A Novel Retinal Vessel Segmentation Based On Local Adaptive Histogram Equalization

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***Abstract*—The appearance and structure of blood vessels in retinal images has an important role in diagnosis of diseases. This paper proposes a method for segmentation of blood vessels in color retinal images. We present a method based on preprocessing of retinal images by enhancing the histogram of grayscale images. We research the effect of linear and non-linear intensity transformation in retinal vessel segmentation. In this paper we focus on two methods of retinal vessel segmentation including first derivative of Gaussian matched filter and Gaussian matched filter. These methods are used by many researchers [1],[6],[7],[8],[24] but still there are some problems in vessel detection. We make use of adaptive histogram equalization to overcome this drawback. The proposed technique is tested on publicly available DRIVE database. The effect of improved matched filter can be seen based on accuracy calculation. The accuracy of 0.9353 shows a raise of about 2 percent compared to existing methods.**

Keywords—retinal vessel segmentation; histogram equalization; local adaptive;matched filter;first derivative of gaussian

I. INTRODUCTION

Retinal images of people are used in diagnoses of diseases such as diabetes and high blood pressure. There is a need for an expert system for taking digital images. Using image processing and pattern recognition methods, the images can be analyzed and specific diagnosis can be made. However traditional edge detection techniques are not w able to segment vessels accurately such as matched filter [1], ridge based vessel segmentation [2], morphology edge detection[3], Hough transform [4] and wavelet transformation [5].

Since many vessel segmentation methods rely on the match filter, improving its response is highly desirable. The classical matched filter (MF) [6] method is representative and has many advantages including simplicity and effectiveness. Using MF method cross section of a vessel can be modeled as a Gaussian function. Therefore a series of Gaussian-shaped filters can detect vessels. Hoover et al. (2000) located blood vessels in retinal images by piecewise threshold probing of matched filter response [6]. However the problem is MF has strong response for vessel and non-vessels. Therefore, after filtering image and applying the threshold many false detected vessels are considered. Al-Rawi et al. (2007) improved MF response by changing its parameters [7].

We believe that by enhancing the images quality the performance of the algorithm can be improved. As a result more vessels can be extracted. In this paper we propose a new approach to enhance the image quality by improving image contrast using histogram.

II. MATERIALS AND METHODS

A. Intensity Transformations

As we know, there are several ways for indicating the images color by Hue, saturation and intensity, and it is obvious that intensity is the most important one. There are many ways for improving the images contrast but using histogram is more effective and common in contrast problem [15-19].

In retinal images, there is an insignificant difference between intensity level of vessels and non-vessels regions. In the proposed approach, in order to improve the algorithm result, we use intensity transformation to increase the intensity level of vessels and non-vessels. There are several ways to do this e.g. Histogram Equalization (HE), adjustment, equalization, stretching and Local Adaptive Histrogram Equalization (AHE). HE uses histogram of original image and converts it to an image with uniform histogram. It improves the visual appearance of images. In HE the width of the peaks that indicates the most frequently used gray levels are widen whereas the width of the valleys are reduced. The peaks and valleys will be shifted. AHE is a way to change the local contrast in image; more details are given in the next Section.

All of the above mentioned methods were applied in order to test their efficiency. Based on the result, most effective method is AHE. Fig 1 shows an example of the original image and its histogram also its transformations using HE and AHE. Fig.1 (a) shows the histogram of original image. Fig.1 (b) shows the local adaptive histogram equalization. Fig 1(c) shows local adaptive histogram equalization. It can be seen that the results obtained by AHE (Fig 1(c)) are more effective. This is because; it clearly shows the contrast between vessels and non-vessels.

