AUTOMATIC DETECTION OF EXUDATES IN RETINAL IMAGES USING NEURAL NETWORK

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Abstract— Diabetic Retinopathy (DR) is one of the major complications of diabetes mellitus and can cause blindness. The diagnosis of DR is performed by visual analysis of retinal images, with exudates (fat deposits) being the main patterns traced by a specialist doctor. Thus, this paper proposes an algorithm for exudate detection in retinal images, whose experimental validation is performed on a public image database, DIARETDB1. The proposed methodology combines fuzzy clustering and classification. Furthermore, it provides a method for optic disc detection, considering that it is a convergence point of vessels. The obtained results confirm the performance improvement provided by the proposed methodology when comparing it to other methods available in the literature.

Keywords— Artificial Neural Network, Digital Image Processing, Exudate Detection, Machine Learning

1 Introduction

The retina is the most internal membrane of the human eye. Figure 1 illustrates the retina and its main components. Digital images of the fundus of the eye can provide information on pathological changes caused by eye and systemic diseases such as hypertension, arteriosclerosis and diabetes mellitus (Bernardes et al., 2011).

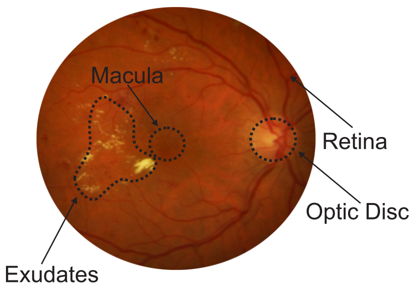


Figure 1: Components of the human retina.

In many situations, digital image processing techniques can be used to detect changes in the retina. The identification of pathologies of the human eye using these techniques have increased day by day and the main applications aim to identify three diseases: Diabetic Retinopathy (DR), Macular Edema and Glaucoma (Giancardo et al., 2012).

Particularly, DR is the largest cause of vision loss in diabetics (Sopharak et al., 2010). This disease occurs as a result of vascular changes in the retina, causing swelling of capillaries known as microaneurysms (MA). With the progress of the disease, these MAs can rupture and, eventually, become a source of extravasation of plasma, creating regions of fat deposits in the retina, known as exudates (Giancardo et al., 2012).

In the early stages of RD, the ophthalmologists look for MAs, which are small and very difficult to detect visually. Thus, at more advanced stages, experts search for exudates that usually form clusters that can be distributed throughout the retina and are easily visible; its presence indicates that the patient has RD (Sopharak et al., 2010). Situations where they occur in the macula region can result in vision loss (Giancardo et al., 2012). The continuous monitoring of DR is very important in order to diagnose the disease before onset of symptoms. Moreover, early treatment may prevent or reduce the vision loss of the patient.

The goal of our work is to develop algorithms for exudate detection capable of supporting medical decision, improving diagnosis quality and decreasing the workload of medical professionals. The automatic exudate detection system proposed in this work extends and modifies the method proposed by Ram and Sivaswamy (2009). The general methodology consists of three steps: clustering pixels, clustering selection and removal of false candidates. The extended algorithm applies the fuzzy k-means algorithm to gather pixels in clusters and removes false candidates by detecting the Optical Disc (OD) as the convergence point of blood vessels and by applying a classification to post-process the segmented image.

The rest of the paper is organized as follows: in section 2, we present the state-of-the-art of automatic exudates detection. Section 3 contains the material and methods used in our experiments, while our proposed system is presented in section 4. Section 5 gives the empirical results, and we draw some conclusions in section 6.

2 State-of-the-Art

Several methods for exudate detection are available in the literature. Furthermore, there are basically three problem solving strategies (Sopharak et al., 2010). These strategies are based on thresholding and region growing (María et al., 2009), clustering techniques (Ram and Sivaswamy, 2009), and a mathematical morphological approach (Basha and Prasad, 2008).

Kavitha and Shenbaga (2005) and María et al. (2009) used multilevel thresholding to extract the OD and the exudates. The former detected the OD as the convergence point of the vessels and then classified the other bright regions as exudates. The later made a classification using Multilayer Perceptron (MLP) and Support Vector Machine (SVM). In all these works, low quality images may interfere in the result of separation of bright and dark lesions. This fact occurs because the selection of threshold values, region seed points, and stopping criteria are difficult to be established automatically.

