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Localization of the Optic Disc in Retinal Fundus Image using Appearance Based Method and Vasculature Convergence

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Abstract

Optic Disc (OD) localization is a basic step for the screening, identification and appreciation of the risk of diverse ophthalmic pathologies such as glaucoma and diabetic retinopathy. In fact, the fundamental step towards an exact OD segmentation process is the success of OD localization. This paper proposes a fully automatic procedure for OD localization based on two of the OD most relevant features of high-intensity value and vasculature convergence. Merging of these two features renders the proposed method capable of localizing the OD within the variously complicated environments such as the faint disc boundary, unbalanced shading, and the existence of retinal pathologies like cotton wall and exudates, which usually share the same color and structure with the OD. To demonstrate the robustness, reliability and broad applicability of the proposed approach, we tested 1614 images from publically available datasets, including Messidor (1200 images), The Standard Diabetic Retinopathy Database (DIARETDB0, 130 images), Digital Retinal Images for Optic Nerve Segmentation (DRIONS, 110 images), The Standard Diabetic Retinopathy Database (DIARETDB1, 89 images), High Resolution Fundus (HRF, 45 images), and Digital Retinal Image for Vessels Extraction (DRIVE, 40 images). The method successfully localized 1599 images and failed in 15 images, with an average success rate of 99.07% and an average computation time of 0.5 second per image.

Keywords: Optic disc, vasculature convergence, intensity thresholding.

تحديد موقع القرص البصري في صور الشبكية باستخدام طريقة المظهر الخارجي وخاصة تقارب الاوعية الدموية

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الخلاصة

ان تحديد موقع القرص البصري هو الخطوة الاساسية في تشخيص امراض الشبكية، وعملية التحديد مهمة جدا في التعرف على الامراض المختلفة التي تصيب الشبكية مثل الجلوكوما واعتلال الشبكية الناتج عن السكري. وهو مرحلة مهمة باتجاه الفصل الدقيق للقرص البصري. أقترحت هذه الورقة البحثية طريقة تلقائية بالكامل لتحديد موقع القرص اعتمدت على اكثر صفات القرص البصري شيوعا وهي الكثافة الضوئية العالية وتقارب الاوعية الدموية. أن الدمج بين هاتين الميزتين يجعل الطريقة المقترحة قادرة على تحديد القرص في

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بيانات صعبة مثل الحدود الغيرواضحة للقرص وكذلك في حالة وجود امراض الشبكية التي تكون متشابهة من حيث اللون والهيكلية للقرص البصري. لأثبات موثوقية ومتانة الطريقة وقابلية التطبيق على نطاق واسع تم اختبار الطريقة على صورة من ستة قواعد بيانات عالمية: Messidor: 1200 صورة, 130 صورة من قاعدة بيانات اعتلال الشبكية بالسكري, 110 صورة من قاعدة بيانات الصور الرقمية للعصب البصري, 89 صورة من صور قاعدة بيانات اعتلال الشبكية بالسكري, 1,40 صورة من صور الشبكية الرقمية لاستخراج الاوعية الدموية. وتم الحصول على تحديد صحيح في 1599 وفشل في 15 وبمعدل 99.07%. ومعدل سرعة التنفيذ 0.5

1- Introduction

Optical Disc (OD) localization has received much attention in recent years due to its ability to locate anatomical and pathological parts in retinal images. The main components of the retina are the OD, blood vessels, and macula/fovea Figure-1. The OD is the departure point for retinal nerve fibers from the eye, while it also represents the access and the departure point for the retinal blood vessels [1]. The location of the OD is very important in ocular diseases such as diabetic retinopathy [2] and glaucoma [3, 4]. Moreover, OD location is used for studying the features of anatomical structures such as the micro aneurysms, which are indicators of diabetic retinopathy, hemorrhage drusen and exudates. In addition, the OD is the spot of the blood vessels convergence and, hence, its position could be employed as a seed point to keep track of retinal blood vessels [5, 6], as shown in Figure-2. The manual methods for localization OD by clinicians as a time consuming and resource-intensive process. The automatic detection process helps ophthalmologists in taking immediate decision of retinal image analysis. Therefore, localization of the OD is the most basic and preliminary step in the automatic analysis of retinal images and in the detection of retinal diseases. This paper proposes a fast, robust, and fully automatic OD localization method based on its most relevant features high intensity values and vasculature grouping. The rest of this paper is organized as follows; Section two includes the literature review, section three includes the proposed algorithm, section four discusses the experimental results, and section five depicts the conclusion of this paper.

