INTERNAL COMPONENTS COMBINATION TO DETECT MICROANEURYSM

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ABSTRACT

Diabetic retinopathy (DR) is one of the most common cause of blindness. Micro aneurysms (MAs) 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. Micro aneurysm appear as small circular dark spots on the surface of the retina. A key feature to recognize DR is to detect micro aneurysms (MAs) in the fundus of the eye.This approach is an effective MA detector based on the combination of pre-processing methods and candidate extractors. We will provide an ensemble creation framework to select the best combination. An exhaustive quantitative analysis is also given to prove the superiority of our approach over individual algorithms. We also investigate the grading performance of our method, which is proven to be competitive with other screening systems.

1. INTRODUCTION

Diabetic retinopathy (DR) is a serious eye disease originating from diabetes mellitus and the most common cause of blind-ness in the developed countries. Early treatment can prevent patients to become affected from this condition or at least the progression of DR can be slowed down. The key to the early detection is to recognize microaneurysms (MAs) in the fun-dus of the eye in time. Thus, mass screening of diabetic pa-tients is highly desired, but manual grading is slow and re-source demanding. Therefore, several efforts has been made to establish reliable computer-aided screening systems in this field.

Computer-aided MA detection is based on the detailed analysis of digital fundus images (an example shown in Fig-ure 1). MAs appear as small circular dark spots on the surface of the retina. The detection of MAs is still not sufficiently re-liable, as it is hard to distinguish them from certain parts of the vascular system. This problem increases the number of false candidates that naturally deteriorates the overall accu-racy of the detectors. To overcome this difficulty, we propose the creation of an ensemble of hpreprocessing method, can-didate extractori pairs using state-of-the-art individual algo-rithms. Since a large number of combinations can be created,

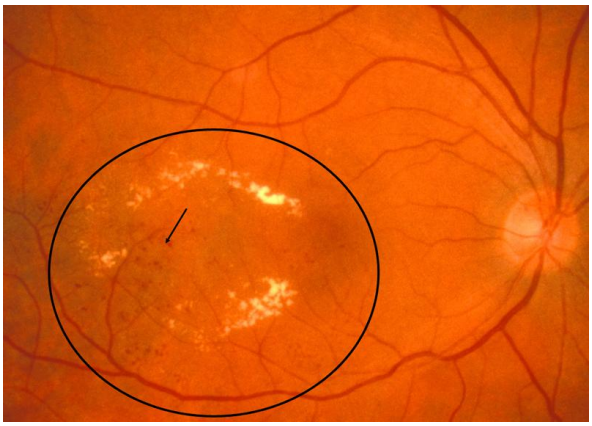

Fig. 1. Sample digital fundus image with a microaneurysm.

we selected the optimal subset of such pairs with a simulated annealing-based search algorithm.

The rest of the paper is organized as follows: in Section 2 and 3, we provide a brief overview of the state-of-the-art preprocessing methods and candidate extractors involved in the ensemble, respectively. In Section 4, we present our com-bination approach to form an optimal ensemble. Section 5 summarizes our experimental results regarding the Retinopa-thy Online Challenge [1], where our proposed algorithm has achieved the best score. Finally, we draw conclusions in Sec-tion 6.

2. PREPROCESSING METHODS

In this section, we present the selected preprocessing meth-ods, which can be applied before executing MA candidate extraction. These algorithms are collected based on current corresponding literature recommendations for medical image processing.

2.1. Walter-Klein contrast enhancement [2]

This preprocessing algorithm aims to enhance the contrast of fundus images by applying a gray level transformation using

the following operator:

$$u = 8^{\frac{2_1(u_{max} \quad u_{min\ r})}{2_1(f_{umax} t_{min} u)_{min}}} (t \quad t)_r + u \quad ; \quad _{min} \quad r \quad _{min} \quad \underline{t} \quad f ;$$

:

where

$$ft_{min}; : : : ; t_{max}g; fu_{min}; : : : ; u_{max}g$$

are the intensity values of the grayscale and the enhanced im-age, respectively, $_f$ is the mean value of the grayscale image and r 2 R.

