VOTING BASED AUTOMATIC EXUDATE DETECTION IN COLOR FUNDUS PHOTOGRAPHS

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ABSTRACT

Diabetic retinopathy is one of the leading causes of preventable blindness. Screening programs using color fundus photographs enable early diagnosis of diabetic retinopathy, which enables timely treatment of the disease. Exudate detection algorithms are important for development of automatic screening systems and in this paper we present a method for detection of exudate regions in color fundus photographs. The method combines different preprocessing and candidate extraction algorithms to increase the exudate detection accuracy. First, we form an ensemble of different candidate extraction algorithms, which are used to increase the accuracy. After extracting the potential exudate regions we apply machine learning based classification for detection of exudate regions. For experimental validation we use the DRiDB color fundus image set where the presented method achieves higher accuracy in comparison to other state-of-the art methods.

***Index Terms*—** diabetic retinopathy, exudate detection, machine learning, ensemble, image processing and analysis

1. INTRODUCTION

Diabetic retinopathy (DR) is one of the leading disabling chronic diseases and one of the leading causes of preventable blindness in the world [1]. Early diagnosis of diabetic retinopathy enables timely treatment that can ease the burden of the disease on the patients and their families by maintaining a sufficient quality of vision and preventing severe vision loss and blindness [2]. In addition to the obvious medical benefits, significant positive economical effects are achieved by maintaining patient's workability and self-sustainability.

In order to achieve early diagnosis of diabetic retinopathy a major effort will have to be invested into screening programs. Screening is important as up to one third of people with diabetes may have progressive DR changes without symptoms of reduced vision [3], thus allowing the disease to progress and making treatment difficult. Systematic screening programs for diabetic eye disease have been developed in many countries.

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In current screening programs color fundus photography is used and an automated screening system, which can detect primary signs of DR on fundus images, would be very useful. Such a system must be able to detect the exudates with high accuracy. Exudates can be identified on fundus photographs as areas with hard white or yellowish colors with varying sizes, shapes and locations. These properties of exudates cause difficulties in automatic detection. They normally appear near the leaking capillaries within the retina. The main cause of exudates are proteins and lipids leaking from the blood into the retina via damaged blood vessels.

A large number of exudate detection algorithms have been proposed in the literature. Quite a few are based on thresholding and region growing [4,5], but although these methods are straightforward, selecting threshold values, region seed points and stopping criteria can be difficult. Clustering has also been proposed as a possible solution for exudate detection problem [6]. The main difficulty with clustering is determining the number of clusters to use. A few other attempts are based on morphological reconstruction and specialized features [7, 8]. All of these techniques are highly sensitive to image contrast. Some methods are based on machine learning techniques and use different feature vectors and classification algorithms [9]. For these methods to work, annotated databases are required which are sometimes hard to obtain.

In this paper we propose a new method, which combines different algorithms into an ensemble and obtains better segmentation results than several state-of-the art approaches, as we will show in the results section.

The rest of the paper is organized as follows: in Section 2 we give a description of the ensemble based exudate detection method with subsections devoted to preprocessing, candidate extraction methods, creating of an ensemble and machine learning based classification. In Section 3 we present the evaluated accuracy of proposed method and finally give a short conclusion in Section 4.

2. VOTING BASED EXUDATE DETECTION

We combine different preprocessing algorithms and different candidate extraction algorithms into an ensemble to increase the accuracy of exudate candidate detection. For each exu-

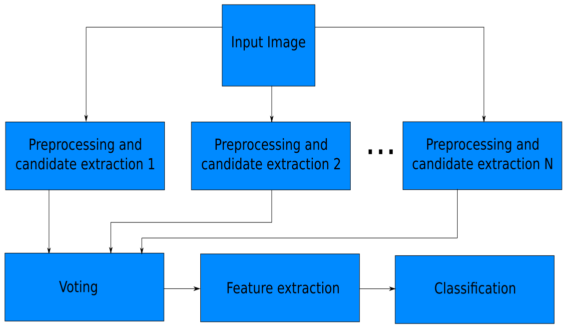


Fig. 1: Flowchart of the proposed method.

date candidate extracted by the ensemble we calculate different morphological and statistical features which are used for classification of each potential exudate candidate. In Figure 1 we can see the flowchart of the proposed method. In the following subsections we describe which preprocessing methods and candidate extraction methods are used, how they are combined into an ensemble and finally how the machine learning based classification is done.

