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Detection of Microaneurysms in Retinal Angiography Images Using the Circular Hough Transform

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Abstract

This paper presents an automated method for detecting microaneurysms in the retinal angiographic images by using image processing techniques. In the presented method, in order to fade or remove the pseudo images, first retinal images are pre-processed. Then microaneurysms are identified by circular Hough transform. In the existing methods of detecting microaneurysms, it is necessary to identify the vessels in the surface of the retina and to remove them from the background of the image. But in the proposed method, first by using the circular Hough transform the central point of the microaneurysms lesion is identified. Then by using the region growing technique, the total areas of pixels associated with these lesions are identified. In this proposed method due to the removal of the vascular diagnosis which has been very time consuming, the speed of the algorithm has significantly been increased. Results received from the retinal images of five patients show that the accuracy of the proposed method in detecting microaneurysms is about %88.5 that in comparison with other existing methods has higher speed and more accuracy.

Keywords: *Angiography, Image processing, Circular Hough transform, Diabetic retinopathy, Region growing process, Microaneurysms*

1. Introduction

World health organization has estimated that 135 million people have diabetes mellitus (diabetic retinopathy) in the worldwide and this number will be increased to 300 million until 2025 [1]. Even in the early stages of development, this disease creates complications on the retina. These complications can be detected by eye specialists with careful examination of retinal angiographic images.

Diabetic retinopathy, by causing changes on the vascular structure and creating new vessels, is one of the main causes of blindness in adults. In order to reduce the lesions caused by the diabetic retinopathy on the retina, it is necessary to examine the images of the retina every six months. Early diagnosis of changes in the structure of the retina can prevent serious problems such as blindness [2][3]. Diabetic retinopathy is treatable, so the main point is finding a low expense method with high sensitivity for detection of the disease in its infancy. The possibility of the images analysis by computer makes it possible to design low-cost systems for diagnosis of diabetic retinopathy.

Regarding the appearance of different symptoms in different stages of diabetic retinopathy [4], several algorithms for detection of retinal lesions have been presented.

For example, one of the earliest visible lesions in diabetic retinopathy is microaneurysms. Figure 1 shows an example of an angiographic image belonging to a diabetic patient. Black circular lesions that are scattered in the surface of the retina are microaneurysms (vessels and lesions are white on a black background in the original image, but in this paper vessels and lesions appear black on a white background for better resolution of the angiographic images). Often the diameter of the microaneurysms is between 15 to 125 microns. This complication is not usually seen in other diseases of the retina. Therefore with its detection in retinal images, the disease can be diagnosed in the early stages and its associated problems and complications can be prevented.

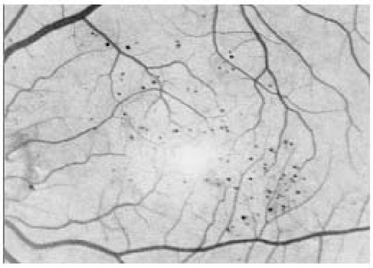


Figure 1. Microaneurysms lesion (the round black spots) in the angiography image of a diabetic patient.

In the next section, several available methods for the detection of microaneurysms are briefly described. In Section 3, data sets used in this research are introduced. Using the Hough transform to detect microaneurysms is described in Section 4. The proposed algorithm is presented in Section 5. Section 6 shows the results, and Section 7 contains the conclusions.

2. Literature Review

There are various methods for identification of diabetic retinopathy by using image processing techniques [5-10]. For the first time, a method based on mathematical morphology was presented for the detection of microaneurysms in 1984 [9]. In this algorithm by using mathematical morphology methods, vessels are separated from the image background and the suspicious areas of microaneurysms are remained to be identified in the next stage. In 2000 an improved version of this method [10] was presented on the high-resolution Red-Free retinal images.

In [5] methods of detecting and counting microaneurysms in angiographic images are presented. In this paper, after the pre-processing stage, a bilinear Top-Hot conversion and matched filtering are used to perform the initial segmentation on the image. Then by thresholding of this image, a binary image containing the candidate for the detection of microaneurysms is achieved. At last, the final decision is made by considering the size, shape and energy characteristics of these candidate regions.

