EVALUATION OF RETINAL VESSEL SEGMENTATION METHODS FOR MICROANEURYSMS DETECTION

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ABSTRACT

Microaneurysms (MAs) are the earliest sign of diabetic retinopathy and manifest as small reddish spots on the retina. Generally, algorithm design for MAs detection starts by separating the vascular system from the background for a posterior analysis of candidate MAs presence. Following this approach, this paper assesses three different methods for vessel segmentation and how they affect posterior MAs detection. The robustness in developing automatic screening systems for MAs detection is discussed and a methodology to detect candidate MAs in retinal images is introduced. The algorithm combines different vessel segmentation methods with region growing to evaluate which is the best to provide candidate MAs detection.

Index Terms— Diabetic retinopathy, vessel segmentation, microaneurysms, mathematical morphology, entropic thresholding, wavelets.

1. INTRODUCTION

Images of ocular fundus provide information about retinal, ophthalmic and even systemic diseases such as diabetes, hypertension and arteriosclerosis. Diabetes affects slowly the circulatory system including that of the retina. As diabetes progresses, the vision of a patient may start to deteriorate and lead to diabetic retinopathy [1]. Diabetic Retinopathy (DR), a frequently observed complication of diabetes, is a major cause of adult blindness due to changes in blood vessels structure and distribution such as new vessel growth (proliferative diabetic retinopathy). Diagnosis requires laborious analysis from specialists [2].

The retina is the only location where blood vessels can be directly visualized non-invasively in vivo. Ocular fundus images provide information about the pathological changes caused by local ocular diseases. Automated analysis of retinal images has the potential to reduce the screening program costs compared to manual image grading.

Therefore, it is important to accurately extract blood vessels from the retinal images to help the specialist in diagnosis, treatment evaluation and clinical study of diseases such as diabetes, hypertension and arteriosclerosis. In addition, blood vessels can also act as landmarks for image-guided laser treatment of choroidal neovascularization and the localization of the optic nerve, the fovea and lesions. Several retinal vessel segmentation methods have been proposed [2, 3, 4, 5] and also compared [6]. Wilkilson et al. [7] displayed the advantages of the morphological shape filters for extraction of filamentous details from medical images, including vessels.

Microaneurysms (MAs) are likely to be the only lesion present at the earliest stage and during the process of disease development. Thus, the study of these lesions on the retina is of major importance to develop automated retinopathy detection systems. MAs are swellings of the capillaries caused by a weakening of the vessel wall. In retinal photographs, although the capillaries are not visible, MAs appear as dark red isolated dots. In common with vessels, MAs appear with highest contrast in the green plane of the color image. In normal retinas, dots are also present though with less contrast compared to MAs [8].

Here, we perform a detailed evaluation of the influence of three different vessel segmentation methods [2, 3, 9] on MAs detection.

2. METHODOLOGY FOR CANDIDATE MICROANEURYSMS DETECTION

A general methodology for candidate MAs segmentation, originally proposed by Spencer et al. [10] and Frame et al. [11] is summarized in Figure 1. In this paper the step concerning candidate MAs extraction is accomplished by using the algorithm proposed in [12]. It was originally proposed to detect red lesions in digital color fundus image and we have adapted it for MAs detection.

Briefly, this system consists in finding the vasculature map \( I_{vas} \) which is subtracted from the original image \( I_{org} \). The resulting image \( I_{lesion} = I_{org} - I_{vas} \) contains mainly nonelongated structures including candidate microaneurysms. The main steps are summarized below.
2.1. Image Preprocessing

In order to prepare the fundus images for red lesions extraction, image preprocessing is performed on the green-plane $I_{green}$ of the original RGB color image $I_{org}$. As red lesions have the highest contrast with the background in the green color plane, information from the red and blue color planes are discarded.

This operation can be viewed as a shade correction procedure and consists in removing low gradient regions from the ground. For a color image, the gray value probability of the image can be given by $p_i = \frac{n_i}{N \times M}$, where $n_i$ is the number of pixels with gray value $i \in \{0, 1, ..., 255\}$.

