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Automatic Mobile Retinal Microaneurysm Detection Using Handheld Fundus Camera via Cloud Computing

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Abstract

This paper presents a new system to monitor retinal microaneurysm which are regarded as the first sign of diabetic retinopathy(DR). The proposed approach to automatic microaneurysm detection aims to enhance screening large populations. Most of the existing computer-aided systems for microaneurysm detection are based on the sophisticated medical device in a clinical environment. However, the popular medical devices such as table fundus camera and portable fundus camera are subject to certain limitations for its usage beyond the scope of clinical practice. The challenges include the complexity of operation, cost issue and requirement of professional maintenance, etc. Unlike the conventional approaches, we developed an automatic mobile retinal microaneurysm detection system by using a handheld fundus camera to facilitate retinal healthcare and monitoring with flexibility and convenience. Our system includes: (1) retinal image capturing by handheld fundus camera;(2) retinal image analysis via cloud computing;(3) microaneurysm detection by Multi-orientation Sum of Matched Filter and SVM. The experimental results demonstrate the feasibility of our system by performance improvement on the aspects of speed, accuracy, and convenience.

Introduction

Diabetic retinopathy (DR) is a common and severe complication of long-term diabetes which damages the retina and cause blindness[1]. Color fundus camera is an easily operated tool to capture human retina so that the color retinal images are suitable for large population screen. The computer aided diagnosis (CAD) on retinal images can help eye specialists to screen larger populations. Since microaneurysms are regarded as the first signs of DR, the automatic detection of microaneurysms is very important[2].

However, the common fundus cameras are very heavy so that the patients cannot use them at home, which caused inconvenient monitoring. Further, the automatic microaneurysm detection accuracy is not satisfied in the clinical practice.

In order to make the microaneurysm monitoring more convenient, we propose an automatic mobile retinal microaneurysm detection system. This system include: (1) retinal image capturing by handheld fundus camera;(2) retinal image analysis via cloud computing;(3) microaneurysm detection by Multi-orientation Sum of Matched Filter and SVM. The proposed system improve the automatic microaneurysm detection in the matter of convenience. And the microaneurysm detection accuracy is fine. The details of this system will be described in follow sections of this paper.

System Framework

In the proposed system, the retinal images are captured using a handheld retinal imaging device in order to improve the automatic microaneurysm detection in the matter of convenience. As shown in Fig. 1, the proposed image capturing device consists of two components: (1) a small ophthalmological lens; (2) a cell phone with camera. The retinal image is revealed by the ophthalmological lens and captured by the camera on the cell phone. Compared to the traditional retinal image capturing device, this device is very small and light. The patients could conveniently use this device in home and on a trip.

Fig.1 Handheld retinal imaging device

Once the retinal image has been captured, it will immediately be sent to the cloud server for analysis. Even modern cell phones have fine computing ability, the automatic microaneurysm detection algorithm is too complicate to run a cell phone. As shown in Fig. 2, the cell-phone(client) is only in charge of image capturing and transmission. Once the image has been received by cloud server, the automatic microaneurysm detection algorithm will be applied on the retinal image. Once the analysis has been done, the results will be sent back to the cell phone.

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The automatic microaneurysm detection algorithm is briefly described as follows:

(1) The Region of Interest (ROI) is located by a morphological operation[3];

(2) The microaneurysm candidate is detected by Multi-orientation Sum of Matched Filter (MSMF) [4];

(3) A feature vector is generated for each candidate;

(4) The support vector machine (SVM) classifier is trained by the manually labeled microaneurysm database, and the microaneurysm candidate is classified as true or false by the trained classifier.

The details of the algorithm are described in the following sections of this paper.

