A TWO-PHASE PRE-FILTERING APPROACH TO THE AUTOMATIC SCREENING OF DIGITAL FUNDUS IMAGES

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Abstract: In this paper, we present an approach to decrease the computational burden of an automatic screening system designed for diabetic retinopathy. The proposed method consists of two steps. First, a pre-screening algorithm is considered to classify the input digital fundus images based on their abnormality. If an image is found to be abnormal, it will not be analyzed further with robust lesion detector algorithms. As an improvement, we introduce a novel feature extraction approach based on clinical observations. The second step of the proposed method detects regions which contain possible lesions for images that have been passed pre-screening. These regions will serve as inputs to lesion detectors later on, which can achieve better computational performance by operating on specific regions only instead of the entire image. Experimental results show that both two steps of the proposed approach are valid to efficiently exclude a large amount of data from further processing to improve the performance of an automatic screening system.

1 INTRODUCTION

Retinal fundus photographs are widely used in the diagnosis and consequent treatment of various eye diseases, such as diabetic retinopathy (DR), age related macular degeneration (AMD) and glaucoma. DR is one of the most frequent causes of visual impairment in developed countries and is the leading cause of new cases of legal blindness among those in the working age. DR can be prevented and its progression slowed down if diagnosed and treated early. Screening for DR is the mainstay of identifying patients at risk. The result of screening is determined by the recognizable lesions of the retina.

Nowadays, automated detection systems have become very popular in medical imaging, including DR screening (Abramoff et al., 2008). Our current interest is to develop an automatic system to detect abnormalities caused by DR. We also consider the insertion of a pre-filtering phase before the detailed analysis, which is, to the best of our knowledge, is not a part of other systems. Our approach is realized in two steps: pre-screening and pre-filtering. During *pre-screening*, we classify the images as severely diseased (highly abnormal) or to be forwarded to further processing. The aim of this step is twofold. On the one hand, we minimize the risk that an abnormal image pass the screening without a warning, since it is immediately spotted by the automatic system before detailed analysis. On the other hand, we save computational time, since only the not abnormal fundus images are analyzed in details. Figure 1 gives an impression about these two classes. In the case of fundus images, machine learning algorithms are often applied to classification based on feature vectors. We extract features based on clinical observations about the inhomogeneity of the diseased retina.

As a second – *pre-filtering* – step of our approach, we extract those candidate subregions of fundus images that are expected to contain specific lesions. The

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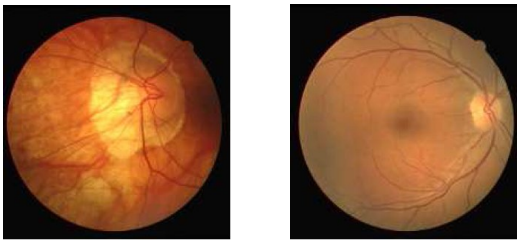
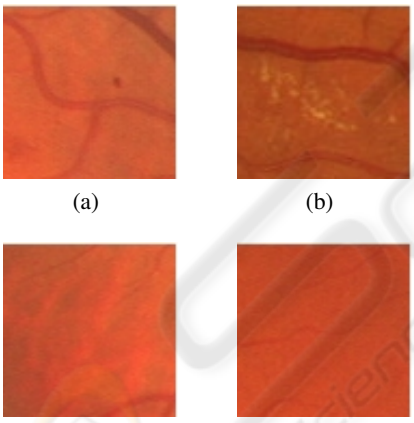
most common lesion on the fundus is the microaneurysm (see Figure 2a), which is an early sign of diabetic retinopathy. A microaneurysm appears as a small red spot on the retina.



(a) (b)

Figure 1: Samples from the image set (both taken from the DRIVE database (Staal et al., 2004)); (a) abnormal fundus, (b) fundus image that needs detailed analysis.

The detection of DR related bright lesions (exudates) has a rich literature, as well. Exudates appear at an advanced stage of diabetic retinopathy (see Figure 2c). The retinal pigment epihelium (RPE) is usually caused by age-related macular degeneration. The sign of RPE is the inhomogeneous surface of the retina, as it is shown in Figure 2c.



