Improvement of the Hard Exudates Detection Method Used For Computer- Aided Diagnosis of Diabetic Retinopathy

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Abstract— Diabetic retinopathy is a severe and widely spread eye disease. Early diagnosis and timely treatment of these clinical signs such as hard exudates could efficiently prevent blindness. The presence of exudates within the macular region is a main hallmark of diabetic macular edema and allows its detection with high sensitivity. In this paper, we combine the k-means clustering algorithm and mathematical morphology to detect hard exudates (HEs) in retinal images of several diabetic patients. This method is tested on a set of 50 ophthalmologic images with variable brightness, color, and forms of HEs. The algorithm obtained a sensitivity of 95.92%, predictive value of 92.28% and accuracy of 99.70% using a lesion-based criterion.

Index Terms— Ophthalmology, Color Fundus Images, Diabetic Retinopathy (DR), Hard exudates, Segmentation, Mathematical morphology, k-means clustering algorithm.

I. INTRODUCTION

The diabetic retinopathy (DR) is a microvascular complication of diabetes [1], which affects blood vessels and causes abnormalities in the retina. It remains an important cause of visual impairment and the first cause of blindness in people under 60 years. The evolution of the disease is slow and there are no salient symptoms in the early stages of diabetic retinopathy, but their number and severity predominantly increase with time. Early detection of DR through screening can help to prevent blindness and vision loss. It's characterized by the development of three kinds of symptoms. First, microaneurysms, Second hemorrhages [2]. Third, the retinal edema and hard exudates appear because of the increased permeability of the capillary walls [3]. For aid to diagnosis of the diabetic retinopathy system, should be detected before state of complications such as the presence of the macular edema.

In this paper, we focus on hard exudates detection in

color fundus image. The location of the exudates in the macular region is valuable information for the ophthalmologist [4-5], their number is an indicator of disease severity. They are not only a perceptible sign of diabetic retinopathy but also an indication for the occurrence of retinal edema. Edema and exudates are major origins of visual loss in the non- proliferative forms of DR.

Sanchez et al [6] proposed a method based on mixture models to threshold images in order to separate exudates from background. They obtained a sensitivity of 90.2%. at a cost of failure in detecting faint exudates. Garcia et al. [7] used classifiers and machine learning techniques for exudate detection. Using a lesion-based criterion, they obtained a mean sensitivity of 88.14%. Dupas et al [8] presented a pixel-based hard exudate detection method in ocular-fundus images. They obtained 92.8% sensitivity by analyzing 30 images set containing 15 exudates ones. Sanchez et al [9] used a contextual information for exudate detection. They obtained 91% sensitivity and 70% specificity they used 144 images (69 with exudates and 75 normals) divided into two 72-image groups. Hussain et al [10] used a combination of coarse and fine segmentation to detect HEs. The result is achieved with 89.7% sensitivity, 99.3% specificity and 99.4% accuracy. A limitation of this method is that it occasionally fails to exclude some non-exudate objects particularly those that have similar features to real exudates. In another work of Hussain et al [11], top-down image segmentation was used to partition the image into homogeneous regions followed by edge detection and region growing to segment HEs candidate before the classification process. This method fails to get rid of some artifacts. Kavitha et al [12] used a method based on color histogram thresholding for identification of hard and soft exudate pathologies in retinopathy images. The overall sensitivity, specificity and accuracy obtained by this approach were 89.78%, 99.12% and 99.07%, respectively. However, this method yields some false

detection because of similarity between some pixels of exudates and those of optic disc and edge of blood vessels.

In this paper, we propose an algorithm which is based on combination of k means clustering algorithm and mathematical morphology to detect hard exudates in retinal images. These techniques are widely used for image segmentation [13]. The advantage of the proposed approach is its adaptation to variability of images in terms of brightness color and contrast acquired by a retinographe from non-dilated pupils.

