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Retinal Microaneurysm Detection Based on Intensity Profile Analysis*

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Abstract

The reliable detection of microaneurysms (MAs) on digital fundus images is essential for any diabetic retinopathy (DR) screening system, since the presence of MAs is usually the first sign of this disease. Manual identification of MAs is time-consuming, and unacceptable in an automatic screening system. Due to the improtance of this task, the literature on automatic MA detection is extensive, the proposed methods have varying accuracy and computational resource requirements.

In this paper we present a novel approach to the extraction of MA candidates. The proposed algorithm is based on the construction of a two dimensional map, where MAs appear as isolated bright spots. To create this map, the entire image is scanned along lines with different directions to obtain one dimensional intensity profiles. Each intensity profile is thresholded through an adaptive thresholding step, and the resulting indicies corresponding to foreground pixels are transformed to two dimensional coordinates. Thresholding of the map results in a set of connected components, whereby MA candidates are selected based on diameter.

Keywords: diabetic retinopathy, retinal image, automatic screening, microaneurysm candidate, intensity profile, image processing

1. Introduction

Diabetic retinopathy (DR) is a disorder of the retina, caused by diabetes mellitus (usually simply referred to as diabetes). It affects up to 80% of all patients who have had diabetes for 10 years or more. In severe cases it eventually leads to blindness;

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moreover, it is the most frequent cause of new cases among adults between the age of 20 and 74, besides other diabetic eye diseases such as maculopathy and cataract. Effective and cheap laser treatement for DR is available, though its effectiveness is superior when it is performed early in the disease. DR is a silent disease in early stages, and many of the cases are only diagnosed when serious vision loss occurs.

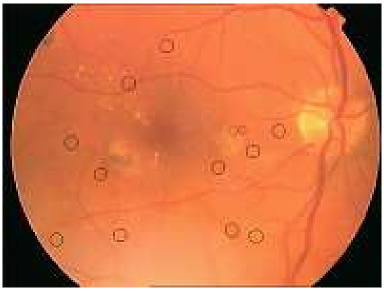

Figure 1: Color fundus image showing MAs.

Thus, the screening of diabetic patients for DR is essential. Furthermore, screening provides an opportunity to diagnose cataract, glaucoma and other eye diseases, though it is not its definite aim. Color fundus images are the main resources used by ophtamologists for screening purposes. The presence of microaneurysms (MAs), as shown in Fig. 1, is the earliest sign of DR, thus their reliable detection is essential in a computer aided screening system. In pathological sense, MAs are blood-filled dilations of capillary walls. In accordance with the general concept, small circular shaped dark lesions, whose diameter is smaller than 125 μm are considered to be MAs. The distinction between MAs and hemorrhages is quite difficult, and as a matter of fact unnecessary in an actual screening system, since MAs and hemorrhages are both symptoms of DR. Pigmentations of the retina also have striking resemblance to true MAs. In fact, even manual selections from different ophthalmologists can vary in certain cases.

In this paper, we present a novel method for the detection of microaneurysm candidates. We are not proposing a complete MA detection algorithm, but a way to precisely locate candidates, that can be the basis for widely used machine learning based decision methods.

The paper is structured as follows: In section 2, we discuss existing methods for MA candidate extraction. Section 3 presents the proposed algorithm, and section 4 discusses the results. In section 5 we draw the conclusions and cast a glance into the further utilization of the proposed method.

2. Review of available MA candidate extraction methods

The varying contrast and nonuniform shade of retinal images make lesion detection a challenging task. Most of the existing methods include some sort of preprocessing step to overcome this problem. Spencer et al. [1] and Frame et al. [2] applied median filtering for the approximation of the background, which was subtracted from the original image to produce a shade-corrected image. In [3] and [4] Walter et al. used polynomial local contrast enhancement for shade correction, and applied convolution with a Gaussian kernel to attenuate noise. The presence of noise at some level in color fundus images is a difficulty indeed, most of the authors address this problem by the usage of convolution with smoothing kernels and median filtering.

Mathematical morphology based methods for MA candidate extraction has a long history in the field. Baudoin et al. [5] used morphological opening with linear structuring elements in different directions, and performed top-hat transformation to extract details corresponding to MA candidates. In [1], Spencer et al. also incorporated this technique. To improve further the segmentation of MAs, a matched filter was applied to the result of the top-hat transformation, and the resulting image was thresholded. Each discrete binary component was shrinked to a single pixel, and constituted the basis of a recursive region growing procedure, in which the candidate objects were dilated and tested in each cycle. Furthermore, they were the first to use a consequent classification step to filter candidates. The method proposed by Cree et al. [6] also relied on the same basis. Frame et al. [2] used the methods described in [1] and [6] to extract MA candidates, and used thirteen features per each candidate for further statistical classification. Walter and Klein [3] were the first to use criteria based morphology operators for candidate extraction. In [4] a complementory classification step was added, using fifteen dimensional feature vectors.

