AN EFFICIENT ALGORITHM FOR EXTRACTION OF ANATOMICAL STRUCTURES IN RETINAL IMAGES

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ABSTRACT
This paper presents efficient methods for automatic detection and extraction of blood vessels and optic disc (OD) both of which are two prominent anatomical structures in ocular fundus images. The blood vessel extraction algorithm is composed of four steps, i.e., matched filtering, local entropy-based thresholding, length filtering, and vascular intersection detection. The OD identification involves the efficient active contour (snake) method. Specifically, we use intensity variation and local contrast to initialize the snake model. Simulation results on a set of retinal images verify the effectiveness of the proposed methods.

1. INTRODUCTION

The retina is the innermost layer of the eye. It is composed of several important anatomical structures which can indicate many eye diseases such as glaucoma, diabetic retinopathy, etc. The two main features required for the retinal image analysis are blood vessels and optic disc (OD), both of which play important role for computer-assisted retinal image analysis and disease diagnosis. In this paper, we focus on these two prominent anatomical structures in a retina image.

The extraction of blood vessels and vascular intersections in the retinal images can help physicians for the purposes of diagnosing ocular diseases, patient screening, and clinical study, etc., blood vessel appearance can provide information on pathological changes caused by some diseases including diabetes, hypertension, and arteriosclerosis. Furthermore, a segmentation of the vascular tree seems to be the most appropriate representation for the image registration applications due to three following reasons: 1) it maps the whole retina; 2) it does not move except in few diseases; 3) it contains enough information for the localization of some anchor points. There are many previous works on blood vessel detection in retinal images [1]. In [2], each vessel segment was defined by three attributes, direction, width, and center point. The intensity distribution of cross section of a blood vessel can be estimated using a Gaussian shaped function. This method required the manual selection of beginning and ending points using a cursor. An efficient piecewise threshold probing technique was proposed in [3] where the matched-filter-response (MFR) image was used for mapping the vascular tree. A set of criteria was tested to determine the threshold of the probed region, and ultimately it was decided if the area being probed was a blood vessel. Since the MFR image was probed in a spatially adaptive way, different thresholds can be applied throughout the image for mapping blood vessels.

On the other hand, information about retinal OD can be used to examine severity of some diseases such as glaucoma. Changes in OD can indicate the current state and progression of a certain disease. The location of the OD is an important issue in retinal image analysis as it is a significant landmark feature, and its diameter is usually used as a reference length for measuring distances and sizes. In [4], the center of OD was located by identifying the area with the highest intensity variation among adjacent pixels. In [5], Hough transform was applied to detect the center and diameter of OD. In [6], Principal Component Analysis (PCA) was applied to the selected candidate regions. The minimum distance between the original image and its projection onto disc space is located the center of OD. In [7], possible regions of optic disc were first located by using a pyramidal decomposition. A Hausdorff-based template matching technique was applied on the edge-map image to find the contour of OD.

In this paper, we propose a new algorithm to efficiently detect and extract blood vessels in ocular fundus images. The proposed algorithm is composed of four steps, matched filtering, entropy-based thresholding, length filtering, and vascular intersection detection. Compared with the method in [2], our proposed algorithm is fully automatic. Since our algorithm can determine one optimal global threshold value, it requires less computational complexity compared to [3]. For OD detection, we have a two-step initialization for the snake active contour model. We use the local window-based variance to select the initial center of OD [4], and we initialize the size and the number of contour points by estimating the local contrast and variance around the center. Then OD boundary is delineated by iteratively fitting the snake contour. Our method is more efficient compared with those in [8] and [7].

2. EXTRACTION OF BLOOD VESSELS

The proposed algorithm is composed of four steps. Since blood vessels have lower reflectance compared to other retinal surfaces, we apply the matched filter to enhance blood vessels with the generation of a MFR image. Secondly, an entropy-based thresholding scheme can be used to distinguish between enhanced vessel segments and the background in the MFR image. A length filtering technique is used to remove misclassified pixels. Vascular intersection detection is performed by window-based probing process.

2.1. Matched Filter

In [1], the gray-level profile of the cross section of a blood vessel can be approximated by a Gaussian shaped curve. The concept of matched filter detection is used to detect piecewise linear segments of blood vessels in retinal images. Blood vessels usually have poor local contrast. The two-dimensional matched filter kernel is de-
signed to convolve with the original image in order to enhance the blood vessels. A prototype matched filter kernel is expressed as

\[ f(x, y) = -\exp\left(\frac{-(x^2 + y^2)}{2\sigma^2}\right), \text{ for } |y| \leq L/2, \]

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. Because a vessel may be oriented at any angles, the kernel needs to be rotated for all possible angles. In [1], twelve different kernels have been constructed to span all possible orientations. A set of twelve 16x15 pixel kernels is applied by convolving to a fundus image and at each pixel only the maximum of their responses is retained.