In [11] the location of microaneurysms in the retinal image is detected by neural networks. First a pre-process is used to make the background light monotonous and to enhance the contrast. Then this image is applied to a neural network. Neural network separates the areas (not the exact location) related to the microaneurysms from the non-related areas existing in the image. To do so, the entire image is divided into small windows, and then each window is considered as an input for the neural network. In the final stage, by using image processing algorithms, those areas that were detected as areas consisting microaneurysms in the previous stage, are examined to determine the exact location of those microaneurysms.

In [12] microaneurysms are identified in two steps. At first, red areas in the gray retinal image are identified by using a recursive region growing method. These red areas may contain vessels or red lesions. Red lesions are separated from the image by another process in the next stage.

In [13] another method for detecting microaneurysms in angiography images is presented. In this method, first blood vessels are removed. Then, rounded components of the image are detected by using the circular Hough transform. Finally by comparing the energy of the detected sections with the threshold amount that is obtained from the energy of the parts that are related to image's background, the round parts are classified as microaneurysms and non-microaneurysms. In this paper after identifying vessels, selected pixels are classified again according to [15] to ensure the right choice of vascular pixels. In [15], piecewise linearity and ant parallel edge are used to determine that the selected vessels are really blood vessels or not.

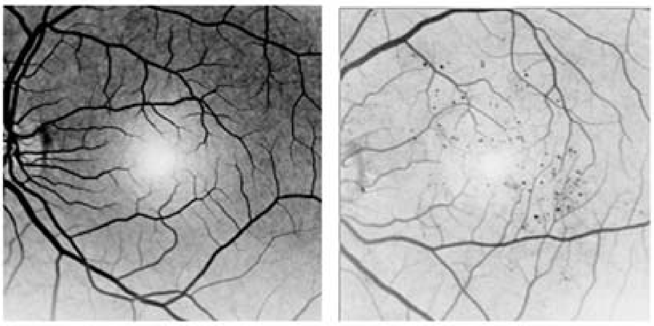
In [15] adaptive edge detection technique is used to detect microaneurysms in angiography images. In this paper, first the edges of the image are identified by Canny edge detector. In the next step, edges which are related to the vascular are removed from the image. In the following, the Sobel edge detector is used to detect the remaining parts. Finally, they are classified into two categories of microaneurysms and non-microaneurysms by using the characteristics such as size, shape and energy of the remaining parts.

Method proposed in this paper eliminates a stage to identify the vessel. In this proposed method after equalization of image background and noise removing, locations of microaneurysms are identified by using the Hough transform. In this algorithm, only the circles within a certain radius (the radius of microaneurysms) have been searched. Thus, in comparison with existing methods, the amount of calculations is reduced and the speed is much increased.

3. Data Acquisition

There are various methods to provide retinal images. According to the imaging system and filters available in the camera, different types of retinal images are produced [16]. The most common images used in the automated analysis of retina include colored image, Red-Free image and fluorescein angiography. In this research, the proposed algorithm is tested on a set consisting five of fluorescein angiography images. The image dimensions are 768×765 pixels in BMP format.

The fluorescein angiography images are provided by the intra-venous injection of flourescein. In this way, by publishing the flourescein in the vessels of the retina, all the red parts, such as vessels and microaneurysms would be perceived brighter than the background. Figure 2 shows an example of two fluorescein belonging to a diabetic patient and healthy person.



(a) *(b)*

Figure 2. Showing the image of the retina angiograph. a) The healthy person b) The sick with microaneurysms.

4. Identification of Microaneurysms

Since microaneurysms have round or oval shape (Figure 1), their approximate location can be determined by searching the circular or elliptical curves. Due to the ability of Hough transform to find points on an arbitrary curve [17], this conversion has a good performance to find microaneurysms. In the following, the basic concepts of Hough transform and its application in identifying microaneurysms are analyzed.

4.1 Hough Transform

The Hough transform is most commonly used for the detection of regular curves such as lines, circles, and ellipses. A generalized Hough transform can find any other arbitrary curve. Let us suppose that we are looking for straight lines in an image. If we take a point (x_i,y_i) in the image, all the straight lines passing through that point satisfy Equation 1 for varying values of m and c.