The prior entropy of the image is defined as:

$$H_T = - \sum_{i=0}^{255} p_i \ln p_i.$$  

(1)

Assuming that object and background are denoted by $\Lambda_1$ and $\Lambda_2$ respectively, and that the segmentation threshold is $t$, the prior probability of the object and the background are defined as:

$$H_{\Lambda_1} = - \sum_{i=0}^{t} \frac{p_i}{p(\Lambda_1)} \ln \frac{p_i}{p(\Lambda_1)},$$  

(2)

$$H_{\Lambda_2} = - \sum_{i=t+1}^{255} \frac{p_i}{p(\Lambda_2)} \ln \frac{p_i}{p(\Lambda_2)}.$$  

(3)

where, $p(\Lambda_1) = \sum_{i=0}^{t} p_i$, $p(\Lambda_2) = \sum_{i=t+1}^{255} p_i$ and $p(\Lambda_1) + p(\Lambda_2) = 1$.

Therefore, the sum of the entropic information for the object and background, $I(\Lambda_1, \Lambda_2)$ is given as $I(\Lambda_1, \Lambda_2) = H_{\Lambda_1} + H_{\Lambda_2}$. The selected threshold $t$ corresponds to the maximum value of $I(\Lambda_1, \Lambda_2)$.

2.2. Vessel Segmentation

This section presents three vessel segmentation methods, which are used separately in the vessel segmentation module, for evaluation and comparison in the experimental results.

2.2.1. Maximal Entropic Thresholding Method

The maximal entropic thresholding algorithm [9] extracts the vessels from the retinal image. This method computes a suitable threshold to segment an image into object and background. For a $N \times M$ image, the gray value probability of the image can be given by $p_i = \frac{n_i}{N \times M}$, where $n_i$ is the number of pixels with gray value $i \in \{0, 1, ..., 255\}$.

The prior entropy of the image is defined as:

$$H_T = - \sum_{i=0}^{255} p_i \ln p_i.$$  

(1)

The selected threshold $t$ is wider than the widest blood vessel in the used set of images and it consists of several morphological operations, summarized by the following equations:

$$S_{op} = \gamma_{S_0}^{rec} \{\text{Max}_{i=1...12}\{\gamma_L(S_0)\}\},$$  

(4)

$$S_{sum} = \sum_{i=1}^{12} (S_{op} - \gamma_L(S_0)).$$  

(5)

The sum of top-hats $S_{sum}$ reduces small bright noise and improves the contrast of all linear parts. Vessels can be manually segmented with a simple threshold applied to $S_{sum}$. However, most images contain noisy data requiring further treatment. Therefore, the curvature $S_{lap}$ is computed and filtered by an alternating sequential filter:

$$S_{lap} = \text{Laplacian}(\text{Gaussian}_{width=7\text{px}}(S_{sum})),$$  

(6)

$$S_{1} = \gamma_{S_{lap}}^{rec} \{\text{Max}_{i=1...12}\{\gamma_L(S_{lap})\}\},$$  

(7)

$$S_{2} = \phi_{S_1}^{rec} \{\text{Min}_{i=1...12}\{\phi_L(S_{1})\}\},$$  

(8)

$$S_{res} = \{\text{Max}_{i=1...12}\{\gamma_L^2(S_{2})\} \geq 1\}.$$  

(9)

In angiographic images, the vessels appear dark, hence the first preprocessing step is a simple inversion of the gray values. It is followed by the main algorithm and no other processing is necessary.

2.2.2. Mathematical Morphology Method

Vessel segmentation is achieved in [10] by applying morphological openings ($\gamma_L$) to the shade-corrected image ($S_0 = I_{bg}$) using long linear single pixel wide structuring elements $L_i$ at various orientations. A total of twelve rotated structuring elements were used with a radial resolution of 15 degrees. These openings are combined by choosing the maximal response at each pixel out of all the openings, also called linear opening by reconstruction ($\gamma_{S_{0}}^{rec}$) [7] of size 15, and then subtracting the result from the reconstructed image ($S_{op}$). The length of a structuring element should be larger than the largest microaneurysm present. The next step introduces the general vessel segmentation algorithm based on mathematical morphology which was proposed by Zana et al. [3]. Originally, it was applied to digital retinal angiography images and it consists of several morphological operations, using a set of linear structuring elements $L_i$ (every 15°) with 15-pixels long and 1-pixel wide, summarized by the following equations:

$$S_{op} = \gamma_{S_0}^{rec} \{\text{Max}_{i=1...12}\{\gamma_L(S_0)\}\},$$  

(4)

$$S_{sum} = \sum_{i=1}^{12} (S_{op} - \gamma_L(S_0)).$$  

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The Gabor wavelet is chosen because it is directional (in the sense of being effective in selecting orientations) and capable of fine tuning specific frequencies. This latter capability is especially important in filtering out the background noise. These characteristics of the Gabor wavelet represent its advantages with respect to other standard filters such as the Gaussian and its derivatives. Its parameters are chosen to make the filter elongated and a low frequency with few significant oscillations is set for the wavelet’s complex exponential. The transform maximum response (in modulus) calculated from a set of orientations for each position is then taken, emphasizing the blood vessels in all directions and filtering out essentially all the noise.