2.1. Preprocessing methods

According to the literature automatic exudate detection algorithms can be improved by some preprocessing step which can make the image more suitable for automatic processing and analysis. In this subsection we present different preprocessing methods used in creation of the ensemble.

- Green Channel Extraction (G): Because the green channel is the channel with the highest contrast between the background and other important parts like lesions, using only the green channel can improve the accuracy of exudate detection algorithm.
- Intensity Channel Extraction (I): If we use only the green channel instead of all channels we can lose some information so we can use the average of the red, green and blue channel as input to other processing steps.
- CLAHE: Contrast-Limited Adaptive Histogram Equalization (CLAHE) is a well-known generic technique used to improve the contrast in the input image. This is important because some exudate detection algorithms rely on good contrast between exudates and the background.
- Illumination correction (IC): The illumination of the input image is non-uniform which is caused by spherical shape of the eye and different tissues present in the eye. We compensate this type of non-uniformity by subtracting a median filtered image from the original image where the median filtering is performed with a large structuring element.
- Illumination Equalization (IE): This procedure is similar to illumination correction but instead of using a median filtered image we use (1).

$$I_{eq}(x,y) = I(x,y) + m - I_w(x,y) \tag{1}$$

  where $I(x,y)$ is the original intensity image, m is the desired average intensity and $I_w(x,y)$ is the mean intensity value within a local neighborhood.
- White Top-Hat Transformation (WTH): This simple morphological transformation can be used for highlighting brighter region like exudates in input image. In this transformation the result of grayscale opening is subtracted from the original image.
- Contrast enhancement (Contrast): This method was proposed in [10] and starts by converting the original RGB image to YIQ color space. In this color space original Y channel is replaced by a weighted sum of the channels Y, I and Q according to (2):

$$Y_{mod} = 1.5 \cdot Y + (-1) \cdot I + (-1) \cdot Q \tag{2}$$

  After this correction we convert the modified image back to RGB color space. In the resulting image the bright regions become brighter and dark ones become darker.
- Adaptive contrast enhancement (AContrast): This method again tries to improve the contrast of the input image and is similar to the illumination equalization method so we change the illumination of the image according to (3):

$$I_{eq}(x,y) = (I(x,y) - I_w(x,y))/\sigma_w(x,y) \tag{3}$$

  where $I(x,y)$ is the original intensity image, $I_w(x,y)$ is the mean intensity value within a local neighborhood and $\sigma_w(x,y)$ is the standard deviation of intensity within a local neighborhood. Areas with low contrast have a smaller standard deviation of intensity in their neighborhood so dividing the difference between original and background image with the standard deviation increases contrast more in areas with low contrast.

2.2. Candidate extraction algorithms

In order to detect the exudates a candidate extraction step is performed in which a simple algorithm is used to coarsely find potential exudate regions. In this subsection we present the candidate extraction algorithms used for the ensemble creation.

2.2.1. Morphological-based candidate extraction algorithm (Morphology)

The morphological-based candidate extraction algorithm uses the approach presented in [7] where authors proposed a method for detection of exudates using morphological operations. This method starts by using morphological closing with a large structuring element in order to eliminate the blood vessels. After the standard deviation in a sliding window was calculated we applied a fixed threshold in order to find the candidate regions which have high standard deviation. With this procedure we find small bright objects and borders of large bright objects. In order to obtain the whole candidate regions the holes can be filled by reconstructing the image from its borders and we also dilate the candidate region in order to ensure that the background pixels next to exudates are included in the candidate regions. In order to find the contours of the exudates and to distinguish them from other well contrasted regions we have set all the candidate regions to zero in the original image and we then performed the morphological reconstruction by dilation of the original unchanged image under the new image. With this procedure exudates are completely removed from the image. The final result is obtained by applying a simple threshold operation to the difference between the original image and the reconstructed image. In this way we take only the candidates that have a contrast level above a minimum threshold level.

