

Three stage red lesions detection using digital color retinal angiographies

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Abstract: Diabetic retinopathy prevention requires the screening of large numbers of patients, and examination of a huge amount of images, since diabetic patients typically have both their eyes examined at least once a year. To effectively manage all this information and the workload it produces, automatic techniques for analyzing the images are required. These techniques must be robust, sensitive and specific to be implemented in real-life screening applications. In this work an algorithm for the detection of red lesions in digital color fundus photographs is proposed. The method performs in three stages: in the first stage points candidates to be red lesions are obtained by using a set of correlation filters working in different resolutions, allowing that way the detection of a wider set of points. Then, in the second stage, a region growing segmentation process rejects the points from the prior stage whose size does not fit in the red lesion pattern. Finally, in the third stage three test are applied to the output of the second stage: a shape test to remove non-circular areas, an intensity test to remove that areas belonging to the fundus of the retina and finally a test to remove the points which fall inside the vessels (only lesions outside the vessels are considered). Evaluation was performed on a test composed on images representative of those normally found in a screening set. Moreover, comparison with manually-obtained results from clinical experts are performed, to set the accuracy and reliability of the method.

Key-Words: Fundus, microaneurysm, red lesions, retina, screening, correlation.

1 Introduction

The retinal fundus photographs are widely used in the diagnosis of eye diseases, like the diabetic retinopathy. Prevalence of the diabetes among the Spanish population is 4%, about 1.6 million people [1], where about 95% of young diabetic and 78% of adult diabetic persons will present diabetic retinopathy in the next 20 years from their diagnosis, with a blindness percentage of 10% from both groups. Processing automatically a large number of retinal images can help ophthalmologists to increase the efficiency in medical environment, and prevent visual loss and blindness. This is specially useful in the diabetic screening programs organized by the different governments, where hundreds of people are examined using images from both of their eyes, captured using fundus cameras (Figure 1). Given the large number of diabetic patients screened yearly, the number of retinal images generated is large and the majority of them is normal (typically over 90% does not present any sign of diabetic retinopathy), so an automatic mean for discarding the patients without abnormalities can reduce the

workload of the doctors in a high amount, improving diabetic patient's quality of life.

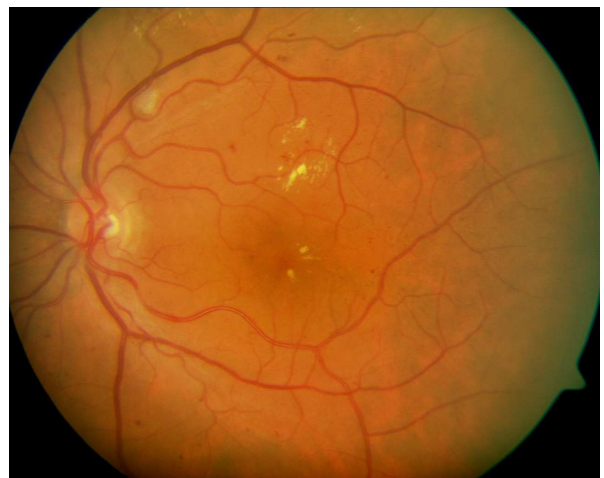


Fig 1: Digital color retinal image used as input for the diagnosis.

One important symptom of diabetic retinopathy is the development of red lesions such as microa-

neurysm and white lesions such as exudates and cottonwool spots. Here only red lesions will be located, since they are among the first absolute sign of diabetic retinopathy. Several studies have been presented to deal with the problem of hard exudates detection. [2] show that using size, shape, texture, etc. in isolation is insufficient to detect hard exudates accurately. This fact is used in this work too. Several other attempts have been made to detect hard exudates using histogram segmentation. If the background color of a retinal image is sufficiently uniform, a simple and effective method to separate exudates from the background is to select proper thresholds [2–4]. In [5] Mahalanobis distance is used as the classifier criteria, but results were inconclusive. Many other approximations can be found in literature, like mathematical morphology based [6, 7] or neural network based [8], with results ranging in sensitivity from 85% and specificity of 76% [9], sensitivity of 77.5% and specificity of 88.7% in [10] or sensitivity 93.1% and specificity of 71.4% [11], this last obtained using a commercially available automatic red lesion detection system.