2.2. Local Entropy Thresholding

As the second step, the MFR image is processed by a proper thresholding scheme, which can be used to distinguish between enhanced vessel segments and the background. An efficient entropy-based thresholding algorithm, which takes into account the spatial distribution of gray levels, is used because an image pixel intensities are not independent of each other. Specifically, we implement a local entropy thresholding technique, described in [9] which can preserve the structure details of an image. Two images with identical histograms but different spatial distribution will result in different entropy (also different threshold values).

The co-occurrence matrix of the image \( F \) is an \( P \times Q \) dimensional matrix \( T = [t_{ij}]_{P \times Q} \) that gives an idea about the transition of intensities between adjacent pixels, indicating spatial structural information of an image. Depending upon the ways in which the gray level \( i \) follows gray level \( j \), different definitions of co-occurrence matrix are possible. Here, we made the co-occurrence matrix asymmetric by considering the horizontally right and vertically lower transitions. Thus, \( t_{ij} \) is defined as follows:

\[ t_{ij} = \sum_{i=0}^{L} \sum_{k=0}^{s} \delta \]

where

\[ \delta = 1 \text{ if } f(l, k) = i \text{ and } f(l, k + 1) = j \]

\[ \delta = 0 \text{ otherwise} \]

The probability of co-occurrence \( p_{ij} \) of gray levels \( i \) and \( j \) can therefore be written as

\[ p_{ij} = \frac{t_{ij}}{\sum_{i} \sum_{j} t_{ij}} \]

If \( s, 0 \leq s \leq L - 1 \), is a threshold. Then \( s \) can partition the co-occurrence matrix into 4 quadrants, namely A, B, C, and D (Fig. 1).

Let us define the following quantities:

\[ P_A = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} p_{ij} \]

\[ P_C = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} p_{ij} \]

Normalizing the probabilities within each individual quadrant, such that the sum of the probabilities of each quadrant equals one, we get the following cell probabilities for different quadrants:

\[ p_{ij}^A = \frac{t_{ij}}{\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} t_{ij}} \]

for \( 0 \leq i \leq s, 0 \leq j \leq s \)

Similarly,

\[ p_{ij}^C = \frac{t_{ij}}{\sum_{i=s+1}^{L-1} \sum_{j=s+1}^{L-1} t_{ij}} \]

for \( s + 1 \leq i \leq L - 1, s + 1 \leq j \leq L - 1 \)

The second-order entropy of the object can be defined as

\[ H^{(2)}_A(s) = -\frac{1}{2} \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} P_A^i \log_2 P_A^i \]

Similarly, the second-order entropy of the background can be written as

\[ H^{(2)}_C(s) = -\frac{1}{2} \sum_{i=s+1}^{L-1} \sum_{j=s+1}^{L-1} P_C^i \log_2 P_C^i \]

Hence, the total second-order local entropy of the object and the background can be written as

\[ H^{(2)}_T(s) = H^{(2)}_A(s) + H^{(2)}_C(s) \]

The gray level corresponding to the maximum of \( H^{(2)}_T(s) \) gives the optimal threshold for object-background classification.

2.3. Length Filtering

There are still some misclassified pixels in the image. Here we want to produce a clean and complete vascular tree structure by removing misclassified pixels. Length filtering is used to remove isolated pixels by using the concept of connected pixels labeling. Connected regions correspond to individual objects. We first need to identify separate connected regions. The length filtering tries to isolate the individual objects by using the eight-connected neighborhood and label propagation. Once the algorithm is completed, only the resulting classes exceed a certain number of pixels, e.g., 250, are labeled as blood vessels. Fig. 2(b) shows the result after length filtering.

2.4. Detection of Vascular Intersections/Crossovers

Vascular intersections and crossovers are the most appropriate representation in registration process because they exist in every retinal images, do not move except in some diseases. If a vascular tree is one-pixel wide, the branching points can be detected and characterized efficiently from the vascular tree. Morphological thinning is applied to the vascular tree in order to get one-pixel-wide vascular tree. In order to save computational time, a 3 x 3 neighborhood
window is used to probe and find the branching points. If the number of vascular tree in the window is greater than 3, it is a branch point. Then a 11 × 11 neighborhood is applied through a detected branching points in order to eliminate the small intersections [10]. We consider only the boundary pixels of a 11 × 11 square. If the number of vascular tree on the boundary is greater than 2, we mark it as an intersection/crossover. Fig. 2(c) presents the vascular tree with the intersections and crossovers.

3. DETECTION OF OPTIC DISC (OD)

3.1. OD Center Estimation

OD usually exhibits a bright round shape in a retinal image. Because the intensity of optic disc is much higher than the surrounding retinal background and there are abundant blood vessels rooted in the OD center, the position of optic disc is roughly located by finding the region or point with the maximum local variance [4].

