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Automatic detection of Microaneurysm in Colour Fundus Images

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Abstract: This paper addresses the automatic detection of microaneurysms (MA) in color fundus images, which may play a key role in computer assisted diagnosis of Diabetic Retinopathy (DR), a serious and frequent eye disease. The algorithm can be divided into 4 steps. The first step consists in image enhancement, shade correction and image normalization of the green channel of the color fundus image. The second step aims to detect the candidates, i.e. all patterns which may correspond to MA, which is achieved by the diameter closing and an automatic threshold scheme. Then, features are extracted, which are used in the last step to automatically classify candidates into real MA and other objects.

Keywords: Fundus; matched filter; microaneurysms; morphology; hemorrhages; retina

I. INTRODUCTION

Diabetic retinopathy (DR) is a common retinal complication associated with diabetes. It is a major cause of blindness in both middle and advanced age groups. According to the National Diabetes Information data (US) a total of 23.6 million people i.e. 7.8 percent of the US population has diabetes out of which only 17.9 million cases are diagnosed. Early detection of the disease via regular screening is particularly important to prevent vision loss. Since a large population has to be screened and that too repeatedly, an automated DR diagnostic system can assist in a big way in this process. Color fundus images are used by ophthalmologists to study eye diseases like diabetic retinopathy.

Microaneurysms are small saccular pouches caused by local distension of capillary walls and appear as small red dots [1]. This may also lead to big blood clots called hemorrhages. Hard exudates are yellow lipid deposits which appear as bright yellow lesions. The bright circular region from where the blood vessels emanate is called the optic disk. The fovea defines the center of the retina, and is the region of highest visual acuity. The paper is organized as follows. In "Methodology" implementation details of the proposed algorithm are presented. In "Experimental Results and Discussion," experimental results are compared to existing methods. Conclusions are in the "Conclusions" section.

II. METHODOLOGY

A. Preprocessing

For detecting red lesions, normally, the green channel of the color retinal image is employed as it shows the best red lesion/background contrast. But the red channel has the advantages of being brighter and distributed over a wider range of gray-level values, which results in less contrast between bright lesions and the retinal background. Hence, we utilized the intensity information from red and green channels of the same retinal image such that the islands formed between the sharp edges of the bright lesions can be eliminated. Histogram matching is used to modify the histogram of the green component using the histogram of the red component (of the same retinal image) to obtain a new image having the advantages of both channels. Then, the contrast of the modified color retina image is enhanced using contrast stretching, and median is filtered to remove the intensity variation in the background across the image. For the image shown in Figure 1a, the histogram matched image is shown in Figure 1b.

B. Candidate Red Lesion Detection

As it can be observed from Figure 2, the gray level profile of the cross section of a red lesion can be approximated by a Gaussian-shaped curve. The concept of matched filter detection12 is used to detect red lesions in retinal images. Red lesions usually have poor local contrast. The two dimensional matched filter kernel is designed to convolve with the original image in order to enhance the red lesions. A prototype-matched filter kernel is expressed as

$$f(x,y) = -\exp\left(-\frac{x^2}{2\sigma^2}\right) \text{ for } |y| \le L/2 \quad (1)$$

Where L is the length of the segment for which the vessel is assumed to have a fixed orientation. A set of twelve 15×15 pixel kernels are applied by convolving to a fundus image, and at each pixel only the maximum of their responses were retained. We have used σ=1.5 and L=9 for our experiments. During this process, the contrast of the blood vessels is also enhanced along with red lesions.