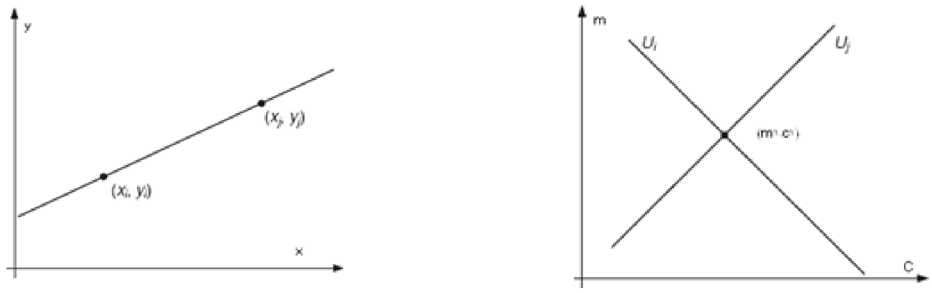
$$y = mx + c \tag{1}$$

We can say each of the possible lines that pass through point (x_i, y_i) has coordinates (m, c) in slope intercept space. In other words, all the lines that pass through point (x_i,y_i) have a different value of m and c. So they can be considered as

$$c = -x_i m + y_i \tag{2}$$

In the Hough transform, the space classifies to a set of cells known as accumulator. Considering the kind of the searched curve, this space can have one dimension, two dimensions or three dimensions.

Each pixels in the (x, y) space are represented by a lines in the (m, c) space. For example, Figure 3(a) shows two pixels (x_i, y_i) and (x_j, y_j) which lie on the same line in the (x, y) space. These two points are represented by two lines which pass through a single point in the (m, c) space (Figure 3(b)).



(a) ***(b)***

Figure 3. (a) Points on the same line (b) The mapping of (x_i,x_i) and (x_j,x_j) from (x, y) space to the (m,c) space.

Figure 4 is an example of a two dimensional space related to a linear Hough transform. In this space (m_{min},m_{max}) (c_{min},c_{max}) are the expected areas for the amount of slope and intercept. Here each cell is the representative of a line with specific slope and intercept.

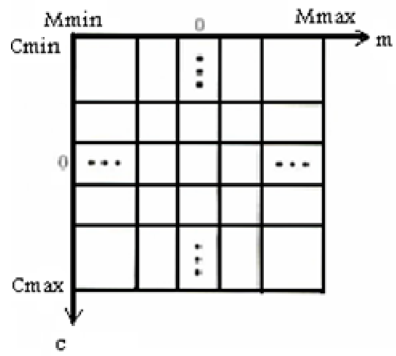


Figure 4. Two dimensional accumulator spaces (related to a straight line).

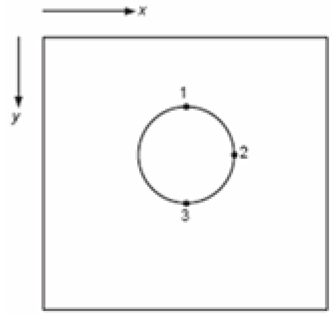
4.2 Circular Hough Transform

The Hough transform can be used to determine the parameters of a circle. A circle with radius r and center (x0, y0) can be described with the parametric equations:

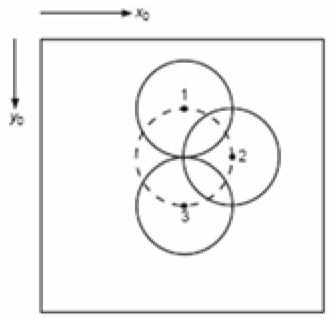
$$(x - x0)^2 + (y - y0)^2 = r^2 \tag{3}$$

For each pixel in the image we draw a circle in the accumulator space with desired radius. If enough circles with the same radius, drawn in the accumulator space intersect in the same point we can conclude that a circle with that radius is found at the position (x0,y0) (Figure 5 (b)).

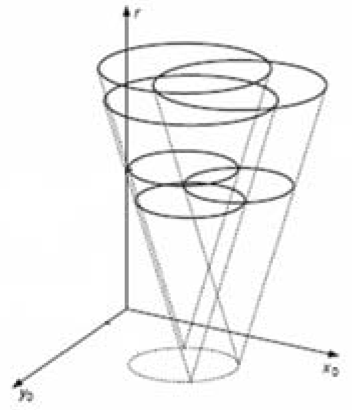
If the radius is not known, then the locus of points in parameter space will fall on the surface of a cone (Figure 5(c)). Each point in parameter space will produce a cone surface in three dimensional accumulator space.