The paper is organized as follows: In section II, properties of HEs are presented. In section III, the K-means clustering algorithm and mathematical morphology are studied. In Section IV, the proposed method is presented. In Section V, Results and Discussions are presented; Finally, Section VI concludes the paper.

II. PROPERTIES OF HARD EXUDATES

Exudates are proteins and lipids leaking from the blood into the retina via damaged blood vessels [14,15]. They are of diverse sizes and forms and are of variable number. HEs are highly reflective and appear bright of yellow color with well defined margins. figure 1 shows fundus image in DR containing hard exudates.

Figure 1. The Presence of Hard Exudates with Different Brightness, Forms In Fundus Images

III. PROPERTIES OF HARD EXUDATES

A. K-means Clustering Algorithm

The K-Means is an unsupervised clustering algorithm that classifies the input data points into multiple classes based on their inherent distance from each other [16]. The algorithm assumes that the data features form a vector space and tries to find natural clustering in them. The points are clustered around centroids $\mu_i, \forall i = 1 \dots k$ which are obtained by minimizing the objective

$$V = \sum_{i=1}^k \sum_{x_j \in S_i} (x_j - \mu_i)^2 \quad (1)$$

Where there are k clusters $S_i, i = 1, 2, 3 \dots k$ and μ_i is the centroid or mean point of all the points $x_i \in S_i$

The algorithm takes a 2 dimensional image as input and can state as follows:

1. Compute the intensity distribution (also called the histogram) of the intensities.
2. Initialize the centroids with k random intensities.
3. Repeat the following steps until the cluster labels of the image do not change anymore.
4. Cluster the points based on distance of their intensities from the centroid intensities.

$$c^{(i)} := \operatorname{argmin}_j \|x^{(i)} - \mu_j\|^2 \quad (2)$$

5. Compute the new centroid for each of the clusters.

$$\mu_i := \frac{\sum_{j=1}^m 1\{c_{(j)} = i\} x^{(j)}}{\sum_{j=1}^m 1\{c_{(j)} = i\}} \quad (3)$$

Where k is a parameter of the algorithm (the number of clusters to be found), i iterates over the all the intensities, j iterates over all the centroids and μ_i are the centroid intensities.

B. Mathematical Morphology (MM)

The proposed approach used mathematical morphology which offers many powerful tools for image processing and analysis. It considers images as geometrical objects, to be analyzed through their interactions with other geometrical objects. It relies on several branches of mathematics, such as discrete geometry, topology, lattice theory, partial differential equations, integral geometry and geometrical probability [17]. The fundamental operations on Mathematical morphology are: dilation and erosion. Dilation expands and erosion shrinks objects marked in the image. Other morphological operations are for example morphological opening and closing which are based on dilation and erosion [18]. An essential part of the dilation and erosion operations is the structuring element (SE) used to probe the input image.

$$\text{-Dilation: } (f \oplus S)(x, y) = \max\{f(x-s, y-t) \mid (s, t) \in S\}$$

$$\text{Erosion: } (f \ominus S)(x, y) = \min\{f(x+s, y+t) \mid (s, t) \in S\}$$

$$\text{Opening: } f \circ S = (f \ominus S) \oplus S$$

$$\text{Closing: } f \bullet S = (f \oplus S) \ominus S$$

Where $f(x, y)$ is a finite-support grayscale image function defined on grid Z^2 , S is a binary structuring element.

IV. PROPOSED METHOD

The proposed method to detect hard exudates from the retinal fundus image is shown in the following flowchart (figure. 2).

