Weighted Ensemble Based Automatic Detection of Exudates in Fundus Photographs*

Pavle Prentasic and Sven Loncaric

Abstract— **Diabetic retinopathy (DR) is a visual complication of diabetes, which has become one of the leading causes of preventable blindness in the world. Exudate detection is an important problem in automatic screening systems for detection of diabetic retinopathy using color fundus photographs. In this paper, we present a method for detection of exudates in color fundus photographs, which combines several preprocessing and candidate extraction algorithms to increase the exudate detection accuracy. The first stage of the method consists of an ensemble of several exudate candidate extraction algorithms. In the learning phase, simulated annealing is used to determine weights for combining the results of the ensemble candidate extraction algorithms. The second stage of the method uses a machine learning-based classification for detection of exudate regions. The experimental validation was performed using the DRiDB color fundus image set. The validation has demonstrated that the proposed method achieved higher accuracy in comparison to state-of-the art methods.**

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

I. INTRODUCTION

Diabetic retinopathy (DR) is a visual complication of diabetes, which has become one of the leading causes of preventable blindness in the world [1]. According to the World Health Organization (WHO), more than 75% of patients who have had diabetes for more than 20 years will develop some form of DR [2]. Early diagnosis of DR enables timely treatment that can ease the burden of the disease on the patients and their families. In order to detect DR in early stages, screening programs have to be developed. 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.

Developing of an automated screening system, which can detect primary signs of DR on fundus images, would be very useful because it would be an important tool for ophthalmologists in the diagnosis of the disease.

Such a system must be able to detect the exudates with high accuracy. Exudates are lipid and lipoprotein deposits and can be identified in retinal images 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.

*This work has been supported by the European Community Seventh Framework Programme under grant No. 285939 (ACROSS)

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Many attempts to detect these lesions can be found in the literature. Quite a few are based on thresholding and region growing [4], [5]. These methods are straightforward but 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 use morphological operations for detection of exudates [7]. Some methods are based on machine learning techniques and use different feature vectors and classification algorithms [8]. 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 outputs of different exudate detection algorithms and performs better 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 II we give a description of the proposed exudate detection method with subsections devoted to preprocessing, candidate extraction methods, creating of an ensemble and machine learning based classification. In Section III we present the evaluated accuracy of the proposed method and finally give a short conclusion in Section IV.

II. WEIGHTED ENSEMBLE BASED EXUDATE DETECTION

Accuracy of existing exudate detection algorithms can be improved by combining different exudate detection algorithms into an ensemble. For each exudate candidate extracted by the ensemble we calculate different morphological and statistical features, which are used for classification of each potential exudate candidate. In Fig. 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.

A. Preprocessing methods

Image preprocessing 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: Green channel is the channel with the highest contrast between the background and other important parts like lesions, so using only the green channel can improve the accuracy of exudate detection algorithm.

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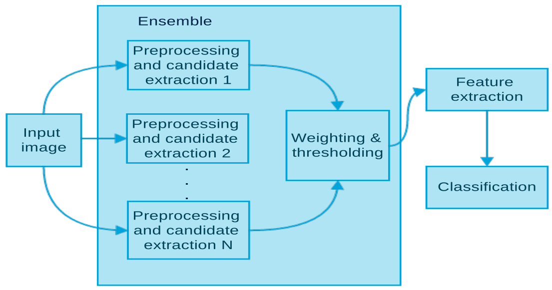


Fig. 1. Flowchart of the proposed method.

- CLAHE: Contrast-Limited Adaptive Histogram Equalization (CLAHE) is a well-known contrast enhancement technique, which is used because some exudate detection algorithms rely on good contrast between exudates and the background.
- Gray-World Normalization: Gray-World Normalization is used as a preprocessing method because it can eliminate effects due to illumination color, so it is used to eliminate the shining along temporal arcades.
- Illumination correction: 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 window.
- White Top-Hat Transformation: This simple morphological transformation is used for highlighting brighter region like exudates in input image. In this transformation the result of grayscale opened image is subtracted from the original image.
- Contrast enhancement (Contrast): This method was proposed in [9] and starts by converting the original RGB image to YIQ color space. In this color space the original Y channel is replaced by a weighted sum of the channels Y, I and Q according to (1).

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

  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: This preprocessing methods tries to improve the contrast of the input image by changing the illumination of the original image according to (2)

$$I_{eq}(x, y) = (I(x, y) - I_w(x, y))/\sigma_w(x, y) \tag{2}$$

  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.
- Chromaticity normalization: This normalization method is used when a scene viewed by a camera and illumination of the object are not uniform during a video. In this case, it can be used for reducing the bright refection of retinal images of young patients.

B. *Candidate extraction algorithms*

After image preprocessing 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.

1) Morphological-based candidate extraction algorithm: The morphological-based candidate extraction algorithm uses the approach presented in [7] where authors proposed a method for detection of exudates using morphological operations. The method assumes that exudate regions are regions with large standard deviation. The method starts with morphological closing of the input image with a large structuring element in order to eliminate the blood vessels, which show large local deviation. After this step, we calculate the standard deviation in a sliding window and apply a fixed threshold to find the candidate regions with high standard deviation. We dilate the candidate regions 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 set all the candidate regions to zero in the original image and then perform 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) Local and global thresholding-based candidate extraction algorithm: The thresholding candidate extraction algorithm is based on work by [10] 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 is set at the gray level of the right tail for which the histogram decreases to a 10% of the histogram maximum. As a result of the histogram thresholding process we obtain two binary images, which we combine using the AND operation to obtain the bright regions in the image.

