Automatic Detection of Microaneurysms and Hemorrhages in Digital Fundus Images

Giri Babu Kande,¹ T. Satya Savithri,² and P. Venkata Subbaiah³

An efficient approach for automatic detection of red lesions in ocular fundus images based on pixel classification and mathematical morphology is proposed. Experimental evaluation of the proposed approach demonstrates better performance over other red lesion detection algorithms, and when determining whether an image contains red lesions the proposed approach achieves a sensitivity of 100% and specificity of 91%.

KEY WORDS: Fundus, matched filter, microaneurysms, morphology, hemorrhages, retina

INTRODUCTION

Diabetic retinopathy is a serious complication of diabetes mellitus and a major cause of blindness worldwide. Signs of diabetic retinopathy include red lesions such as microaneurysms (MA), intraretinal hemorrhages, and bright lesions, such as exudates and cotton wool spots. Red lesions are the first clinically observable lesions indicating diabetic retinopathy. Therefore, their detection is critical for a prescreening system.

Several methods for detecting red lesions have been reported in the literature. Morphological top-hat transform has been applied for eliminating the blood vessels from fundus images in Spencer et al. and Fleming et al.^{1,2} The residual regions were considered as candidate MA. For the MA detection from the candidates, region-growing algorithm was employed in Spencer et al.¹ It was further improved in Fleming et al.² using watershed region growing and contrast normalization to improve the ability to distinguish MA from other dots that occur on the retina. In Walter and Klein,³ bounding box closing is used for the detection of dark details in the gray-level images. A diameter criterion was then used to eliminate all holes with a diameter smaller than a constant λ . In Niemeijer et

al.,⁴ pixel classification based on supervised learning is used to separate the vasculature and red lesions from the background. An extensive number of new features were then added to those proposed in Spencer et al.¹ In Hatanaka et al.,⁵ candidate red lesions were detected using density analysis and then classified using rule-based method and three Mahalanobis distance classifiers with a 45-feature analysis. The method proposed in Marino et al.⁶ was performed in three stages: in the first stage, candidate red lesions are obtained by using a set of correlation filters working in different resolutions. Then, in the second stage, a region-growing segmentation process rejects the candidates from the prior stage whose size does not fit in the red lesion pattern. Finally, in the third stage, the red lesions were classified. Gray-level grouping-based contrast enhancement is used in Balasubramanian et al.⁷ to enhance the contrast of the green channel. Then, candidate red lesions are extracted by employing automatic seed generation. Spatiotemporal feature map classifier was used to classify true red lesions from nonred lesions. In Bhalarao et al.,⁸ an orientation-matched filter is applied to the

¹From the Vasireddy Venkatadri Institute of Technology, Nambur, 522508, Guntur, Andhra Pradesh, India.

²From the Department of Electronics and Communication Engineering, Jawaharlal Nehru Technological University, Hyderabad, Andhra Pradesh, India.

³From the Amrita Sai Institute of Science and Technology, Paritala, Andhra Pradesh, India.

Correspondence to: Giri Babu Kande, Vasireddy Venkatadri Institute of Technology, Nambur, 522508, Guntur, Andhra Pradesh, India; tel: +91-9885263148; e-mail: kgiribabu@yahoo.com

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preprocessed retinal image. The output of orientation-matched filter is thresholded to obtain a set of potential candidates. Then eigen image analysis is used to eliminate certain noise artifacts which resemble the shape profile of an MA. Finally, a second threshold is applied on the eigen-space projection of the candidate regions to remove the false positives. In Prasad et al.,⁹ MAs and hemorrhages are treated as holes, and morphological filling is performed on the green channel to identify them. The unfilled green channel image is then subtracted from the filled one and thresholded in intensity to yield a resultant image with MA patches. To remove noise vessel segments, the full blood vessel network skeleton is dilated and subtracted from the resultant image. The remaining patches are further classified using intensity properties and a color model based on the detected blood vessels. In Fleming et al.,¹⁰ candidate MA are detected by taking the maximum of multiple linear top-hats (MMLTH) applied to the inverse image. In Fleming et al.,¹¹ MMLTH was adapted to detect larger objects like hemorrhages at multiple scales by repeating with multiple structuring elements. Later, the candidate hemorrhages are classified by using a support vector machine (SVM) classifier.

