IMPROVING MICROANEURYSM DETECTION IN COLOR FUNDUS IMAGES BY USING AN OPTIMAL COMBINATION OF PREPROCESSING METHODS AND CANDIDATE EXTRACTORS

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ABSTRACT

In this paper, we present an approach to improve microaneurysm detection in color fundus images. This task is usually realized by candidate extraction, which is followed by a classification step. The proposed method aims to increase the number of true positives in the first phase of the microaneurysm detection process. Thus, we establish a framework for selecting an optimal combination of preprocessing methods and candidate extractors. Our investigation shows that the state-of-the-art candidate extractors provide significantly improved results, when they are optimally combined with preprocessing approaches. We show that this performance can be further increased with an ensemble formed by a globally optimal combination of the preprocessing methods and candidate extractors.

1. INTRODUCTION

Diabetic retinopathy (DR) is the most common cause of blindness in the developed countries. DR can be prevented and its progression can be slowed down if diagnosed and treated early. Proper medical protocols have been established [1], but the actual grading required for diagnostics has been performed manually. Manual grading is slow and resource demanding, so several efforts have been made to compose an automatic computer-aided screening system in this field [2]. The screening is based on the processing of digital fundus images (see Figure 1).

Microaneurysms (MA) are early signs of DR, so the detection of these lesions is essential in an efficient screening process. Microaneurysms appear as small circular dark spots on the surface of the retina. The most common appearance of microaneurysms is near thin vessels, but they cannot actually lie on the vessels. In some cases, microaneurysms are hard to distinguish from parts of the vessel system. For example, the intersections of two thick vessels or a few very thin vessels are rather misleading for the detectors. The detection of microaneurysms is still an open issue. Thus, several recent works focus on this problem, including an online challenge for MA detectors [3].

Microaneurysm detection is based on the analysis of digital fundus images. The detection process starts with preprocessing of the images, which is followed by a candidate extraction phase. Then the extracted candidates are classified (see Figure 2). In this paper, we present an approach to increase the microaneurysm detection rate by using an optimal combination of preprocessing methods and candidate extractors.

Individual candidate extractors do not provide sufficient number of true positives. Consequently, the classification stage will be less accurate, as well. Besides the preprocessing recommendations for the individual extractors, there are other methods which can further improve the extractibility of the microaneurysms from the other parts of the fundus. Since the preprocessing methods provide rather different image input, further improvement can be reached if we merge the output sets of a candidate extractor for the different preprocessed outputs. We introduce an approach for selecting the optimal combination dynamically. We show that most of the candidate extractors provide improved results using this method. This achievement can be further increased, when we organize the candidate extractors and the preprocessing methods into a system, and perform a combination. With this approach, a globally optimal solution has been found, which resulted in the detection of the 99% of the microaneurysms in our test dataset. As it can be seen later, in the ensemble system it is not evident to select the individually best performing combinations for the global solution.

The rest of the paper is organized as follows: in section 2, we introduce four state-of-the-art candidate extractors. In section 3, we present a brief summary of the inves-

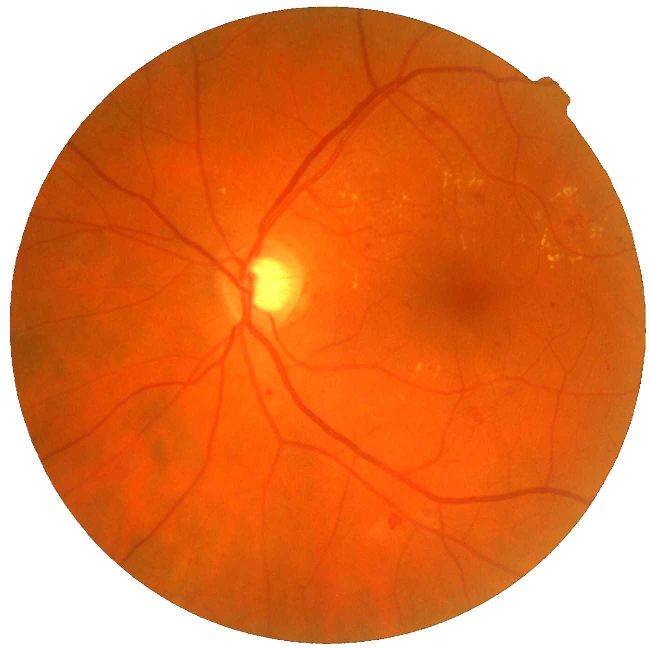

Figure 1: Sample digital fundus image from the dataset without preprocessing.

