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Automatic Detection of Optic Disc from Retinal Fundus Images using Dynamic Programming

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Abstract. Automatic detection of optic disc (*OD*) in fundus images is used to determine potential clinical parameters for diagnosis of retinopathic diseases. Due to the presence of vascular-tree blood vessels, the detection of *OD* area is a complicated task for a computer-aided diagnosis (*CAD*) system, desirable by ophthalmologists. In this paper, a novel system for the detection of *OD* area has been developed. It consists of four major steps: preprocessing with a color space transformation and contrast normalization; segmentation of the vascular-tree through radial projection (*RP*) and weighted-derivative of Gaussian (*WDOG*) techniques; feature preserving removal of the detected vessels by a fast marching inpainting algorithm, detection of candidate to *OD* pixels via dynamic programming and *OD* area location using ellipse fitting methods. The proposed technique has been tested on 129 retinal images from to public and widely used datasets, *DRIVE* and *DIARETB1*. Experiments on this dataset indicate that this algorithm is computationally fast and able to achieve 92.5 % of accuracy for *OD* detection.

Keywords: Diabetic Retinopathy, Optic Disc Detection, Vascular-Tree Segmentation, Inpainting, Dynamic Programming

1 Introduction

Diabetic retinopathy, age related macular degeneration, and glaucoma [1] are common eye diseases that cause retina-related visual impairment and blindness worldwide. For early and routinely diagnoses, ophthalmologists [2] make use of non-invasive acquisition techniques to visualize the human retina. As a result, color images are visually inspected in the search of abnormalities. Computer-aided diagnosis (*CAD*) tools are, then, suitable for the task and desirable for saving time in mass screening programs and helping non-experience physicians in the difficult assessing an early diagnosis. Glaucoma disease main indicator is the cup to disc ratio, that is, the relation between the *OD* area and its head, the so called cup. Therefore, for any *CAD* system intended to be used in glaucoma diagnosis, the detection of *OD* [4] is a crucial stage, often complicated due to presence of the vascular-tree structure. To address this issue, several techniques were developed. The *OD* detection methods are broadly categorized into clustering-based [5], Principal Component Analysis (*PCA*) [6], active contours [4], [7], ellipse fitting [8] and wavelet analysis [9], Hough transform [10] and Bayesian classification [11] techniques. In all of them, the authors used linear interpolation or smoothing operation to repair vascular-tree disturbing other structures of the retinal image and even boundaries of the *OD* region. Moreover, these methods required high computational cost. In this paper, a novel and fast *OD* detection algorithm is presented. It is based on vascular-tree removal and dynamic programming (*DP*) approaches. In the preprocessing step, the fundus image is transformed from *RGB* to *CIE* $L^*a^*b^*$ color space and then contrast is enhanced by contrast-limited adaptive histogram equal (*CLAHE*) [12] method. Next, for vascular-tree removal, radial projection (*RP*) [13] and weighted-derivative of gaussian (*WDOG*) are used for the detection and morphological reconstruction functions are utilized for enhancement. Afterwards, these structures are repaired by a fast marching algorithm [14], without disturbing other parts of the image. Moreover, the *DP* [15] technique is adapted to detect candidate points of *OD* region. The *DP* technique is very effective due to its edge-based segmentation capabilities that avoid local minima or overlapping problems, computational efficiency, and excellent performance in a variety of domains. Finally, the *OD* area is approximately detected by an ellipse fitting algorithm [16] on these selected candidate points. The proposed system is tested on two publicly available datasets *DRIVE* [17] and *DIARETDB1* [18].

2 Method

This new *OD* detection system consists of four main steps: preprocessing, vascular-tree segmentation; vascular-tree removal; detection of *OD* candidate points and *OD* area locating. The flow diagram of the proposed method is shown in Fig. 1. The following sections describe these steps in detail.

2.1 Preprocessing

In order to achieve the best adaptation to human perception, in the preprocessing step, the fundus image is transferred from *RGB* color space, in which original images are represented, to *CIE* $L^*a^*b^*$ uniform color space where the perceived color difference between two colors is correlated with the Euclidean distance between them. Moreover, L^* is a *CIE*-defined quantity intended to match perceptual lightness response and, therefore, L^* appears similar in lightness to the original color image.

