New Feature-Based Detection of Blood Vessels and Exudates in Color Fundus Images

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***Abstract*—Exudates are one of the earliest and most prevalent symptoms of diseases leading to blindness such as diabetic retinopathy and wet macular degeneration. Certain areas of the retina with such conditions are to be photocoagulated by laser to stop the disease progress and prevent blindness. Outlining these areas is dependent on outlining the exudates, the blood vessels, the optic disc and the macula and the region between them. The earlier the detection of exudates in fundus images, the stronger the kept sight level. So, early detection of exudates in fundus images is of great importance for early diagnosis and proper treatment. In this paper, we provide a feature-based method for early detection of exudates. The method is based on segmenting all objects that have contrast with the background including the exudates. The exudates could then be extracted after eliminating the other objects from the image. We proposed a new method for extracting the blood vessel tree based on simple morphological operations. The circular structure of the optic disc is obtained using Hough transform. The regions representing the blood vessel tree and the optic disc are set to zero in the segmented image to get an initial estimate of exudates. The final estimation of exudates are obtained by morphological reconstruction. This method is shown to be promising as we can detect the very small areas of exudates.**

***Keywords*—Fundus image, Exudates, Diabetic retinopathy, snakes, Mathematical morphology.**

I. INTRODUCTION

Blindness is an intimidating problem every where in the world. Efforts are hardly being done to prevent blindness. Diabetic retinopathy and age-related macular degeneration are among the strong causes of sight degradation and blindness. Early diagnosis of these two conditions is of great importance as it can help stopping the progress of these diseases thus keeping the sight and preventing blindness. Since diabetic retinopathy is more common, patients need to have their eyes screened each year, but, unfortunately in many countries, there are too few ophthalmologists to meet the demand [1-3]. Although appearance of exudates is the earliest and most prevalent symptom of diabetic retinopathy, other retinal abnormalities could be found such as microaneurysms and haemorrhages. The amount of exudates, microaneurysms and haemorrhages increases as the degree of disease [2]. So, early detection of exudates is an early diagnosis of these two diseases.

Exudates are formed by the leakage of proteins and lipids from the bloodstream into the retina via damaged blood vessels [1]. In retinal images, hard exudates appear as bright yellow lesions with varying sizes, shapes, and locations. They also have a considerable contrast with respect to the background. The optic disk, bright circular region from where the blood vessels emanate, is the only area in the fundus images having the same brightness and colour range like the exudates. Figure 1 illustrates the appearance of the exudates and the optic disc in the colored fundus images. So, detection of exudates could accurately be done by extracting the bright yellow regions after elimination the optic disc area from the image.

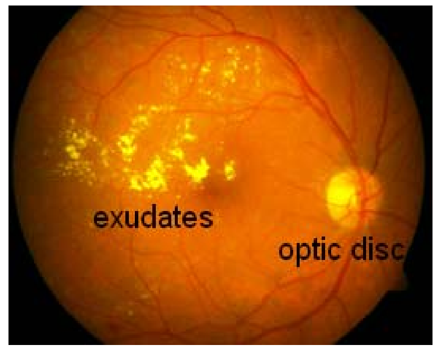

Figure 1, Image with hard exudates

Several techniques have been developed for exudates detection in fundus images. Akara et al [4] use maximum variance to obtain the optic disk center and a region growing segmentation method to obtain the exudates. Blood vessel intersection property is used in [5], [6] to obtain the optic disk. Based on its color characteristics, the authors in [7] composed a simple Bayesian classifier to detect the exudates. Extraction of exudates and blood vessels by computing the difference map and k-means clustering is introduced in [8]. Color normalization and local contrast enhancement followed by fuzzy C-means clustering and neural networks were used by Osareh et al [1]. The system works well only on Luv color space but in the case of non-uniform illumination the detection accuracy is low. In [9], a naïve Bayes classifier for diagnosis of diseases from retinal image is applied and this can provide a good decision support to ophthalmologist. Walter et al [10] proposed a method for automated identification of exudates in colour fundus images using mathematical morphology techniques . Morphological operations are also used to detect the exudates and optic disc in [4] and [11].