2.2.2. Local and global thresholding (Thresholding)

The thresholding candidate extraction algorithm is based on work by [11] where the authors segment the bright regions in the preprocessed image that show high global and local gray levels. The method starts by calculating a global histogram and several local histograms by partitioning the original image into non-overlapping square blocks. The blocks have to be large enough to ensure that enough background pixels are present in each block, which allows the local differentiation of background from bright regions but small enough to capture the local properties of the image. Global and local histograms are usually bell shaped and they show one maximum corresponding to the background and one tail on each side of the maximum. To separate the bright regions a threshold was set at the gray level of the right tail for which the histogram decreased to a 10% of the histogram maximum. As a result of the histogram thresholding process we obtained two binary images in which the pixels above the threshold were marked with the label “one” and pixels below the threshold were marked with the label “zero”. These two images were combined using the AND operation to obtain the bright regions in the image.

2.2.3. Machine learning (ML)

Machine learning approaches tend to yield good results when used for candidate regions classification but they can be used for candidate extraction to. In this approach, we extracted various features for each pixel and used a classifier to decide if the pixel belongs to an exudate region. The features were selected from a range of various features, which are relevant for exudates such as the mean, standard deviation, maximum value, range (difference of maximum and minimum) of the intensities within a window, and the intensity from the input image. In [9] the authors proposed six difference of Gaussian filters for exudate detection. We applied these filters and obtained six DoG descriptors which we added to the feature vector. Moreover we calculated some descriptors that are based on the strength of the edge in the neighborhood of the pixel. For this, we applied the Frei-Chen edge detector and added the highest gradient value, average and standard deviation of the strength of the edge pixels and number of them.

These features can be used with any of existing classification algorithms where the classifier can be trained using the ground truth data available in the dataset. Output of the classifier is a binary image with potential exudate candidates marked with the label “one” and background pixels marked with the label “zero”.

2.2.4. Clustering-based approach (Clustering)

The clustering-based candidate extraction algorithm uses the approach described in [6] where the authors uses a two step procedure where the coarse segmentation is done using fuzzy C-means clustering and the fine segmentation is done using morphological operators. For fuzzy C-means clustering authors used four different features. Intensity of the image is selected as one of the classification features because exudates can be easily distinguished from normal pixels by their intensity. The standard deviation was also added as a feature because exudates are regions characterized by a large local variance. The hue was added because exudates appear in a yellowish or white color. Normally, exudates gather together in small clusters so they tend to have many edge pixels around the area so the number of edge pixels was added as the fourth feature. After performing the fuzzy C-means clustering we obtain several clusters representing different anatomical parts of the image.

The result from the clustering step is a rough estimation of the exudates. The cluster, which contains most of the background information is used as a marker while the original intensity image is used as a mask. The morphological reconstruction is then applied using the marker and mask images. The final result is obtained by applying a threshold operation to the difference between the original and the reconstructed image.

2.3. Combining candidate extraction algorithms

The main advantage of combining different preprocessing and candidate extraction algorithms together is to increase the accuracy of exudate candidate selection. We start the procedure by creating a pool of all possible pairs of preprocessing methods and candidate extraction methods. In the case of <preprocessing method, candidate extraction method> pair, the given preprocessing method is applied on the image before performing the given candidate extraction method.

We used a simulated annealing-based search algorithm to find the optimal ensemble of <preprocessing method, candi-

Method	Morphology	Thresholding	ML	Clustering
G	×		×	
I	×			
CLAHE				×
IC			×	
IE	×	×		
WTH		×	×	
Contrast	×			
AContrast		×		

Table 1: Preprocessing and candidate extraction pairs used in optimal candidate extraction method.

date extraction method> pairs. The energy function used in evaluating the goodness of the solution is given by (4).

$$E = -F_{score} = -\frac{5 \cdot \text{sensitivity} \cdot \text{PPV}}{4 \cdot \text{PPV+sensitivity}} \tag{4}$$

which we want to minimize by the optimal combination of <preprocessing method, candidate extraction method>pairs. In the equation above, sensitivity is defined as $TP/(TP + FN)$ and positive predictive value (PPV) as $TP/(TP+FP)$.