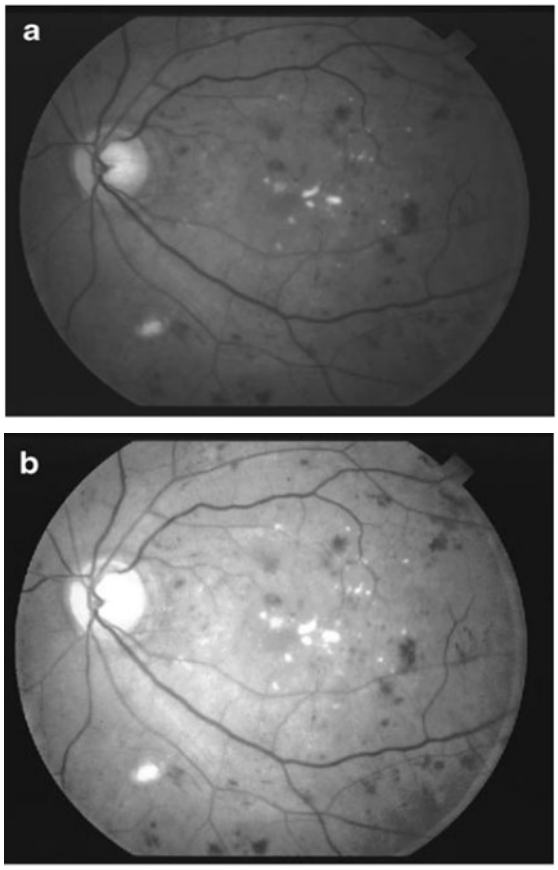


Fig 1. Pre-processing steps (a) Fundus image in green plane. (b) Histogram-matched image.

In order to properly extract the enhanced red lesion segments in the matched filter response (MFR) images, an effective thresholding scheme is necessary. An efficient relative entropy-based thresholding algorithm, which takes into account the spatial distribution of gray levels, is used, because some MFR images have complicated relationships or overlap between foreground and background. Particularly, we implement a local relative entropy thresholding technique, described in Chang which can well preserve the structure details of an image. The relative entropy thresholding is to minimize the discrepancy, i.e., the relative entropy, between the co-occurrence matrix of the original image and that of the binaries one. Therefore, the thresholder image will be the best approximation to the original one. Due to the narrow intensity distribution of dark areas (red lesions and blood vessels), the co-occurrence matrix of dark regions has strong and narrow peaks, and the relative entropy-based thresholding was found effective to keep all red lesions along with blood vessels. The relative local entropy-based thresholding result is as shown in Figure 3b. For effective detection of candidate red lesion segments, the enhanced blood vessels in relative entropy-thresholder image must be suppressed. Morphological Top hat Transmission Method is used .This operation is based on morphologically opening the image with a linear structuring element at different orientations. A total of 12 rotated structuring elements