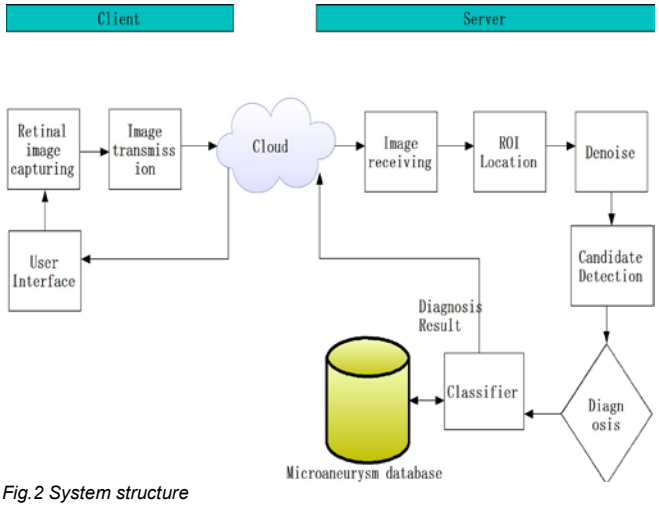

Fig.2 System structure

Microaneurysm Candidate Detection

The task for microaneurysm candidate detection is to identify all possible microaneurysm candidates in a retinal image. In color retinal images, we apply a median filter with a 3×3 pixel kernel and the morphological opening to denoise the images firstly. Then the vessels are suppressed by morphological closing in the image I_{green} which represents the green channel of the original retinal image, and the result is an image I_{lesion} containing mainly non-elongated structures such as red lesion. Because the shape of a microaneurysm is a circle, its cross-sections are the same at all orientations but cross-sections of the vessels are different at different orientations. To enhance the center response of a microaneurysm and suppress the vessel response, an approach Multi-orientation Sum of Matched Filter (MSMF) [4] where the matched filter is rotated an anisotropic Gaussian function to different orientations was proposed. The MSMF where the matched filter was defined on the anisotropic Gaussian function defined in Equation (1) as

$$m(x,y)=\frac{x^2-\sigma^2}{\sqrt{2\pi}\sigma^5}exp\left(\frac{-x^2}{2\sigma^2}\right),\quad for\quad |x|\le 3\sigma,\quad |y|\le L/2 \qquad (1)$$

where σ is the standard deviation of the Gaussian function, L is the length of the neighborhood along y-axis to smooth noise. And the MSMF defined in equation (2) as

$$R(x,y)=\sum_{\phi} I(x,y)*m^{\phi}(\bar{x},\bar{y}),\quad \phi=0,\pi/12,\pi/6,...,11\pi/12 \qquad (2)$$

$$\begin{cases} m^{\phi}(\bar{x},\bar{y})=m(x,y) \\ \bar{x}=x\cos\phi+y\sin\phi \\ \bar{y}=y\cos\phi-x\sin\phi \end{cases} \qquad (3)$$

Since microaneurysms vary in size, different sigma values for the Multi-orientation Sum of Matched Filter are required to enhance the microaneurysms. We choose five sigma values of the anisotropic Gaussian function defined in equation (1) to represent microaneurysms of different sizes being 1.1, 1.2, 1.3, 1.4 and 1.5. The maximum values from each of the five responses are combined to form a final response I_{match}. To determine the number of microaneurysms candidates, a threshold is applied to produce a binary image I_{bin}.

Then, the blood vessels are segmented using the scale product defined by Li et. al[5] and the candidates on the blood vessels are removed in I_{bin}. The extracted binary objects are not a good representation of the pathologies. Then a region growing algorithm proposed by Zhang et. al[6] is used to grow back the original pathologies.

Feature Extraction

Selection of features is an important aspect for lesion classification. Prior works had introduced a feature set comprised of 68dimensional features obtained using the system of Niemeijer et. al[3] and 31 dimensional features obtained using the system of Zhang. et. al[6] Similarly to the B. Zhang system, other 6 features also automatically extracted and recorded for each segmented candidate in this paper. These new features are based on the maximum, minimum and average of Multi-scale and Multi-orientation Sum of Matched Filter (MMSMF) response, and the maximum, minimum and average of the morphology matched filter response for each microaneurysm candidate in this paper. Because the true microaneurysms are uniformity in grey scale, to produce output to represent the uniformity of images, the morphology matched filter is defined as the ratio of the maximum and the minimum of morphological closing operation in the image I_{green}. The ratio is defined in Equation (4) as

$$M_{mor}(x,y)=I_{cmax}(x,y)/I_{cmin}(x,y) \qquad (4)$$

where $I_{cmax}(x,y)$ and $I_{cmin}(x,y)$ are the maximum and the minimum of morphological closing operation which rotate a linear structuring element to different orientations in order to suppress microaneurysms in all orientations.