However, the major challenges in red lesion detection are: (1) segmentation of small MA in the areas of low image contrast and (2) the presence of bright pathologies. As bright lesions have sharp edges, small “islands” of normal retina are formed between them, when they lie close together. These can be picked up as false positives. Our primary focus in this paper is to develop an automated method which can detect images containing red lesions with a very high sensitivity and a reasonable specificity by extracting all the possible red lesions, while avoiding false responses near bright pathologies and other nonred lesion structures.

The main contribution of this paper is the development of a new candidate detection scheme based on pixel classification and mathematical morphology. The proposed approach extracts both vasculature and possible red lesions at once, and subsequently the vasculature is separated from the red lesion candidate objects. The proposed algorithm uses the intensity information from red and green channels of the same retinal image and the thresholding based on local relative entropy. We are interested in using the information of the red

channel in preprocessing of color fundus images for two reasons: firstly, to improve the visual appearance of retinal images in cases of nonuniform illumination and, secondly, to improve the performance of red lesion detection. Hence, the retinal image is preprocessed to modify the histogram of the green channel by using the histogram of the red channel (of the same retinal image) to obtain a new image. Then, the contrast of red lesions against the background is improved by using matched filter. The relative entropy-based thresholding is employed to distinguish between red lesion segments and the background in the matched filter response image. Then morphological top-hat transformation is used to suppress the enhanced vasculature. SVM are used to classify the candidate red lesions from other dark segments. Our primary focus in this paper is to detect images containing red lesions with a very high sensitivity and a reasonable specificity. The performance of the proposed algorithm is compared to the bounding box closing method proposed in Walter and Klein³ and mathematical morphology scheme proposed in Spencer et al.¹

The paper is organized as follows. In “[Proposed Algorithm](#),” implementation details of the proposed algorithm are presented. In “[Experimental Results and Discussion](#),” experimental results are presented and compared to existing methods. Conclusions are in the “[Conclusions](#)” section.

PROPOSED ALGORITHM

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. Figure 1c is the result after contrast enhancement and median filtering.

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

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

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 $\sigma=1.5$ and $L=9$ for our experiments. During this process, the contrast of the blood vessels is also enhanced along with red lesions. The matched filter response for the image shown in Figure 1c is shown in Figure 3a.

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 et al.¹³ 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

Fig 1. Preprocessing of a fundus image. a Fundus image in green plane. b Histogram-matched image. c Image after applying contrast stretching and median filtering.

binarized one. Therefore, the thresholded 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-

Fig 2. a Green channel view of a red lesion. The pixels belonging to the lesion are darker than the background. b Profile of the center of a red lesion.

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-thresholded image must be suppressed. Morphological top-hat transformation is used for this purpose. This operation is based on morphologically opening the image with a linear structuring element at different orientations. A total of 12 rotated structuring elements were used with a

Fig 3. a Matched filtering result for the image shown in Fig. 1c. b Relative entropy thresholding result. c Morphological top-hat transformation result.

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-thresholded 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 4a.

Classification of Red Lesion Candidates Using Support Vector Machines

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 hyperplane in the feature space is given by Burges¹⁴:

$$f(x) = \text{sgn} \left(\sum_{i=1}^l y_i \alpha_i K(x_i, x) + b \right) \quad (2)$$

where y_i are the labels; K is the kernel function; b is the bias, and α_i 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 nonred lesion areas, relevant features need to be selected properly. For this purpose, we have considered the feature set proposed in Niemeijer 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)

Fig 4. 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.

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

Method	No. of candidates	True red lesions extracted missed out
Mathematical Morphology method	11,476	95
Bounding Box Closing	9,681	103
Proposed method	13,823	26

difference variance, (11) difference entropy, and (12) information measurements for correlation.

EXPERIMENTAL RESULTS AND DISCUSSION

Eighty-nine color retinal images are tested by the proposed algorithm of red lesion detection. Fifty-four images are provided by an eye hospital. The other 35 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 sets—set 1 of 20 images for training and set 2 of 69 images for testing the classifiers. We implemented the proposed algorithm in MATLAB (version 7) on a Pentium IV. 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 pro-

Fig 5. ROC curve of the proposed method. The sensitivity and specificity are on a per image basis.

posed 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 2. A sample of our results is shown in Figure 6.

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

Table 2. 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%

The sensitivity and specificity are on a per image basis

Fig 6. Red lesion detection on two images. a, c Fundus images in green plane. b, d Detected red lesions.

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 prefiltering patients which present some kind of red lesion.

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