In this work a new algorithm for the detection of red lesions is proposed. The method performs in three stages. In the first stage, working on the green channel of the input (color) image, several correlation filters are applied, each with a different resolution, detecting this way a wider spectrum of features. The output of this stage serves as input for the second stage, where a region growing process is used to obtain the red lesion candidates set. Finally, in the third stage the previous set of candidates is filtered by means of four filtering processes: a shape (circularity) filter, which rejects regions with “low circularity”, an intensity filter, which removes from the set the candidates which does not fulfill the intensity criteria, a correlation mean filter, which removes the candidate areas which represent an outliers in the correlation filter response and finally a last filter which, using the creases of the digital angiography [12, 13], removes that areas inside or next to vessels. In the following sections each of these stages will be described. In section 2 description of the correlation filters of the first stage is included. Section 3 provides details on the region growing algorithm. Once the regions have been obtained, the filtering process to discard false positives is described in section 4. Experiments and results are given in section 5 for the different stages of the algorithm, and finally section 6 provides discussion and conclusions.

2 Correlation filters set

The goal in this stage is to get the set of candidate red lesions. Since the regions corresponding to lesions have a wide variety of sizes, three correlation filters

are applied to the image. As proposed in [14], since red lesions have the highest contrast in the green plane [15], in place of applying the correlation to the gray-level version of the image, green plane I_g is used as the input.

The kernels of the filters are square-shaped, with a circle inside. The size of the kernels is, from bigger to smaller, 43, 23 and 15 pixels, with the circle sized 10, 5 and 3 respectively. In Figure 2 the bigger size kernel is shown.

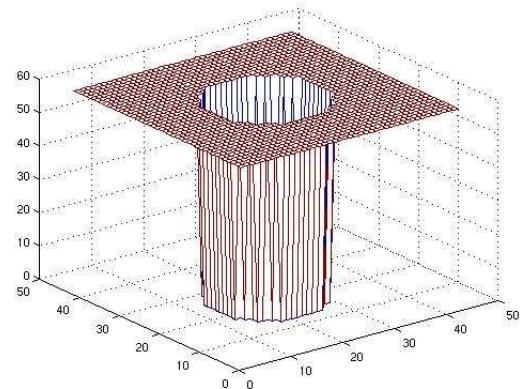


Fig 2: Example of one of the three kernels which the image is correlated with.

The three images resulting from the correlation, C_1, C_2 and C_3 , each of size $M \times N$, are combined using equation 2, so that output from this stage R' is an image where each pixel corresponds to the maximum output value from the correlations in its location. Then, a threshold with value 0.5 is applied to the output, to discard low value correlation pixels, and finally connected regions are built with the values over that threshold. The result from this process will be the candidate red lesion regions. Figure 3 shows an example of image resulting from this stage.

$$R' = \max\{C_1(x, y), C_2(x, y), C_3(x, y), \forall x, y | 1 \leq x \leq M, 1 \leq y \leq N\} \quad (1)$$

As can be clearly seen in Figure 3, many areas not belonging to red lesions are obtained in this stage. These areas must be discarded to remove false positives from the result. This will be the objective of the second stage of the algorithm.

3 Region growing algorithm

To remove false positives from the output of the stage 1, a growing region algorithm is used. The regions



Fig 3: Cropped region from the output image after applying the correlation filters, equation 2 and thresholding to image from Figure 1. Candidate red lesions are marked in red, green and blue.

which contain less than a given threshold will be removed, since they correspond to noise and false features detected as lesions. In an growing region algorithm, first step consists on finding the seeds for the growing regions. Here the point with the higher correlation value from each region output from stage one will be considered as seed (which will be the center of the lesion, if the region comes from a lesion). Once the seed has been found, the threshold t for the growing process is determined following equation 2 [14].

$$t = i_{seed} - \alpha(i_{seed} - i_{bg}) \quad (2)$$

where i_{seed} is the intensity at the starting seed position, i_{bg} is the intensity of the same pixel in an image resulting from applying a median filter with kernel size 41×41 to I_g and $\alpha \in [0, 1]$. Here $\alpha = 0.5$. Growing starts in the seed pixel and stops when no more connected pixels below the threshold can be found. The grown objects together form the final candidate object set. If the region size is above $200px$ it will be discarded, since it will be considered as a background area or vessel area. This threshold value has been set empirically, analyzing the sizes of the red lesions in the test set of images, composed by 100 images. Figure 4 depicts the result from this stage applied to image from Figure 3.