Figure 2. Proposed Technique

A. Contrast Enhancement

Usually, the acquired retinal images are noisy and of low contrast and nonuniform illumination. Noises can be generated by acquisition devices, movement of the patient, differences in the illumination of the eye that depend on technology and on the geometry of the patient's eye. Therefore, a preprocessing step of the fundus photographs are needed before detecting hard exudates. Initially, the original color fundus retinal images of red, green and blue (RGB) space are transformed to CIELab color space [12] (figure 3.b). This color space is a the second of two systems adopted by CIE in 1976 as models that better showed uniform color spacing in their values. CIELAB indicates these values with three axes: L^* , a^* , and b^* . L^* defines lightness, a^* denotes the red/green value and b^* the yellow/blue value. This color space is not as easy to visualize, because L is a value between 0 and 100. The CIELab color space colour space is more appropriate for contrast enhancement as it allows the intensity to be treated separately from the other two components. Relations for L^* , a^* , and b^* are as follows:

$$L^* = \begin{cases} 116 * \left(\frac{Y}{Y_n}\right)^{1/3} - 16 & \text{for } \left(\frac{Y}{Y_n}\right) > 0.008856 \\ 903.3 * \left(\frac{Y}{Y_n}\right) & \text{otherwise} \end{cases} \quad (4)$$

$$a^* = 500 * \left(f\left(\frac{X}{X_n}\right) - f\left(\frac{Y}{Y_n}\right)\right) \quad (5)$$

$$b^* = 200 * \left(f\left(\frac{X}{X_n}\right) - f\left(\frac{Z}{Z_n}\right)\right) \quad (6)$$

$$f(t) = \begin{cases} t^{1/3} & \text{for } t > 0.008856 \\ 7.787 * t + \frac{16}{116} & \text{otherwise} \end{cases} \quad (7)$$

Where X_n , Y_n and Z_n are the tristimulus values of the reference white

In order to reduce noise and preserve edges, a median filter is applied on the L band (figure 3.c). a Contrast-Limited Adaptive Histogram Equalization (CLAHE) technique [19] is used to improve the contrast of the image and enhance the separability between exudats and the background (figure 3.d).The CLAHE technique consists in subdividing the image into non-overlapping rectangular regions, then applying their local equalization histogram.

B. Hard Exudates Regions Extraction

Hard exudates are considered to be bright intensity regions in the fundus images with distinct boundaries. To extract these regions, the k-means clustering algorithm is applied. This algorithm requires pre-processing on the enhancement filtered image (figure.3.d), which consists in converting the pixel matrix into a vector of gray levels. When the algorithm is applied to the vector, it is converted into a matrix of each cluster value for each pixel of the image. Figure 3, shows the results obtained by applying the k-means with 3, 4, 6 and 10 clustered.

(a) Typical color retinal image

(b) CIELAB color space Conversion

(c) L bande image

(d) The result after preprocessing

(e) the result of k-means with k = 3 (f) The result of k-means with k=4

(g) the result of k-means with k=6 (h) the result of k-means with k=10.

Figure 3. Detection Of Hard Exudates Regions By Using The The K-Means Clustering Algorithm

The figures (3. e. f. g and h) show, that all regions containing exudates are detected and separated from the background. However regions that do not correspond to exudates which are mainly on the edge of the image.

For $k = 3$ and $k = 4$ (figure 3.e and f), all exudative regions were defined by the algorithm. When we increase the number of clusters ($k=6$, $k=10$) (Figure.3.g and h), many clusters appear in the images at discrete places. Therefore, the exudative zone gradually splits into several parts which affect information on pixels containing exudates. After several tests, the best result obtained corresponds to $k = 3$.

The papillary region and other yellow lesions, such as cotton wool spots, are detected (figures 3. e, f. g and h), because of their similar attributes to hard exudates in terms of brightness, color and contrast. Therefore, these regions should be removed to keep only the hard exudates.

C. Optic Disc Segmentation

The optic disc is one of the main elements of the retinal image. It is considered the exit region of the blood vessels and the optic nerves from the retina. It appears as a bright yellowish or white region, circular or elliptical form. The optic disc size varies from one person to another, occupying about one tenth to one fifth of the image.