(a)



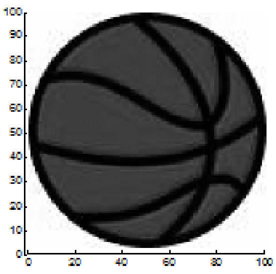
(b)



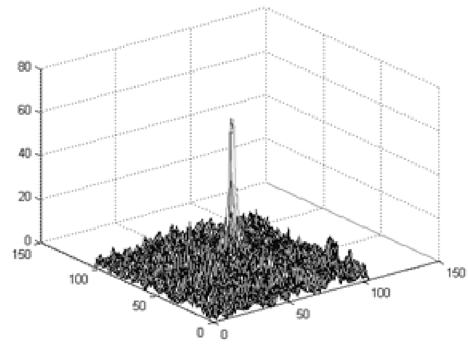
(c)

Figure 5. (a) Image space, (b) Hough space with known radius, (c) Hough space with unknown radius.

In Figure 6, there is an example of the circular Hough transform's application for finding the circle related to a basketball ball. In Figure 6(b), the three dimensional accumulator space resulted by the circular Hough transform is drawn. It is perceived that one of its cells has greater amount comparing to other cells. By interpreting circular accumulator, the existence of a circle with the center of [50, 50] and the ray of 40 is identified.



(a)



(b)

Figure 6. The use of circular Hough transform for finding the circle (a) The main image containing the circle. (b) The space of three dimensional accumulator resulted from circular Hough transform. This figure shows that there is a circle with the center of [50,50] and the ray of 40.

More complicated curves like oval can be identified by the use of Hough transform. In the oval Hough transform each cell represents an oval with five characteristics related to it. These characteristics contain center, the big diameter, the small diameter and the angle of the oval compared to horizon (in this condition the space of the accumulator has five dimensions). It is clear that by increasing the space dimensions of the accumulator, the number of accounts would increase. Reference [17] shows how by reducing dimensions, multiple dimensions spaces can be transformed into spaces with fewer dimensions. In this reference various types of Hough transforms are described completely.

5. The Proposed Method

In the proposed method, first a preprocessing step is performed on the image by a 5×5 average filter. The purpose of this stage is to create monotonousness for eliminating the pseudo-imaging (virtual parts that may be created in the image when shooting) and the probable existing noise in the image. Then the central parts of microaneurysms are approximately determined by Hough transform.

Since these lesions are not perfectly round, the Hough transform is not used to determine the total areas of each lesion. But the areas identified in the previous step are considered as the seed of the region growing process until at this stage total areas of each microaneurysms are identified.

In [13], after removing all the vessels of the retina and using of Sobel or Canny edge detectors, the scope of microaneurysms is determined by circular Hough transform. This matter causes those parts of the vessels that have a cyclic mode to be wrongly diagnosed as microaneurysms (Figure 7). To eliminate this problem it is necessary that all vessels in the retina be removed from the background before applying the Hough transform. Many different methods have been introduced in [18-20] for detecting of the retinal vessels in angiography images. But the removal of the vessel for microaneurysms detection also has its own problems. In most images that microaneurysms lesions are scattered in the retina, a number of microaneurysms are mistakenly diagnosed as vascular and are removed in the first stage along with the vascular. In the proposed method due to the lack of need to the stage of the vascular elimination which is very time consuming, not only the speed increases a lot, but also the error rate in detecting retinal lesions significantly reduces compared to previous methods. At the end, in the post processing step due to the color intensity and the average energy of selected areas, parts that have been mistakenly diagnosed as a lesion are removed. The proposed algorithm is seen in the Figure 8.

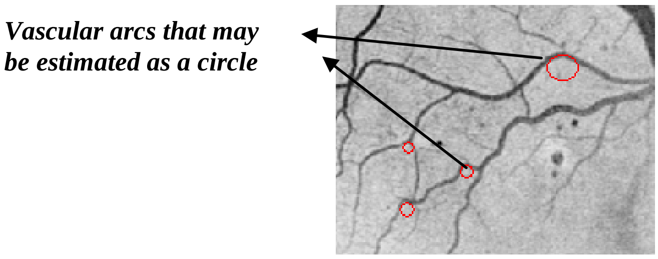


Figure 7. Vascular arcs that may be estimated as a circle and consequently as a microaneurysms in the existing methods.