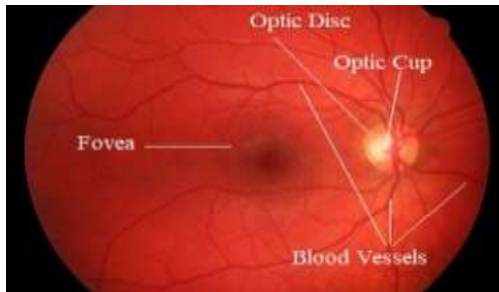


Figure 1-shows retina main parts

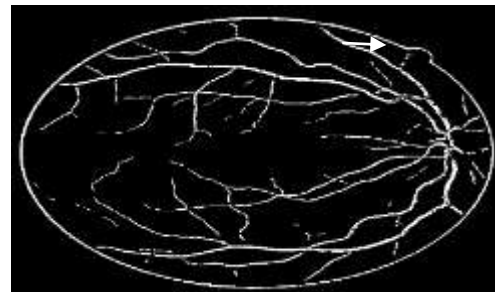


Figure 2-shows retina blood vessels

2- Related Work

Diverse strategies have been suggested for OD localization by employing the anatomical structures of the eye. These include:

- Luangruangrong *et al.* (2019) proposed a method for OD localization that combines circular Hough transform and edge generation using a smoothed gradient. After that, a simple voting method was employed to locate the OD location from the candidate results. The method was applied to different datasets and resulted in 98% accuracy [7].
- Devasia *et al.* (2018) proposed a methodology that used the morphological operations and edge detection techniques, followed by the Circular Hough Transform, to localize the OD. The technique was tested on 549 images from publicly available datasets (DRIVE, DRION, HRF, DIARETDB0 and DIARETDB1) and achieved an average success rate of 97.27% [8].
- Huang *et al.* (2018) proposed a model that exploited the spatial context and intrinsic features of the pixel. The procedure proposed the usage of the Convolution Neural Network (CNN) to classify the RGB fundus image, followed by the employment of a linear combination of Gaussian kernel to

construct the first and second-order potential functions (CRF), respectively. The labels of the connected regions were corrected by analyzing the consistency through the usage of the regional restriction method by calculating the mean of the superpixel. The method was applied on six datasets (Messidor, DRIVE, STARE, DIARETDB0, DIARETDB1, and DRIONS) and gained an average success rate of 99.5% [9].

- Wuet *al.* (2018) presented a new OD localization method, in which the RGB fundus image is preprocessed first, then a saliency map of fundus image is obtained using Graph improving based on visual saliency (GbvS). These steps are followed by the extraction of the skeleton line of venous vessels and the application of parabola-fitting to it. Finally, OD is localized by comparing the saliency within the neighborhood of parabola vertex and the average saliency of the whole fundus. The method was evaluated on four retinal image databases (DRIVE, MESSIDOR, STARE, and DIARETDB0) and its average accuracy was 97% [10].

3- Materials & Methods

3.1 Materials

Six different datasets have been used in this paper, the characteristics of which are as follows.

1. Messidor

A dataset of 1200 RGB images that were captured at three different image sizes: 1440×960 , 2240×1488 , and 2304×1536 pixels. All images were stored in a TIF format.