In this work, we propose a fast and an accurate method for early detection of exudates in fundus photographs. The proposed method is based on detecting areas of higher intensities, yellow color and high contrast by detecting their contours. The marker image is estimated by dilating the final contours. Then, the full extent of the exudates could be obtained selectively by morphological reconstruction. This method could be fully automated after the automatic extraction of the blood vessel tree, hemorrhage and optic disc or it may be semi automated to save the calculation time while maintaining the accuracy. The paper is divided into four main sections. An introduction to the problem with a brief review is given in section I. In section II, we describe the materials used in this work and give an explanation of the proposed method. The results are discussed in section III. Finally, we conclude our work and point to our intended future work.

II. MATERIALS AND METHODS

Some of the color fundus images used in this paper were collected from the ophthalmology clinic in the National Institute of Laser Enhanced Sciences (NILES), Cairo university, Egypt using a Topcon TRC fundus camera. The others were downloaded from the STARE database. We collected images of about one hundred patients of different retinal disorders; among them, a number of seven images were found to have different degrees of exudates. The proposed methods were applied to these seven cases. The images were first pre-processed for enhancement before applying the algorithms of selective detection of exudates.

A. Preprocessing

Generally, retinal images are to be pre-processed to correct the problems arise from nonuniform illumination. The low contrast of the images and the presence of noise are among these problems. The colored images used in this study were read as RGB images. The green component always have the highest contrast and contains the information that can be extracted from the fundus images. Because of that, we used the green component to extract the exudates. First, the images were pre-processed for noise removal using median filtering. The contrast enhancement technique described in [11-12] was applied to the green component.. This technique is based on top-hat morphological operations. First, we applied the top-hat by opening which results in an image of bright regions only. Second, the top-hat by closing was applied and this results in an image of dark regions. The subtraction of the two results gives a contrast-enhanced image. The method is described mathematically in equation (1).

$$I_{out} = I_{in} + \gamma_{TH}(I_{in}) - \phi_{TH}(I_{in}) \qquad (1)$$

Where, I_{in} , I_{out} , γ_{TH} *and* ϕ_{TH} are the input (green component), output images, the image result after applying top-hat by opening and the result of applying top-hat by closing respectively. The result of enhancement by this algorithm is shown in figure 2.

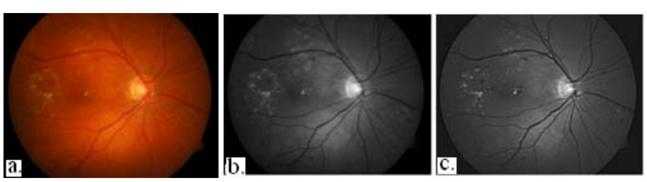

Figure 2. Image enhancement: (a) original image, (b) green component and (c) contrast-enhanced green component

B. Proposed method

As mentioned above, the proposed method could be used fully automatically or semi automatically. To be fully automated, we have to extract the regions that share the exudates in their features like the optic disc. Also, our method is based on edge detection as a major step in segmenting the image. All edge detection algorithms must detect the edges of the blood vessels as they always have some contrast with the background. So we need to extract the optic disk and the blood vessels before extracting the exudates.

1) Optic disc extraction

The optic disc is of *circular* structure in almost all cases. So, we used Hough transform which is well-known for its robustness in detecting circular objects in images [13]. The *Canny* edge detector was used to detect pixels to be candidates of the required circle. Although, exudates are best appear in the green component of the image, the optic disc is best appear in the red component. Figure 3 shows the result of detecting the optic disk from the red image component.

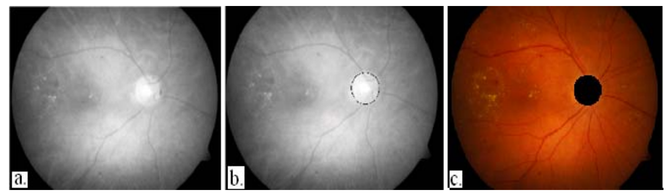

Figure 3. The detection of the optic disc: (a) Red component, (b) red channel with superimposed marker, (c) result of optic disc detection