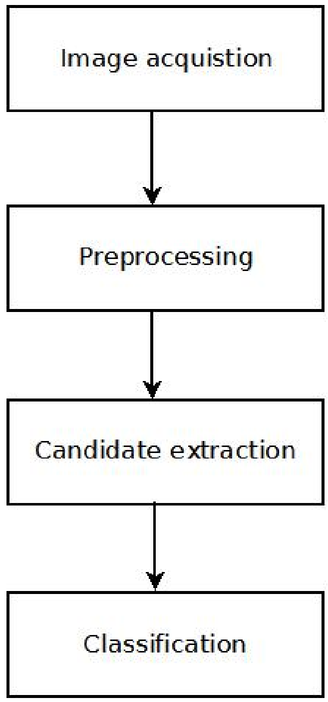

Figure 2: Stages of microaneurysm detection.

tigated preprocessing methods. Then, in section 4 we establish a method to combine these methods. Section 5 contains our quantitative results regarding the selection of the optimized preprocessing methods both for the individual algorithms and also for their combination. Finally, some conclusions are drawn in section 6.

2. MICROANEURYSM CANDIDATE EXTRACTORS

Candidate extraction is an effort to reduce the number of objects in an image for further analysis by excluding regions which do not have similar characteristics to microaneurysms. Individual approaches define their own measurement for similarity to extract MA candidates. In this section, we provide a brief overview of the selected candidate extractors, as the current state-of-the-art literature recommendations.

2.1 Walter et al.

The approach proposed in [4] is a mathematical morphology based one, which recommends contrast enhancement and shade correction as preprocessing steps. Candidate extraction is then accomplished by grayscale diameter closing.

2.2 Spencer-Frame

This approach is one of the most popular candidate extractors, originally proposed by Spencer [5] and Frame [6]. The algorithm uses shade correction as preprocessing. The actual candidate extraction is accomplished by subtracting the maximum of multiple morphological top-hat transformation. The resulting image is binarized after applying a Gaussian filter. Since the obtained candidates are not good representations for the actual lesions, a region growing step is also applied.

2.3 Circular Hough-transformation based

Based on the idea presented in [7], we established an approach based on the detection of small circular spots in the image. The obvious choice for this procedure is to use circular Hough-transformation.

2.4 Lazar et al.

This method has been developed by our research group. The green channel of the image is inverted and smoothened with a Gaussian filter. A set of scan lines with equidistantly sampled tangents between -90° and +90° is fixed. For each direction the intensity values along the scan lines are recorded in a one dimensional array, and the scan lines are shifted vertically and horizontally to process every image pixel of the image. On each intensity profile, the heights of the peaks, and their local maximum positions are used for an adaptive thresholding. The resulting foreground indices of the thresholding process are transformed back to two dimensional coordinates, and stored in a map that records the number of foreground pixels of different directions corresponding to every position of the image. The maximal value for each position equals the number of different directions used for the scanning process. This map is smoothened with an averaging kernel and a hysteresis thresholding procedure is applied. The resulting components are filtered based on their size. For more details, see [8].

3. PREPROCESSING METHODS

In this section, we present the selected preprocessing methods, which can be inserted before executing candidate extraction. These algorithms were collected from corresponding literature recommendations. They do not replace the built-in preprocessing methods of the candidate extractors, but are realized as independent steps.

The use of the selected preprocessing methods aims to enhance the accuracy of the microaneurysm detection in different ways. Namely, our experiments showed that Contrast Limited Adaptive Histogram Equalization is very effective in emphasizing locally salient values, but also produces noise. The contrast enhancement technique by Walter and Klein resulting in a grayscale image with a smooth background and emphasized salient parts, while the vessel removal and extrapolation method aims to reduce the false positives which caused by the similar appearance of vessel parts and microaneurysms. Our results showed that applying these preprocessing methods increase the accuracy of the individual candidate extractors.

3.1 Contrast Limited Adaptive Histogram Equalization (CLAHE)

Contrast Limited Adaptive Histogram Equalization [9] is a common preprocessing method for medical imaging, because it is very effective in making the interesting parts more visible. It is based on local histogram equalization of disjoint regions extracted from the image. To eliminate the boundaries between the regions, a bilinear interpolation is also applied. An example can be seen in Figure 3.

3.2 Walter-Klein contrast enhancement (WK)

This preprocessing algorithm is proposed in [10]. It aims to enhance the contrast on fundus images by applying a gray

Figure 3: Sample image from the dataset with CLAHE applied.