The main steps to extract the optic disc are presented as flow:

- Presentation of the original image in the luminance channel.
- Elimination of the retinal network

- Thresholding operation
- Morphological reconstruction by dilation
- Final result of the optic disc segmentation

The luminance channel of the retinal image (figure.4.a) is used to enhance the contrast in the papillary region. The vascular network should be removed from the image to favor the optic disc to be clear. This operation is carried out by a morphological closing operation [19] using a circular structuring element of larger size than the width of the vessels (figure.4.b).

$$O_{p_1} = \varphi_{e_1}(O_p)$$

- O_p : luminance channel of the original image,
- φ_{e_1} : morphological closing using a structuring element e_1
- O_{p_1} the closed image.

To separate the optic disc from the background, a thresholding operation is applied. To ensure a good extraction of this element, (figure.4.c).

$$O_{p_2} = [Ts_1(O_{p_1})]$$

As shown in figure (4.c), it is not possible to find a good threshold which segments all optic disc. To solve this problem we apply a morphological reconstruction by dilation under the image of the luminance channel (figure.4.a) considered as a mask.

To obtain a marker image, all pixels included in dilated image of the figure (4.c) are set to 0 in the image of the luminance channel. The marker image is shown in figure (4.d).

$$O_{p_3} = R_{luminance}(image.4.c)$$

All papillary regions (figure 4.e), are not reconstructed during reconstruction of the image. To segment the optic disc, the operation of subtraction is carried out between the image of the luminance channel (figure.4.a.) and the reconstructed image (figure.4.e), as illustrated in figure.4.

(a)The luminance channel Of the original image

(b) Elimination of the vascular tree

Figure.4 Result Of Optic Disc Segmentation.

In order to eliminate the optic disc from the result of a binary image of Figure (3.e), we applied a subtraction operation between this image and a binary dilated version of the segmentation result of the optic disc (figure 4.f).

$$Ex_1 = Ts_2(image(3.e)) - [(\delta(b_1))(Ts_3(image(4.f)))]$$

Ts_2 : binary image of image (3.e); $\delta(b_1)$: binary dilation using a structuring element b_1 ; Ts_3 : thresholding of image(4.f) using a threshold s_3 .

D. Elimination Of Lesions With Blurred Edge

To detect only hard exudats characterized by yellowish color and sharp edge and remove all lesions with high intensity but blurred edges such as cotton wool spots ...etc, we calculate the edge strengths. This task can be accomplished using the The Kirsch operator [20], which detects edges using eight compass filters. All eight filters are applied in a few predetermined directions to the green channel of original image with the maximum being retained for the final image (Figure 5.c). The kirsch operator is defined as flow:

$$Kirsch = \frac{1}{15} \begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} \quad (8)$$

We combine then, the thresholding result of figure (5.c) by using a threshold s_4 with image of figure (5.b) using a boolean operation AND as show in figure (5.d). Thus, we can we apply, a morphological reconstruction by dilation under the retinal image of the green channel (figure.5.e).

The results of hard exudates detection are presented in figure.5.

Figure.5 Results Of Hard Exudates Extraction In The Retinal Image.

V. RESULTS AND DISCUSSION

The algorithm that we have developed has been tested on a set of retinal images of database Messidor [21]. The images were acquired in three different ophthalmology departments, 400 images in each department, using a nonmydriatic digital retinal camera (TRC NW5; TopCon, Tokyo, Japan) with 45 ° field of view. Image sizes were 1440 *960 in 588 images, 2240* 1488 in 400 images, and 2304 *1536 in 212 images. All the images were saved in uncompressed TIFF format. For each image, indicated the level of exudation: the level depends on the area occupied by the exudates and their positions relative to the center of vision (macula). The diagnoses were considered to be the reference standard for the performance analysis in our work. From 1200 images, we randomly choose 40 images affected by one or more types of bright lesions (hard exudates, cotton wool spots

and drusen) characterized by variable color, brightness and quality and 10 were determined by an expert to have no bright lesion to validate the effectiveness our method. A retinal specialist performed manual annotations outlining hard exudates on all images. These annotations were taken as the reference standard.