2. DIARETDB0

The Standard Diabetic Retinopathy Database (DIARETDB0) database consists of 130 RGB images that were captured with a size of 1500×1152 pixels. All images were stored in a PNG format.

3. DRIONS

Digital Retinal Images for Optic Nerve Segmentation (DRIONS) dataset consists of 110 retinal images with resolution of $600 \times 400 \times 3$ pixels. All images were stored in a JPEG format.

4. DIARETDB1

Diabetic Retinopathy Database (DIARETDB1) database has 89 retinal images with a resolution of $1500 \times 1152 \times 3$. All images were stored in a PNG format.

5. HRF

High Resolution Fundus (HRF) is a database that contains 45 images with a size of $3504 \times 2336 \times 3$ pixels. All images were stored in a JPEG format.

6. DRIVE

Digital Retinal Image for Vessels Extraction (DRIVE) is a dataset of 40 images that were acquired with a resolution of $768 \times 584 \times 8$ bits per a color plane. All images were stored in a TIF format.

3.2 Methodology

The OD localization is a prerequisite step in eye diseases screening. The proposed methodology shown in Figure-3 is based on the OD most relevant features which are the high intensity values and vasculature convergence. The OD localization methodology of this paper can be divided into three main stages:

1. Preprocessing.
2. Initial OD region
3. Blood vessels segmentation.

1. Preprocessing

In this research, six different databases were used, each having a different resolution. To deal with these images, resizing was required for standardizing. Then, the green channel of the images was used as it shows better discrimination for the OD. Furthermore, inadequate illumination required normalization. Finally, to correct the variation caused by the acquisition and illumination conditions, a Contrast Limited Adaptive Histogram Equalization [11] was used.

2. Initial OD Region

The appearance-based method, which distinguishes the shape of the OD as the brightest round object in the fundus image, was employed to recognize the OD region from the entire fundus image. To obtain the brightest region, a maximum intensity value was used (Eq. 1). After that, a decreasing factor was required to obtain a correct thresholding value (Eq. 2). The value of the factor depends on the average intensity value of the image. Next, a simple global thresholding was used to convert the intensity image to a binary image (Eq. 3). Finally, the morphological open operation was used to

remove the noise. The binary image reveals the primary location of the OD, and sometimes it may contain more than one OD candidate region due to the similarity in the structure and the color between the OD region and pathologies such as exudates and cotton wool spots.

$$m = \max (g (x , y)) \tag{1}$$

$$\text{Th_Value} = m - \gamma, \gamma = 0.01 \tag{2}$$

$$h(x, y) = \begin{cases} 1 & \text{if Th_Val} > g(x, y) \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

0 otherwise

Where $g(x, y)$ is the equalized image and Th_Value is the threshold value used to convert the intensity image to a binary image, γ is the decreasing factor (in this work, γ is set to 0.01 because it led to best thresholding results), and $h(x, y)$ is the binary image.

3. Blood Vessels Segmentation

To overcome the issue of the existence of more than one OD candidate area, the property of vessel density was used to identify the exact OD location. To reveal the region with maximum vessels density, segmentation for blood vessels was required; however, the precise segmentation of blood vessels in the whole image is complex and time exhausting; therefore, A fast technique for OD localization was improved. The computation time for the localization process is significantly enhanced by segmented blood vessels only to the candidate OD regions instead of the entire image. The green channel of fundus image gives the best results in segmented blood vessels. At the beginning of this stage, blurring to the candidate OD regions was required to remove noise, using Gaussian filter (Eq. 4)[12]. Then, the candidate image was convolved with the 3×3 neighborhood of the Gaussian filter. After that, Canny edge detection technique[13] was employed to find the blood vessels network. The variance for each of the candidate regions was then calculated and the exact OD location was determined by the region with the maximum variance (Eq. 5).

$$a(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{4}; v = \max (v_i) \tag{5}$$

Where $a(x, y)$ is the Gaussian filter, σ is the standard deviation, v is the maximum value for variance and i is the number of OD candidate regions.

