Proceedings of the 8th International Conference on Applied Informatics
Eger, Hungary, January 27–30, 2010. Vol. 1. pp. 149–156.

Novel Approaches to Improve Microaneurysm Detection in Retinal Images

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Abstract

In this paper, we present a novel approach to improve microaneurysm candidate extraction in color fundus images. The individual algorithms published so far can be hardly considered in an automatic screening system. To improve further the sensitivity, specificity and image classification rate of microaneurysm detection we propose an appropriate combination of individual algorithms. Thus, we investigate the detection of microaneurysms through the following phases: first, we use different approaches to extract microaneurysm candidates. Then, we select candidates voted by a sufficient number of candidate extractor algorithms. Finally, we classify the candidates with a machine-learning based approach. Our framework improves the positive likelihood ratio and outperforms both state-of-the-art individual candidate extractors and microaneurysm detectors in these terms.

Keywords: Biomedical image processing, Image classification, Pattern recognition, Medical decision-making, Statistics

1. Introduction

Diabetic retinopathy (DR) is the most common cause of blindness in the developed countries. Microaneurysms (MA) are early signs of this disease, so the detection of these lesions is essential in the screening process. DR can be prevented and its progression can be slowed down if diagnosed and treated early. A proper medical protocol has been established, 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 establish an automatic computer-aided screening system [1]. However, the detection of microaneurysms is still an open issue. Thus, several recent works focus on this problem, including an online challenge for MA detectors [2].

In this paper, we propose an ensemble-based approach to MA detection to suppress the errors of individual algorithms. The proposed process consists of three main stages (see Figure 1): first, we extract MA candidates from fundus images. For this task, we select three state-of-the-art approaches and include a novel one, as well. In the second phase, we combine the results provided by the four candidate extractors and reduce the number of candidates with a voting scheme. We also investigate the effect of using different number of votes for selection. Finally, we introduce a novel machine-learning based algorithm to classify the candidates. With this ensemble method state-of-the-art microaneurysm candidate extractors are outperformed.

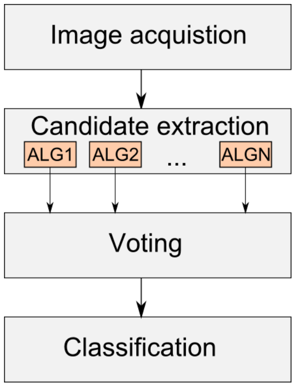

Figure 1: Steps of microaneurysm detection using an ensemble of candidate extractors.

2. Microaneurysm detection

Microaneurysms appear as small circular dark spots on the surface of the retina (see Figure 2). 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.

2.1. Candidate extraction

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

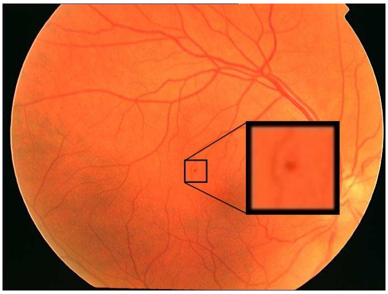

Figure 2: Fundus image containing a microaneurysm.

currently popular candidate extractors that will be considered later on in the ensemble system. Namely, we cite Walter et al. [3], the Spencer-Frame method [4] [5] in its original form, and a slightly modified version of [6]. A new approach is also involved, whose development was partly motivated by to improve the MA candidate extraction efficiency of the proposed ensemble-based system. As we will see later on, these methods sufficiently diverse to form a successful ensemble.

2.1.1. Walter et al.

The approach proposed in [3] is a mathematical morphology based method, which recommends contrast enhancement and shade correction as preprocessing steps. Candidate extraction is then accomplished by grayscale diameter closing.

2.1.2. Spencer-Frame

This approach is one of the most popular candidate extractors, originally proposed by Spencer [4] and Frame [5]. 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 candidates are not a good representation for the actual lesions, a region growing step is also applied.

2.1.3. Circular Hough-transformation based

Based on the idea presented in [6], 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, which is preceded by contrast limited adaptive histogram equalization for preprocessing.

2.1.4. Lazar et al.

This method has been developed by our research group to improve MA detection. 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.

2.2. Combining the candidate extractors

As the most straightforward measure, we aim to raise the the positive likelihood ratio (true positive (TP) / false positive (FP)) using an ensemble. It is important to use diverse candidate extractors, that is, to reduce the number of false positives efficiently and keep only those candidates on which multiple methods agree. In 2.2.1 we show the diversity of the methods measured by the double fault and disagreement measure. For the proper comparison of the candidates extracted by the individual approaches, we will have to merge them if they are sufficiently close to each other, as well.

2.2.1. Diversity of the candidate extractors

The pairwise diversity of the classifiers can be measured by the disagreement (D) and double fault (DF) measure [7]. The disagreement measure sums the cases where the extractors disagree, but one of them is correct. The double fault measure is the number of candidates, where both extractors agree and both are incorrect. For our aims, a high disagreement and a low double fault measure is ideal. As it can be seen in Table 1, the selected candidate extractors are quite diverse.

Walter	Spencer	Hough	Lazar	D	DF
x	x			0,73	0,09
x		x		0,77	0,04
x			x	0,49	0,10
	x	x		0,79	0,06
	x		x	0,69	0,14
		x	x	0,74	0,12

Table 1: Diversity of the candidate extractors.