Fifty images were tested on Intel Core 2 Duo 2.66 GHz PC with 3GB of RAM using Matlab 2009.b. Each image took approximately 19 seconds for running the whole process. However the approach of [20] and [2] require 4.3 and 3 minute respectively.

In 9 of the 10 images, that not contain exudates, the algorithm succeeds (it found no exudates). In one image, there were very few false positives.

However, in 34 images that contain bright lesions, all hard exudates are detected by using a low value of cluster k (Figure.6.b). In the remaining images few exudates were missed by our algorithm. This false detection is due to very low contrast and artifacts during acquisition in exudative regions. Therefore, the very small exudates are not well defined.

The choice of threshold values, structural elements, and the cluster k are considered as main parameters to get correct detection of small exudates in the retinal image. figure (6.d) shows inadequate choice of these parameters

Figure 6. Result Of Exudates Extraction With Varying Sizes In The Image

To evaluate the performance of the presented approach, we compared our results with the performance of ophthalmologist, who marked manually hard exudates as a marker for DR in these images. The sensitivity, specificity, predictive value and accuracy [22-23] are to

be determined in terms of lesion-based criterion for each image in the test set.

$$Sensitivity = \frac{TP}{TP + FN} \quad (9)$$

$$Specificity = \frac{TN}{TN + FP} \quad (10)$$

$$PV = \frac{TP}{TP + FP} \quad (11)$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (12)$$

-TP (true positive): number of pixels classified as exudates by both the ophthalmologist and the algorithm.

-FP (false positive): number of non-exudates pixels which are wrongly detected as exudates pixels by the algorithm.

-TN (True negative): number of no exudates pixels which are identified as non-exudates pixels by both the ophthalmologist and the algorithm.

-FN (false negative): number of exudates pixels that are not detected by the algorithm but are considered as exudates by ophthalmologist

- PV (predictive value): the probability that a pixel classified as belonging to the lesion is really an exudates.

The obtained results of TP, FP, FN, TN, sensitivity, specificity, predictive value and accuracy from the images containing one or more types of bright lesions are summarized in Table 1

TABLE.1 COMPARISON OF THE RESULTS FROM K-MEANS CLUSTERING FOLLOWED BY MORPHOLOGICAL RECONSTRUCTION WITH OPHTHALMOLOGIST.

Images	TP	FP	TN	FN	Sensitivity	Specificity	Predictive value	Accuracy
1	2380	150	152320	151	94,03	99,90	94,07	99,81
2	5250	166	120610	124	97,69	99,86	96,94	99,77
3	5160	153	131205	112	97,88	99,88	97,12	99,81
4	1475	292	121012	184	88,91	99,76	83,47	99,61
5	3429	244	153214	52	98,51	99,84	93,36	99,81
6	6570	177	123101	144	97,86	99,86	97,38	99,75
7	2290	125	137135	134	94,47	99,91	94,82	99,81
8	3120	170	133575	160	95,12	99,87	94,83	99,76
9	1719	134	136050	52	97,06	99,90	92,77	99,87
10	1897	110	15270	85	95,71	99,28	94,52	98,88
11	1480	130	132320	140	91,36	99,90	91,93	99,80
12	1126	144	173406	42	96,40	99,92	88,66	99,89
13	1838	122	165259	38	97,97	99,93	93,78	99,90
14	381	125	165485	76	83,37	99,92	75,30	99,88
15	1247	168	136157	20	98,42	99,88	88,13	99,86
16	1239	102	103205	99	92,60	99,90	92,39	99,81
17	1489	165	135928	22	98,54	99,88	90,02	99,86
18	1657	147	198754	20	98,81	99,93	91,85	99,92
19	13698	113	114782	69	99,50	99,90	99,18	99,86
20	6898	127	168684	41	99,41	99,92	98,19	99,90
21	3478	89	198756	154	95,76	99,96	97,50	99,88
22	2654	165	141695	136	95,13	99,88	94,15	99,79
23	2018	157	146520	163	92,53	99,89	92,78	99,79
24	1063	132	132740	134	88,81	99,90	88,95	99,80
25	2310	465	100206	96	96,01	99,54	83,24	99,46
26	2963	284	110392	73	97,60	99,74	91,25	99,69
27	2296	56	12593	23	99,01	99,56	97,62	99,47
28	3621	203	173691	153	95,95	99,88	94,69	99,80
29	2596	563	153160	39	98,52	99,63	82,18	99,61
30	2496	105	136026	109	95,82	99,92	95,96	99,85
31	3036	100	162874	146	95,41	99,94	96,81	99,85
32	2896	276	149830	151	95,04	99,82	91,30	99,72
33	1003	120	112360	50	95,25	99,89	89,31	99,85
34	2936	214	13644	128	95,82	98,46	93,21	97,98
35	2530	106	11508	69	97,35	99,09	95,98	98,77
36	366	51	100380	21	94,57	99,95	87,77	99,93
37	3214	289	131710	40	98,77	99,78	91,75	99,76
38	3256	288	121360	59	98,22	99,76	91,87	99,72
39	2375	229	132801	22	99,08	99,83	91,21	99,81
40	4280	228	125041	60	98,62	99,82	94,94	99,78
A.V					95,92	99,78	92,28	99,70