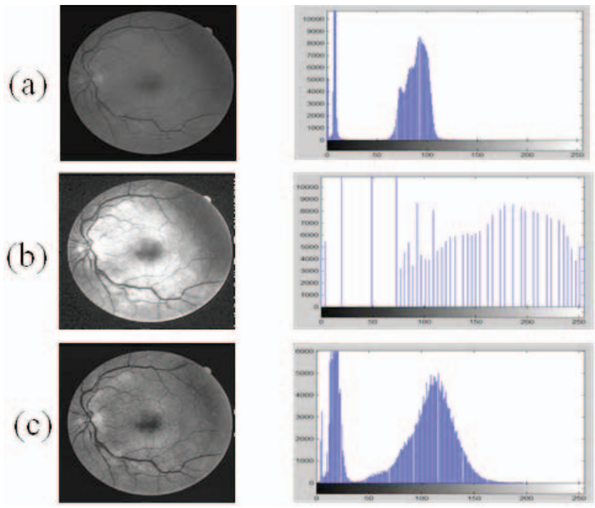

Fig. 1. (a) Gray scaled original image and histogram (b) histogram equalized image (c) local adaptive histogram equalization

B. *Adaptive Histogram Equalization*

Adaptive histogram equalization is a method that uses the HE in multiple local window size area. It emphasizes local contrast, rather than overall contrast. AHE algorithm finds local mappings using local histograms. Recently, many researches in the medical field have begun using AHE as an enhancement method for various diagnosis using radiographs images [9-10].

The contrast enhancement mapping applied to a particular pixel is a function of the intensity values immediately surrounding the pixel [12-13]. For each pixel in the image, a region centered about the pixel is assigned. This region is called contextual region. The intensity values in that region are used to calculate a histogram equalization mapping which is then applied to the pixel in question. AHE has properties such as:

a) The size of the neighborhood region is a parameter of the method. It constitutes a characteristic length scale: contrast at smaller scales is enhanced, while contrast at larger scales is reduced.
b) Due to the nature of histogram equalization, the result value of a pixel under AHE is proportional to its rank among the pixels in its neighborhood. This allows an efficient implementation on specialist hardware that can compare the center pixel with all other pixels in the neighborhood [13]. An un normalized result value can be computed by adding 2 for each pixel with a smaller value than the center pixel, and adding 1 for each pixel with equal value.
c) When the image region containing a pixel's neighborhood is fairly homogeneous, its histogram will be strongly peaked, and the transformation function will map a narrow range of pixel values to the whole range of the result image. This causes AHE to over amplify small amounts of noise in largely homogeneous regions of the image [14] .

C. *The Matched Filter*

The matched filter is one of the template matching algorithms that are used in the detection of the blood vessels in retinal images. It is based on the spatial properties of the object to be recognized. Matched filter takes samples for a cross section of retinal blood vessels; the gray level of these samples is then estimated by a Gaussian curve. MF designing is derived from a number of characteristic for blood vessels:

a) Vessels can be estimated as anti parallel segments.

b) Vessels have lower reflectance than other retinal surfaces, so they appear darker.

c) The intensity varies by a small amount from vessel to vessel.

d) The intensity has a Gaussian shape.

The MF was first proposed in [6] to detect vessels. In [8] a Gaussian function is proposed as a model for a blood vessel profile. The model is extended to two dimensions by assuming a vessel has a fixed width and direction for a short length. The filters are implemented using twelve 16×16 pixel kernels. The details for computing the actual values in the kernels may be found in [8].Aforementioned fact that the cross-section of vessels can be estimated by Gaussian function are used in this algorithm. The MF is defined as:

$$f(x,y)=\frac{1}{\sqrt{2\pi s}}\exp(-\frac{x^2}{2s^2})-m \qquad (1)$$

for $x \le t.s \quad |y| \le L/2$

L is the length of the neighborhood along the y-axis to smooth noise; the criterion t is a constant and is usually set to 3 because more than 99% of the area under the Gaussian curve lies within the range [-3s,3s]. The parameter L is also chosen based on s. When s is small, L is set relatively small, and vice versa. In the implementation, f(x, y) will be rotated to detect the vessels of different orientations [9].

Figs. 2(a)-(b) indicated the problem of matched filter in vessel detection [9]. It can be seen that how matched filter respond to non-vessel parts as vessel.

