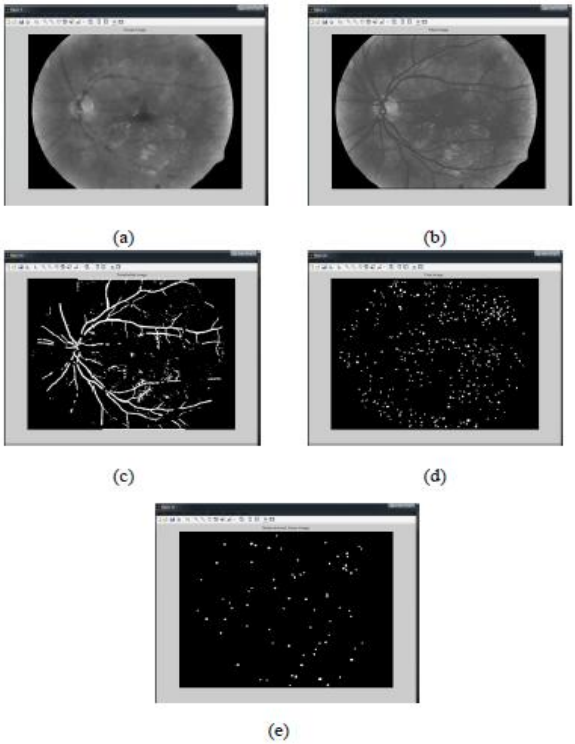

Fig. 8. Vessel Segmentation and removal (a) Closed image (b) Filled image (c) Vessel extraction (d) Candidate after removal of vessel (3) Noise removed image

VII. CONCLUSION AND FUTURE WORK

Based on the properties of microaneurysm, preprocessing and candidate extraction methods are used with the goal of providing a suitable tool for diabetic retinopathy screening. The Contrast Limited Adaptive Histogram Equalization makes the salient parts of the image more visible and the Gray level transformation improves the overall contrast of the image. The main difficulties in the detection of microaneurysms are the non uniform illumination and interference of similar objects. The candidates extracted by Diameter closing and Gaussian mask methods have to be classified to detect true microaneurysms. The results show that microaneurysm detection is a challenging task and further work is necessary to achieve more reliable results to improve the diagnosis. Real time implementation of the algorithm is possible using FPGA. The processed images can be sent to an expert without degrading the quality of the image which can be used in telemedicine. Hand held image acquisition devices can be developed so that experts are not needed to operate the device.

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