The number of non exudates which are classified in the lesion by ophthalmologist and by algorithm is high (table 1) is the reason that the value of specificity is near to 100%. Therefore the rate of specificity is not well adapted to evaluate the performance method.

The sensitivity, the PV and the accuracy values achieved are higher at 96%, 90% and 99% respectively because a few false negatives and false positive were detected. However, where exudates appear with a very

low contract or are in the vicinity of blood vessels are not detected by the algorithm but they are extracted by the ophthalmologist. In addition, the pixels with level of gray close that of the exudates are wrongly detected as exudates by the algorithm. Consequently the rate of the sensitivity, PV are lower at 88% and 83% respectively. For normal retinal image detection, the specificity proportion is 100%. The sensitivity cannot be calculated in which TP and FN values are all zero due to no exudates in ground-truth images.

In order to assess the algorithm performance with respect to change of the parameters k and s_4 . The sensitivity is plotted as a function of predictive value for different value of k and s_4 (figure.8). This procedure is carried out for each image in our data set contains bright lesions.

Figure 7, show that performance goes down for $k = 10$. The best results were obtained for $k=3$ and $s_4=0.9$ with an average sensitivity, PV and an accuracy of 95.92%, 92.28% and 99.70% respectively.

Our results are compared with a manual detection of hard exudates by ophthalmologist based on lesion criterion. Due to many images databases in ophthalmologist and different evaluation methods is difficult to compare our algorithm with other work published throughout the years. However some works [8], [9] and [24] report algorithms proximate performances than our approach with average sensitivity value of 92.08%, 91% and 97,49% respectively.

Figure 7. the sensitivity as a function of the PV for different values of K and a threshold s_4

VI. CONCLUSION

In this paper, a fast method to hard exudates detection in ophthalmology images based on k-means clustering and mathematical morphology operators is presented. This approach will be used to improve the precision of the diagnosis of the diabetes retinopathy before the stage of complications. We started in a first step with a preprocessing operation of contrast enhancement in order to enhance the quality of the input image. In the second step the k-means clustering are used in order to detect exudates regions. In the third step, the optic disc is segmented to be removed. Finally, applying a kirsch operator to detect elements with sharp edges, and morphological reconstruction to keep HES. The final results are compared quantitatively with a manual exudates segmentation produced by an expert in ophthalmology. Performances of our method are measured by sensitivity predictive value and accuracy because they combine true positive and false positive

rates. Our results suggest that the proposed method can help the ophthalmologist to detect exudates at the early stage from diabetic patients. In future works we will further to detect other types of such as microaneurysms, cotton-wool spots and hemorrhages in order to classifiers different stages of DR.

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