Image in Figure 4 shows some regions that are not red lesions, and should be removed from results. This goal will be fulfilled by stage three of the algorithm, commented in the next section.

4 Filtering process

In the last stage, several high-level knowledge based filters have been designed to improve detection re-



Fig 4: Cropped region from the output image after applying the growing region process to image (Figure 3). Regions are marked as green and blue areas.

sults. This improvement is acquired by removing false positives and not doing so with the true positives.

4.1 Shape filtering

The first applied filtering process consists on removing the regions which does not fit in the regular shape of the red lesions, which are circular shapes. In this step, the degree of circularity for each region is measured, and using a threshold, non-circular shapes are delete from the set of candidate regions. Circularity C is computed by means of equation 3.

$$C = \frac{p^2}{4\pi a} \quad (3)$$

where p represents the perimeter of the candidate region and a represents its area. Then, equation 4 is applied, in order to choose only circular-like regions.

$$Threshold(C) = \begin{cases} \geq 0.375, \text{ region accepted} \\ < 0.375, \text{ region rejected} \end{cases} \quad (4)$$

The value 0.375 was determined empirically by evaluating the set of test images. In Figure 5 the result obtained from this filter is depicted, showing the regions accepted marked as blue and green areas.

4.2 Intensity filtering

The second filtering process performed in this third stage is a intensity-based filtering. Since red lesions are dark structures, lighter structures can be removed from the set of candidate regions. Since illumination is not constant among images, a robust threshold is needed, and it can not be a constant. From the set



Fig 5: Cropped region from the output image after applying the shape filtering process. Regions are marked as green and blue areas.



Fig 6: Cropped region from the output image after applying the intensity filtering process. Regions are marked as green and blue areas.

of test images, a functional threshold was designed, so that it depends only on the mean value of the green plane image. In each of the images, an expert clinician set the right threshold so that minimum of false positives was zero, minimizing the number of false negatives. Equation 5, the intensity threshold, I , was obtained by a minimum square error fitting of a straight line to the set of values obtained from this manual validation.

$$Threshold(I) = 0.8054\bar{I}_g + 27.3723 \quad (5)$$

where \bar{I}_g represents the mean value of the green plane of the image. Candidate regions above the threshold will be removed. In Figure 6 the result from this process is shown, with candidate regions marked as green and blue areas.

4.3 Correlation filtering

The third of the filters consists on a correlation-based filter. Taking as basis the correlation image R' from first stage, this filter remove every region whose mean value for this correlation image is not above value 0.4. This value was computed empirically from the set of test images.

4.4 Creases-based filtering

Finally, in the last of the filtering processes the creases computed from the original digital retinal image are used as landmarks (in Figure 8 the cropped creases image of the Figure 1 is shown).

Regions intersected by creases will be removed if its mean value is over 0.25. This filter removes the regions near inside the vascular tree, which must be



Fig 7: Cropped region from the output image after applying the correlation filtering process. Regions are marked as green and blue areas.



Fig 8: Creases of the cropped region of the image in Figure 1, used to remove regions inside or near vessels.

discarded in the analysis of red lesions. Figure 9 depicts the output result from this filter, which is also the final result of the algorithm. Again, red lesions are marked as green and blue areas.



Fig 9: Cropped region from the output image after applying the creases-based filtering process. Regions Ara marked as green and blue areas.