2.2. Contrast Limited Adaptive Histogram Equalization [3]

Contrast Limited Adaptive Histogram Equalization (CLAHE) [3] is a popular technique in biomedical image processing, since it is very effective in making the usually interesting parts more visible. The image is split into disjoint regions, on which local histogram equalization is applied. Then, the boundaries between the regions are eliminated with a bilinear interpolation.

2.3. Vessel removal and extrapolation [4]

We investigate the effect of processing images with the com-plete vessel system being removed, based on the idea pro-posed in [4]. We extrapolate the missing parts to fill in the holes caused by the removal using the inpainting algorithm presented in [5].

2.4. Illumination equalization [6]

This preprocessing method aims to reduce the vignetting effect, which causes uneven illumination of retinal images. Each pixel is set according to the following formula:

$$u_{eq} = u + m \quad A;$$

where u_{eq}; u are the new and the original pixel intensity val-ues, respectively, m is the desired average intensity and A is the local average intensity.

2.5. No preprocessing

We also include in the ensemble the results of the candidate extractors on the original images without any preprocessing.

3. MICROANEURYSM CANDIDATE EXTRACTORS

Candidate extraction is a process which aims to spot objects in the image showing MA-like characteristics. Individual MA detectors follow their own way to extract MA candidates. In this section, we provide a brief overview of the candidate ex-tractors involved in our analysis.

3.1. Walter et al. [7]

Candidates appear as sufficiently small dark patterns on the green channel of the image, which are extracted using grayscale diameter closing. The final MA candidates are the remaining objects in the image after executing this operation.

3.2. Spencer-Frame [8] [9]

This approach is one of the most popular candidate extrac-tors, originally proposed in [8] and [9]. The actual candi-date extraction is accomplished by subtracting the maximum of multiple morphological top-hat transformations. For this step, twelve rotated structuring elements are used with a ra-dial resolution of 15 . Then, the resulting image is subtracted from i_{SC} to remove the largest components from the image. In the next step, a 2D Gaussian matched filter is applied on the obtained image. Finally, the resulting image is thresholded and a region growing step is applied.

3.3. Circular Hough-transformation [10]

Candidate extraction is executed by detecting circles on the images in this method. For this purpose, we use circular Hough transformation [11]. The radius of the circles are set according to the size of MAs from a training set.

3.4. Lazar et al. [12]

Pixel-wise cross-section profiles with multiple orientations are used to construct a multi-directional height map. This map assigns a set of height values that describe the dis-tinction of the pixel from its surroundings in a particular direction. In a modified multilevel attribute opening step a score map is constructed, from which the MAs are extracted by thresholding.

3.5. Zhang et al. [13]

This method is based on multi-scale correlation filtering and dynamic thresholding. For the first task, it uses five Gaussian masks with different sigmas. The maximum coefficients from the five responses are then combined.

4. ENSEMBLE CREATION

A pair from each preprocessing method and candidate ex-tractor is formed by generating the output of the candidate extractor on the training images with the given preprocess-ing method applied. We combine such pairs by applying a voting among their outputs. We use a simulated annealing-based search algorithm [14] to select an optimal combination. The search space consists of each possible combination of hpreprocessing method, candidate extractori pairs. Elements of the search space are evaluated using an energy function E

which is the average specificity at seven predefined false positive rates (from 1=8 to 8) as described in [1]. The optimal solution provides the highest energy value.

The formal general description of the proposed combination is as follows:

Algorithm 1*:* Optimal combination of preprocessing methods and candidate extractors.

Input:

An initial temperature T 2 R.

A minimal temperature T_{min} 2 R.

A temperature change q 2 R with 0 q 1.

A set

$$S = fhPP_i; CE_{jij}\ i = 1; : : : ; N; j = 1; : : : ; Mg$$

containing all hpreprocessing method, candidate extrac-tori pairs.

A search space U = P (S), where P is the power set containing all collections of hpreprocessing method, candidate extractori pairs.

A function rand (X), which chooses a random element x from the set X.

A function accept : R R R [0; 1] ! ftrue; falseg, which is defined in the following way:

$$\text{accept}(e; e_i; T; r) = \begin{cases} \text{true}; & \\ \text{false}; & \text{otherwise}: \end{cases} \quad \exp^{\frac{e\ e_i}{T}} > r;$$

An energy function E : U ! R, as described above.

