An Optic Disc Detection Scheme on Retinal Images

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***Abstract*— For a computer aided detection system of retinal lesions, optic disc (OD) detection is the first and the most importance. Since the OD is once detected then other clinical importance regions such as fovea or macula can easily be determined, and the OD shape is often used to evaluate abnormal retinal features for diagnosis of abnormalities such as hypertensive retinopathy. In this paper, an approximate OD region is detected by an upper outlier detection scheme. And the final OD is extracted by the random walk scheme with seeds selected automatically. The presented OD detection scheme is assessed quantitatively in 89 images of the Standard Diabetic Retinopathy Database Calibration level 1 (DIARETDB1) database by comparing the detection results with ophthalmologist's hand-drawn ground-truth images. The experimental results show that the OD detected by the presented algorithm approximately follows that extracted by an expert radiologist.**

***Keywords*— Optic disc, retinal, outlier, random walk, DIARETDB1.**

1. INTRODUCTION

World Diabetes Foundation estimated about 135 million people around the world are suffering from diabetic, and predicted that the number will grow to be 438 million in 2030 [1- 15]. Diabetic retinopathy eye diseases harm the vision of the sufferers, even make them blind. Diabetic retinopathy working population suffering from the disease can impact the economy of a country [8- 20]. Early detection can potentially decrease the risk of blindness and effectively controlling the illness for these patients [5, 16]. Current manual methods of detection and assessment of diabetic retinopathy are slow and expensive; they prevent many patients from receiving effective treatment [7]. On the other hand, the computer aided detection system (CADS) of retinal lesions, which allows the examination of a large number of images in less time with low cost and is able to assist doctor's diagnosis to reduce the workload of trained graders [19- 24] .

For a retinal lesion CADS, to locate anatomical landmarks such as optic disc (OD), fovea, the center of the retina, and retinal vasculature is the first requirement. Among them, OD detection is the first and the most importance [3, 12]. On the basis of OD locating, the central macula (fovea) can be approximately located [17, 21].While the OD is once detected then other clinical importance regions such as fovea or macula can easily be determined by the geometric relationships between the optic disc location and the vascular structure. Moreover, the intensity and color characteristics of OD are almost the same as bright lesions such as hard exudates, a retinal lesion CADS has to avoid including OD information. On the other hand, the OD is also significant for creating a reference frame in a retinal image for diagnosis of abnormalities such as hypertensive retinopathy [2]. Furthermore, OD detection often offers additional diagnostic information for the ophthalmologist such as the OD size derived from the OD detection has been commonly used in glaucoma diagnosis [4]. Any change in the structure of the optic disc is a sign of various retinopathies especially for glaucoma [10]; therefore, the shape of optic disc is often used to evaluate abnormal retinal features [20, 24].

In normal retinal images, the optic disc usually appears as bright, yellowish, circular or slightly oval shape enclosed by surrounding darker retinal tissues, roughly one-sixth the width of the image in diameter [5]. The appearance of the OD may vary significantly due to the affect from glaucoma, peripapillary atrophy (PPA), myopic crescents, and myelinated nerve fibers.

Automatic OD detection is a difficult task due to retinal images' irregular illumination, bad contrast and color variation [10] [11]. These factors can degenerate the performance of an OD detection system. Many techniques have been developed for OD detection in retinal images. Sinthanayothin et al. [17] assume that the OD area has a higher variance of intensity than that of the retinal lesions. They utilized an 80*80 pixels window to detect the OD by identifying the largest local variation. However, Lowell et al. had already shown that Sinthanayothin et al. algorithm often fails in retinal images with a large number of white lesions, light artifacts or strongly visible choroidal vessels [11]. At the same time, Walter et al. applied shade-correction and the local variation of the image to detect an initial OD region, and then they used morphological filtering techniques and watershed transformation to modify the initial OD contour [23]. Osareh et al. [15] adopt the template image obtained by averaging the color-normalized optic disc region in 25 fundus images and the correlation coefficient to specify the best match between the template and the candidate regions to detect the OD. Li and Chutatape applied the machinery of principal component analysis (PCA) and a modified active shape model (ASM) to detect OD [10]. However, their algorithm may not be suitable to detect the various disc shapes from many pathological changes. Foracchia et al. [4] fitted a parametric geometrical model to the main vessels to detect the OD.