2) Edge detection algorithm

Since our proposed method is based on contour detection, and to be fully automated, we have to apply the contour detection algorithm on the whole image. The contour detection algorithm introduced in [14], was used which is a simplified snakes algorithm. In this algorithm, a contour is to be initialized close to the contour to be detected. Then, the algorithm checks the energies of a point on the initial contour and its 8-neighbors and replaces this point by the point of minimum energy among the nine points. The check and replacement is repeated for all points on the contour. So, the shape of the contour will change accordingly. The process is to be repeated until no changes in the shape of the contour occurs and the final contour will rest at the shape of minimum energies. The energies considered for the points of the contour have different forms and are classified into internal and external energies. In the retinal images, the internal energies could be neglected and from the external energies, the energy due to the difference between intensity value of a point and its neighbor (i.e. if there is an edge) is the most affecting energy as stated in [14]. So, the contour will finally rest at the points of higher edge values demarcating the required contour. The authors in [14] used a grid of seed contours to cover the whole image. In this work, we used the same technique for contour detection taking into account all neighbors of the point on the contour of energy greater than a threshold. This allowed us to obtain not only the salient contours but also the full extent of narrow objects in the image. It is feasible here to mention that the points chosen to replace a point on the contour are those having an edge value greater than a fraction of the maximum edge value in the image where the edge values were calculated by the *Sobel* operator. A sample result of this step is shown in figure 4.

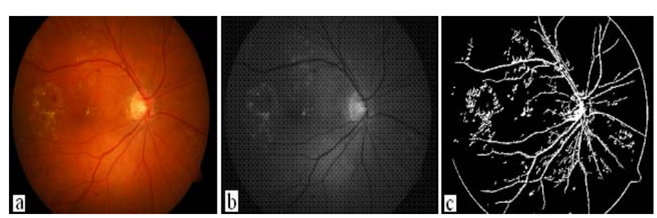

Figure 4. edge detection: (a) original image, (b) green component covered by a grid of seed contours and (c) result of applying the edge detector

It is clear from figure 4 that, the simplified snakes algorithm detects the exudates together with the blood vessel tree and the bright area of the optic disk. So, we need to eliminate the optic disk and the blood vessel tree from the image. The optic disc could be simply eliminated by setting the area surrounded by the Hough circle to zero. The result of this step is shown in figure 6 a. To eliminate the blood vessels, we have to accurately detect them and then setting their areas to zeros.

3) Detection of the blood vessel tree

In our method we select the green component for the detection of blood vessels because the vessels have higher contrast in this component. Since the blood vessels appear as dark regions in brighter background, we can narrow them by morphological dilation. If the dilated image is then eroded using the same structuring element, the very small dark region should be eliminated from the image while the larger area return to their initial size. Dilation followed by erosion is defined as the morphological closing. The proposed vessels detection algorithm is based on closing the image with two line structuring elements of different sizes. Closing by the bigger element would make the vessels to disappear. So, subtracting the two closed images would result in brighter areas of blood vessels and darker background with contrast higher than that of the original image.

It is noticed that the vessels may be oriented at any angle θ $(0 \leq \theta \leq \pi)$. So to extract the vessels at different orientations, the structuring elements have to be rotated. Assuming an angular resolution of 15°, we need twelve orientations and the maximum of the twelve subtracted closed images are only retained. The small regions that may represent noise or hemorrhage could be removed by opening. If I_{in} is the original image (green component), b_1 and b_2 are two structuring elements (b_2 is longer than b_1) and I_{out} is the output image, then the pseudo algorithm of the proposed blood vessels detection technique is as follows:

$$I_{in} = I_{in} + \gamma_{TH}(I_{in}) - \phi_{TH}(I_{in})$$
$$I_{out} = zeros(size(I_{in}))$$
$$for\,\theta = 0:180:step15$$
$$Temp1 = Morpho\log icalClose(I_{in}, b_1)$$
$$Temp2 = Morpho\log icalClose(I_{in}, b_2)$$
$$Temp = (Temp2 - Temp1) \geq threshold$$
$$rotate(b_1, \theta)$$
$$rotate(b_2, \theta)$$
$$I_{out} = I_{out} + Temp$$
$$endFor$$
$$I_{out} = Morpho\log icalOpen(I_{out})$$

Where the first line of the algorithm is to pre-process the image for contrast enhancement. The result of blood vessel detection is shown in figure 5 with a result of the fourth iterative step to explore the closing by two different elements and their subtraction. The elimination of the optic disc and blood vessels and the initial estimate of the exudates are shown in figure 6.