Microaneurysm Classification

After features were extracted from the candidates, the feature vectors will be divided into two groups: true microaneurysms and false microaneurysms.SVM is considered one of the most robust and accurate methods among all well-known algorithms. In a two-class learning task, the aim of SVM is to find the best classification function to distinguish between members of the two classes in the training data. There are four basic kernels to map the training vectors into a higher dimensional space for finding the maximum margin linear hyperplanes. SVM classifier adopts the RBF kernel function which is more reasonable than other kernels. We use a

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grid search to identify two parameters for RBF kernel: C and γ. But standard SVM does not provide probabilities. One method to map the SVM outputs into probabilities is to use a parametric form of a sigmoid function:

$$P(y=1|f)=\frac{1}{1+exp(Af+B)} \quad (5)$$

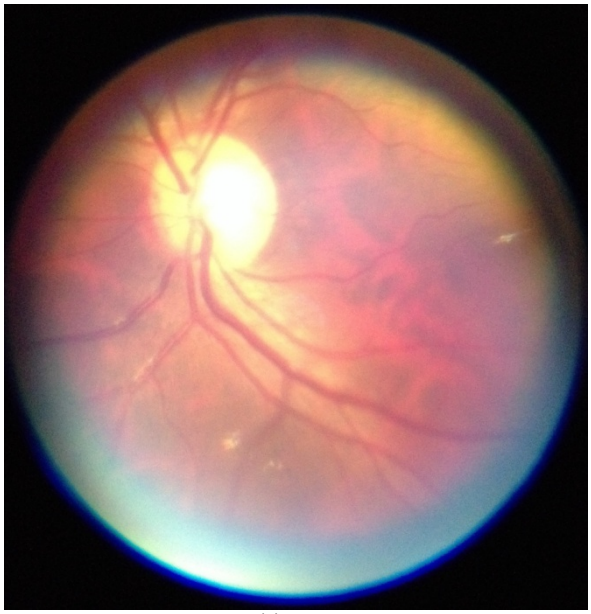
where f is the un-thresholded output of an SVM, parameters A and B are fit using maximum likelihood estimation [7] from the training set in the manually labeled microaneurysm database.

Experimental Results

The experimental images were captured using IEXAMINER, which is a small fundus lens that could be easily installed on any cell phone with a camera. The image captured is 2042*2124 pixels in size and 32 bits in color. In order to analyze the experimental results, we compared the microaneurysm detection results by IEXAMINER and APS-AER, which is a table fundus camera capturing image 3200*2400 pixels in size and 32 bits in color.

Fig. 3 and 4 demonstrated the microaneurysm detection results by IEXAMINER; fig. 5 demonstrated the microaneurysm detection results by APS-AER.

As shown in fig. 3-5, the handheld fundus camera represent well for the bright lesions in the retinal image, but represent poor for the red lesions. That will cause low sensitivity of the microaneurysm detection. And, there is heavy noise in the peripheral region of the image. That will cause false positives. Compared to table fundus camera, the handheld fundus camera provide lower accuracy. But using our system, the accuracy is fine for the general DR monitoring. And, the processing time for each image is within 3 minutes, which make our system achieve good user experience.