Due to non-uniform illumination and vessel occlusion, general detection schemes usually fail to detect the OD accurately. On one hand, the performance of an OD detector depends extremely on the illumination uniform and the vessel occlusion. For improving these two technical defects, this article presents a novel algorithm for automatic OD detection in retinal images. OD detection is achieved by applying the upper outlier detection and the restrain for searching area to determine the initial OD. In addition, the final OD is extracted by the random walk scheme with seeds selected automatically. The presented OD detection scheme is assessed quantitatively in 89 images of the Standard Diabetic Retinopathy Database Calibration level 1 (DIARETDB1) database by comparing the detection results with ophthalmologist's hand-drawn ground-truth images [25, 26]. The experimental results show that the OD detected by the presented algorithm approximately follows that extracted by an expert radiologist. The remainder of this paper is organized as follows. Section 2 describes the proposed optic disc detection methodology on a retinal image. Section 3 presents the experimental results. Finally, the conclusions of this paper are presented in Section 4.

2. PROPOSED METHODS

This paper presents an approach for optic disc detection, which can be divided into two phases: approximate segmentation and modification. The former focuses on locating the optic disc, and the latter modifies the optic disc contour.

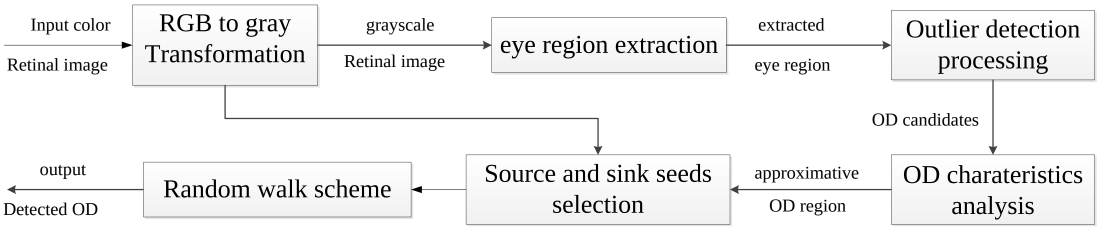

Fig. 1 Flow chart of the presented optic disc detection algorithm.

Fig. 1 shows a flow chart of the presented scheme. Details of the presented optic disc scheme are described in the following subsections.

2.1. Eye Region Extraction

Since to extract the OD in a region of interesting (ROI), eye region, is more effective than that in the whole retinal image. In the proposed computer aided detection system of OD, we apply median filter to filter out noises and smooth the input retinal image, utilize the Sobel edge detector and the most outmost edge detecting scheme to extract the eye region from the noise-deleted and smoothed retinal image.

2.1.1. Median filtering [20]

The median filter is a nonlinear spatial filter, is a powerful tool at removing outlier type noise. It does suit for the job at preserving edges of an image. The filter mask simply defines what pixels must be included in the median calculation. The computation of the median filter starts at ordering those n pixels defined by the filter mask, in the order from minimum to maximum value of the pixels as given in equation (1).

$$F_0 \leq F_1 \leq F_2 \cdots \leq F_{n-2} \leq F_{n-1} \qquad (1)$$

where F_0 denotes the minimum and F_{n-1} is the maximum of all the pixels in the filter calculation. The output of the median filter is the median of these values and is given by

$$F_{med} = \begin{cases} \dfrac{F_{n/2} + F_{n/2-1}}{2} & for \quad n \quad even \\ F_{n/2} & for \quad n \quad odd \end{cases} \qquad (2)$$

Typically, an odd number of filter elements are chosen, to avoid the additional step in averaging the middle two pixels of the order set when the number of elements is even.

The input retinal image may be interfered by noise. So, it needed a filter to reduce noise and get rid of misjudgment in image recognition. The median filter has the suitable filter property that we need, so, we take it as a processor in eye extraction system to reduce the noise and increase the extraction rate.

2.1.2. Eye contour detection

The Sobel gradient mask is one of popular edge detection methods [20]. Fig. 2 shows the Sobel gradient mask; Fig. 2(a) is a mask type, Fig. 2(b) and Fig. 2(c) are the values of masks that are used for detecting the horizontal and vertical edge, respectively. In eye contour detection stage, we first apply the Sobel gradient mask on the noise-deleted and smoothed retinal image to detect all edges in the image. Then we detect and combine the uppermost edge, the lowest edge, the leftmost edge, and the rightmost edge to form the eye contour. The inside region of the eye contour is taken as the extracted eye region.