Non mathematical morphology based methods, such as Quellec et al. [7] and Abdelazeem [8] have also been proposed. In [7] a technique for the extraction of candidates using template matching in wavelet domain is shown, and [8] relies on detecting circular objects using Hough transform. Sinthanayothin et al. [9] described a method that uses a recursive region growing procedure that segments both vessels and red lesions. After segmentation, an arificial neural network is used to separate vessel segments from MA candidates.

The large number of proposed algorithms indicates the importance of developing a reliable MA detector for DR screening purposes. Though, automated MA detection has been the subject of exhausting research for more than 20 years, the available algorithms cannot be recommended for clinical practice, according to Abrŕmoff et al. [10]. In [11] Niemeijer et al. compares the results of MA detectors in an online challenge that focuses on the automated detection of retinal disease.

3. The proposed method

3.1. Preprocessing

Images to process may arrive in various spatial resolution. Input images, whose size exceeds a previously fixed dimension, needs to be resized, while maintaining the original aspect ratio. The parameters of the candidate extraction are related to the resolution of the image. Namely, the parameter values reported in this paper correspond to a maximal width and height of 768 pixels. To preserve the quality of the source image, bi-cubic interpolation is used for resampling.

Lesions and vessels in the retina have the highest contrast in the green channel of a color image. Due to this, the inverted green channel of the image is used for further processing. The necessity of the invertation is explained later on.

3.2. Identifying MA candidates

MAs appear as two dimensional Gaussian-like peaks in a fundus image. The basic idea for candidate extraction is to simplify the location of these peaks. Instead of detecting two dimensional objects directly, the task is divided into detecting peaks on one dimensional intensity profiles, and use the resulting information to construct a two dimensional peak map. MAs will appear as bright isolated spots in this map and can be segmented easily by a simple thresholding method. Figure 2 shows the intensity profiles of scan lines passing through the same MA.

3.2.1. Peak map construction

The construction of the peak map consists of scanning the entire image along lines with different directions to obtain one dimensional intensity profiles, and applying an adaptive thresholding method to each profile. The resulting foreground indices are transformed back to two dimensional space, in order to be stored in a temporal map. The dimensions of the temporal map equals to the dimensions of the source image, i.e., each value of the temporal map corresponds to a specific position in the source image.

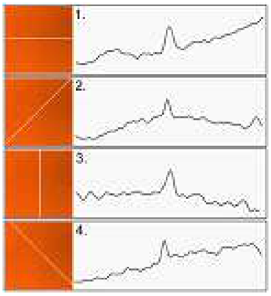

Figure 2: Intensity profiles of scan lines passing through the same MA at 0° (1), 45° (2), 90° (3) and -45° (4).

The range of the directions used for the scanning procedure is [-90°, +90°[. During the scanning process, every pixel of the image has to be accessed from all of the directions. To achieve this, each scan line corresponding to a specific direction is shifted horizontally and vertically to cover the entire image. The scanning itself is realized in such a way that at each position of the scan line, the average intensity of a perpendicular intersecting scan line is recorded. This results in a directional smoothing effect, and makes a more decent noise suppression attainable, considering the results of simple two dimensional filterings. In the case of particularly noisy inputs, the resulting individual intensity profiles can be additionally smoothened, e.g. using a one dimensional Gaussian filter. To threshold an individual intensity profile, first the local maxima need to be found. This is accomplished by searching monotonically increasing segments forward and backward on the profile. Segments are categorized as left- and right sides, and only those ones are recorded, whose height is greater than or equal to a minimal height. Left and right sides with the proper height are then used to form full peaks. Local maximum indices within a peak are trivial to find. Each full peak is thresholded the following way: starting from the local maximum position, those indices will be considered to be foreground in both directions, where the intensity difference between the local maximum and the actual index is less than the recorded height of that side multiplied by a scale constant. Scale constant is a real number less than 1.0, and it controls how much a component will "grow" into the background (Fig. 3). As previously mentioned, the resulting foreground indices are transformed to two dimensions, and are recorded in the temporal map. The bits of each value of the temporal map correspond to the used scan directions. Each bit denotes whether any foreground pixel has been segemented during thresholding a scan line with that direction passing through that specific position.