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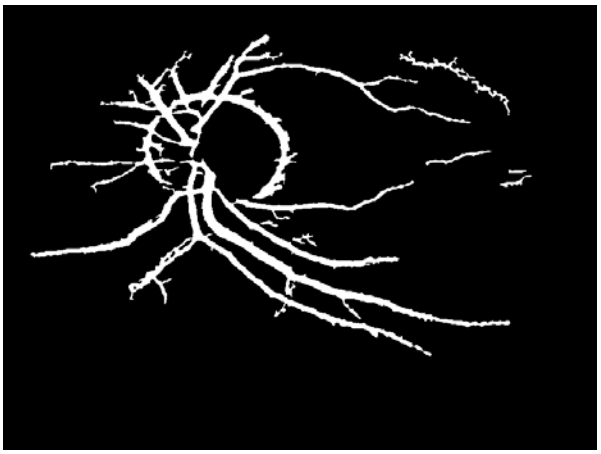

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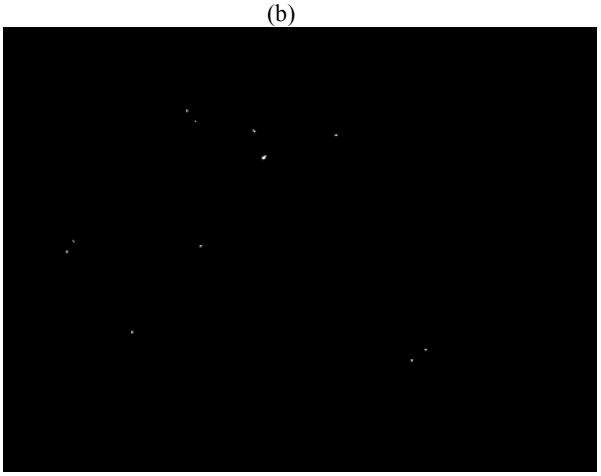

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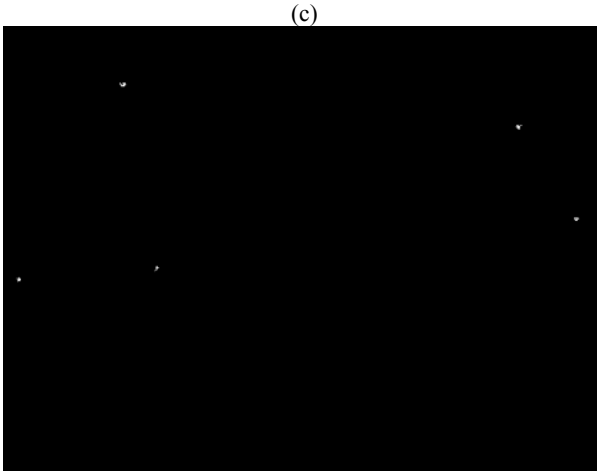

(d)

Fig.3microaneurysm detection results by IEXAMINER: Case 1. (a) Original image; (b)segmented vessels; (c) microaneurysm candidate detection; (d) microaneurysm classification.

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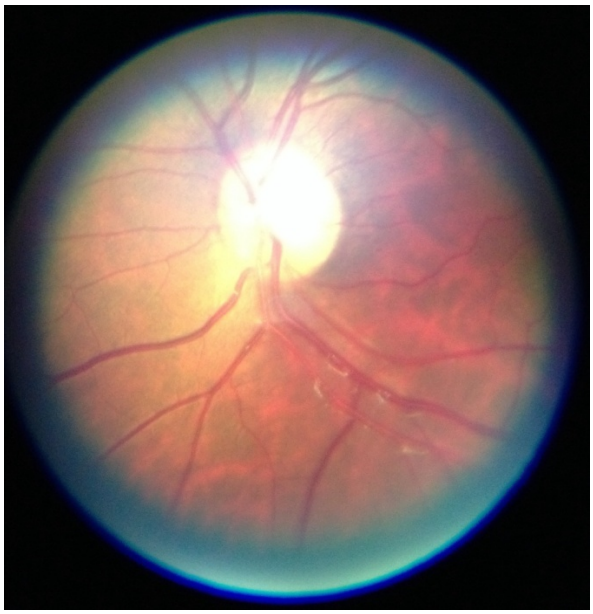