Z1	Z2	Z3
Z4	Z5	Z6
Z7	Z8	Z9

(a)

-1	-2	-1
0	0	0
1	2	1

(b)

-1	0	1
-2	0	2
-1	0	1

(c)

Fig. 2 The Sobel gradient mask, (a) the mask pixels, (b) $f_x(x,y)$, (c) $f_y(x,y)$.

2.2. Optic disc segmentation

In this stage, we want to extract one or more suspicious areas from the eye region; which is to extract and locate several areas as the suspicious OD candidates of a retinal image. Region-based segmentation schemes are more suitable for retinal images since a suspicious region is always brighter than its surrounding tissues and has a fuzzy boundary with almost uniform intensity [16]. In this paper, region segmentation based-thresholding scheme is utilized for extracting suspicious ODs from an eye region.

For acquiring a better initial segmentation of OD from an eye region, the presented algorithm repeatedly utilizes the upper outlier detection scheme with different thresholds to binarize the eye region into a black-white image. The binarization procedure shall be terminated while the area ratio of white area to the black area is within in the interval [0.01, 0.1] and the absolute difference ratio of white area between two adjacency iterations is less than 5%. Then the white regions are taken as the OD candidates. And the morphological erosion processing, area value filter, main-axes ratio filter and texture analysis are then used in series on these OD candidates to find the real OD.

2.2.1. Suspicious areas locating

An OD segmentation algorithm usually requires an initial rough OD area. Usually, the OD appears as bright yellow lesions in eye fundus images. The fact means that the OD shall be in the outliers of the gray values distribution of the eye region. So, the presented algorithm repeats the outlier determination scheme with different thresholds to binarize the eye region to determine the OD candidates. In statistics an outlier is defined as an observation that deviates substantially from the other observations that it is considered generated by a different system. Outliers frequently have an effect on the parameters estimating a model being fitted to the data. This could cause inaccurate predictions and mistaken conclusions.

In many cases, outliers are frequently removed to improve the accuracy of the estimators. To define the outliers of a data set, let $\bar{x}$ be the mean and let σ be the standard deviation of the data set. One observation is declared a lower outlier if it is no more than ($\bar{x} - k\sigma$), and declared as an upper outlier if it is no less than ($\bar{x} + k\sigma$), and the others are declared as inliers, where the value of upper-outlier parameter (UOP) k is usually taken as no more than 3 and no less than 1.

The brightest areas in a grayscale eye region are the OD candidates. These bright regions are always located in the upper outliers of the pixel value distribution of a grayscale eye region. It should be reasonable and effective that the proposed algorithm calculate the mean and standard deviation of a grayscale eye region by taking the upper outlier points of the grayscale eye region as the OD candidates. For obtaining real OD from the eye region, the presented algorithm will apply the morphological operation and connected component scheme on the upper outlier regions (suspicious OD) to extract the real OD in following processes.

2.2.2. OD characteristics analysis

The presented upper outlier detection scheme although can effectively determine the OD candidates. However, the detected OD candidates may contain other regions of higher grayscale value such as extrudes and various kinds of noise. On the other hand, the

OD is usually a brighter area with special shape and texture characteristics [17, 18]. There are several qualitative and quantitative features for characterizing the shape of OD in a retinal image. The shape feature of OD contains the geometric parameters such as area, area ratio, perimeter, circularity, mean and standard deviation of radial distance, eccentricity, and orientation moment invariants, etc [19]. In this paper, area, area ratio, and ratio of two main axes are taken as criteria to evaluate whether a suspicious OD is a real OD or not.

2.3. Random walk

For image segmentation, random walk scheme is a semi-automated interactive algorithm proposed by Grady [1, 22]. The main steps are: The original image is first presented with its corresponding weighted graph G= (V, W), in which each pixel is the vertex V, and W is the weight between the neighbor vertices. The weight is defined by the Gaussian weight function:

$$w(\upsilon_i, \upsilon_j) = \exp(-\beta(g(\upsilon_i) - g(\upsilon_j))^2), \quad (3)$$

where $g(\upsilon_i)$ is the intensity of the pixel υ_i and β is a free parameter.