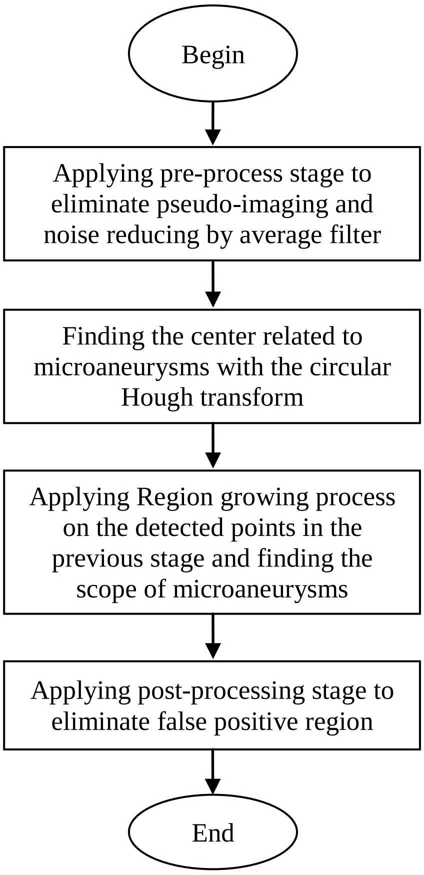


Figure 8. The proposed algorithm for detecting microaneurysms in retinal images.

6. Experimental Results

In this study, the proposed algorithm is tested on data sets introduced in Section 3. This algorithm has been performed with MATLAB 7 and by a computer Pentium IV, 2.42GHz with 512 Mb memory. Observations on the five retinal image show that the proposed algorithm has average ability about %89 for detecting microaneurysm lesions.

The output of the algorithm on different images is shown in the Figures 9 and 10. Also results are briefly shown in Table 1. In this table, the total number of microaneurysms available in each image, percentage of truly detected microaneurysms (true positive), system error rate in the identification of microaneurysms (false positive) and the algorithm execution time are expressed. For example in Figure 9, the proposed algorithm has detected 26 microaneurysms in the image that 23 of them are really microaneurysms (true positive) and three of them have been mistakenly identified as microaneurysms (false positive). The actual number of microaneurysms in this image is 25 and the algorithm failed to identify two of them. Average results of the algorithm introduced in [13] on three angiographic images has been reported %85.5 for true detection of microaneurysms and %35.5 for false detection of microaneurysms. The average execution time of this algorithm by MATLAB software has been reported 140 minutes (this algorithm is executed with MATLAB 6 and by a computer Pentium III,1 GHz with 128 MB of memory). By comparing these results with the observations in Table 1 it is clear that the proposed algorithm has good accuracy furthermore, it has the ability to detect microaneurysms in much shorter time.

7. Conclusions

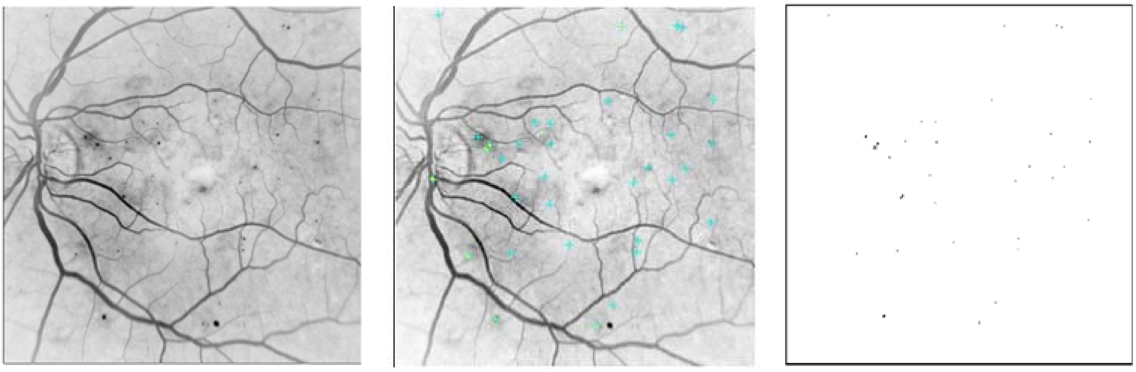
In this paper a new algorithm for identifying microaneurysms lesions in the retinal angiography images is presented. The evaluation results presented in this paper on five images shows that the proposed method has good accuracy in the detection of microaneurysms. In addition, because of high speed this method is very suitable for practical applications. In the proposed method after pre-processing steps, without the need to remove the retinal vessels, the central point of any microaneurysms is approximately identified by circular Hough transform. In the following, the specified central point is considered as seed by using region growing techniques and the total areas of microaneurysms is determined. An interesting ability of this method is its high speed of detection of lesions by eliminating the vascular diagnosis.