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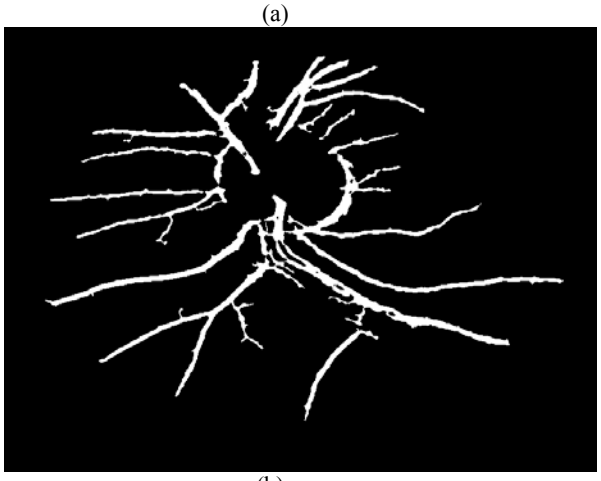

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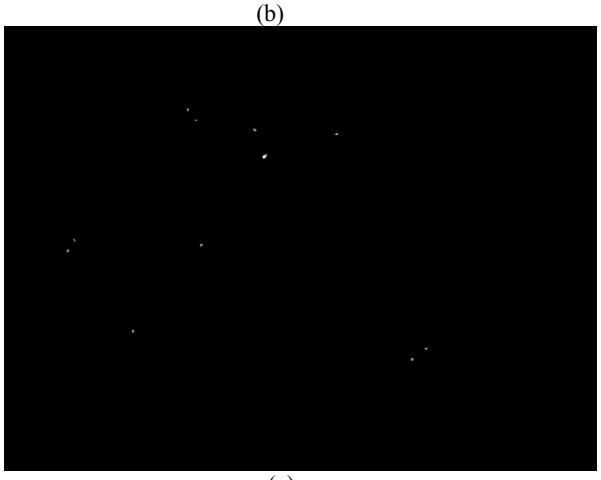
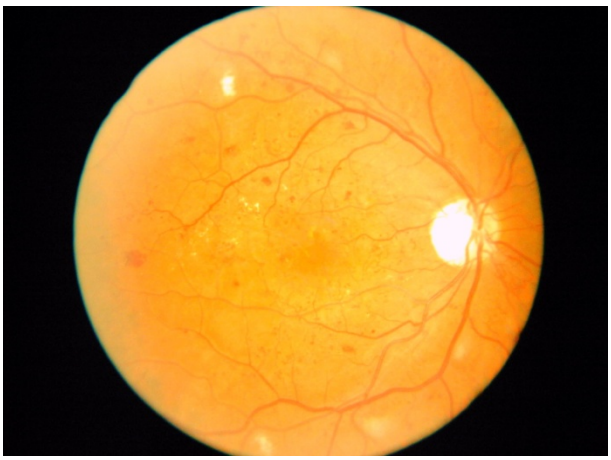


(c)

(d)

Fig.4microaneurysm detection results by IEXAMINER: Case 2. (a) Original image; (b)segmented vessels; (c) microaneurysm candidate detection; (d) microaneurysm classification.



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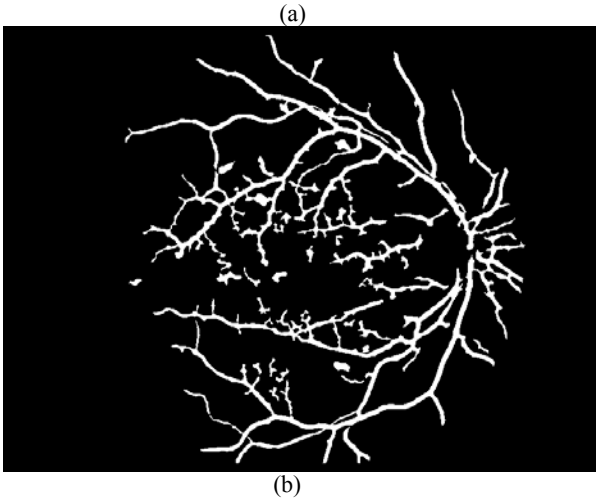

(b)