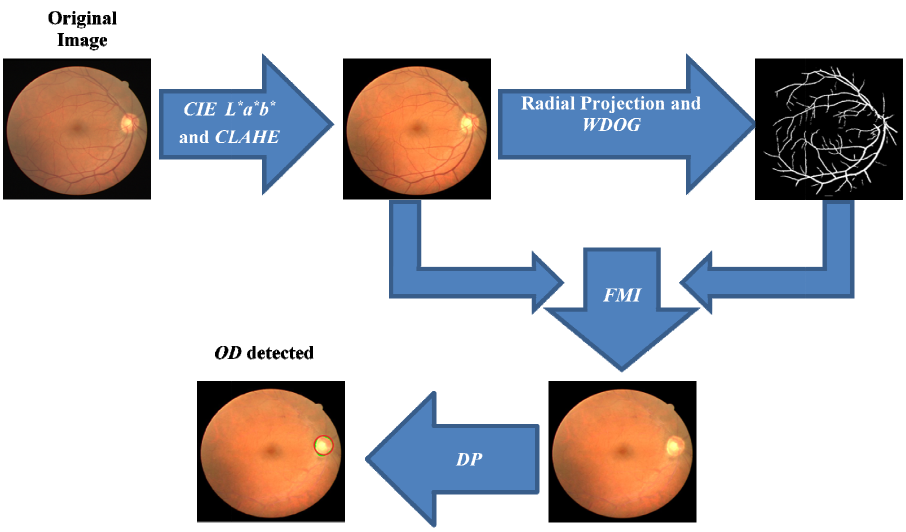


Fig. 1. Diagram of the proposed system. Original image is transformed to *CIE* $L^*a^*b^*$. An adaptive histogram equalization (*CLAHE*) normalizes contrast and vessels are detected with radial projection and Weighted Derivative of a Gaussian (*WDOG*). These vessels are eliminated with a Fast Marching Inpainting technique (*FMI*) and finally *OD* is detected with Dynamic Programming (*DP*).

After color space conversion, contrast is enhanced by using contrast-limited adaptive histogram equalization (*CLAHE*) method in the L^* color plane. The histogram of an image represents the relative frequency of occurrence of gray levels within an image. Histogram modeling techniques modify the gray level input image so that its histogram has a desired shape. In histogram equalization (*HE*), the objective is to obtain a uniform histogram improving the overall image contrast. This technique is not useful when the contrast of the elements present in the image need to be locally enhanced. On the other hand, in adaptive histogram equalization (*AHE*) the image gray levels are not redistributed in base to one unique histogram. In *AHE*, the image is divided into subimages and a histogram is computed for each of them. Image gray levels are locally redistributed in base to each of these obtained local histograms providing a more detailed contrasted image. The combination with the contrast limited (*CL*) approach is performed to reduce the amplification of noise that often occurs in *AHE*. *CLAHE* limits the amplification of contrast by limiting to a maximum, level the slope of the cumulative distribution function that is proportional to the amount of amplification. The value at which the histogram is truncated is called limit. The technique redistributes the histograms to compensate the part that exceeds this limit. By using *CLAHE* technique, the fundus image area is enhanced and illumination is balanced, helping subsequent steps. In fact, the grayscale distribution of L^* plane is highly non-uniform and, therefore, histogram equalization methods that are not adaptive would not properly work. Then, in the process of *CLAHE*, the *2D* fundus image is divided into distinct non-overlapping regions of equal sizes and each region histogram is calculated based on a desired limit for contrast, in this case, the maximum histogram bin value of that region. As a result, the enhanced fundus image is obtained, which is shown in Fig.1.

2.2 Vascular-tree segmentation

The identification and removal of the vascular structure is a necessary prerequisite to obtain the *OD* area. The L^* plane of *CIE* $L^*a^*b^*$ color space is used to segment the vascular-tree by using radial projection (*RP*) [12] for thin blood vessels and weighted-derivative of gaussian (*WDOG*) technique for thick lines. The so obtained linear structures are enhanced by morphological reconstruction. In this paper, the vascular-tree segmentation algorithm is presented. This technique is fully automatic obtaining effective results. Let $L(x,y)$ be the two-dimensional L^* plane image with x and y pixels coordinates. Previous to the segmentación of thick curvature lines, a Gaussian filtering operation with a weight towards the centre of the $L(x,y)$ is performed, which is defined as:

$$T_{map}(x',y') = \cos\left(\frac{\pi x}{2\alpha}\right) \times \cos\left(\frac{\pi y}{2\alpha}\right) \exp\left(-(x^2+y^2)/(2\alpha)\right) \quad (1)$$