Acknowledgment

Thanks to the Cheshme Negah and Cheshme Novin Didegan Clinics that help us in providing the digital retinal images used in this study. And also we appreciate Doctor Majd Hassan Nataj for interpreting retinal images.

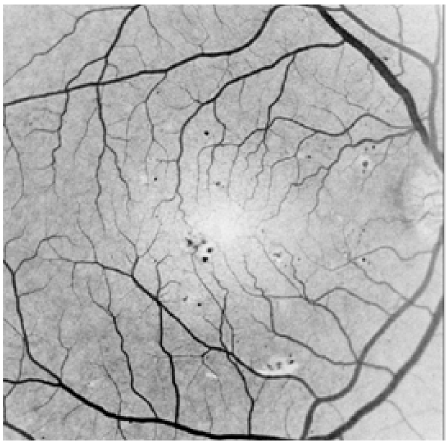
Table1. Results of the proposed method on five retinal angiography images (This algorithm has been performed with MATLAB 7 and by a computer Pentium IV, 2.42GHz with 512 Mb memory).

Image	True positive	False Positive	False Negative	Execution time according to second	The total number of detected microaneurysms by the proposed method	The actual number of microaneurysms
P1	92%	11.5%	8%	24.90014	26	25
P2	94%	8.9%	6%	28.203432	67	65
P3	83.72%	10%	16.28%	24.259850	40	43
P4	84.37%	1.8%	15.6%	27.696815	55	64
P5	88.88%	3%	11.12%	19.467485	33	36
Total	88.5%	6.7%	11.5%	-	221	233

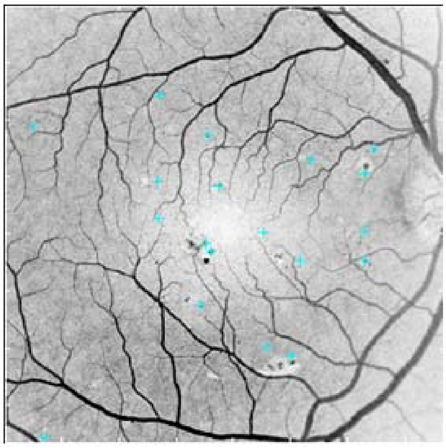


(a) *(b)* *(c)*

Figure 9. The output of the proposed method on the data analyzed in this paper, (a) original image (b) finding the center of area containing microaneurysms by the circular Hough transform (c) finding microaneurysms by the use of region growing process.



(a)



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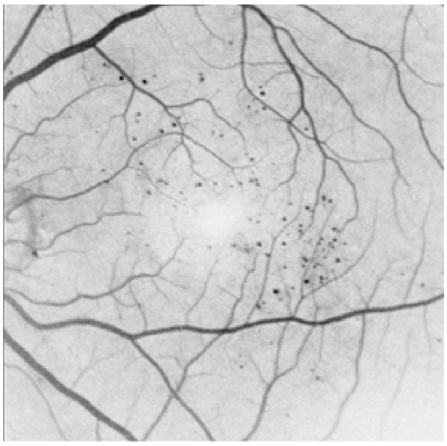
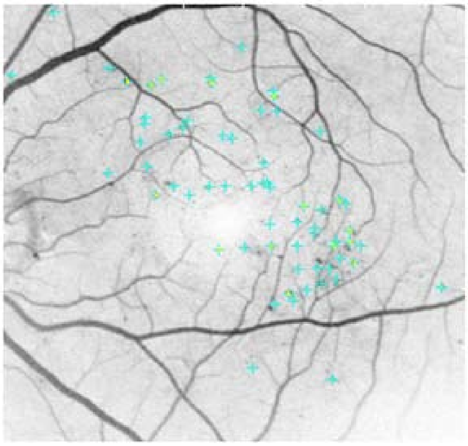
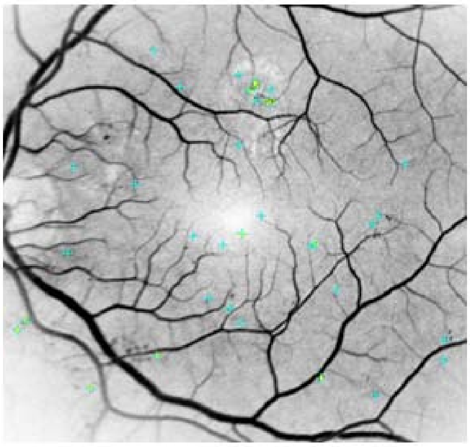