Osareh et al. (2002), Zhang and Chutatape (2005) and Sopharak et al. (2009) proposed the use of fuzzy k-means algorithm to segment the retina in groups with similar colors. The work of Osareh et al. (2002) used the RGB color model while Zhang and Chutatape (2005) used the Luv color space. In both works a SVM was used to separate exudate and non-exudate regions. Sopharak et al. (2009) used four input attributes for the fuzzy k-means: intensity value, standard deviation of intensity, value of hue and number of edge pixels in a region around the pixel. The use of clustering techniques in the detection of exudates can produce results with good success rate. However, these methods are dependent on the choice of the attributes set input, the choice of the clustering method and the determination of the number of clusters.

Recently Sopharak et al. (2010) and Harangi et al. (2012) performed a pixel by pixel classification as belonging or not to a exudate region. The former used a SVM classifier and the latter an improved Naive-Bayes classifier. Despite the successful results reported, the use of pixel by pixel classification requires a high computational power for training and classification processes. The approach of Köse et al. (2012) was based on the information that the background images of a healthy retina has regular patterns of color and texture. Therefore, the background image was estimated and other patterns were considered abnormal. The method was able to identify the existence or not of exudates; however, detection of the exudates regions is not part of the objectives of this work. The problem of this method is the determination of the background image that shows susceptibility to non-uniform illumination and still depends on the OD and blood vessels detection.

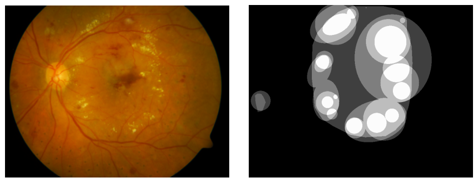
The method proposed by Ram and Sivaswamy (2009) was used as the basis for the development of this work. The authors proposed a method of multi-space clustering to exudate segmentation. The results of the clustering step were very promising, but the final result was not satisfactory. This fact occurs because the process of elimination of false candidates is inefficient.

3 Material and Methods

3.1 Image Database

We tested our approach on the publicly available DIARETDB1 color fundus image database (Kauppi et al., 2007). The DIARETDB1 consists of 89 images, all of same size (1500 $\times$ 1152 pixels). It is used in detection of exudates works because it presents the ground-truth spatial coordinates of findings related to four pathologies: hemorrhage, hard exudates, soft exudates and red spots (Giancardo et al., 2012).

On this database, the marking of pathologies was performed by four ophthalmologists, in some images, there was no consensus among all of them. This work considered exudates only regions marked by three of the four ophthalmologists, as suggested by the database authors. Figure 2(a) shows an example of image from DIARETDB1. Figure 2(b) shows the marking of regions of exudates. Lighter regions represent more agreement in the diagnosis. Regions in white represent areas where there was 100% agreement among ophthalmologists.



(a) (b)

Figure 2: DIARETDB1 image: a) retinal image with various exudates and bleeding, b) ground-truth image of Figure 2(a).

3.2 Ram and Sivaswamy's Method

The automatic exudate detection system proposed in this work extends and modifies the method proposed in Ram and Sivaswamy (2009). The general methodology for exudate detection consists of three steps and is shown in Figure 3.

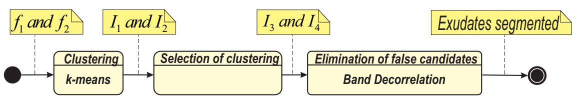


Figure 3: Methodology proposed by Ram and Sivaswamy.

The first step of the method is the clustering. In this step, each retinal image in the RGB model was converted to three different color spaces: Luv, HSV, HSI (Rafael C. Gonzalez, 2008). Using these color spaces two feature vector were built f_1 = (H,S,V,I) and f_2 = (R,G,L,u,v), which were used as input of the k-means algorithm. The output of this algorithm consists of two images (I_1 and I_2). These images are the results of clustering with the feature vector f_1 and f_2.

After obtaining images I_1 and I_2, the clusters that represent the exudates regions were selected. In I_1 the goal was to select the clustering corresponding to bright lesions and bright background. Considering that these regions are the brightest, it was selected the clustering of the original image with the highest intensity value I in the HSI space. In I_2 the clustering selected corresponds to the OD and exudates. Because these regions have a yellowish color, it was selected the clustering with the smallest value α for $\alpha = max(R) - max(G)$ in the RGB color space. In order to improve the exudates detection, two new images I_3 and I_4 are formed: the first is formed by all I_2 regions present in I_1 and the second is formed by other I_1 regions not present in I_2.