Figure 3: Effect of the adaptive thresholding method on a single intensity profile. Resulting foreground segments are marked red.

After the scanning and thresholding steps are finished for all the directions, each value of the peak map is calculated as the number of bits of value 1 in the temporal map at that specific position. That is, the value of the peak map at each position equals the number of foreground pixels resuling from the thresholding of intensity profiles at that specific position (Fig. 4). Obviously, the maximal value equals to the number of directions used for the scanning procedure.

3.2.2. MA candidate extraction

MA candidates are extracted from the peak map as a result of hysteresis thresholding. Thresholding with hysteresis requires two thresholds, a high threshod T_1 and a low threshold T_2.

Figure 4: Original image and the normalized image of the constructed peak map.

Those points, whose value is greater than T_1 are immediately considered to belong to the foreground (strong foreground pixels). Points of a connected component, whose values are above T_2, and are connected to a strong foreground pixel are also considered as foreground points. Using thresholding with hysteresis, the components of the vessel system become more connected, and can be easily filtered out based on diameter. Thus, the final step of MA candidate extraction is selecting the resulting components that whose diameter is less than the previously fixed maximal diameter parameter.

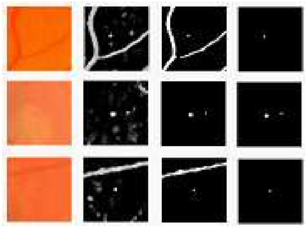

Figure 5: Steps of the algorithm: a) original image b) peak map c) hysteresis thresholded peak map d) MA candidates afer size based component removal

4. Results

To evaluate the performance of the proposed method, publicly available training set from the Retinopathy Online Challenge [11] was used. The training set contains 50 fundus images with the manual location of MAs segmented by ophthalmologists. Currently this is the only publicly available dataset dedicated to the performance measure of MA detectors.

Unfortunately, the results of candidate extractors used in the publicly available methods are unavailable. In [11] Niemeijer et al. reported the results of MA detectors participating in the Retinopathy Online Challenge. However, these algorithms all use further classifiaction methods to reduce the number of false positive candidates, and the performance of individual candidate extractors are unknown.

Traditionally, to demonstrate the performance of binary classifiers ROC curves are used. A ROC curve shows the relation between sensitivity (True Positive Rate, TPR) and False Positive Rate (FPR) of a binary classifier. The high number of True Negative (TN) candidates in the images makes FPR values unsuitable for measuring the performance of MA candidate extractors or detectors. Therefore, a Free Response ROC (FROC) [12] curve has been plotted to evaluate the proposed method. A FROC curve exposes the relation between the sensitivity and the average number of FPs per image, thus it is a more appropriate way to evaluate MA candidate extractors and detectors.

During testing, the following parameter settings were applied to the proposed method:

1. Directions used for scanning during the construction of the peak map: 4° changes,
2. Length of perpendicular scan line during scanning: 5,
3. Minimal monotical segment height during intensity profile thresholding: 6,
4. Maximal difference between left and right peak segments: 5,
5. Maximal component diameter for selecting MA candidates: 15.

To see how the true/false positive ratio changes, the low and high threshold for hysteresis thresholding was between 50 and 90 with a difference between low and high values of 5. Manual ROI area was used on every image: a disk covering the fundus area, and candidates located outside the ROI were excluded.

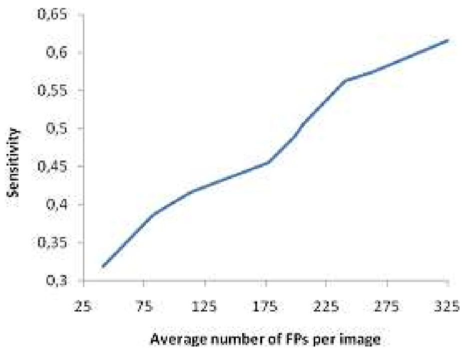

Figure 6: FROC curve of the proposed method.

5. Discussion

In this paper, we have proposed a novel approach to MA candidate extraction in color fundus images. The proposed method also has the advantage that it is well parallelizable: the scanning procedure discussed in section 3.2.1 is executable to different directions separately. We have demonstrated the performance of the method by plotting it's FROC curve. The FROC curve shows that relation between the average number of false positives per image and the sensitivity of the proposed method is approximatly linear, thus it is a reliable MA candidate source for further classification methods.

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