SEGMENTATION OF BLOOD VESSELS IN RETINAL IMAGES USING 2-D ENTROPIES OF GRAY LEVEL-GRADIENT CO-OCCURRENCE MATRIX

Zhu HongQing

School of Electronics and Information Technology, Shanghai Jiaotong University, Shanghai, China, 200030, Email: hqzhu@sjtu.edu.cn

ABSTRACT

In this paper, a novel automated method for the segmentation of blood vessels in retinal images based upon the enhancement and maximum entropy thresholding is proposed. Blood vessels usually have poor local contrast. Before thresholding fundus images, several matched filters are employed to enhance the contrast of blood vessels. The matched-filter-response (MFR) image is processed by thresholding scheme in order to extract blood vessel form the background. Then, the proposed thresholding approach evaluates two-dimensional entropies based on the gray level-gradient co-occurrence matrix. The 2-D threshold vector that maximizes the edge class entropies is selected. This thresholding method utilizes the information of gray level and gradient in MFR image. It is found that the proposed algorithm works well in normal or abnormal retinal images.

1. INTRODUCTION

Blood vessel in retinal images is an important indicator for many diagnoses including diabetes, hypertension, and arteriosclerosis. The diameter and shape of a retinal vessel are often key indicators in ophthalmologic studies. These changes represent progression of the disease or their response to various therapies. Furthermore, there has been an increasing trend for personal verification methods by using human biometic features. Retinal is usually regarded as one of such features.

Previous methods to segment blood vessels generally fall into two categories: Window-based method, such as edge detection-based method [1]. Since local gradient maximal occur at the boundary of the vessels, the important edges along these boundaries are extracted. In [2], a window surrounding a vessel pixel was modeled by a neural network trained on user-selected examples. Tracking-based method. Individual segments are identified using a search procedure, which keeps track of the center of the vessel and makes some decisions about the future path of the vessel based on certain vessel properties. An efficient piecewise threshold probing technique was proposed in [3] where the matched filter-response (MFR) image is used for mapping the vascular tree. A set of criteria is tested to determine the threshold of the probe region, and ultimately to decide if the area being probed is a blood vessel [4].

This paper proposes a novel method to segment blood vessels. The proposed algorithm is composed of two steps: image enhancement process and entropy-based thresholding. We apply the matched filter to enhance blood vessels with the generation of a matched-filter response (MFR) image. This method achieved better detection results than all the other methods mentioned previously by allowing detection of much smaller vessels and developing more complete and continuous blood vessel maps [5]. Entropy-based thresholding is an automatic technique for thresholding of digital image based on gray level-gradient co-occurrence matrix and the maximum entropy principle. This entropy-based thresholding is different from other 2-D entropies segmentation show in [4][6][7][8]. This method attempts to utilize the information of both gray level and gradient in an image. The present approach evaluates two-dimensional entropies based on the gray level-gradient co-occurrence matrix. The 2-D threshold vector that maximumizes the edge class entropies is selected. Compare with the other method [9], our proposed algorithm does not involve human intervention. Since our algorithm can automatically estimate one optimal threshold vector.

2. ALGORITHM

2.1 Enhancement blood vessels by matched filter

In [10], a more robust approach to blood vessel detections was described. This edge fitting based method used the concept of signal detection using matched filters to detect piecewise linear systems of blood in retinal images. The cross section of a vessel in a retinal image was modeled by a Gaussian shaped curve and than detected using rotated matched filters. Twelve 15×15 different templates were

constructed and used to search for vessel segments along all possible directions by convolving with the image, pixel by pixel only the maximum of their response is retained. Because the gray level of blood vessels is darker than the background's. We make the curve negative. A prototype matched filter kernel is expressed as:

$$f(x,y) = -\exp(-x^2/2\sigma^2), \text{ for } |y| \le L/2 \quad (1)$$

Where L is the length of the segment for which the vessel is assumed to have a fixed orientation. Here the direction of the vessel is assumed to be aligned along the Y-axis.