After these previously performed steps it is possible to observe the existence of parts of the OD and retinal bright regions marked as exudates. The main characteristic of these regions is that they are bounded and cut across by blood vessels. Therefore they should be identified and removed.

In Ram and Sivaswamy (2009) this removal is performed using band decorrelation that results in a strong accentuation of the vessel contrast. After this operation, the vessel region has the highest values of the component (R). On the other hand, the exudates areas and bright regions have the highest values of the component (G). Thereby, if the average values of the pixels of each object in component (R) are higher than the average values of these objects in the original image, it is removed. Therewith, it is expected that the objects belonging to the OD region can be eliminated because the larger vessels of the retina are in this region.

At the end of this process, the two resulting images are thresholded using the Otsu method (Rafael C. Gonzalez, 2008) and the combination of these two images is the final result of the algorithm proposed by Ram and Sivaswamy (2009).

4 Proposed System

Some images resulting of the original algorithm presented isolated pixels and the OD regions classified as exudates. This fact may be consequence of some fault in the process of clustering or in the step of removing false candidates. Modifications towards correcting this problem were introduced in the method, as shown in the diagram of Figure 4.

4.1 *Clustering*

The proposed exudate detection system uses a fuzzy k-means algorithm in substitution to k-means.

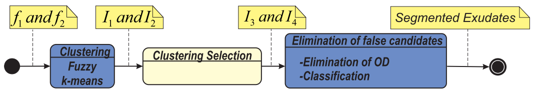


Figure 4: Diagram of the proposed system. Blue regions represent the modified steps of the original algorithm.

During tests, the fuzzy k-means algorithm was less susceptible to errors of clustering caused by difference in patterns of image illumination.

As an initial reference for the adjustment of the fuzzy k-means, parameters presented in Sopharak et al. (2009) were used: fuzzy degree 2, number of interactions 200 and maximum error of 10^{-6}. For this paper, variations of these parameters were tested aiming to find values where there was no difference in the clustering. Thus, the fuzzy degree used was maintained as 2, the maximum number of interactions was fixed in 2000 and the maximum error was 10^{-8}. The choice of these values ensured that the randomness of the choice of initial clusters did not interfere in the final result of the clustering. In other words, independent of the initial clusters choice, the algorithm always converges to the same result.

4.2 *Elimination of false candidates*

A. Optic Disc Detection

The main challenge in detecting exudates is to distinguish them from the OD, since they are similar in shape and color. Another contribution of this work consists of detecting the region of the OD as the focal point of the blood vessels. This technique was used because strategies that use the information that the OD is the region of convergence of the vessels are more successful than techniques based only on the image color properties. Therefore, the blood vessels of the original image (I_o) are segmented by the algorithm proposed by Zana and Klein. (2001), resulting in a vessel image (I_v).

Thereafter, the vessels in I_v are converted into straight lines by application of a Hough transform (resulting in I_l) and a search for three square windows of side equal to half radius of the OD (70 pixels) was performed, with the largest amount of straights being found in I_l. The OD center is chosen as the center of the window that has a higher quantity of white pixels on I_v. This choice was made due to the fact that the vessels that converge to the OD are of a greater caliber. The elimination of the OD was performed by removal of the region connected to the center.

B. Candidates Classification

Classification techniques were used towards eliminating other false candidate regions. We tested the classifiers Multilayer Perceptron (MLP), Radial Basis Function (RBF) and Support Vector Machine (SVM).

Initially, the classifiers were tested using classical literature features, (Osareh et al., 2002) and (Sopharak et al., 2010), which were divided into two groups: NON-COLOR (6 features) - area, perimeter, circularity, homogeneity and x, y coordinates of the region center; COLOR (18 features) - average and standard deviation of all components of the color models RGB, Luv and HSI. However, tests show that elimination of some features used initially improved the quality of the classification, resulting in a final set with 12 features (5 of the non-color group and 7 of the color group). The 12 features that performed best were: area, perimeter, circularity, average of components (L), (u), (v), (H), (I), (G), standard deviation of the component (G), and x and y coordinates of the region center.

5 Results

The evaluation over regions validates a detected exudate candidate when it matches 50% of a region of the retinal image marked by the experts as exudate. This evaluation method was used by Ram and Sivaswamy (2009) and it is justified by the fact that exudates are small, irregular and appear in group.

