DISC AND CUP SEGMENTATION FOR GLAUCOMA DETECTION

Suha Dh. Athab1*, Nassir H. Selman2

1, 2Department of Computer Science, Collage of Science, University of Baghdad

Corresponding Author Email: Suha.Athab@gmail.com

https://doi.org/10.26782/jmcms.2019.12.00026

Abstract

Glaucoma is a visual disorder, which is one of the significant driving reason for visual impairment. Glaucoma leads to frustrate the visual information transmission to the brain. Dissimilar to further eye diseases such as myopia and cataracts, the influence of glaucoma can’t be cured; however, the disease ranked as 2nd driving reason for blindness according to the organization of the health world. Among eye sickness anticipated to influence around 80 million individuals by 2020. Raising the fluid pressure well-known by intraocular pressure (IOP) is the prime cause of Glaucoma disorder. Diagnoses of glaucoma could be achieved through observing the adjustment in the structure of Optic Nerve Head (ONH) to get its features. The proposed methodology suggests to extract region of Interest (ROI) and blurred its red band to enable the segmentation of Optic Disc (OD); followed by inpainting blood vessels stage to facilitate the work of the next stage, which was segmentation of the Optic Cup (OC), the accuracy rate, sensitivity and specificity for detection OD segmentation was 94.7549%, 95.058%, and 95.93%, respectively. The accuracy rate, sensitivity, and specificity for OC segmentation 94.3254%, 0.7877%, 0.9848% respectively.

Keywords: Optic Disc, Optic Cup, Drishti_GS, Retinal fundus, Glaucoma Diagnosis

I. Introduction

Considerable screening programs for retinopathy are in effect at many healthcare centers around the world. Such programs require tremendous quantities of retinal images to be analyzed for the presence of diseases. Ophthalmologists examine retinal images, search for prospect inconsistencies then give the diagnostic results. Many benefits are given by Computer-Aided Diagnosis (CAD) such as diminishing the workload and give objective decision-making tools to ophthalmologists [II]. Analysis of the vascular architecture, as well as recognize changing in the shape, width, of the Optic Disk (OD) and the Optic Cup (OC) could facilitate in observe the effects of glaucoma[XII]. This disease is a consequence of an accumulation of aqueous humor in the eye because of a defect in its drainage system [XV]. Diagnoses of glaucoma can
be accomplished through monitoring the adjustment in the structure of Optic Nerve Head (ONH) and the Layer of Retinal Nerve Fiber (RNFL) [IV]. The head of Optic Nerve can be examined for the ratio of the cup to disc (CDR) which is the main feature to diagnose Glaucoma [V]. Moreover to the features extracted from ONH such as the Disc Damage Likelihood Scale (DDLS) [IX], ISNT violation, and notching. All the characteristic that lead to the discovery of the retinal pathologies require to segment the OD and its Cup.

Diverse research have been launched to segment the OD and the OC, the performance of the segmentation adds significant role in the examination of retinal pathologies. (Yin et al., 2012) [XIV], suggested to use circular Hough transform to segment OD by exploiting the red band of the fundus image, the segmented OD used as input for the segmentation of the OC. Initially local entropy thresholding was used to eliminate the blood vessels. After that median filter was used to smooth the free from blood vessels image. Finally to get exact OC boundary active contour was used. The method was tested on Origa dataset which consist of 650 image. Dice similarity measure was used to evaluate the proposed method the result was 0.92 and 0.81 for OD and OC accuracy respectively. (Xue, Lin, Cao, Zheng, & Yu, 2018) [XIII], suggested to detect OD using “Saliency model based clustering” initial candidate of OD was extracted using K-mean, next two saliencies of sub regions were computed. The candidate OD region was the one with maximum saliency. After that the OD margin was determined using ellipse fitting. Finally the accurate margin was extracted using active contour. The method was tested on Drishti_GS dataset with average segmentation accuracy 88%. (Thakur & Juneja, 2019) [XI], suggested to use “Level set Adaptively Regularized Kernel Based Intuitionistic Fuzzy C-Means” (LARKIFCM), which was hybrid clustering approach divide the fundus to three clusters, to segment both OD and OC. Initially the image was cropped manually to increase the accuracy and decrease the computation time, then the cropped image used in super pixel classification. Followed by global thresholding step with 70 and 120 values for OD and OC respectively. Then level set based contouring stage, the initial seed was provided by the user each time. The contour was determined towards outside. Whereas for the region growing initial seed coordinate value for the pixel in the center of OD provided by the user. The hybrid method was tested on Rim-one dataset, Drishti_GS and Messidor datasets and got 94.84, 93.23, 95.34 accuracy for OD segmentation for the three datasets respectively. For OC segmentation the method was tested for the Rim-one and Drishti GS only and obtained 93.4, 92.6 for the two datasets respectively. (Bhat & Kumar, 2019) [I], suggested to enhance the image by normalizing it. Then the morphological operation was employed to remove the blood vessels followed by exploiting circular Hough transform to determine the region of interest in fundus image, which was the input to the segmentation step, then active contour used to get OD margin. The method tested on RIM-ONE dataset and used the overlapped score as evaluation method and obtained 90.5 result. The rest of
this paper is organized as follows. Section two contains brief description for the dataset used in testing the results, section three describe the proposed system, section four discuss the experimental results and section five depicts the discussion of this paper.