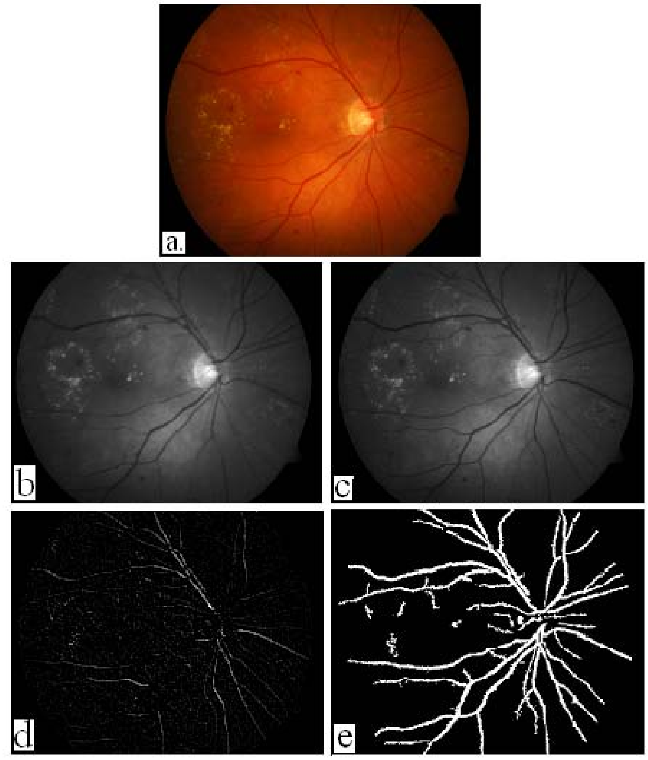

Figure 5. Detection of blood vessels tree: (a) original image, (b) green component closed by a structuring element, (c) the same image closed by a larger structuring element, (d) subtraction of (b) and (c) and (e) extracted blood vessels.

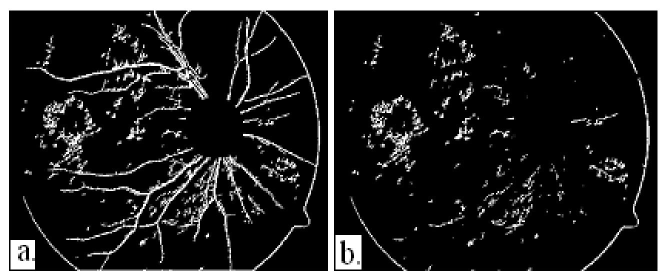

Figure 6. Initial estimation of exudates: (a) elimination of the optic disc and (b) elimination of blood vessels.

4) Detection of Exudates

After eliminating the blood vessels and the optic disc from the image resulted from edge detection, the result is only an initial estimate of the exudates. We used morphological reconstruction algorithm described in [15, 16] to get the final estimate of exudates. The reconstruction is given by the iterative formula given by equation (2):

$$h_{k+1} = (h_k \oplus b) \bigcap I_{in} \qquad (2)$$

Where, h_k is the marker image at the k^{th} iteration (h_1 the image contains the initial estimate of exudates superimposed on the original image), b is the structuring element and I_{in} is the input image (the green component). This is an iterative process which must be repeated until no changes occur in h. The final iteration result is then subtracted from the input image to get the final estimate of exudates in I_{out} as give by:

$$I_{out} = I_{in} - h_{final} \quad (3)$$

The pixels of intensities higher than a threshold related to the maximum intensity of the image could be taken as the final detected exudates. The result of this algorithm is shown in figure 7.

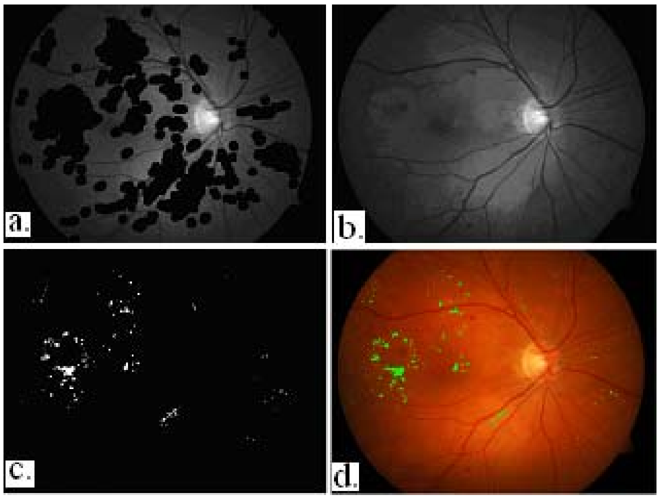

Figure 7. Exudates detection: (a) the marker image, (b) the result of iterative equation, (c) the subtraction of the image in b. from the original image and (d) the obtained exudates superimposed on the original colored image.