D. MF with First Derivative of Gaussian

As it is mentioned above matched filter also has strong response to some non-vessel parts. In order to overcome this problem, instead of Gaussian function, first derivative of Gaussian is used in [24]. Based on the fact that the vessel cross-section is a symmetric Gaussian function while the step edge is asymmetric, we propose a simple scheme. This scheme uses a pair of filters, instead of only one filter, to distinguish Gaussian vessel structures from non-vessel edges.

The first derivative of Gaussian can be drawn from equation (1):

$$g(x,y) = -\frac{x}{\sqrt{2\pi}s^{3}}\exp\left(-\frac{x^{2}}{2s^{2}}\right)$$

$$\text{for } \; x \le t.s \quad |y| \le L/2 \tag{2}$$

In [24] it can be seen that the response is asymmetric. In above mentioned figs we can see the response of Gaussian function and step edge. Figs.2 (b-1) and (b-2) show the MF and its response to the synthetic signal. Figs. 2 (c-1) and (c-2) show the FDOG and its response. However, if we could properly exploit their different responses to the FDOG, as shown in Fig. 2(c-2), the vessels and non-vessel edges can be better distinguished by thresholding their responses to MF. Unfortunately, in the original FDOG responses, the magnitude around the Gaussian peak (position100) and the step edge (position 300) changes rapidly. Therefore, directly using the FDOG response is not robust to tell the two types of structures [24].

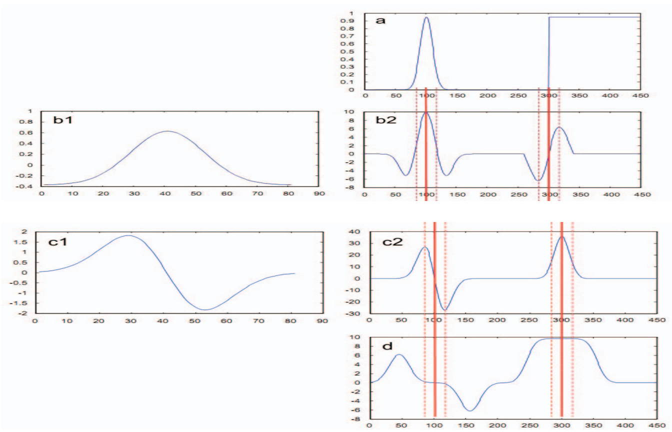

Fig. 2. (a) A Gaussian line cross-section an ideal step edge, (b-1) the MF and (b-2) its filter response, (c-1) the FDOG and (c-2) its filter response, (d) the local mean of the response to FDOG [24]

They propose a thresholding scheme by using the MF-FDOG for retinal vessel extraction. The threshold is applied to images and is adjusted by its response to FDOG. After filtering the image with FDOG the response image is called D. Then for finding the best threshold at first step we should filter it with mean filter:

$$D_m = D \times W \tag{3}$$

Where W is a w×w filter.

Secondly, The D_m must be normalized. The threshold T is then calculated with this equation:

$$T = \left(1 + \overline{D_m}\right) \cdot T_c \tag{4}$$

T_c is the reference threshold that can be set as follows:

$$T_c = c \cdot \mu_H \tag{5}$$

μ_H is the mean value of response of original image to MF. By using this method for vessel extraction, it is obvious that the rate of true detection will be increased and false ones decreased.

III. The Proposed Approach

In the proposed approach in the preprocessing phase the image was changed to gray scale. Then local transformation with different algorithms was used on the gray scaled image. As it is explained in the Section II, it is concluded that using local adaptive histogram is most efficient intensity transformation approach. In the next phase, the developed images were exposed to matched filter which makes a satisfactory change in the accuracy of the image. This images was experimented on the matched filter with first derivative of Gaussian [9]. This caused the accuracy to be improved about 2 %. The details of this approach are given in Fig 3 and the next Section.