For the weighted graph, all vertices are divided into a marked vertices set V_M , and an unmarked vertices set V_U , such that $V_M \cup V_U = V$ and $V_M \cap V_U = \phi$. Finally, due to the probability problem for a random walk is the same as a Dirichlet problem, and Dirichlet problem can be evaluate from the graph Laplacian matrix defined as the follows.

$$L(i,j) = \begin{cases} \sum_{\upsilon_i} w(\upsilon_i, \upsilon_j), & \upsilon_i = \upsilon_j \\ w(\upsilon_i, \upsilon_j), & \upsilon_i \text{ and } \upsilon_j \text{ are adjacent vertices.} \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

So the image segmentation with random walk is transformed to the Dirichlet problem and the image segmentation results are obtained by solving the corresponding Dirichlet problem. In the random walk step, the pixels of eroded approximate OD is taken as the corresponding source seed, and the pixels of the contour of ROI are taken as the sink seeds, respectively.

3. Experimental Results

To characterize the proposed algorithm for optic disc detection over a large number of retinal images, a comprehensive analysis on a publicly available diabetic retinopathy database, the Standard Diabetic Retinopathy Database Calibration level 1 (DIARETDB1) database [25, 26], of color retinal fundus images is performed. The DIARETDB1 database is made up of 89 color retinal images taken in the Kuopio university hospital, in which 84 have slight no proliferative signs of the diabetic retinopathy at any rate, and 5 are normal that do not have any signs of the diabetic retinopathy. These images were captured with the same 50 degree field-of-view digital fundus camera with varying imaging settings controlled by the system. The optical aberrations and photometric accuracy of these images are the same, but some of them may contain a varying amount of imaging noise. Fig. 3 shows an example of OD detection utilized the presented algorithm on a retinal image of DIARETDB1 database.