(c)

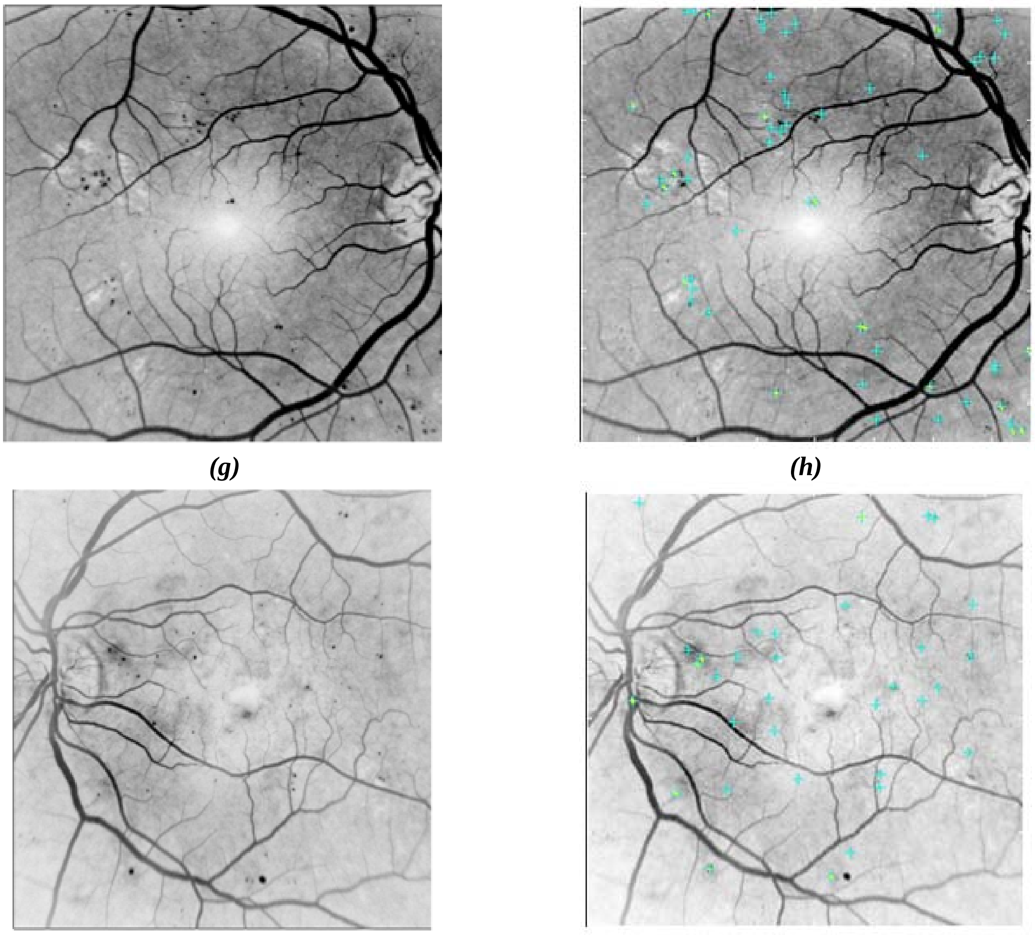


(d)

(e)



(f)



(g) (h)

(i) (j)

Figure 10. The output of proposed method on the data sets analyzed in this paper.

8. References

[1] A.F. Amos, D.J. McCarty, P. Zimmet, “The rising global burden of diabetes and its complications: estimates and projections to the year 2010,” Diabetic Med 1997;14: S57-85.

[2] J. Schmier, D. Covert, E. Lau, P. Matthews ”Medicare expenditures associated with diabetes and diabetic retinopathy”, Retina, vol. 29, 2009, pp. 199-206.

[3] H. R. Taylor and J. E. Keeffe, “World blindness: a 21st century perspective,” British Journal of Ophthalmology, vol. 85, 2001, pp. 261-266.