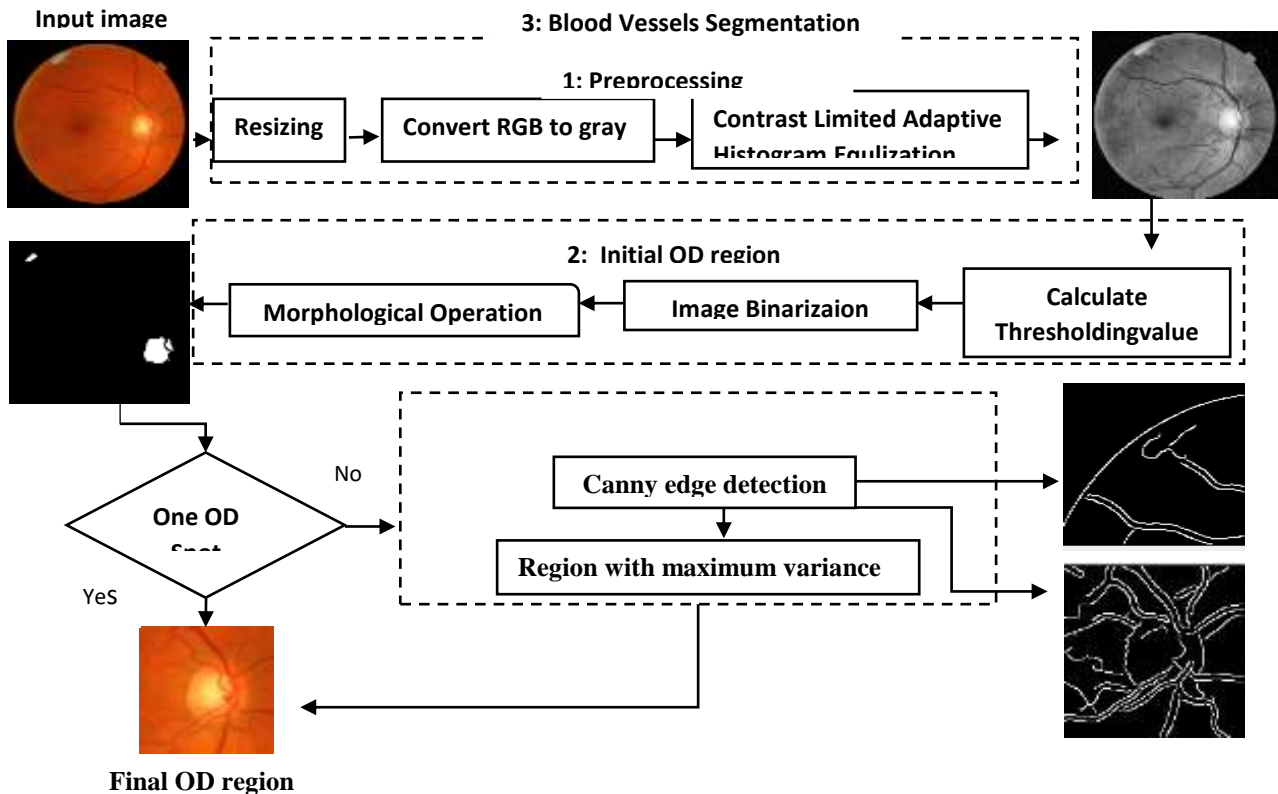


Figure 3-The proposed methodology

4- Results

To demonstrate robustness reliability and broad applicability, the proposed approach was tested on 1614 images from publicly available databases: Messidor, DIARETDB0, DRIONS, DIRETDB1, HRF, and Drive database. The average success rate was 99% and the average computation time was 0.5380 second per image. Table 1 shows the details of the results, while Figures-4, 1-4.6 show the results of samples from the different datasets used. The first and the third columns show the original fundus images after marked optic nerve head, while the second and the fourth columns show their regions of interest, as shown in Table-1. The OD was 100% localized in DRIONS, HRF, and DRIVE datasets, even in the existence of areas brighter than the OD, as shown in the 1st and the 2nd columns of Figure-(4, 3). The result of the success rate of images from the Messidor dataset was 99.33 %, with an average execution time of 0.6 seconds for each image. The proposed method was capable to detect the OD location in the cases of the cotton wall spots, as shown in the 3rd and 4th columns in Figure-(4.1), and in the presence of microaneurysms as shown in the 1st and 2nd columns in Figure-(4.1), which are indicators of diabetic retinopathy. Our method could successfully detect 1192 from 1200 images, despite the large similarity between the side effects of laser therapy and the