3) SVM-based candidate extraction algorithm: In this approach, we extract various features for each pixel and use a linear SVM classifier to decide if the pixel belongs to an exudate region. The features are 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 [11] the authors used Gaussian derivatives taken at different scales so we add responses to zero, first and second order Gaussian derivatives to our feature vector. Moreover we calculate some descriptors that are based on the strength of the edge in the neighborhood of the pixel. For this, we apply the Frei-Chen edge detector and add the highest gradient value, average and standard deviation of the strength of the edge pixels and number of them to our feature vector. Output of the classifier is a binary image with exudate candidates marked with the label "one" and background pixels marked with the label "zero".

4) Clustering-based candidate extraction algorithm: The clustering-based candidate extraction algorithm uses the approach described in [6] where the authors used a k-means based procedure to find exudate regions. The procedure starts by using raw image data for k-means clustering. After applying k-means clustering the papillary region and other yellow lesions, such as cotton wool spots are detected, because of their similar attributes to hard exudates in terms of brightness, color and contrast. In order to detect only hard exudates characterized by yellowish color and sharp edges and remove all lesions with high intensity but blurred edges such as cotton wool spots we use an edge strength criterion. We apply the Kirsch operator and threshold the obtained image. We then apply a boolean AND operation between the original k-means clustered image and the edge image. This operation finds only the edges of bright objects. Finally, in order to find the exudate regions we perform morphological reconstruction by dilation under the retinal image of the green channel from the original image.

C. Combining candidate extraction algorithms

Combining different preprocessing and candidate extraction algorithms into an ensemble increases the accuracy of exudate candidate detection. The procedure starts by creating a pool of 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 then use the simulated annealing search algorithm to find the optimal weights for each of the <preprocessing method, candidate extraction method> pairs present in the ensemble.

The energy function used in evaluating the goodness of the solution is given by (3).

$$E = -F_{score} = -\frac{5 \cdot \text{sensitivity} \cdot \text{PPV}}{4 \cdot \text{PPV+sensitivity}} \qquad (3)$$

In the equation (3), sensitivity is defined as $TP/(TP+FN)$ and positive predictive value (PPV) as $TP/(TP+FP)$. When the simulated annealing algorithm picks the weights we create a weighted image of the binary images produces by each <preprocessing method, candidate extraction method> pair. The weighed image is normalized to [0,1] interval by dividing each image element with the sum of weights, which are used for creation of the weighted image. In order to evaluate the energy function we have to threshold the weighted image. Because the image is normalized the thresholding procedure is very straightforward so we pick value 0.5 as an appropriate threshold. This value is picked because we can look at our normalized image as a probability function of given pixel being an exudate.

The energy function used is actually the F_2 score measure and we use it because we want to increase the effect of sensitivity in the energy function and we do that because in exudate classification step we will eliminate a lot of false positive exudate clusters, which will lead to increased PPV value and finally overall accuracy of the whole algorithm.

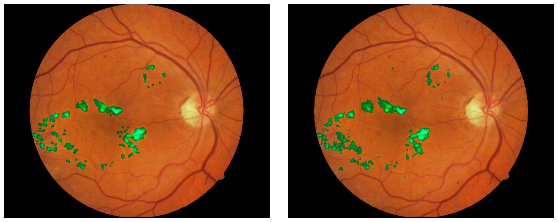
D. Exudate classification

After picking the optimal ensemble weights we extract different features for each exudate candidate and classify each exudate candidate according to the feature vector. To find efficient features for classification, we calculate several shape and statistical descriptors for exudate candidates and select the most useful ones by using a Wilcoxon rank test.

Initially we start 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 corrected 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 add several 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 we use a Frangi vesselness based approach where we filter the green channel of the input image with Frangi vesselness filter at a large scale and threshold the image with a fixed threshold.

The presented method is based on the results of manual segmentation of macula and optic disk. Automatic segmentation of macula and optic disk can be achieved using any



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

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

of the methods published in literature, and is outside of the scope of this paper.

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 use the Wilcoxon rank test.

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

III. 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 have 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) was 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.

Table I presents the results of the experimental validation after 3-fold cross-validation. The proposed method outperforms all algorithms used in the validation process.

TABLE I

RESULTS OF DIFFERENT EXUDATE DETECTION METHODS.

Method name	Sensitivity	PPV	F-Score
Walter [7]	0.69	0.48	0.57
Sánchez [9]	0.34	0.1	0.44
Harangi [8]	0.66	0.65	0.66
Harangi [13]	0.71	0.66	0.68
Amel [6]	0.41	0.09	0.15
Proposed method	0.75	0.77	0.76

IV. CONCLUSION

In this paper we present 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. The method shows excellent results in comparison to other state-of-the-art methods and enables inclusion of other exudate detection methods in the processing pipeline, which could potentially improve the performance of the whole system or other state-of-the-art methods.

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