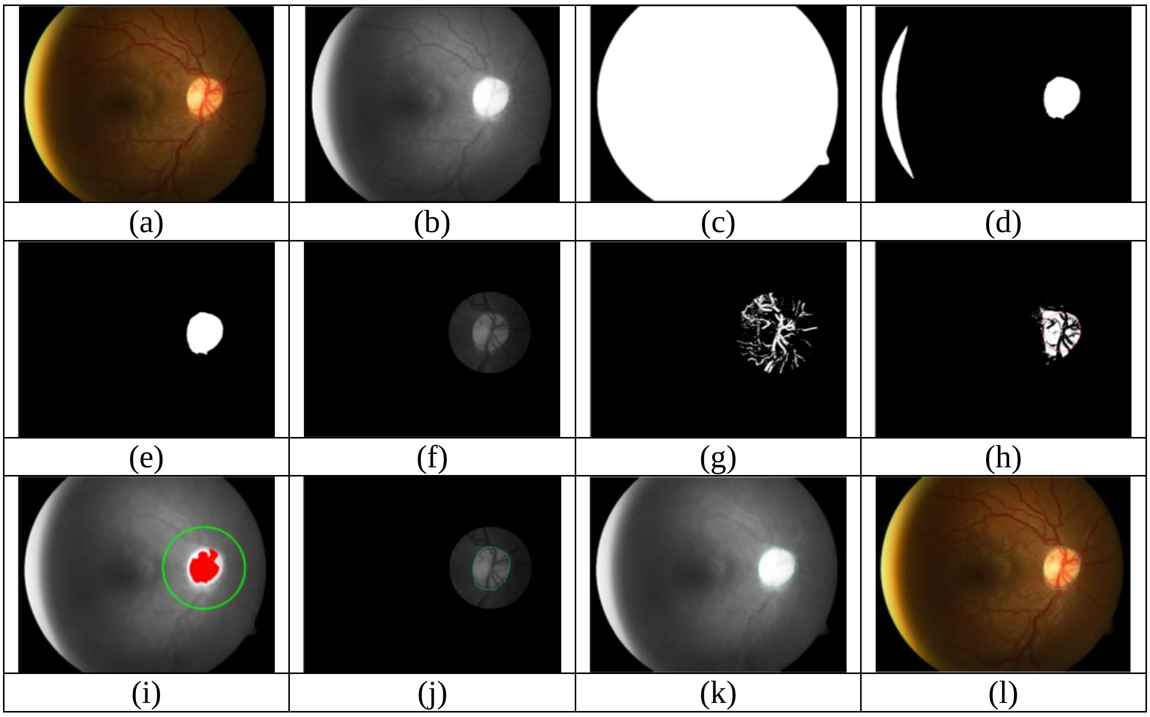

Fig. 3 An OD detection example utilized the presented algorithm, on a retinal image of DIARETDB1 database, (a) original color retinal image, (b) corresponding grayscale image, (c)extracted eye region, (d) OD candidates extracted by outlier detector, (e) approximate OD area selected by OD characteristics analysis, (f) region of interest (ROI), (g) detected vessels in ROI, (h) constraint area for source seeds selection, (i) selected source seeds (red pixels) and sink seeds (green pixels), (j) final OD region modified by random walk scheme, (k) automatically detected boundaries (blue color) overlapped on the grayscale retinal image, (l) automatically detected boundaries (blue color) overlapped on the color retinal image.

These experimental results show that the proposed algorithm is an effective and precise scheme for OD extracting from retinal images. Fig. 4 shows the optic disc detection by the presented algorithm on 5 retinal images of DIARETDB1 database. Where, row 1 are image numbers, row 2 are original color retinal images, row 3 shows the detected OD region (closed by blue pixels), and row 4 shows the OD clos-up view of the detected OD region (closed by blue pixels).

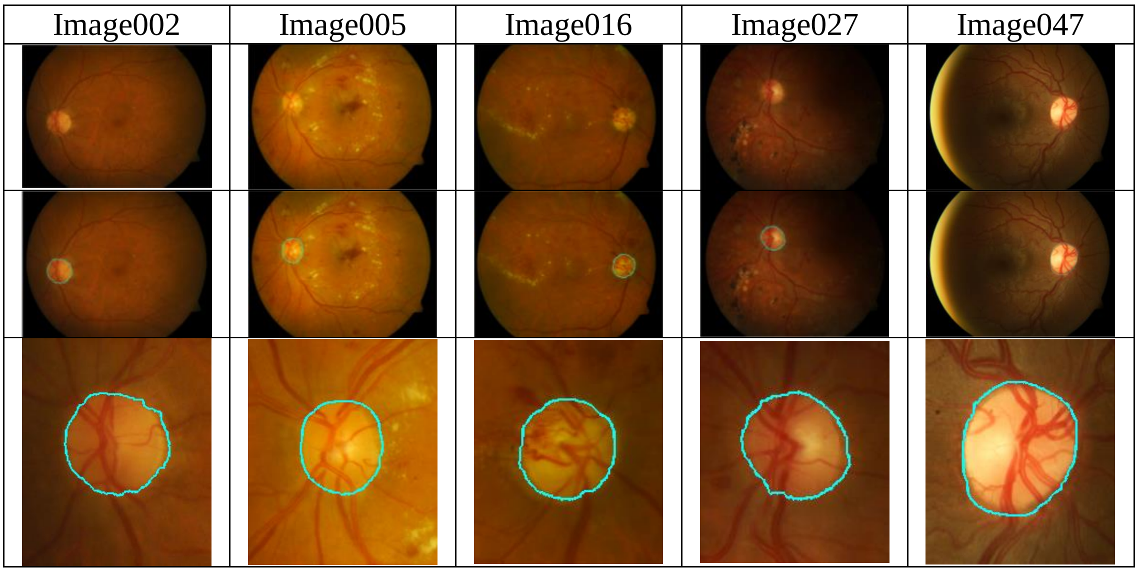

Fig. 4 The OD detected by the presented algorithm on 4 retinal images of DIARETDB1 database.

4. CONCLUSIONS

This paper based on the upper outlier theory and the random walk algorithm to develop a novel algorithm of automatic detection of the optic disc in retinal images. In the random walk step, the pixels of eroded approximate OD is taken as the corresponding source seed, and the pixels of the contour of ROI are taken as the sink seeds, respectively. The presented OD detection scheme is assessed quantitatively in 89 images of the Standard Diabetic Retinopathy Database Calibration level 1 (DIARETDB1) database by comparing the detection results with ophthalmologist's hand-drawn ground-truth images. The experimental results show that the OD detected by the presented algorithm approximately follows that extracted by an expert radiologist.

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