(a) (b)

(c) (d)

Figure 2: (a) microaneurysms, (b) bright lesions (exudates), (c) retinal pigment epihelium, (d) normal retina.

To find candidate regions containing lesions, our approach is based on the fact that asides form its anatomical parts, the intensity values of the normal retina surface have small saliences (see Figure 2d). If there is a connected set of salient values with a given cardinality, we can assume that there is a lesion within the examined region. The goal is to preserve those regions only, which possibly contain lesions. The rest of the paper is organized as follows. In section 2 we present our approach for classifying the images as abnormal or not (pre-screening). Section 3 exhibits how candidate regions are pre-filtered on fundus images that have passed the pre-screening phase. The datasets and corresponding experimental results are shown in section 4. Finally, some conclusions are drawn in section 5.

2 PRE-SCREENING – CLASSIFYING THE INPUT IMAGE

As the first step of our approach, we check whether the image has so severe abnormality that the patient should be sent directly to a medical expert. In the case of high-loaded automatic systems, skipping these images will enhance the performance, since detailed analyses do not take place. The pre-screening is realized based on machine learning algorithms. Next, we summarize the components of pre-screening organized into consequent steps.

2.1 Pre-processing

As a pre-processing step, we convert the input RGB images to grayscale ones as proposed e.g. in (Sopharak et al., 2008), to get a suitable representation for possible disorders. Then, we apply adaptive histogram equalization (AHE) as an intensity normalization step proposed by (Youssif et al., 2006). Finally, we rescale the images to the size of 90×90 pixels.

2.2 Feature Vectors and Classifiers

We also take advantage of the clinical observation that fundi with severe diabetic retinopathy often have inhomogeneity caused by retinal pigment epithelium (RPE) atrophy, which is the waste of the pigmented cell layer of the retina. Composing feature vectors based on this observation leads to more accurate results both in classification and computational performance, as will be presented in the results section. To extract these features, we used the following approaches:

- **Inhomogeneity.** Let the image be split into disjoint subimages of size $s \times s$, e.g. with $s = 5$. Then, for each pixel within a subimage, we compute the sum of intensity differences larger than a given threshold t for every subsequent subimage pixels. After this step, we divide this sum with the size of the subimage. If this number is larger than zero, the feature is set to 1, otherwise to 0.

- **Standard Deviation.** For each subimage we calculate the standard deviation. This approach is for referential purposes.
- **Combined.** The combination of the inhomogeneity feature and the standard deviation.

3 PRE-FILTERING – EXTRACTING REGIONS WITH LESION CANDIDATES

As the second step of our approach, we extract regions with lesions candidate in the images that passed the pre-screening phase. Since these images must undergo detailed image analyses to extract specific lesions later on, this pre-filtering is highly recommended to restrict the input of the corresponding detector algorithms. Now we summarize the steps how the candidate regions are extracted.

3.1 Pre-processing

Similarly to the pre-processing steps discussed for the pre-screening phase, we use the green plane of the image by following literature recommendations (Youssif et al., 2006). Then, we perform histogram equalization on the image to reduce the vignetting effect (see Figure 3a) and calculate the background image by applying a strong median filter of size $A \times A$ (e.g. with $A = 25$).

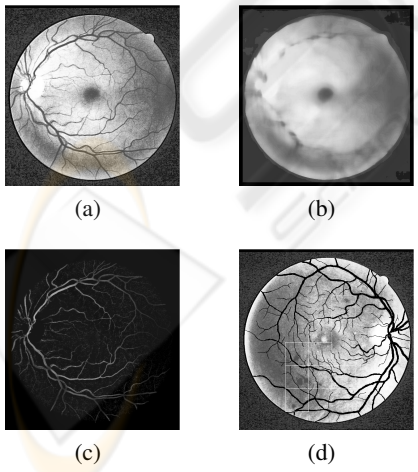


Figure 3: (a) the green plane after histogram equalization, (b) the background image, (c) the pre-processed image for candidate region extraction, (d) regions with lesion candidates.