where, α is a fixed parameter with a value of 0.5 and is determined by experiments. By this operation the Cartesian coordinates (x,y) are transformed into polar coordinates(x', y'). Afterwards, the thin vascular-lines are segmented using radial projection on the polar coordinates of the $L(x,y)$ as:

$$R_P(x,y) = R_P\left(\delta_r \cos\theta, \delta_r \sin\theta\right) \quad (2)$$

where $x = \delta_r \cos\theta$, $y = \delta_r \sin\theta$ and δ_r is the radius of projection at different radial orientations (θ) experimentally fixed to four directions such as $(0^0, 45^0, 90^0, 135^0)$. Finally, the radial projection is computed at given angles as:

$$L(\theta) = \sum_{\delta_r=0}^{12} R_P\left(\delta_r \cos\theta, \delta_r \sin\theta\right) \quad (3)$$

As a result, $L(\theta)$ contains total number of pixels along the radial direction θ and the value of radial projection. The 36 values of radial projection are used as the center of each region-of-interest along different radial directions. In practice, the value of the thin vascular-tree network is determined by the pixels from the peak value, which is used to generate an edge map of thin vessels. Finally, the detected vascular-tree lines from both thick and thin lines (as shown in Fig. 2 (d) and (e)) are enhanced by morphological reconstruction functions.

2.3 Vascular-tree removal

The retinal information hidden by the blood vessels needs to be recovered in such a way that an observer could not appreciate the previous presence of the vasculature.

Therefore, an inpainting technique must be selected. The inpainting technique which combines non-linear-Partial Differential Equation (*PDE*) diffusion and texture synthesis methods, is called exemplar-based inpainting. Non-linear-Partial Differential Equation diffusion image inpainting techniques fill the holes in the images by propagating linear structures into the target region via diffusion. They are inspired by the *PDE* of physical heat flow, and work convincingly as restoration algorithms. Their main drawback is that the diffusion process introduces some blur, which becomes noticeable when filling vessel regions [14]. Texture based inpainting methods are used to fill missing information with the texture synthesis technique and therefore are suitable for restoring a damaged region saving its [14]. The exemplar-based technique combines the strengths of both of the above mentioned approaches into a single, efficient algorithm. However, according to our knowledge, the number of iterations and the size of the processing window are required; parameters which are difficult to determine in general. Consequently, the exemplar-based inpainting method does not provide, in practice, an effective solution for blood vessels removal, obtaining less impressive results than expected. Therefore, to repair vessels-occluded information from retinal fundus images, the fast inpainting method proposed by Bornemann and Marz [19] is utilized and improved by introducing a perceptually uniform color space $CIE\ L^*a^*b^*$. This technique utilize a fast marching method to traverse the inpainting domain while transporting the image values in a coherence direction, (as shown in Fig. 2(e)), by means of a structure tensor. Through the measure of the strength of the coherence, this inpainting technique switches between diffusion and directional transport. By adding this robust coherence strength, the fast marching inpainting method is more effective than other inpainting methods such as exemplar-based one. Moreover, other structures present in the fundus image such as microaneurysms, exudates or *OD* region are not affected. Due to the use of its tensorial equation, the technique can switch between diffusion and transport direction becoming a fast and reliable method for eliminating vascular-tree network without damaging other structures of the fundus image. The resulting vascular-tree removal is visually shown in Fig.2(c)

2.4 Candidate points detection and location of the optic disk

In the literature, many methods have been developed to detect *OD* area in the green (*G*) and red (*R*) planes of the *RGB* representation of the fundus image. However, the (L^*) channel of $CIE\ L^*a^*b^*$ color space is used in this approach due to its better adaptation to human perception. The dynamic programming (*DP*) technique has been adopted for the segmentation in this color plane. Traditional segmentation algorithms such as thresholding, region growing, and active contours are widely used in the literature but they do not incorporate the global pixels values for weak edges. In contrast with these approaches, the *DP* technique is applied to determine the global contour incorporating both, strong and weak edges, from a set of candidate points. These candidate points are selected in order to obtain an optimal level by introducing a local cost function (*LCF*) on each point of the radial profiles. This *LCF* function selects the edge candidate points based on the minimum cost from the gradient magnitude, which is different from the other areas of the fundus image. Afterwards, to obtain a smooth outline, an ellipse fitting algorithm is used. Some resultant images are shown in Fig.3.