1. Find minimum and maximum size of the image
2. Find height of addition/subtraction boxes
3. Extra padding dependent on window size
4. Remove pixels on the left edge
5. Create histogram
6. Remove pixels on the left edge
7. Modify histogram size
8. Add pixels on the right edge
9. Create histogram after adding pixels
10. Modify histogram size
11. Determine CDF value
12. Local adaptive histogram equalized image

Fig. 3. The procedure of methods

A. Procedure of the Proposed Method

Using AHE method a window around each pixel is generated. Then cumulative sum over the histogram is calculated. Throughout the process the input image is compared with the output image. If a pixel has GL lower than others in the surrounding window the output is black; if it has median value in its window the output is 50% gray.

The output is an image in which the mapping applied to each pixel is different. It is adaptive to the local distribution of pixel intensities rather than the global information content of the image. It is clear that AHE allows the simultaneous visualization of the major vessels and thin vessels.

After all procedures done on the image, the local adaptive histogram image was generated and the algorithms were tested on that.

To make this clearer, an example was discussed. An image was selected from DRIVE database. Fig.4 (a) shows an original image from DRIVE database. Fig.4 (b) shows the response of MF on the image. It is noticeable that it has strong response to vessels and also non-vessel parts. Fig.4(c) shows the response of MF-FDOG. It can be seen the number of false detections seriously reduced. Fig.4 (d) shows the the response of proposed method. It can be clearly seen that the false detection caused by bright lesion is greatly reduced. By comparing Fig 4(c) and Fig 4 (d) it can be seen that many fine vessels missed in Fig.4(c) are detected in Fig.4(d). The ground truth for this image is shown in Fig.4 (e). Fig.4 (f) shows the enhanced image after local histogram equalization.

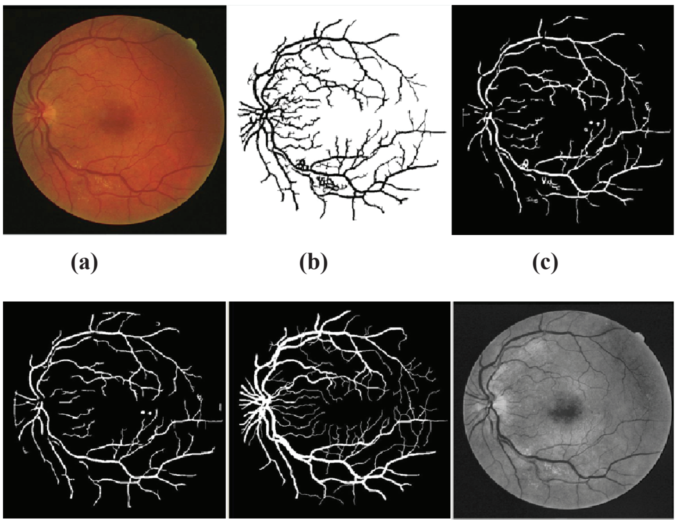

Fig. 4. (a) original image, (b) response of MF, (c) response of MF-FDOG, (d) the proposed method, (e) The ground truth, (f) the enhanced image after local histogram equalization

IV. Experimental Results

A. Material

The proposed method was tested on DRIVE database which contained 40 TIFF formatted RGB retinal images. Images were divided to two parts as training and testing.

Database included hand labeled images that could be used for comparison. The performance of algorithm with preprocessing was measured by accuracy. Accuracy was estimated by ratio of truly classified pixels and by the number of pixels in field of view (FOV).

B. Experiments on DRIVE Database

Experiments were applied on 20 DRIVE test images for matched filter with first derivative of Gaussian based on local adaptive histogram equalization. Table.1 shows the algorithms result and compares with others.

Table1: Vessel extraction results for DRIVE database

Vessel detection method	Average accuracy
GMF[6]	0.8850
MF/ant[20]	0.9293
Kirsch[21]	0.8939
Sobel operator	0.8936
Prewitt operator	0.8951
This work	0.9353
Jiang	0.9212
Cinsdikici [22]	0.9293

V. Conclusion

In this paper, a novel retinal vessel segmentation method based on local adaptive histogram equalization was proposed. This method was implemented. In addition, the effect of this method was compared with existing methods. The results showed that the proposed method could be used in retinal vessel segmentation based on threshold. The performance of the proposed method was shown by accuracy measurements on DRIVE database. This approach increased the rate of accuracy about 2 percent.

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