2.2 Two-dimensional entropic segmentation

Sahoo et al. (1997) published an excellent review of theory behind their entropic thresholding method [11]. They define the optimal threshold by minimizing the difference of the entropies. In [7], the line produced from the two thresholding points is then used to separate the object data set from the background data set. Obviously, the co-occurrence matrix is a commonly used example of this type of 2-D histogram. But the choice of features is extremely important in determining the separability of the object and background classes. Here an efficient maximum entropy thresholding algorithm, which takes into account the information of both gray level and gradient in an image. In this approach, the threshold vector is selected through evaluation two-dimensional entropies based on the gray level-gradient co-occurrence matrix and maximizing the edge region entropies. Gray level-gradient space clearly describes the gray level and gradient among each pixel. It also provides the space relationship between each pixel and its adjacent pixels.

In [12], a gray level-gradient co-occurrence matrix of the image F is a $L' \times L$ dimensional matrix $T = [c_{ij}]_{L' \times L}$, which is consist of normalized gray-level image $F(m,n)$ and normalized gradient image $G(m,n)$. c_{ij} is a frequency of gray level value is i in $F(m,n)$ and gradient value is j in $G(m,n)$. Therefore, the co-occurrence matrix T provides the spatial relationship between gray level and gradient.

In MFR image, Sobel operator gives each pixel's gradient. Hence, the gradient normalized is shown as follows:

$$G(m,n) = INT(g(m,n) \times L' / g_{\max}) + 1 \quad (2)$$

Where $g(m,n)$ is gradient image. $g_{\max}$ is the maximum gradient value in a image. L' is normalized maximum gradient value, here $L' = 128$.

Similarly, we give the gray level normalized, that is

$$F(m,n) = INT(f(m,n) \times L / f_{\max}) + 1 \quad (3)$$

The gray level scale of the proposed algorithm is from 0 to 255 in image $F(m,n)$; hence, it's unnecessary to normalize the gray level value.

The a priori probability P_{ij} of a pair (i,j) is given by the total number of occurrences of the pair. p_{ij} can therefore be written as:

$$p_{ij} = c_{ij} / (\sum_i \sum_j c_{ij}) \quad (4)$$

If the vector (s,t) is threshold vector, then (s,t) can partition the co-occurrence matrix into 4 quadrants. Namely A, B, C and D, (Fig.1). It's suggested the gray levels of object are lower than the gray level of background. Let us define the following quantities:

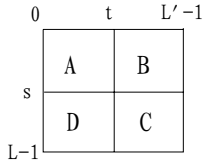

Figure 1- Quadrants of gray level-gradient co-occurrence matrix

$$P_A = \sum_{i=0}^{s} \sum_{j=0}^{t} p_{ij}, \quad P_B = \sum_{i=0}^{s} \sum_{j=t+1}^{L'-1} p_{ij},$$

$$P_C = \sum_{i=s+1}^{L-1} \sum_{j=t+1}^{L'-1} p_{ij}, \quad P_D = \sum_{k=s+1}^{L-1} \sum_{j=o}^{t} p_{ij} \quad (5)$$

Then, normalizing the probabilities with in each individual quadrant, such that the sum of the probabilities of each quadrant equals one. We get the follow probabilities for different quadrants:

$$p_{ij}^A = \frac{p_{ij}}{P_A} = c_{ij} / \sum_{i=0}^{s} \sum_{j=0}^{t} c_{ij}, \quad (6)$$

for $0 \le i \le s, 0 \le j \le t$

$$p_{ij}^B = \frac{p_{ij}}{P_B} = c_{ij} / \sum_{i=0}^{s} \sum_{j=t+1}^{L'-1} c_{ij}, \quad (7)$$

for $0 \le i \le s, t+1 \le j \le L'-1$

$$p_{ij}^C = \frac{p_{ij}}{P_C} = c_{ij} / \sum_{i=s+1}^{L-1} \sum_{j=t+1}^{L'-1} c_{ij} \quad (8)$$