Output:

$x_{optimal}$ 2 U, where E ($x_{optimal}$) = max$_{x \in U}$ E (x) .

1. X r(U)
2. E E (x)
3. U U x
4. **while** U 6= ; and T > T_{min} **do**
5. x_i r(U)
6. e_i E (x_i)
7. U U x_i
8. **if** e_i > e **then**
9. x x_i
10. e e_i
11. T T q
12. **else**
13. r rand (R)
14. **if** accept (e; e_i; T; r) = true **then**
15. x $\hat{x}_i$
16. e e_i
17. T T q
18. **end if**
19. **end if**
20. **end while**
21. **return** x

5. RESULTS

Retinopathy Online Challenge (ROC) [1] is a worldwide competition dedicated to measure the accuracy of microa-neurysm detectors. Each participant has the opportunity to train their algorithm on a dataset consisting of 50 im-ages. The detectors are compared based on the results on an independent test set of 50 images. We have used this training set to determine the optimal set of hpreprocessing method, candidate extractori pairs. The following pairs were selected by the algorithm: hNo preprocessing, Walteri, hCLAHE, Walteri, hNo preprocessing, Lazari, hVessel Re-moval, Lazari, hCLAHE, Lazari, hIllumination equalization, Lazari, hNo preprocessing, Zhangi, hWalter-Klein, Zhangi, hVessel Removal, Zhangi.

Table 1 shows the comparative results of the participat-ing algorithms, with the proposed one (DRSCREEN) high-lighted. Each row contains the average sensitivity at seven predefined false positive rates (from 1/8 to 8). The FROC curve showing the performance of the algorithm can be seen in Figure 2.

	1/8	1/4	1/2	1	2	4	8	avg.
DRSCREEN	**0.173**	**0.275**	**0.380**	**0.444**	**0.526**	**0.599**	**0.643**	**0.434**
Niemeijer et al.	0.243	0.297	0.336	0.397	0.454	0.498	0.542	0.395
LaTIM	0.166	0.230	0.318	0.385	0.434	0.534	0.598	0.381
OKmedical	0.198	0.265	0.315	0.356	0.394	0.466	0.501	0.357
Lazar et al.	0.169	0.248	0.274	0.367	0.385	0.499	0.542	0.355
GIB	0.190	0.216	0.254	0.300	0.364	0.411	0.519	0.322
Fujita	0.181	0.224	0.259	0.289	0.347	0.402	0.466	0.310
IRIA	0.041	0.160	0.192	0.242	0.321	0.397	0.493	0.264
ISMV	0.134	0.146	0.202	0.249	0.286	0.345	0.430	0.256
Waikato	0.055	0.111	0.184	0.213	0.251	0.300	0.329	0.206

Table 1. Comparative results of the ROC competition.

As we can see from the table, the proposed ensemble out-performed the individual algorithms.

6. CONCLUSION

In this paper, we have proposed an ensemble-based microa-neurysm detector, which have proved its high efficiency in an open online challenge. This approach relies on a set of hpreprocessing method, candidate extractori pairs, from

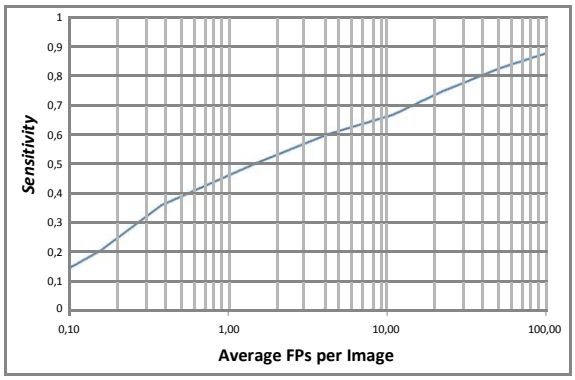

Fig. 2. FROC curve of the detector based on the ROC com-petition.

which a simulated annealing-based search algorithm selects an optimal combination. Since our approach is modular, we can expect further improvements by adding more preprocess-ing methods and candidate extractors.

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