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Microaneurysm Detection Using Vessels Removal and Circular Hough Transform

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Abstract

A digital image processing system has been developed to quantify the presence of microaneurysms in retinal fluorescein angiographic images. Automatic detection of microaneurysms in retinal angiographic images provides a valuable tool for early diagnosis of diabetic retinopathy. In this paper, a novel approach for detecting microaneurysms in retinal angiographic images is presented. The proposed scheme is based on the removal of blood vessels from the image and then classifying all detected circular objects whether they are microaneurysms. The new technique provides significant improvement in the detection of microaneurysms over other currently available schemes in the literature.

1. Introduction

Diabetic retinopathy is an eye disease that can lead to partial or complete loss of eye sight [1]. It is one of the most common causes of blindness [1]. Microaneurysms (MAs) are the first clinically observable signs of diabetic retinopathy [2]. MAs appear as small, round, hyperfluorescent objects visible in fluorescein angiographic images of the retina. There exists a positive correlation between the number of MAs in the image with both the severity and the likely progression of the disease [2]. Thus, MA counting is considered a tool to quantify the progression of diabetic retinopathy. Manual counting, usually done by ophthalmologists, is time consuming and subject to observer error. Automated computer techniques offer fast, objective, and reproducible ways of quantifying diabetic retinopathy.

2. Review

Spencer *et al.* developed a successful technique for the segmentation and quantification of MAs [3-5]. Because of the circularity of MAs, Spencer *et al.* used bilinear top hat transformation to distinguish between circular and linear segments of the angiographic image [5]. The top hat transformation applied to an image results in an image containing only linear segments in different orientations [6]. The resulting image is subtracted from the original one to produce an image of nonlinear segments. Matched filtering and thresholding are then used to produce an image containing candidate MAs. Candidates are classified if they represent MAs according to the size, shape, and energy of each candidate [5].

Abdelazeem *et al.* exploited the circularity of MA to develop a scheme for MA detection based on using circular Hough transform [7]. Circular Hough transform proved to be an effective method for detecting circular features in an image [8]. Applying circular Hough transform to the angiographic image results in the detection of objects having circular shapes such as MAs as well as other spurious objects of circular shapes such as vessel segments. Classification is used to distinguish MAs from spurious objects based on the relative energy between the candidate and its background. Results reported in [7] show significant improvement in the detection of MAs over the top hat approch [5].

3. False Detection of MA

Currently available techniques for MA detection suffer from the problem of wrong classification. Objects that are not MAs are falsely classified as being MAs. False MAs are usually vessel segments that are wrongly considered as MAs because of the circular nature of the vessels cross section. Needless to say, false detection of MAs defeats the purpose of having automatic detection methods for quantifying diabetic retinopathy. Therefore, previous schemes for MA detection have attempted to alleviate the problem of false detection.

Spencer *et al.* used top hat transformation because of its ability to detect linear structures which are usually vessels. Detected linear segments are then subtracted from the original angiographic image in order to reduce flase MA detection. However, false detection persists because most vessel segments are not strictly linear and many vessel segments remain after the top hat transformation [5].

Abdelazeem *et al.* attempted to avoid false MA detection at the classification stage. Energy of a detected circle is compared with the energy of its background. If the energy difference is below a certain threshold, then the object is rejected as a vessel segment because true MAs have much higher energy levels than their backgrounds unlike vessel segments. Despite the fact that the use of circular Hough transform proved to be more successful than top hat transformation approach in MA detection, false detection still exists in this approach as well [7].

4. Need for Vessel Removal

The root of the problem of false MA detection is the circular nature of the vessel cross section which causes small vessel segments to be mistakenly classified as MAs. Removing all vessels from the angiographic image before MA detection would be the perfect solution. The problem of blood vessels detection and tracking in retinal images has been extensively studied in the literature [9-11]. Several techniques can be used to detect blood vessels in the angiographic image. However, vessel detection is always accompanied with the detection of some non-vessel segments. Hence, removing detected vessels from the angiographic image would result in removing other objects from the image, some of which might be true MAs.

Thus, reducing false MA detection would result in reducing true MA detection as well. This tradeoff always exists in the problem of MA detection.

A novel approach to vessel detection that significantly reduces non-vessel detection has been developed by Abdelazeem and Auda [12]. This technique is based on the use of a postprocessing step after the actual detection of the vessels. Postprocessing is used to test whether the detected object is truly a vessel segment using the two major properties of vessels: piecewise linearity and antiparallel edges [12]. The possibility of a circular structure such as a MA being falsely detected is greatly reduced. The results shown in Fig. 1 clearly reveal that only vessel segments are detected using postprocessing. Removing the detected vessels from the angiographic image should greatly improve the results of MA detection as demonstrated in the results reported in the next section.

5. Results

The first step in this proposed scheme is to detect vessels in the angiographic image. Then, the detected vessels are removed from the image. Circular Hough transform is then applied to the resulting image. A candidate object is classified as a MA if its energy relative to the energy of its background is above a certain threshold as explained in [7]. Otherwise, the candidate is rejected.

Three retinal angiographic images have been used to test the proposed scheme. The images are shown in Figs. 2.a, 3.a, and 4.a. The same images have been tested by an ophthalmologist to have MAs labeled. Results of our classification have been compared to those of the ophthalmologist. Objects classified as MAs that matched the expert opinion have been considered as true MAs (TMAs) and those that did not match the expert opinion have been considered false MAs (FMAs). The numbers of TMAs and FMAs for the three test images are reported in Table 1. Counts of TMAs and FMAs for the same three images obtained using the top hat approach and the Hough transform approach without vessel removal are also reported in Table 1. All TMAs and FMAs of the three schemes are shown in Figs. 2.b,2.c,2.d; 3.b,3.c,3.d; and 4.b,4.c,4.d. It is clear from the results given in Table 1 and Figs 2,3, and 4 that vessels removal significantly improves MA detection.