for $s+1 \le i \le L-1$, $t+1 \le j \le L'-1$

$$p_{ij}^D = \frac{p_{ij}}{P_D} = c_{ij} / \sum_{i=s+1}^{L-1} \sum_{j=0}^{t} c_{ij} \quad (9)$$

for $s+1 \le i \le L-1$, $0 \le j \le t$

In an object, the gray level of it is uniform, but the gradient level is zero or very small. The more of gradient level, the most possible of edge of an image. Therefore quadrant $A(0 \le i \le s, 0 \le j \le t)$ is possible show object class. Quadrant D is show background class. In quadrant B, c_{ij} is the translation number of i belongs to object

and j belong to edge. Similarly, in quadrant C, c_{ij} is the translation number of i belongs to background and j belong to edge. The second-order conditional entropy can be written as

$$H(edge/object) = H(E/O) = -\sum_{i=0}^{s}\sum_{j=t+1}^{L'-1} p_{ij}^{B} \log_2 p_{ij}^{B}$$

$$H(edge/background) = H(E/B) = -\sum_{i=s+1}^{L-1}\sum_{j=t+1}^{L'-1} p_{ij}^{C} \log_2 p_{ij}^{C}$$

Hence, the total second-order conditional entropy of the image can be written as

$$H_{(c)}^{T}(s,t) = (H(E/O) + H(E/B))/2 \qquad (10)$$

The maximum of $H_{(c)}^{T}(s,t)$ gives the optimal threshold vector for object-background classification. The optimal threshold vector (s^*,t^*) is

$$(s^*,t^*) = Arg\{\max_{0\le s\le L-1, 0\le t\le L'-1} H_{(c)}^{T}(s,t)\} \qquad (11)$$

In this case the process involves finding a threshold vector (s^*,t^*) which maximizes the $H_{(c)}^{T}(s,t)$. This threshold vector is selected to perform the segmentation.

3. EXPERIMENT RESULTS

In order to evaluate the performance of our algorithm, we select normal retinal image in the first row of Fig.2. The segmentation results of diabetic retinopathy (proliferative) image are presented in the second row of Fig.2. The last row presents the results of the age-related macular degeneration retinal image. The first column shows original fundus images. These given images have low contrast between blood vessels and background. The enhancement results of the application of this matched filter are shown in the second column, respectively. We use the green color plane only since this plane provides the highest vessel contrast. Where we can see blood vessels are significantly enhanced. The third column presents simulation results by our algorithm. The proposed algorithm performs very well in segmentation blood vessels form the background. The last column shows the thinning results.

From the study of the vessel segmentation, we observed that some segmented small vessels and capillaries were disconnected short line segments. This is due to the fact that the local contrast is very low and their intensity values are discontinuous in nature. A post-processing scheme might sometimes be needed to increase the continuity of the small vessels and capillaries. Fig.2shows that proposed method produced some false segmentation of the vessels like optic disk, macula and noises. This is due to the fact that the local contrast is very high and the edges of these objects partially match the shape of the matched filter kernels. Thus, to completely avoid the false detection, a post-processing step is still needed to add to the existing algorithm to eliminate those non-vessel objects whose edges are well matched to the shape of the kernels. In the future work, we want to improve the robustness of our algorithm.

4. CONCLUSIONS

The difficulty in binariization is due to the gray level confusion between local background and image of retinal blood vessels. In this paper, we have proposed a novel approach to retinal image segmentation by enhancement the contrast of blood vessels and the maximum entropy thresholsing algorithm based on the gray level-gradient co-occurrence matrix. This method achieved accurate segmentation results even if abnormal fundus. It should be pointed out that proposed maximum entropy thresholding algorithm use not only the gray level information but also the gradient information. This thresholding algorithm achieved better segmentation results than other 2-D entropies thresholding methods.