3 Experimental Results

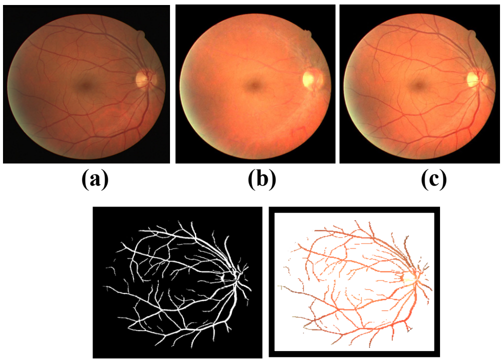
To evaluate the proposed optic disk detection algorithm, 129 fundus images from two public databases *DRIVE* [17] and *DIARETDB1* [18] has been used. The quantitative performance of the proposed method has been computed with the ground truth (*GT*) of *OD* regions, which was provided by the experts from Brunel University [20], developed in other to test their own developed algorithms. For quantitative computation, true positive (*TP*); false positive (*FP*); true negative (*TN*) and false negative (*FN*) metrics are derived. In order to perform quantitative analysis, from preprocessing to vascular-tree removal steps are performed. Afterwards, an automatic *OD* detection result is compared one by one by the corresponding *GT* image. The accuracy of the proposed algorithm is derived based on *TP*, *FP*, *TN* and *FN* values as:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \times 100\% \quad (4)$$

With the term *TP* we refer to a pixel considered as part of the *OD* for both the algorithm and the *GT*, the reverse is called a *TN*, that is, a pixel considered outside the *OD* for the proposed technique and the manual segmentation. In the case that a pixel is considered as part of the *OD* by the algorithm while the manual segmentation considers it as outside the desired *OD* region we encounter a *FP*. When the algorithm considers that a pixel does no belong to the *OD* region while the manual *GT* considers the opposite we have a *FN*. The accuracy value is, therefore, calculated from the ratio of misclassified pixels to the total number of pixels. On average, 92.5% accuracy is obtained with the set of 129 color fundus images. This accuracy indicates that the proposed system is an effective solution for *OD* detection from the existing approaches. Figure 3 also shows the result of *OD* detection system (red contour draw by automatic) as compared to ground truth (green contour draw by expert). The proposed technique draws a circular contour very similar to the manually marked one although smother because of the ellipse fitting step.

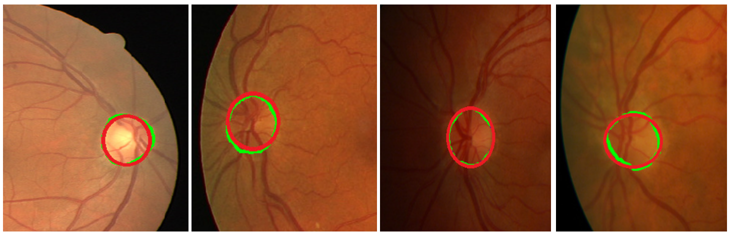
4 Conclusions

In this paper, a novel *OD* detection system has been presented. In the preprocessing stage, the *RGB* fundus image is transformed to *CIE* $L^*a^*b^*$ color space because its adaptation to human perception. L^* plane has been employed in all the subsequent steps due to its close relation with human perception of lightness. The vascular-tree detection algorithm provided effective and fast results for thick and thin linear structures segmentation. Weighted-derivative of gaussian (*WDOG*) and radial projection (*RP*), were used in this stage. The so obtained structures were as well enhanced by morphological functions to reduce possible noise. In the *OD* detection step, this vascular-tree structure was repaired by a fast marching inpainting technique. Afterwards, *DP* edge-based approach provided acurate *OD* contour candidates that were taken as input for a final ellipse fitting method. Experimental results on the images from two public datasets have probed that the system is capable of achieving 92.5 % accuracy for detection of *OD* region. This accuracy indicates that this system could have high clinical impact for automatic screening of glaucoma and other diseases that need *OD* to be isolated.



(a) **(b)** **(c)** **(d)** **(e)**

Fig. 2. Image (a) is the original fundus image that is preprocessed to improve contrast (b). Vascular-tree detection (d), (e) and repairing (c) by proposed technique.



(a) **(b)** **(c)** **(d)**

Fig. 3. Fundus segmentation algorithm by using dynamic programming technique, where the contour manually drawn by an expert is presented in green while the red contour is the OD border obtained by proposed technique.

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