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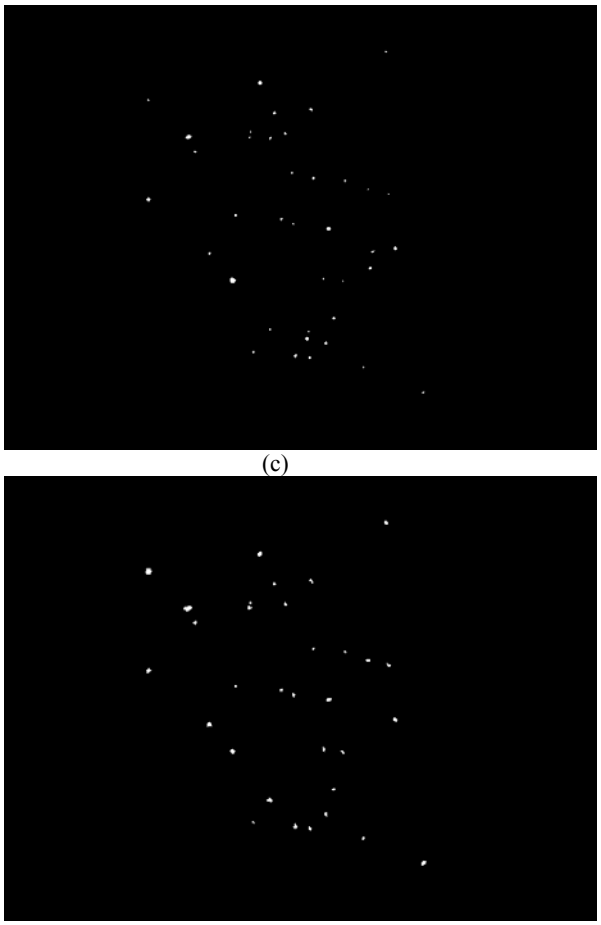

Fig.5microaneurysm detection results by aps-aer: Case 1. (a) Original image; (b)segmented vessels; (c) microaneurysm candidate detection; (d) microaneurysm classification.

Conclusion and Future Work

We conclude that our automatic mobile retinal microaneurysm detection system using handheld mobile camera offers a new healthcare service by screening and monitoring diabetic retinopathy conveniently in a flexible environment. Although the accuracy provided by handheld device is not as high as what is achieved by the sophisticated table fundus camera, the performance of our system is acceptable because it is a computer-aided system for screening and monitoring. Considering the improvement in processing time and general use without technical restrictions, our system demonstrates its potential for further development.

In the future, we will explore the development of a large retinal image database captured by handheld fundus camera and effective algorithms for retinal image analysis incorporated with heterogeneous data enhancement and fusion for better performance.

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Author Biography

Jane You is currently a professor in the Department of Computing at the Hong Kong Polytechnic University. Prof. You obtained her BEng. in Electronic Engineering from Xi'an Jiaotong University in 1986 and Ph.D in Computer Science from La Trobe University, Australia in 1992. Prof. Jane You has worked extensively in the fields of image processing, medical imaging, computer-aided detection/diagnosis, pattern recognition. So far, she has more than 200 research papers published. She has been a principal investigator for two ITF projects (Innovation Technology Fund), four GRF projects (General Research Fund) supported by Hong Kong Government and many other joint grants since she joined PolyU in late 1998. Her research output on retinal imaging has been successfully led to technology transfer with clinical applications. Prof. You is also an associate editor of Pattern Recognition and other journals.

Qin Li received his B.Eng. degree in computer science from the China University of Geoscience, Wuhan, China, in 2001, his M.Sc. degree (with distinction) in computing from the University of Northumbria at Newcastle, Newcastle,U.K.,in2003,and his Ph.D. degree in computing from the Hong Kong Polytechnic University, Hong Kong,in 2010. Now, he is a Lecturer at the School of Software, Shenzhen Institute of Information Technology, Shenzhen, China. His research interests include medical image analysis, biometrics, image processing, and pattern recognition.

Zhenhua Guo received his M.S. and Ph.D. degrees incomputer science from the Harbin Institute of Technology and the Hong Kong Poly technic University in 2004 and 2010 respectively. Since April 2010, he has been working at the Graduate School at Shenzhen, Tsinghua University. His research interests include pattern recognition, texture classification, biometrics, video surveillance, etc.