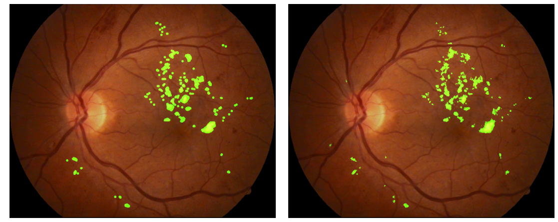
The energy function used is actually the F_2 score measure and we used it because we wanted to increase the effect of sensitivity in the energy function. In Table 1 we can see the selected preprocessing methods and exudate candidate extractor pairs found for optimal combination.

After the optimal ensemble of <preprocessing method, candidate extraction method>pairs is found a voting scheme is applied for the binary output of all participating pairs. A voting rule can be defined arbitrarily but the simplest rule is to mark the pixel as an exudate if more than 50% of the pairs mark the given pixel as an exudate.

2.4. Exudate classification

After picking the optimal ensemble we extracted different features for each candidate cluster and classified each vector into exudates or no exudates class. To find efficient features for classification, we calculated several shape and statistical descriptors for exudate candidates and selected the most useful ones by using a Wilcoxon rank test.

Initially we started with a large pool of different features which are mentioned in the literature: mean, standard deviation, difference between maximal and minimal value, minimal and maximal values of gradients under the given region and under the boundary of the region; the mean, standard deviation, difference between maximal and minimal value, maximal and minimal values of the intensities under the region and under the boundary of the region in the green channel, CLAHE image, illumination normalized image; mean and standard deviation of zero, first and second order Gaussian derivatives taken at different scales; homogeneity of the the region measured in terms of the Shannon's entropy of the RGB values calculated for each channel. We added several



(a) Ground truth data (b) Output of the method

Fig. 2: Comparison of ground truth with output of the method.

morphological features like exudate candidate area, major and minor axis length and compactness. During experimentation we have noticed that a lot of false positive exudates are visible near the main arteries and veins, especially in younger patients so we decided to add distance from main veins and arteries as a feature. Since exudates often appear close to the center of the image we added distances from the optic disk and macula as features to the feature vector.

To coarsely detect the main veins and arteries approach based on Frangi vesselness was used where we filtered the green channel of the input image with Frangi vesselness filter at a large scale and after that we thresholded the image to obtain the main vessels. Macula region and optic disk were not detected because the database contains macula region and optic disk marked by an expert for each image from the database so we decided to use the information provided.

Most of the mentioned descriptors are appropriate for distinguishing between exudate and non-exudate regions. However, there are some irrelevant descriptors and these can decrease the generalization performance of the trained classifier. To select the most significant descriptors we used the Wilcoxon rank test.

After selecting the best features we used the AdaBoost classifier for exudate classification. In Figure 2 we can compare the ground truth marked by an expert with output obtained by our method.

3. RESULTS

We have evaluated the performance of our method on DRiDB database [12], an open-access dataset available on request, which contains 50 color fundus images for which all the main structures like blood vessels, optic disk and macula are marked along with pathological changes like hard and soft exudates, dot and blot hemorrhages and neovascularizations. We split the database into two disjoint sets for training and testing purposes.

To test our method and other methods we used the ground truth data available in the mentioned dataset. For each image number of true positives (TP), false positives (FP) and false negatives (FN) were calculated. We omitted the true negative

(TN) pixels from our analysis because the number of true negative pixels can be very high since all non-exudate pixels are actually true negatives. Instead, we used sensitivity, positive predictive value and F-Score to measure the performance of our system. To obtain the results we performed 3-fold cross-validation.

Table 2 presents the results of the experimental validation. The proposed method outperformed all algorithms that are used in the validation process. The advantage of the proposed method is a possibility of inclusion of other exudate detection methods that could potentially improve the performance of the whole system.

Method name	Sensitivity	PPV	F-Score
Walter [7]	0.69	0.48	0.57
Sánchez [10]	0.34	0.1	0.44
Harangi [9]	0.66	0.65	0.66
Harangi [13]	0.71	0.66	0.68
Sopharak [6]	0.45	0.12	0.19
Proposed method	0.72	0.75	0.74

Table 2: Results of different exudate detection methods.

4. CONCLUSION

In this paper we presented a method for detection of exudates in color fundus photographs which combines different preprocessing and exudate candidate extraction methods in order to increase the exudate detection accuracy. We used machine learning classification techniques for final exudate classification. The proposed method achieved excellent results measured by higher F-Score in comparison to other state-of-the art algorithms.

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