Table 1: Results of the proposed scheme compared with previous MA detection techniques

Image	Top Hat Transform		Hough Transform (HT)		HT with Vessels Removal	
	TMA	FMA	TMA	FMA	TMA	FMA
A	47	68	63	58	60	10
B	43	100	58	57	55	18
C	82	118	125	30	130	25

6. Conclusion

A new technique for MA detection in digital fluorescein angiograms of the retina has been presented. This scheme significantly reduces the number of falsely detected MAs compared to other MA detection schemes. The reason behind the improved performance is due to proper blood vessels removal from the angiographic image prior to MA detection.

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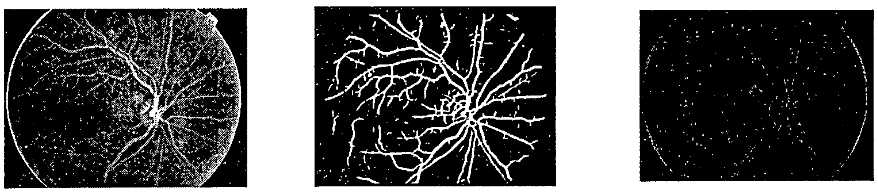
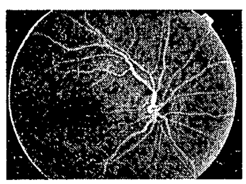
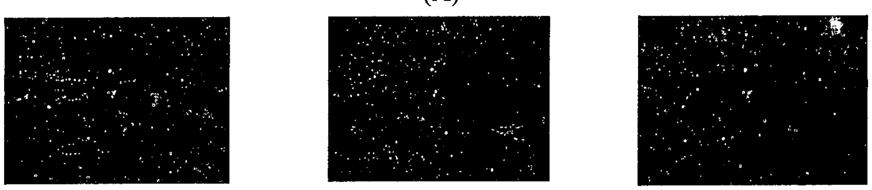


(A) (B) (C)

Fig. 1.(A) Originl image. (B) Detected vessels.(C) Candidate MAs after vessels removal.



(A)



(B) (C) (D)

Fig. 2.(A) Original image. (B) MAs by top hat. (C) MAs by HT without vessels removal. (D) MAs by HT with vessels removal.

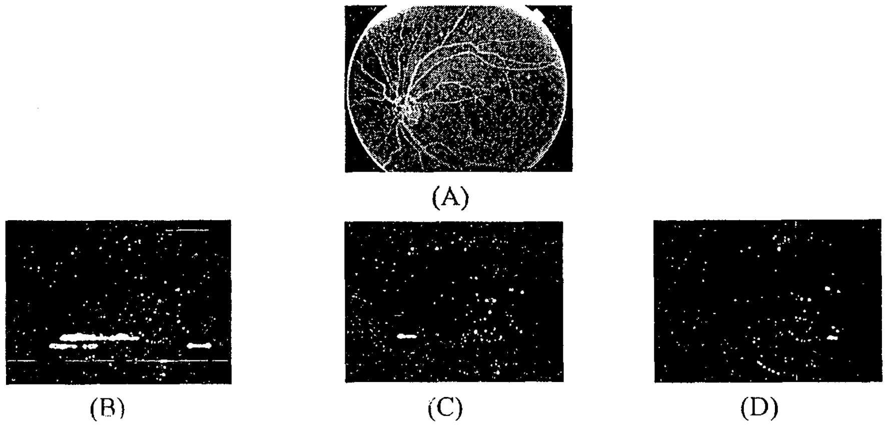


Fig. 3.(A) Original image. (B) MAs by top hat. (C) MAs by HT without vessels removal.
(D) MAs by HT with vessels removal.

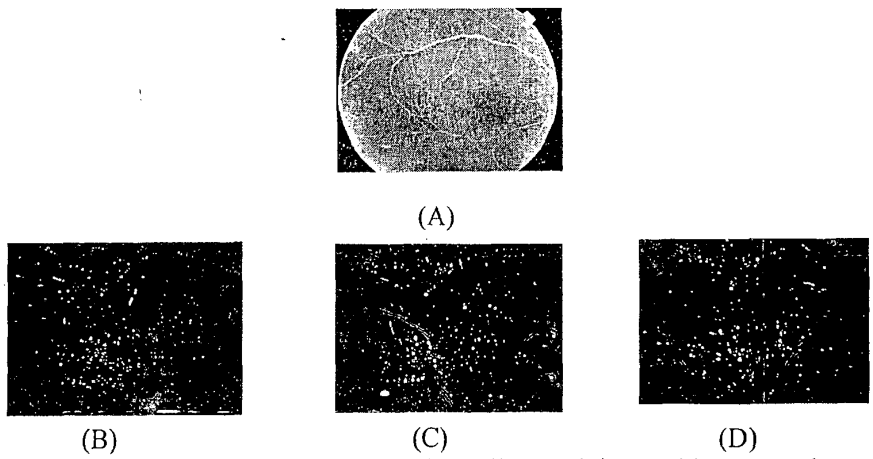


Fig. 4.(A) Original Image. (B) MAs by top hat. (C) MAs by HT without vessels removal.
(D) MAs by HT with vessels removal.