We use the background image shown in Figure (see Figure 3b), to perform shade correction by subtracting it from the original image.

To suppress noise, we apply a median filter of size $B \times B$ (e.g. with $B = 13$) to the shade corrected image. As the final pre-processing step, we apply unsharp masking to increase the acutance (see Figure 3c).

3.2 Removal of Anatomical Parts

Detecting the anatomical parts of the fundus is an important step before lesion detection. For example, the optic disc appears as the brightest circular patch on the fundus, whose presence may disturb the detection of exudates. Removing the vessel system is also relevant, since a small portion of it appears basically the same as haemorrhages. Besides these two anatomical parts, we also remove the macula, because for certain region sizes, some parts of it can appear as a locally salient object. For these tasks, we use the vessel detector published by (Staal et al., 2004), the macula detector of Petsatodis (Petsatodis et al., 2006) and the optic disc detector described in (Sopharak et al., 2008).

3.3 Statistical Analysis of Regions

We split the image into disjoint regions of size $s \times s$ (e.g. with $s = 75$). For each region, we compute the local mean μ and the standard deviation σ of its intensity values. Let $d_{sig}(x, y) = x - y$. We label the pixel $P(x, y)$ having intensity $I(x, y)$ as *high*, if $d_{sig}(I(x, y), \mu) > \sigma$, while $P(x, y)$ is *low*, if $d_{sig}(I(x, y), \mu) < -\sigma$. Otherwise, P remains unlabeled. After labeling, we select connected components, which composed of pixels with identical labels and with cardinality at least n. If a component satisfied these conditions, we consider that as a lesion candidate. We use the areas which possibly contain lesions as input for specific lesion detectors, designed for e.g. microaneurysms or exudates.

4 RESULTS

4.1 Results on Pre-screening

Our experimental dataset consisted of 34 training and 28 test images, classified by ophthalmologists. We selected images from three databases: the publicly available DRIVE (Staal et al., 2004), DIARETDB1 (Kauppi et al., 2007) and the database provided by the Moorfields Eye Hospital, London, UK for our research purposes. We label the elements of the test

database as images with serious disorder (first class) and images to be processed further (second class). We used a Naive Bayes classifier and trained for the combined features extracted from all regions of the images as disclosed in section 2.2. With this approach, we have successfully classified all elements of the test dataset. To make the approach faster, we used backward elimination for feature subset selection. That is, we have selected the best 11 regions each image to be extracted the features from for classification. In this case, our approach still provided no false predictions with the computational time below milliseconds.

4.2 Results on Pre-filtering

We have tested our approach on those images which have been classified as "to be processed further" by the previous pre-screening phase and the positive samples of the training set. The detector missed only 1 fundus image which contained lesions. Our results are summarized in Table 1 in details containing the value of the size parameters s, the number of correctly / incorrectly (true / false) identified regions, the number of misclassified images and the percentage of the remaining pixels.

Table 1: Experimental results on pre-filtering.

Size (s)	True	False	Mis-classified	Percentage
10	24	10	4	0.05
25	26	10	4	0.34
50	25	9	5	1.28
75	27	3	1	2.5
100	16	7	5	3.47
200	4	4	5	4.82

With this regions candidate detection, we can reduce the total number of pixels of the database from more than 6 millions to 168 750, which is nearly 2,5% of the original data. To demonstrate how its reduction affected consequent detailed image processing analysis, we tested a specific lesion detector. Namely, the computational time of the state-of-the-art microaneurysm detection algorithm (Fleming et al., 2006) reduced by 90% after this candidate selection step.

5 CONCLUSIONS

We have presented an automatic approach that can separate fundus images with serious lesions from the ones that should undergo detailed screening. This step can direct patients with serious lesions immediately to ophthalmologists by automatic screening systems. With a use of a Naive Bayes classifier, we were able to classify all the test images correctly. As a secondary pre-filtering step for images passing pre-screening, we have presented an approach which is eligible to detect areas which possibly contain lesions. As a fair trade off with accuracy, we gain high computational performance with using only small regions to detect the actual lesions within.

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