OD; the proposed method was able to detect the OD as shown in Diaretdb0 dataset in the 2nd and 3rd columns of Figure-(4.2). Total number of detected images in DIARETDB0 dataset was 125 from 130 images, with an average computation time of 0.635 seconds per image. Finally, the DIARETDB1 dataset detected 86 of 89 images and the average execution time was 0.58 seconds per image. The proposed method was also proved effectiveness in the case of diabetic retinopathy, as shown in the 3rd and 4th columns of Figure-(4.4, 4.5, 4.6). The reason of the failure of the algorithm in detecting 16 images was the low contrast between the OD and the background. The appearance-based method, combined with the vasculature convergence model that we proposed, do not only integrate the most important features of the OD but also achieves high accuracy in optic disc localization in normal and diseased images.

Table 1- The performance of the proposed methodology.

| DATASET NAME | DATASET COUNT | DETECTED IMAGE | FAILED IMAGE | TIME SECOND | PERFORMANCE PERCENTAGE |
|--------------|---------------|----------------|--------------|-------------|------------------------|
| MESSIDOR | 1200 | 1192 | 8 | 0.6 | 99.33 |
| DIARETDB0 | 130 | 125 | 5 | 0.635 | 96.15 |
| DRIONS | 110 | 110 | 0 | 0.45 | 100 |
| DIARETDB1 | 89 | 87 | 3 | 0.58 | 97.75 |
| HRF | 45 | 45 | 0 | 0.7 | 100 |
| DRIVE | 40 | 40 | 0 | 0.55 | 100 |
| TOTAL | 1614 | 1598 | 16 | 0.585 | 99 |