C). Semi automated detection of exudates

As mentioned above, the technique of exudates detection could be applied fully automatically; as described; or semi automatically. To fully automate a process, it always needs to optimize between the accuracy, the calculation complexity and the execution time. We sometimes go to the semi automated performance to get the best results in the shortest time. So, we can detect exudates from the retinal images by defining a region of interest to enclose the area containing the extent. In this work, we can select one or many regions on the image, to accurately detect the exudates. In this case, the grid of seed contours must cover the region(s) of interest as shown in figure 8.a. Same steps described above are to applied to get the final estimate of exudates. The result of the semi automatic detection of exudates is shown in figure 8. b.

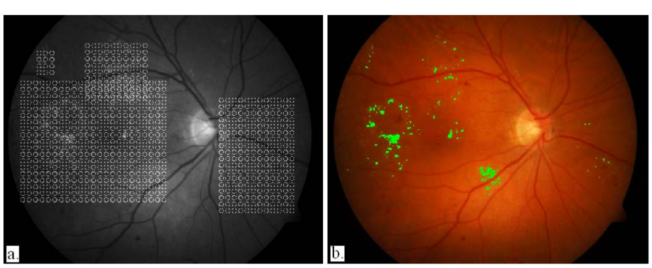

Figure 8. Semi automated detection of exudates: (a) original image with four manually-selected ROIs covered by grids of seed contours and (b) detected exudates superimposed on the original colored image.

III. RESULTS AND DISCUSSION

In this work, we collected a number of one hundred retinal images with different retinal disorders to be used in building a diagnostic tool for ophthalmologists. From this collection, we found a number of seven images with exudates appear in different patterns and degrees. The proposed algorithms were applied to these seven images for contrast enhancement, removal of optic disk, detection and removal of blood vessel tree and finally for the detection of exudates. Since we provide a new method for the detection of blood vessel tree, the results of applying the proposed method are shown for the seven collected images in the flowing six figures while the seventh is given for the above-presented clarification. It is obvious that the proposed blood detection algorithm outlines the extent of the blood vessel tree with a high degree of accuracy, since it outlines even the very small vessels while eliminating the noise that may arise from some hemorrhage spots in the image. This is due to the fact that, the blood vessels appear as dark structures in a brighter background. Closing of the image with a line structuring element of size 15 leads to vanishing of the dark areas of the blood vessels and hemorrhage. Closing with another line element of size 9 keeps the cores of the blood vessels. The sizes of 15 and 9 are chosen as they represent the width of the widest and narrowest vessels as stated in [14]. Hence, subtraction of the two results gives the extent of dark areas in same orientation as the line element. We applied this method for different element orientation to get the full extent of the blood vessels. The connected components of a number of pixels less than 150 were removed by opening.

Also, the proposed blood detection algorithm helps greatly in enhancing the detection of exudates. It was always a challenge to eliminate the other objects from the image to get higher accuracy of detected exudates. The results of detection of exudates are shown in the following six figures together with the results of blood vessel detection.

It is clear from figures 9 to 13 that the blood vessel trees are very accurately outlined in all of these figures. Although of the non uniform illumination of images shown in figures 11, 12 and 13, the complete extent of the blood vessels were extracted. The image shown in figure 10 is of low contrast beside the presence of hemorrhage which may affect the detection of blood vessels. But the figure reveals the complete outlining of the blood vessel tree in this image.

Not only non uniform illumination is observed in the image shown in figure 14 but also the very low contrast could be clearly observed. Although of these problems, a reasonable extraction of the blood vessel tree was obtained. All of these indicates the robustness of the proposed blood vessel detection algorithm.

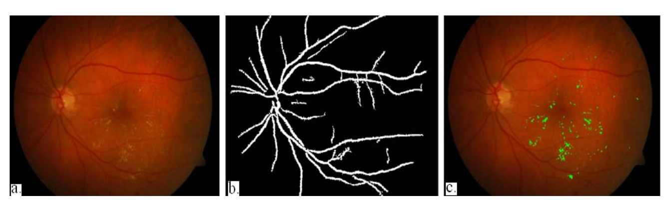

Figure 9. (a) original image, (b) extracted blood vessels and (c) detected exudates.