5. REFERENCES

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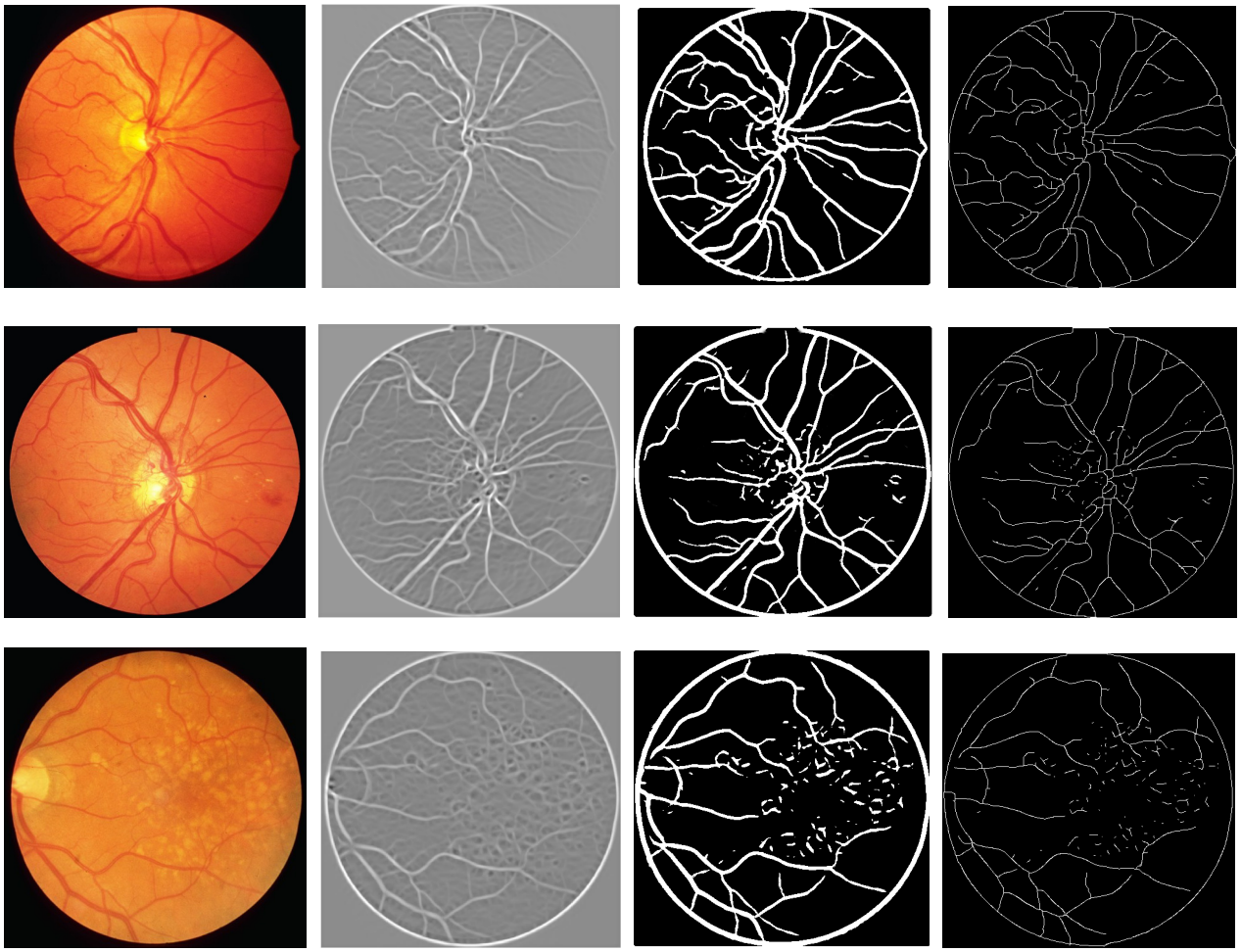

Figure 2-First column are original retinal images, Second column are the results of application of the matched filter, third column are the results of segmentation, last column are the results of thinning.