In order to evaluate algorithm performance, we used sensitivity (S), specificity (SP), positive predictive value (PPV), negative predictive value (NPV) and accuracy (A). All these measures can be calculated based on four values: true positive (TP), the number of region of exudates correctly detected; false positive (FP), the number of region of non-exudates wrongly detected as exudate; false negative (FN), the number of region of exudates not detected and true negative (TN), the number of regions of non-exudates correctly identified (Ram and Sivaswamy, 2009).

From these quantities, the sensitivity, specificity, positive predictive value, negative predictive value and accuracy are computed using equations 1, 2, 3, 4, and 5 respectively.

$$S = \frac{TP}{TP + FN} \tag{1}$$

$$SP = \frac{TN}{TN + FP} \tag{2}$$

$$PPV = \frac{TP}{TP + FP} \tag{3}$$

$$NPV = \frac{TN}{TN + FN} \tag{4}$$

$$A = \frac{TP + TN}{TP + FN + FP + TN} \tag{5}$$

The results of the algorithm developed by Ram and Sivaswamy (2009) are shown in first row of Table 1, this algorithm was called *Original*. In order to improve the rates of correct answers, the clustering algorithm was changed and one more step to remove the false candidates was added. Comparative tests between k-means and its fuzzy version showed that the fuzzy k-means algorithm was able to differentiate better the lesions from other bright regions present in your neighborhood. Therefore, exudates candidates resulting from the clustering algorithm performed by fuzzy k-means were similar contours to those of exudates labeled by experts. Another improvement proposal to this algorithm was the removal of the OD by their location in relation to blood vessels. This method is used for better removal of false candidates because in many occasions the OD is marked as exudate. The results of this modification are shown in second row of Table 1 and this algorithm was called *Modified*$_1$.

Table 1: Evaluation of the algorithms.

	S	SP	PPV	NPV	A
Original	84.94	98.45	7.98	99.97	73.90
Modified$_1$	80.31	99.44	15.57	99.99	99.25

Analyzing the results of Table 1, it was observed that the use of fuzzy k-means and the removal of the OD implied in an increased in performance evaluation by regions (25.35%). Analyzing this table, we also observed that there was a slight reduction in Sensitivity performance, but it is normal, because there was a greater rigidity in the elimination of false candidates.

After all steps of the image processing, the images resulting from the algorithm execution contained 6.835 candidate regions. 484 were exudates and 6.351 were non-exudates. Aiming to keep the proportion between the number of regions of exudates and non-exudates, we created a set of training with regions present in 25 images: 20 pathologic images (with regions of exudates and non-exudates) and 5 healthy images (with only regions of non-exudates). As the proportion of regions of non-exudates is higher than exudates, in each of the 20 pathologic images, we used for training the percentage of 30% more of non-exudates regions.

The feature vector used for training had 226 exudates and 280 non-exudates candidates. The data used for validation was created with all the remaining candidates of the other images, containing a total of 6.104 candidates (222 exudates and 5.882 non-exudates). The result of this classification is shown in Table 2.

Table 2: Classifier evaluation results.

		Exudates	Non-Exudates
MLP	Exudates	**97.29**%	2.71%
	Non-exudates	18.43%	**81.57**%
RBF	Exudates	52.70%	47.30%
	Non-exudates	0.22%	99.78%
SVM	Exudates	77.03%	22.97%
	Non-exudates	16.68%	83.32%

Analyzing Table 2 we observe that the MLP presented the best performance: 97.29% of exudates and 81.57% of non-exudates. Thus, we chose the MLP to classify candidates regions. In a classification performed with candidates of images that had only exudates the success rate was 97.83% and for images that only had non-exudates the success rate was 82.42%.

Table 3 presents the result of evaluation using the complete methodology, this algorithm was called *Modified*$_2$. For this evaluation we used all regions that were not used in training. In order to facilitate the understanding, we repeat the results presented in Table 1.

Table 3: Evaluation of the algorithms.

	S	SP	PPV	NPV	A
Original	84.94	98.45	7.98	99.97	73.90
Modified$_1$	80.31	99.44	15.57	99.99	99.25
Modified$_2$	79.19	99.87	29.07	99.99	99.87

Analyzing the results of Table 3 was observed an increase in performance by 25.97% in relation to the algorithm of Ram and Sivaswamy (2009). Analyzing this table, we also observed that there was a slight reduction in Sensitivity performance, but it is normal, because there was a greater rigidity in the elimination of false candidates.