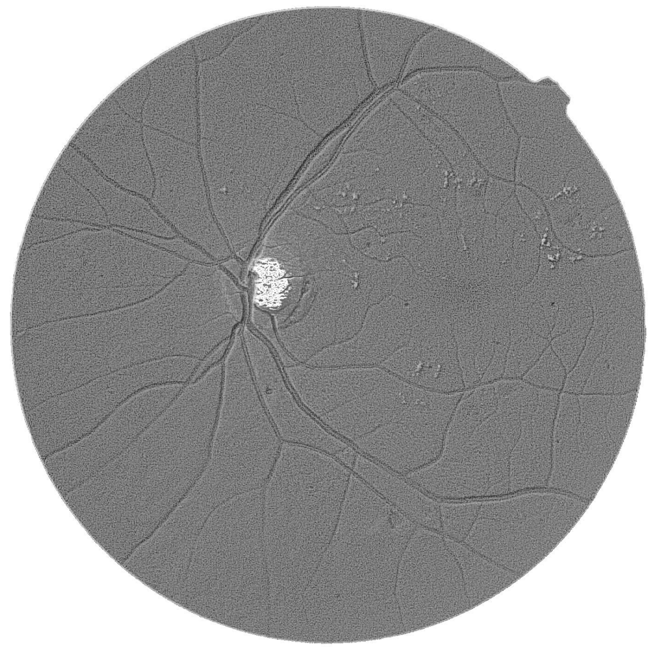

Figure 4: Sample image from the dataset with Walter-Klein contrast enhancement applied.

level transformation. Walter et al. defined the local contrast enhancement operator in the following way:

$$u = \begin{cases} \frac{\frac{1}{2}(u_{max}-u_{min})}{(\mu_f - t_{min})^r} \cdot (t - t_{min})^r + u_{min}, & t \leq \mu_f, \\ \frac{-\frac{1}{2}(u_{max}-u_{min})}{(\mu_f - t_{max})^r} \cdot (t - t_{max})^r + u_{max}, & t \geq \mu_f, \end{cases}$$

where $\{t_{min}, \dots t_{max}\}$ are the intensity values of the grayscale image, $\{u_{min}, \dots u_{max}\}$ are the intensity values of the enhanced image, μ_f is the mean value of the grayscale image and $r \in \mathbb{R}$. For a result with WK applied, see Figure 4.

3.3 Vessel removal and extrapolation

Most of the false positives during microaneurysm detection caused by the similar appearance of a few parts of the vessel system. Based on the idea proposed in [11], we investigate the effect of processing images with the complete vessel system removed. To fill in the holes caused by the removal, we extrapolate the missing parts. Figure 5 shows an example for this preprocessing method.

4. COMBINATION

The proposed framework aims to find an optimal combination of preprocessing methods and candidate extractors. For this task, we generate the results for each candidate extractors using the selected preprocessing method. We also consider the output generated for the original dataset. That is, we combine the results of candidate extractors applied on preprocessed images, and we also include the results on the non-preprocessed images. Then, we search for the optimal combination with simulated annealing.

Simulated annealing [12] is a widely used global optimization method. This approach is inspired by the annealing in metallurgy. It is effective for large search space problems by using random sampling to avoid stuck in a local minimum. For the optimization, we use the following energy function to be minimized:

$$E = \frac{1}{TP} \cdot \ln \frac{FP}{TP},$$

where TP stands for the number of the true, while FP stands for that of false positive candidates, respectively. This function provides low values for a high true positive count, but it penalizes the growth of false positives with the increase of the true ones. Thus, we search for an optimal solution, where the highest number of TPs found with keeping the TP / FP ratio small.

To minimize the target energy E by simulated annealing, each element of the search space S relies on a combination of preprocessing methods and candidate extractors, and consists of a set of candidates which is created by the union of the outputs of the algorithm using the corresponding approaches.

The proposed combination can be described formally by the following algorithm:

1. Let T be an initial temperature, T_{min} a minimal temperature, $0 \leq q \leq 1, q \in \mathbb{R}$ the temperature change, $S = P\{R_{c,p}\}$ the search space, where R is the result of the candidate extractor c using the preprocessing method p, and $P\{X\}$ is the power set of X.
2. Choose $x \in S$ randomly, and let $e = E(x)$.
3. Choose $x_i \in S$ randomly, and let $e_i = E(x_s)$.
4. If $T < T_{min}$, stop.
5. If $e_i < e$ then $x = x_i$, $e = e_i$ and $T = T \cdot q$,. Go to step 4.
6. Choose a random number $r \in \mathbb{R}$. If $accept(e, e_i, T, r) = true$, then $x = x_i$, $e = e_i$, where
$$accept(e, e_i, T, r) = \begin{cases} true, & if \exp\left(\frac{e-e_i}{T}\right) > r, \\ false, & otherwise. \end{cases}$$
7. Let $T = T \cdot q$. Go to step 4.