Figure 4.1- samples of MESSIDOR database



Figure 4.2- samples of DIRETDB0 database

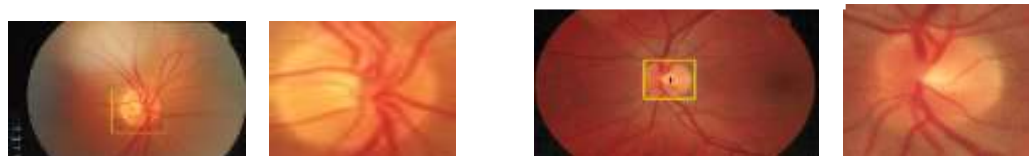


Figure 4.3- samples of DRIONS database

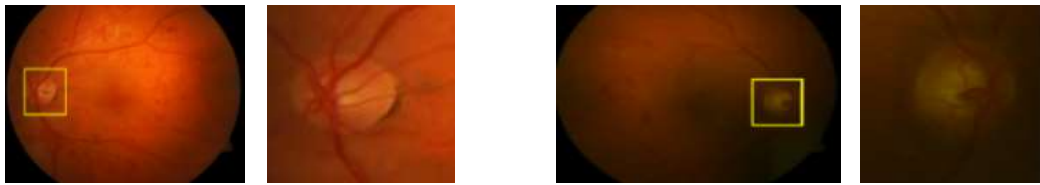


Figure 4.4- samples of DIRETDB1 database



Figure 4.5-samples of HRFdatabase

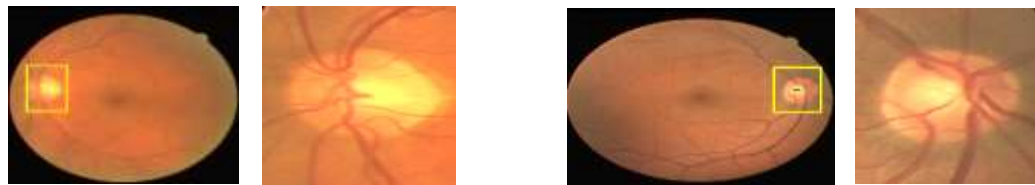


Figure 4.6-samples of DRIVE database

5- Conclusions

A fast, powerful and fully automatic OD localization in fundus image was developed. The proposed procedure in this paper increases the robustness by exploiting both the appearance features of the OD and the main vessel orientation inside it, without excluding any image for its poor quality. The proposed algorithm succeeds to localize the existence of the OD, even with blurred OD margins or the existence of different retinal pathologies like exudates or cotton wall, and despite the similarities of these pathologies with the OD. OD localization methodology has a 99% success rate and an average computation time of 0.585 seconds per image.

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References

1. Devasia, T., Jacob, P., Thomas, T. and Journal, I.T. **2015**. Automatic Optic Disc Localization and Segmentation using Swarm Intelligence. **5**(6).
2. Ahsan, H. **2015**. Diabetic retinopathy--biomolecules and multiple pathophysiology. *Diabetes Metab Syndr.* **9**(1): 51-4.
3. Chen, X., Xu, Y., Wong, D.W.K. Wong, T.Y. and Liu, J. **2015**. Glaucoma detection based on deep convolutional neural network. in 2015 37th annual international conference of the IEEE engineering in medicine and biology society (EMBC): IEEE.
4. Siegner, S.W. and Netland, P.A. **1996**. Optic disc hemorrhages and progression of glaucoma. **103**(7): 1014-24.
5. Gagnon, L., Lalonde, M., Beaulieu, M. and Boucher, M.C. **2001**. Procedure to detect anatomical structures in optical fundus images. in Medical imaging 2001: image processing: *International Society for Optics and Photonics*.
6. Tobin, K.W., Chaum, E., Govindasamy, V.P. and Karnowski, T.P. **2007**. Detection of anatomic structures in human retinal imagery. **26**(12): 1729-39.
7. Luangruangrong, W. and Chinnasarn, K.J. **2019**. Optic Disc Localization in Complicated Environment of Retinal Image Using Circular-Like Estimation. p. 1-18.
8. Devasia, T., Jacob, P. and Thomas, T.J. **2018**. Automatic optic disc localization in color retinal fundus images. **11**(1): 1-13.

9. Huang, W.-B., Wen, D., Dewan, M.A.A., Yan, Y. and Wang, K. **2018**. Automatic Detection of Optic Disc in Retina Image Using CNN and CRF. in 2018 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCOM/IOP/SCI): IEEE.
10. Wu, J., Liu, M., Xiao, Z., Geng, L., Zhang, F., Wang, W., Yang, S., Zhang, D., Song, S. **2018**. Optic Disc Localization Combining Improved Graph Based Visual Saliency Model and Distribution Feature of Retinal Blood Vessels.**8**(1): 127-33.
11. Sinthanayothin, C., Boyce, J.F. and Cook, H.L. **1999**. Automated localisation of the optic disc, fovea, and retinal blood vessels from digital colour fundus images.**83**(8): p. 902-10.
12. Davies, E. **1997**. *Machine Vision: Theory, Algorithms and Practicalities*. 1990. 1997, Academic Press.
13. Gonzalez, R.C., Woods, R. and Eddins, S.J.G. and Richard E. **2009**. Woods, Steven L. Eddins. SI],: Gatesmark Pub. *Digital Image processing using MATLAB/Rafael C*.