Additionally, to obtain better performance than the algorithm of Ram and Sivaswamy (2009), this new method also presented better results than other algorithm in the literature such as Osareh et al. (2002), Sopharak et al. (2009), and Walter et al. (2002).

Figure 5 presents the resulting images of the main steps of the proposed method for a image with many exudates region. Figure 6 shows the process of elimination of false candidates in image without exudates.

6 Conclusion and Future Work

This paper presented an extended methodology for exudates detection in retinal images that combined pixels clustering and elimination of false candidates. An algorithm that utilizes fuzzy clustering, OD detection and classification was proposed.

The success of the algorithm was obtained, mostly, by introduction of the detection of the OD and classification. The proposal of locating the OD region was based on the fact that it is a convergence point of vessels. After removal of the OD, three classifiers were tested for eliminating false candidates (MLP, RBF and SVM). The MLP performed better (performance of 97.29% for exudates and 81.57% for non-exudates), so it was chosen to classify the candidates regions and eliminate false candidates.

As future work, the study of principal component analysis (PCA) and sensitivity analysis was proposed. The goal of PCA is to eliminate features that are less influential in the classification, in order to decrease network complexity and increase its efficiency. The

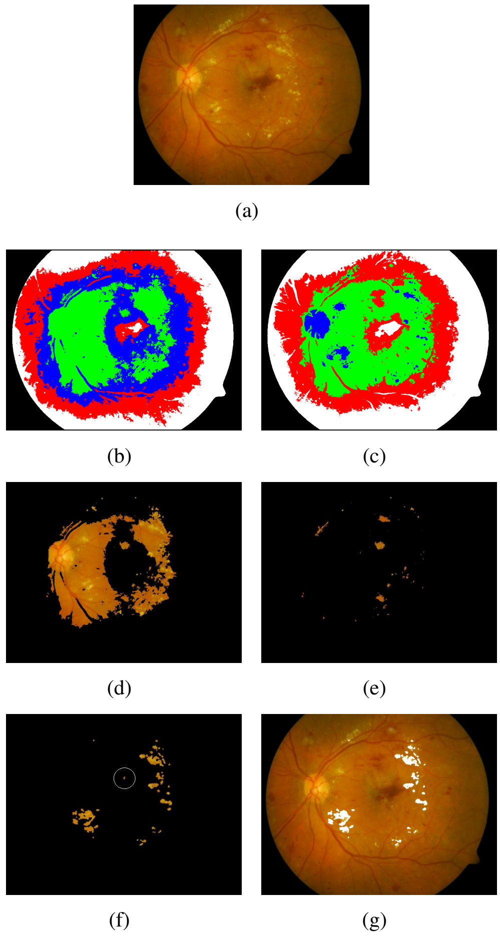


Figure 5: Application of the new algorithm: a) original image, b) clustering result with the vector f_1 (I_1 image), c) clustering result with the vector f_2 (I_2 image), d) groups selection in I_1 (image $I_{1.3}$), e) groups selection in I_2 (image $I_{2.3}$), f) candidate regions before classification (the region marked with a white circle contains false candidates), g) overlay of the result in the original image.

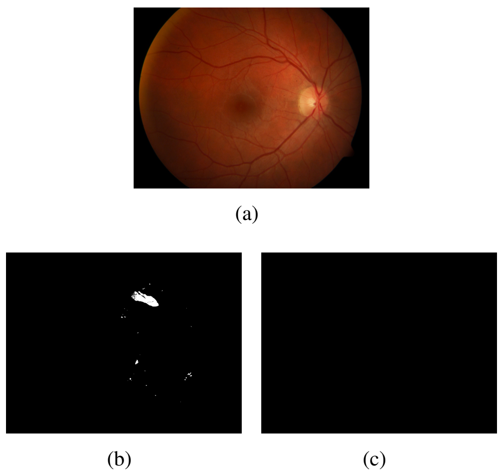


Figure 6: Application of the new algorithm: a) original image, b) candidate regions before classification, c) eliminations of all false candidates.

goal of sensitivity analysis is to verify how the network reacts to noise. Another future work proposal is the study of new descriptors and a new methodology for to classify an image into pathological or non-pathological.

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