5 Validation and results

To validate the algorithm described in previous sections, an experiment was designed in collaboration with the oculists of the Complejo Hospitalario Universitario de Santiago. From the set of 75 images, captured using a Canon CR5 nonmydriatic 3CCD camera at 45° field of view, the clinician manually marked the red lesions detected in 50 of the images. Then, the same images were input to the system, and obtained results were compared. 25 images without lesions were also input to the system, in order to evaluate its response to healthy people images, and to count the number of false positives. Figure 10 shows an image analyzed by the clinician, with the red lesions marked as yellow areas. To visually compare the results obtained with the algorithm described, the red lesions also detected by the system (true positives) are also rounded by a blue circle, the false positives are marked as green circles, and false negatives are marked as red circles.

Results obtained with the whole test set of 75 images reported the numbers in Table 1, for the images with (first column) and without (second column) red lesions. First and second row show the total number of features detected (not applicable in the case of images without lesions for the manual process) for the manual segmentation and using the algorithm, respectively. In the third row the number of false positives is shown (N.A. in the case of images without red le-

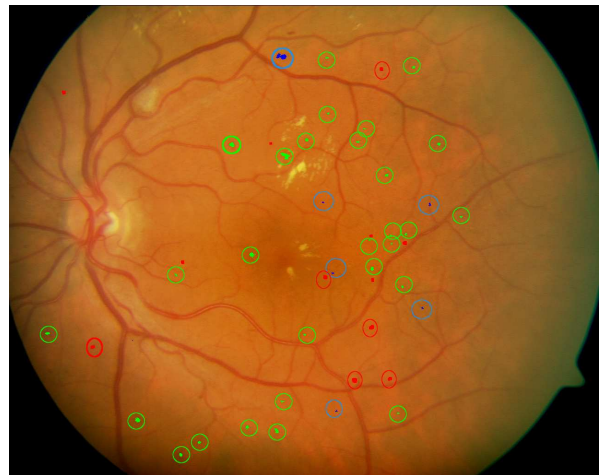


Fig 10: Comparison of the manual and automatic red lesions detection in image from Figure 1. True positives are rounded by a green circle, the false positives are marked as blue circles, and false negatives are marked as red circles.

sions). Fourth row contains the number of successfully recovered lesions, and finally fifth row display the number of false negatives (N.A. in the case of images without red lesions).

	Images with red lesions	Images without red lesions
# candidates (manual)	1570.0	N.A.
# candidates (automatic)	1470.0	220.0
# F.P.	1040.0	N.A.
# T.P.	430.0	220.0
# F.N.	530.0	N.A.

Table 1: Numbers obtained in the evaluation of the system for the images with (first column) and without (second column) red lesions. First and second rows show the total number of features detected (not applicable, N.A., in the case of images without lesions for the manual process) for the manual segmentation and using the algorithm, respectively. In the third row the number of false positives is shown (again, N.A. in the case of images without red lesions). Fourth row contains the number of successfully recovered lesions, and finally fifth row display the number of false negatives (N.A. in the case of images without red lesions).

From the results in Table 1, it can be seen that 70.7% of the detected lesions are correctly detected, with a sensitivity of 0.785%, which compared with the results from the introduction indicates that our system could be a really helpful tool in a real screening system, reducing workload of expert clinicians by pre-filtering patients which present some kind of lesion.

6 Conclusions

In this work a system to assist in the detection of red lesions on digital retinal angiographies have been presented. We consider this is a first work, since the set of test images (75) is not enough to validate the system, but first results are promising. The system performs in three stages: in the first stage candidate areas to be red lesions are detected by means of a set of correlation filters, adapted to different resolutions. This way features of different sizes can be detected. Then, in the second stage, a growing region algorithm together with a matched threshold allows the rejection of candidates which does not fit in the size of the red lesions. Finally, in a third stage, false positives are removed by filtering the output with four matched filters, which analyze several high level knowledge of the candidate regions: shape (searching for circularity), intensity (searching for dark areas), size (with a correlation filter) and finally discarding regions inside the vascular tree by means of the crease lines.

The whole algorithm has proven to be robust and accurate, with a sensitivity of 0.785%, although a bigger set of images and further validation is needed.

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