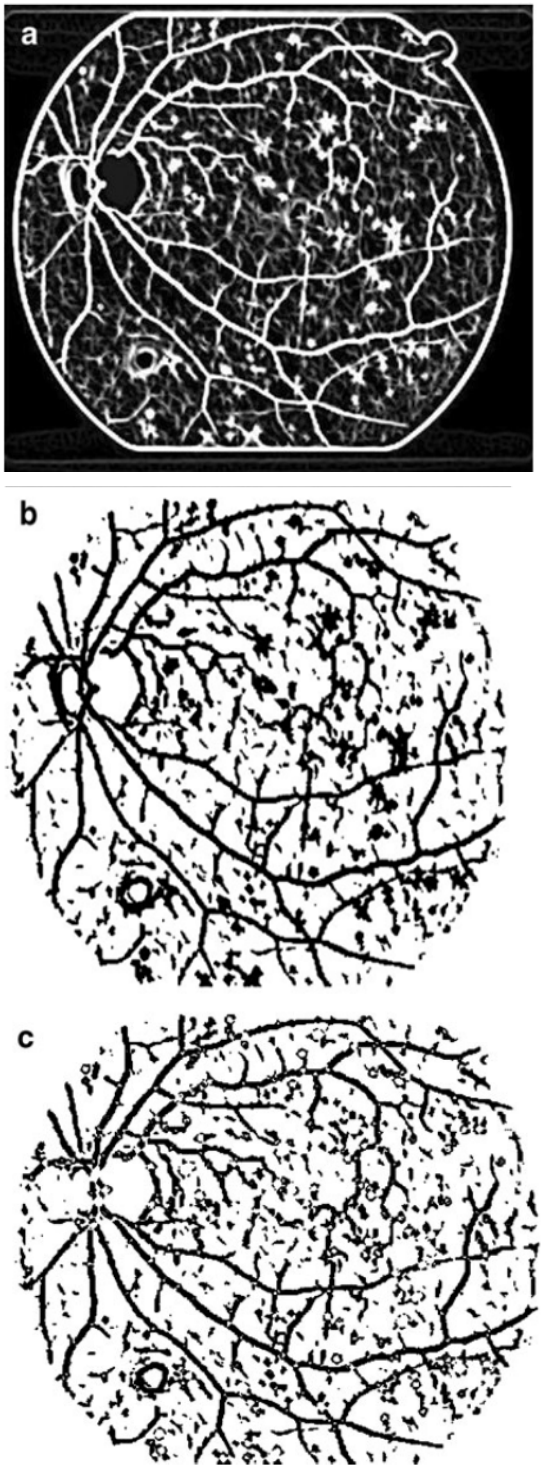


Fig 2. (a) Matched filtering result (b) Relative entropy thresholding result. (c) Morphological top-hat transformation result.

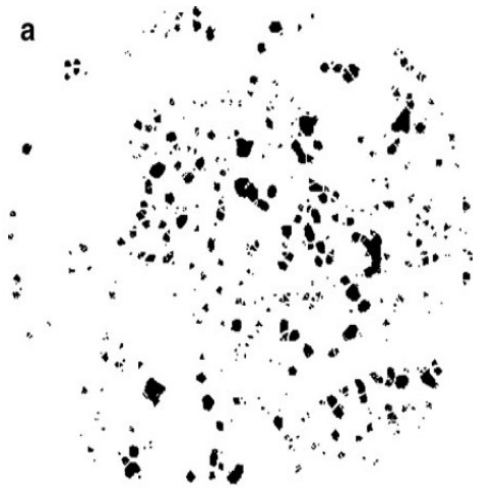
were used with a radial resolution of 15°. In each of the 12 opened images, only those parts of the vasculatures in which the linear structuring element can fit remain. The morphological top-hat transformation result is shown in Figure 3c. Then, the top-hat-transformed image is subtracted from the relative entropy thresholder image to

get candidate red lesion segments. Because red lesions in general do not appear on larger (visible) vessels, they are disconnected from the vasculature. To obtain possible candidate locations, connected component analysis was applied on the binary objects. Any object which was too large to be a red lesion was removed. A threshold of 300 pixels was found to include 98% of all red lesions. Most of the vasculature is connected, forming objects larger than 300 pixels and will, thus, be removed by this step. What remains are a number of small vessel fragments and those red lesions not connected to the vasculature. The remaining connected components are shown in Figure 3a.

SVM is a statistical learning method based on structural risk minimization. It can map the input vector x into a high-dimensional feature space by choosing a nonlinear mapping kernel. The optimal separating hyper plane in the feature space is given by Burges

$$f(x) = \mathrm{sgn}\left(\sum_{i=1}^{l} y_i \alpha_i K(x_i, x) + b\right)$$

Where yi are the labels; K is the kernel function; b is the bias, and αi is the Lagrange multiplier. We have used a linear kernel and regularization parameter C=10 for our experiments. In order to classify candidate red lesion areas and non-red lesion areas, relevant features need to be selected properly. For this purpose, we have considered the feature set proposed in Niemeyer et al.4 To improve the performance, we have added another 12 features calculated from co-occurrence matrix.15 The 12 features from the co-occurrence matrix are (1) angular second moment, (2) contrast, (3) correlation, (4) sum of squares, (5) inverse difference moment, (6) sum average, (7) sum variance, (8) sum entropy, (9) entropy, (10) difference variance, (11) difference entropy, and (12) information measurements for correlation.