Figure 5: Sample image from the dataset after vessel removal and extrapolation.

Currently, we consider four preprocessing methods and four candidate extractors, but with the use of simulated annealing it can be easily extended to more methods in the future.

5. RESULTS

We have tested our approach on 50 images selected from the Retinopathy Online Challenge (ROC) database [3]. Currently, it is the only publicly available fundus image database dedicated to measure the accuracy of microaneurysm detectors. In Table 1, we give the number of true positives (TP) and the false ones (FP) found by the individual algorithms with considering only one preprocessing method.

		Original	WK	CLAHE	Vessel
Walter	TP	120	202	199	154
	FP	6748	27811	15173	8801
	E	0.034	0.024	0.022	0.026
Spencer	TP	45	29	60	31
	FP	1632	1526	3063	1342
	E	0.080	0.137	0.066	0.122
Hough	TP	6	41	125	3
	FP	3090	5967	14467	1221
	E	1.041	0.121	0.038	2.003
Lazar	TP	113	116	191	69
	FP	771	7469	20888	539
	E	0.017	0.036	0.025	0.030

Table 1: Performance of the candidate extractors using a single preprocessing method.

Table 2 shows the optimal selections of preprocessing methods for all the individual candidate extraction algorithms. As we can see, all but one candidate extractors earned higher performance after combination. That is, the method by Lazar et al. provided better results using the non-preprocessed images. The highest TP increase was achieved by the Spencer-Frame algorithm. For a more intuitive interpretation of the results presented in Table 2 we include Figure 6, as well.

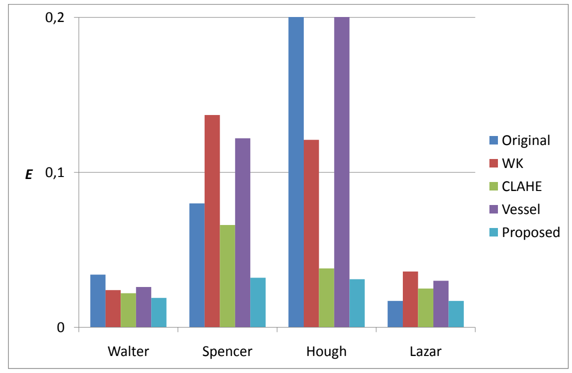

Figure 6: Energy function values for the candidate extractors combined with preprocessing methods. The lower the value the better the performance.

Walter	
Preprocessing:	WK, CLAHE, Vessel
TP:	254
FP:	33695
E:	0.019
Spencer	
Preprocessing:	all
TP:	124
FP:	6686
E:	0.032
Hough	
Preprocessing:	WK, CLAHE, Vessel
TP:	151
FP:	18429
E:	0.031
Lazar	
Preprocessing:	Original
TP:	113
FP:	771
E:	0.017

Table 2: Performance of the candidate extractors combined with preprocessing methods.

We also formed an ensemble from all the candidate extractors using all the preprocessing methods. The ensemble of the candidate extractors and preprocessing methods is composed by merging their candidate output sets by a simple set union. For these data a simulated annealing algorithm is performed, which is analogous to the above disclosed one, to find the combination of the preprocessing algorithms and candidate extractors that are optimal for this ensemble. The corresponding results and optimal selection of the algorithms are shown in Table 3. This approach outperforms the individual algorithms, since the ROC database contains 336 microaneurysms from which the ensemble successfully recognized 331. This number is much higher than the ones found by the individual approaches. Besides the successful extraction of TP candidates, the comparison of Table 2 and 3 reflects the power of the ensemble-based approach. Namely, we can see in the ensemble that not exactly those preprocessing methods and candidate extractors are recommended that gave the optimal results for the individual algorithms.

Candidate extractor	Preprocessing
Walter	WK
Walter	CLAHE
Walter	Vessel
Hough	WK
Hough	CLAHE
Lazar	Original
Lazar	WK
Lazar	CLAHE
TP:	**331**
FP:	**46434**
E**:**	**0.015**

Table 3: Optimal solution for the ensemble.

6. CONCLUSION

In this paper, we have presented an approach to optimally combine preprocessing methods and candidate extractors for microaneurysm detection. With this approach, we have successfully increased the number of TPs in the individual cases. We have also formed an ensemble from the methods, and this approach resulted in a 99% sensitivity. Our method significantly improves the detection of actual microaneurysms with respect to the increment of FPs.

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