[4] J. Kanski. Diabetic Retinopathy, Clinical Ophthalmology. Butterworth-Heimann, Oxford. 1997.

[5] T. Spencer, J. Olson, K. McHardy, P. Sharp, and J. Forrester, “An image processing strategy for the segmentation and quantification in fluorescein angiograms of the ocular fundus,” Comput. Biomed. Res., vol. 29, 1996, pp. 284-302.

[6] A. Frame, P. Undrill, M. Cree, J. Olson, K. McHardy, P. Sharp, and J. Forrester, “A comparison of computer based classification methods applied to the detection of microaneurysms in ophthalmic fluorescein angiograms,” Comput. Biol. Med., vol. 28, 1998, pp. 225-238.

[7] T. Spencer, R. P. Phillips, P. Sharp, and J. Forrester, “Automated detection and quantification of microaneurysms in fluorescein angiograms,” Graefe’s Arch. Clin. Exp. Ophthalmol., vol. 230, 1992, pp. 36-41.

[8] M. Cree, J. Olson, K. McHardy, P. Sharp, and J. Forrester, “A fully automated comparative microaneurysm digital detection system,” Eye, vol. 11, 1997, pp. 622-628.

[9] C. Baudoin, B. Lay, and J. Klein, “Automatic detection of microaneurysms in diabetic fluorescein angiographies,” Revue D’Épidémiologie et de Sante Publique, vol. 32, 1984, pp. 254-261.

[10] J. Hipwell, F. Strachant, J. Olson, K. McHardy, P. Sharp, and J. Forrester, "Automated detection of microaneurysms in digital red-free photographs: a diabetic retinopathy screening tool," Diabetic Med., vol. 17, 2000, pp. 588-594.

[11] Mohamed Kamel, Saeid Belkassim, Ana Maria Mendonqa, AurClio Campilho, " A Neural Network Approach for the Automatic Detection of Microaneurysms in Retinal Angiograms," Neural Networks Proceedings. International Joint Conference, 2001.

[12] C. Sinthanayothin, J. Boyce, T.Williamson, H. Cook, E. Mensah, S. Lal, and D. Usher, "Automated detection of diabetic retinopathy on digital fundus images," Diabetic Med., vol. 19, 2002, pp. 105-112.

[13] S. Abdelazeem . Microaneurysm Detection Using Vessels Removal and Circular Hough Transform. NINETEENTH NATIONAL RADIO SCIENCE CONFERENCE, ALEXANDRIA, March, 19-21,2002.

[14] S. Abdelazeem and G. Auda, "A postprocessing scheme for accurate vessel detection in retinal images," Submitted to the Journal of Artificial Intelligence in Medicine.

[15] M. Hafez, Sh. Abdel Azeem. Using Adaptive Edge Technique for Detecting Microaneurysms in Fluorescein Angiograms of the Ocular Fundus. IEEE MELECON, , Cain,, EGYPT, May 7-9,2002.

[16] basic and clinical science course section 12 (American Academy of Ophthalmology),2000-2001.

[17] Mark S. Nixon, Alberto S. Aguado. "Feature Extraction and Image Processing," Newnes, 2002.

[18] J. J. G. Leandro, J. V. B. Soares, R. M. Cesar Jr., and H. F. Jelinek, "Blood vessels segmentation in non-mydriatic images using wavelets and statistical classifiers," in Proc. 16th Brazil. Symp. Comput. Graphics Image Process. (ISIBGRAPI), 2003, pp. 262-269.

[19] D. J. Cornforth, H. F. Jelinek, J. J. G. Leandro, J. V. B. Soares, R. M. Cesar-Jr, M. J. Cree, P. Mitchell, and T. Bossamaier, "Development of retinal blood vessel segmentation methodology using wavelet transforms for assessment of diabetic retinopathy," in Proc. 8th Asia Pacific Symp. Intell. Evolution. Syst., Cairns, Australia, 2004, pp. 50-60.

[20] J. V. B. Soares, J. J. G. Leandro, R. M. Cesar-Jr, H. F. Jelinek, and M. J. Cree, "Using the 2-D morlet wavelet with supervised classification for retinal vessel segmentation," presented at the 18th Brazil. Symp. Comput. Graphics Image Process. (SIBGRAPI), Oct. 9-12, 2005.