2.3. MAs Candidate Extraction

A matched filter is used to enhance the contrast between background and microaneurysms in $I_{lesion}$. The matched filter is a 2-D Gaussian with $\sigma = 1$ pixel and size of 11x11 pixels. The resulting filtered image $I_{filt}$ is thresholded to produce a binary image $I_{bin}$. The threshold is fixed at a certain level above the modal value of the image. A region growing procedure is used to grow back the original pathologies in $I_{org}$ from the binary objects in $I_{bin}$. The darkest pixel under each of the binary objects provides the starting point. The background image $I_{bg}$ obtained in the preprocessing step can be used to find the threshold $t$ for the region growing procedure as follows: $t = t_{seed} - x(t_{seed} - i_{bg})$, where $t_{seed}$ is the intensity at the starting position, i.e., the pixel under the binary object with the lowest gray value, $i_{bg}$ is the intensity of the same pixel in the background image and $x \in [0, 1]$. We use $x = 0.5$ as suggested by Spencer et al. [10] and Frame et al. [11]. The region growing algorithm starts in the seed pixel and stops when no more connected pixels below the threshold can be found. The set of grown objects forms the final candidate object set.

3. RESULTS

The methods described in the previous section have been tested on images of publicly available DRIVE database [4], consisting of 40 images (seven of which present some pathology), with manual segmentation of the vessels. Figure 2 shows an example of a green band image provided for test and its corresponding manual segmentation results generated by two observers.

Figure 3 presents the results for vessel segmentation and candidate MAs detection algorithms applied to the image in Figure 2(a). Each vessel segmentation method provided a different result as Figures 3(a), 3(b) and 3(c) show. The candidate MAs appear highlighted in white on the images in Figures 3(d), 3(e) and 3(f). They were obtained according to the general method presented in Section 2.

The wavelet method generated the best vessel segmentation results with sensitivity (true positive ratio) of 0.73498 and specificity (true negative ratio) of 0.98310. The entropic thresholding method presented a slightly worse result, with sensitivity equal to 0.69637 and specificity equal to 0.98288. Although this method has achieved better vessel segmentation results than the mathematical morphology method (sensitivity equal to 0.65630 and specificity of 0.98222) the number of candidates per image (CpI) detected was 0.0, as observed in Figure 3(d) where none candidate appeared highlighted in this retinal image. We conclude that the entropic thresholding method was not able to distinguish between vessels, MAs and background noise properly. This method takes into account only the gray levels, disregarding the shape (morphology) of the image area to be segmented (vessel). On the other hand, methods that take into account the linear shape of the vessels are more suitable to candidate MAs detection.
applications. In this paper we observed from the results that the higher is the vessel segmentation quality the lower is the number of candidate MAs detected. The Cpl values for the morphological (7.4) and wavelet (2.2) methods confirm this inverse relation between vessel segmentation and candidate MAs detection. The inherent smoothing effect provided by the wavelet method, associated with the matched filter in the candidate extraction step, contribute to the smallest number of detected candidates when compared with the morphological method. Furthermore, MAs are present in capillaries in general, which explains the performance of these refined methods. It is worth noting that all candidates detected by the wavelet based method were also detected by the morphological method, as Figures 3(e) and 3(f) highlight.

4. CONCLUSION

Blood vessels segmentation of retinal images is an important step for candidate MAs detection. Once vessels are well-segmented and adequately removed from the image, other lesions resulting from DR can be analyzed. In this paper, three algorithms for vessel segmentation were reviewed, coded, tested and compared. The main purpose of this review is to investigate how these algorithms affect the candidate MAs detection.

Since vessels and candidate MAs present similar tonalities of color, segmentation methods that take only into account gray scale similarities may cause missegmentation of these object in retinal images, i.e. they are inadequate for candidate MAs detection, as the entropic thresholding method. The empirical tests clearly reflect that vessel segmentation methods take into account the linear shape of vessels, as well as the morphological and wavelet based methods, perform better in detecting candidate MAs than the entropic thresholding method.

5. REFERENCES