2.2.2. Preprocessing the candidates

Before letting the algorithms vote, we must ensure that there are no candidates too close to each other within the output of an individual algorithm. This issue is addressed by merging them. It is also important to remove any candidates falling on the vessel system. For this purpose, we have detected the vascular system with the algorithm proposed in [8].

2.2.3. Voting on the candidates

Each individual algorithm produces an initial set of microaneurysm candidates. Then, we establish a set of final candidates, where these candidates are voted by at least $n \geq 2$ candidate extractors. The voting procedure has the following steps:

1. For each candidate c provided by one of the algorithms, check whether there is another candidate detected by another algorithm within a distance $r \in \mathbb{R}$ from c.

2. Let sum be the number of candidates satisfying the above proximity criterion and remove all these candidates from their respective initial sets.

3. If $sum \geq n$, then add the centroid of the candidates found by step 2 to the final set.

4. Repeat the procedure until all the initial sets become empty.

2.3. Candidate classification

To improve the TP / FP ratio we can use a classifying step, which is based on certain unique features of microaneurysms. We use a new approach to demonstrate the effect of this step, instead of other literature recommendations. The reason to introduce a new approach is that the existing methods use objects and not single pixels representations to extract features, while our ensemble-based system provides the latter.

Candidates are classified as actual MAs or not MAs in two steps. First, we train our approach with several fixed size (e.g. 21×21 pixels) subimages for both microaneurysm and random non-microaneurysm examples. Then, for each pixel of the examples, we establish a kernel density estimator for both classes. After the training step, we can classify new instances. We establish a new instance by producing a subimage of the candidate pixel and its neighborhood with the same size as the training step. The classification procedure is the following: for each pixel of the instance we compare the probability provided by the kernel density estimators for both classes. Then, the candidate is considered as a microaneurysm if more comparisons confirm that this is a positive example.

3. Results

We have tested our approach on 50 images selected from the Retinopathy Online Challenge database [2]. Currently, it is the only publicly available fundus image database dedicated to measure the accuracy of microaneurysm detectors.

To increase the positive likelihood ratio we consider those candidates only, which have a given number of votes. As it can be seen in Table 2, this ratio increases with the number of votes. It is also clearly visible that the ensemble system (independently of the number of votes) outperforms the individual candidate extractors. The largest positive likelihood ratio has been found, when all the 4 votes were required. The number of candidates decreases with the raise of votes, while the positive likelihood ratio shows an increase, as it can be observed in Figure 3 with requiring 4 votes instead of 3.

3.1. Comparison with individual candidate extractors

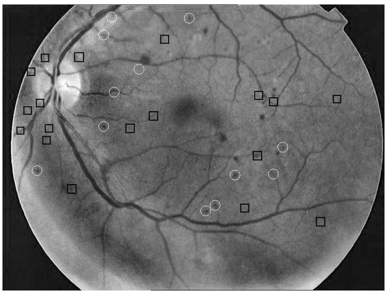

Figure 3: The effect of using different number of votes. The black rectangles represent the candidates voted by three algorithms, while the white circles are considered as a microaneurysm by four candidate extractors.

3.2. Comparison with a microaneurysm detector

It is also interesting to compare our approach to a state-of-the-art microaneurysm detector. [9] uses a similar candidate extraction algorithm as the Spencer-Frame method, but it relies on a different approach for the final candidate classification. The ensemble system outperforms this algorithm (See Table 3) without even classifying the candidates. However, if we apply our classification procedure explained in section 2.3, we can gain further improvement as it is also shown in Table 3.

Algorithm	**Candidates**	**TP**	**FP**	**TP / FP**
Walter	2831	110	2721	0,040
Spencer-Frame	5821	115	5706	0,020
Hough	15664	94	15570	0,006
Lazar	11040	197	10843	0,018
Ensemble (2 votes)	868	69	799	0,086
Ensemble (3 votes)	847	72	775	0,093
Ensemble (4 votes)	441	44	397	0,117

Table 2: Comparison of microaneurysm candidate extractors. In the ensemble system, we consider the combination corresponding to the largest TP / FP value for each voting.

Algorithm	**Candidates**	**TP**	**FP**	**TP / FP**
Mizutani [9]	225	20	205	0,097
Ensemble (4 votes)	441	44	397	0,117
Ensemble (4 votes, classified)	270	36	234	0,153

Table 3: Comparison with a microaneurysm detector.

4. Conclusion

In this paper, we have introduced a novel approach for microaneurysm detection which is based on an ensemble of several candidate extraction methods. With this technique, we have successfully reduced the number of candidates using a voting scheme. Besides the reduction of the number of false candidates, we have increased the positive likelihood rate. We have also showed that with a consequent classification step, these results can be improved further.

Acknowledgement

This work was supported in part by the János Bolyai grant of the Hungarian Academy of Sciences, and by the TECH08-2 project DRSCREEN - Developing a computer based image processing system for diabetic retinopathy screening of the National Office for Research and Technology of Hungary (contract no.: OM-00194/2008, OM-00195/2008, OM-00196/2008). We also acknowledge the Moorefields Eye Hospital, London for their clinical support.

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