3.2. OD Boundary Detection

3.2.1. Snake active contour

Automatic OD boundary detection is determined by fitting a snake active contour based on the iterative greedy algorithm [11]. The snake method has been found very useful and efficient for extracting the object boundaries of arbitrary shapes by iteratively minimizing an energy function. Since an optic disc has an approximately circular shape, a group of points, v(s), are put around the center point in circular shape. The energy of snake is given by

$$E_{snake} = \int_0^1 [E_{int}(v(s)) + E_{image}(v(s))] ds,$$  \hspace{1cm} (10)

where $E_{int}$ represents the internal energy of the snake points which measures the continuity and smoothness of the contour. $E_{image}$ is external forces, which can be lines, edges and terminations derived from the image. The internal energy is written:

$$E_{int} = \alpha | \frac{dv}{ds} |^2 + \beta | \frac{d^2v}{ds^2} |^2,$$ \hspace{1cm} (11)

where the first-order differential is approximated as

$$| \frac{dv}{ds} |^2 = \text{Average Distance} - \| v_s - v_{s+1} \|,$$ \hspace{1cm} (12)

and the second-order differential can be approximated as

$$| \frac{d^2v}{ds^2} |^2 = | v_{s+1} - 2v_s + v_{s-1} |^2.$$ \hspace{1cm} (13)

The energy in (12) measures the continuity of the contour. This term encourages even spacing of the contour points. (13) measures the smoothness or curvature of the contour. This term tries to reduce the roughness of the contour curve. During the iteration, the snake points move to the directions that minimize the overall internal and external energy defined in (10).

3.2.2. Snake initialization

The relative importance between internal and external energy during the iteration is also an important factor to the accuracy and robustness of OD boundary, because the OD region is usually fragmented into multiple sub-regions by blood vessels that have comparable gradient values. Therefore, we have the following considerations for the snake method. ODs are usually in the round shape and have smooth and regular contours. We adopted larger weights on the smoothness in (11), so that we can suppress the effect of blood vessels in the OD.

In practice, we found that the initialization of size and shape of snake model is critical to the final result of OD detection. In order to make sure that contour points do not fit into the small fragment or overestimate the boundary, the diameter of the initial contour and the number of snake points also need to be determined based on the OD size and local intensity variation. In this work, the 200 × 180-pixels OD region is extracted from each retinal, where the local contrast and local variance are computed. The local contrast
can be a good indicator for the OD size due to the bright intensity of OD. Based on local contrast values, we empirically set the initial size of OD. On the other hand, the local variance can indicate the intensity variation of OD which is related to the blood-vessel and small structures inside the OD. The larger variance, the more snake points should be used to overcome the disturbing gradient from can be a good indicator for the OD size due to the bright intensity of OD. Based on local contrast values, we empirically set the initial size of OD. On the other hand, the local variance can indicate the intensity variation of OD which is related to the blood-vessel and small structures inside the OD. The larger variance, the more snake points should be used to overcome the disturbing gradient from blood vessels and/or internal intensity variations.

4. SIMULATION RESULTS

In this work, we use twenty $605 \times 700$ retinal images (24bpp), as given in [12], to test our algorithms. Simulation results show that the proposed four-step method performs very well in extracting blood vessels. Even the small blood vessels can be extracted in the final vascular tree, as shown in Fig. 2. On a Pentium-4 PC with Matlab implementation, it takes about 2.5 minutes to accomplish blood vessel extraction. The most time-consuming part is the matched filtering and local entropy computation. It is possible to speed up the process by filtering and thresholding the given image in a spatially adaptive or block-wise way. On the other hand, our algorithm is sensitive to lesions due to the fact that some lesions have been mis-enhanced after matched-filtering. We expect to improve the blood vessel detection results by involving both pre-processing and post-processing to remove the effect from lesions. We also test our OD detection algorithm. For most cases, the OD can be correctly located and identified. However, for some retinal images with low contrast or blurred OD appearance, the OD detection results have some error. The snake initialization can be further improved in order to make the OD detection more robust. Some experimental results of OD detection are illustrated in Fig. 3.

5. CONCLUSIONS

In this paper, we have introduced efficient algorithms for detecting and extracting important anatomical features in ocular fundus images. Specifically, for blood-vessel detection, the proposed four-step method retains the computational simplicity, and at the same time, can achieve excellent results. However, the presence of lesions in the retinal image will complicate blood vessel extraction. In the future, we want to improve the robustness of our algorithm by involving the segmentation scheme to separate the lesions before the matched filtering (pre-processing) or by incorporating anatomical constraints to refine the vascular tree (post-processing). For OD detection, the snake active contour has proved useful and efficient to locate and identify OD where the initialization of snake model has been found important. In the future, we expect to involve geometrical and/or anatomical constraints in the snake model to improve the robustness, accuracy, and efficiency of OD identification. As two prominent anatomical structures in a retinal image, both the vascular tree and OD will be used as the landmark or region-of-interest to further detect, extract, and identify some abnormalities associated with certain diseases.

6. REFERENCES


Figure 3: OD boundary detection