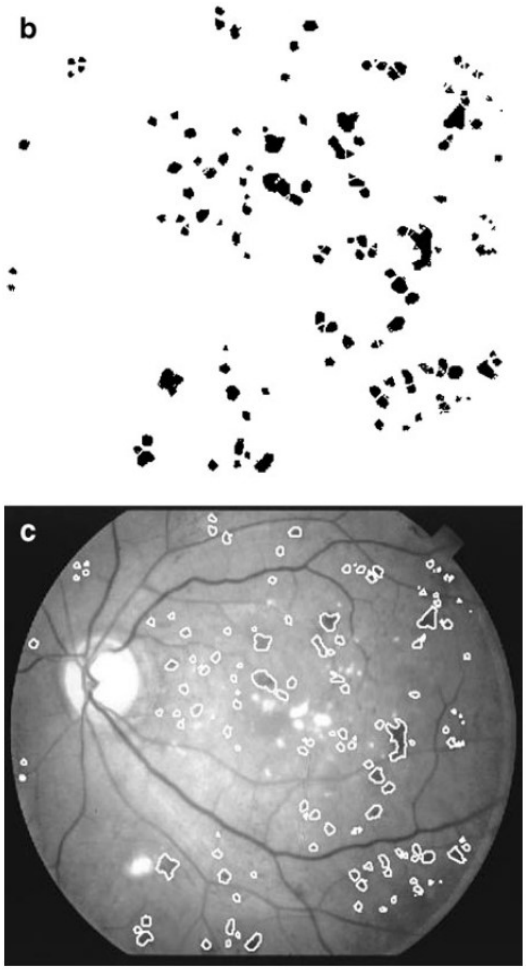


Fig 3. (a) The remaining objects after connected component analysis and removal of the large vasculature. (b) Red lesion candidates after SVM classification. (c) Final result of the proposed red lesion detection algorithm.

III. Experiment Discussion and Result

The images were selected randomly from STARE,16 DIARETDB0,17 and DIARETDB118 databases. As the testing images are from different sources, the sizes of the images are different. The sizes of the images are resized to 512×512 pixels if they are squares; otherwise, the height of an image is resized to 512 pixels while its width is resized according to the same scale. To qualitatively evaluate our algorithm, all the images have been annotated by an expert ophthalmologist. We divided all the images into two set 1 of 20 images for training and set 2 of 69 images for testing the classifiers. We implemented the proposed algorithm in MATLAB. The computational time for the whole process of the proposed algorithm takes approximately 35 s for each retinal image. We also implemented two red lesion detection algorithms 1 and 3 for comparative studies. Though these methods are proposed for MA detection, we amended these for red lesion detection by adjusting the diameter parameter. Table 1 shows an overview of the performance of

proposed algorithm when extracting candidate red lesion objects from the test set. The number of true lesions that were not extracted indicates the number of lesions that were in the reference standard but were not extracted during the candidate object extraction step. These lesions are missed by the systems and are not present in the subsequent candidate classification step. For comparison, the performances of the algorithms proposed in 1 and 3 have been added. The receiver operating characteristic (ROC) curve (Fig. 5) of the automatic red lesion detection demonstrates the range of options in setting the balance between sensitivity and specificity. The area under the ROC of the proposed algorithm is 96.2%. The performance comparison in terms of sensitivity and specificity on a per image basis is given in Table 1.

Table 1. Performance Comparison of Mathematical Morphology Method, Bounding Box Closing, and the Proposed Method

Method	Sensitivity	Specificity
Mathematical Morphology method	83%	89%
Bounding Box Closing	74%	86%
Proposed method	100%	91%

IV. CONCLUSIONS

In this paper, we have proposed a novel method for red lesion detection in fundus images based on pixel classification and mathematical morphology. The proposed approach takes into account the advantages of the intensity information from both red and green channels of the same retinal image, matched filtering, and the local relative entropy based thresholding. For efficient detection of red lesions, it is desirable to have high contrast between red lesions and the retinal background.

The sensitivity and specificity are on a per image basis while there should be low contrast between the retinal background and bright lesions. Combining the advantages of both channels, brightness in red channel and high contrast in green channel, results in increasing the contrast between red lesions and retinal background and decreasing the contrast between bright lesions and the retinal background. This results in the effective reduction of false positives during candidate red lesion extraction. Local entropy thresholding algorithm, which takes into account the spatial distribution of gray levels, performs efficiently in distinguishing between enhanced red lesion segments and the background since it can preserve the structure details of an image. The proposed method performs very well in detecting red lesions even in low-contrast regions as the intensity information of both red and green channels is used. However, Table 1 shows that there is still room for improvement. The proposed method retains the computational simplicity and, at the same time, performs better when compared to algorithms proposed in 1 and 3 with a high sensitivity and reasonable specificity of 100% and 91%, respectively. Hence, our system could be a really helpful tool in a real screening system, reducing workload of expert clinicians by profiteering patients which present some kind of red lesion.

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