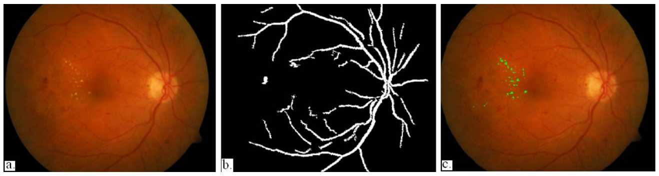

Figure 10. (a) original image, (b) extracted blood vessels and (c) detected exudates.

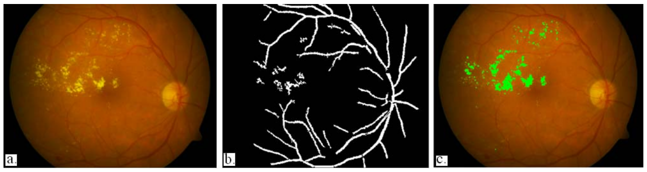

Figure 11. (a) original image, (b) extracted blood vessels and (c) detected exudates.

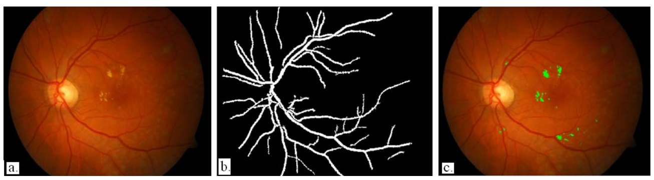

Figure 12. (a) original image, (b) extracted blood vessels and (c) detected exudates.

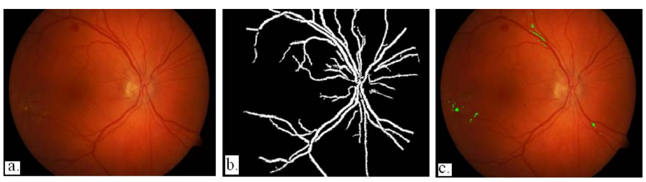

Figure 13. (a) original image, (b) extracted blood vessels and (c) detected exudates.

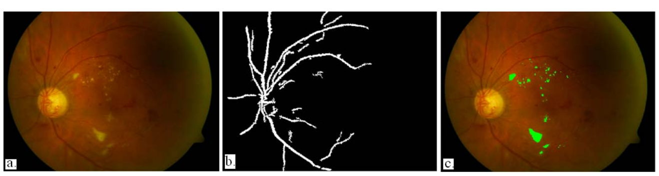

Figure 14. (a) original image, (b) extracted blood vessels and (c) detected exudates.

The result of exudates detection are shown in the right parts of figures 9 to 14. Figure 9 shows a full detection of exudates although of the small sizes of the exudates regions. This result coincide exactly with that manually outlined by the ophthalmologist. A beautiful result of exudates detection is shown in figure 10 which is an image containing hemorrhage and very early exudates and again the detection is typical to that done by the ophthalmologist. The result shown in this figure reveals the robustness of the proposed algorithm. This robustness could also be noticed from the detection of exudates in figure 11 despite the fact that the image in this figure is of very low contrast. Although of the low quality of the image, the algorithm well detects the exudates of figure 11 to be identical to that done by the physician. Figure 12 shows the detection of non exudates region together with the exudates according the opinion of the ophthalmologist. This is because the patient of this image had been exposed to laser irradiation for treatment by photocoagulation. This treatment always changes the color of the exposed area to the yellow color and begin to darken gradually. So, it is logic to have some errors in such images. Figure 13 reveals that some false positive detection of exudates in case of very early generation of exudates. Although of the very bad quality of the image shown in figure 14 which has more hemorrhage areas beside the very low contrast and bad illumination, the exudates are fully outlined in this image according to the ophthalmologist observation.

IV. Conclusion

In conclusion, we propose a new algorithm for the detection of blood vessel tree in retinal images based on closing the image with two different sizes of line structuring elements and subtracting their results. This algorithm can work properly with lower quality retinal images and images containing hemorrhage and exudates. The proposed algorithm not only detects the blood vessel tree very accurately but also helps in enhancing the detection of exudates using morphological construction methods. In future, we intend to extend out proposed method to help enhancing the detection of hemorrhage and a build an integrated diagnostic system.

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