II. Materials

Drishti GS, contains 101 images. Patients age were 40-80 years, with the same number of males and females. All images were stored in PNG with dimension range from 1944 to 2896 pixels. For each image, ground truth was gathered from four glaucoma experts with experience of 3, 5, 9, and 20 years, respectively [VIII].

III. Methods

Optic Disc Segmentation

It is an indispensable step for the segmentation of the rest of the hallmarks of the retina, the normal and the pathological ones. The proposed method suggest to locate the Optic Disc region, which called Region of Interest (ROI), as initial step for segmentation of Optic Disc (OD). The aim of this step is to extract the areas nominated as OD regions and to remove all bright regions that may exist within retina region. In color fundus image, the optic disk characterizes by its sharp margin, bright yellowish orange to creamy pink color and the round or oval shape. The optic disk shares the attributes of hard and soft exudates in terms of color, brightness and contrast; therefore it becomes necessary to localize the optic disk (which is a normal feature of the retina).

a. Initially, the retinal images, which obtained from digital fundus camera, are directly represented by 24-bit/pixel, where one byte (eight bits) are used to represent each of the three channels (red, green and blue). These three channels are stored in 3 different arrays; one array for each band as shown in Fig. (1).

![Figure (1) color bands of the fundus images: (a) original RGB image, (b), (c), (d),](attachment:figure1.png)

Are the green red and blue bands for the original image respectively

A Fundus images have orange dominant color which indicates that the blue channel doesn’t have significant information, while the red and the green are more informatics, In addition, when calculating the mean by Eq. (1) and standard deviation (12) values for each channel, it was noticed that the blue band values are low. As a result, the blue channel is discarded in the next coming stages and only the red and the green channels were used [VII].
\[ \mu = \frac{\sum_{a=1}^{Z} x_a}{Z} \]  
\[ \sigma = \sqrt{\frac{\sum_{a=1}^{Z} (x_a - \mu)^2}{Z}} \]  

Where \( \Sigma \) is the summation symbol, \( X_a \) are the samples values, and \( Z \) is the number of samples.

b. The fundus images was resized into (250,310) for standardizing the different sizes of images in the dataset. Then the retinal images were transformed to intensity images using the Eq. (3)

\[ gray_{img} = (0.5 \ast r_{img}) + (0.5 \ast g_{img}) \]  

Where \( gray_{img} \) the result grayscale image, \( r_{img}, g_{img} \) are the red and green band of fundus image respectively. Then grayscale images were normalized to reduce inter and intra image variabilities; after that, a square window with size (100\times100) was cropped as ROI using the appearance-based method and vasculature convergence[X], the merging between these two features makes the proposed method capable of localizing the OD within the variously complicated environments. Such as faint disc boundary, unbalance shading, and the existence of retinal pathologies like cotton wall and exudates, which share the same color and structure with the OD, Fig. (2) Shows the proposed system for OD and OC segmentation.

c. The images were enhanced using contrast limited adaptive histogram equalization, then global thresholding was applied to convert the intensity image to binary image. With global value depending on the maximum intensity value and detection factor. by subtracting the maximum intensity value from the detection factor which was set to 0.4.
d. Followed by calculating the number of white spots results from binarization. If it was one then crop (100×100) as ROI otherwise the vasculature convergence for the blood vessels used to crop the region with maximum blood vessel variance $X$.

e. As shown in fig. (1-c) The red channel of the fundus is the most discriminative for the OD and less appear for Blood vessels; therefore, it was exploited for the segmentation of the OD. In addition, fig. (3) Clarifies the main steps for OD segmentation.
Initially the red band of ROI was blurred to ease the junction of blood vessels by applying average filter with kernel size $(5 \times 5)$. After that, multilevel Otsu’s thresholding was used to get the exact OD margin, the number of level was set to 2 to divide ROI into 3 different regions Eq. (4).

$$s(x, y) = \begin{cases} 
0 & \text{if } f(x, y) \leq T_1 \\
255 & \text{if } f(x, y) > T_2 \\
128 & \text{if } T_1 < f(x, y) \leq T_2 
\end{cases}$$  \hspace{1cm} (4)$$

Where $(x, y)$ is the result from thresholding image, $f(x, y)$ is the input blurred image, $T_1, T_2$ are the first and second threshold value respectively

Then make scan to all image's pixels to label each object result from multilevel thresholding by checking four neighbors for each pixel. If all neighbor pixels having the same color, they will be owned by the same object. After that collect the pixels of each object in a separate matrix and give a label for this object, for example $L_1$. For Optic Disc the first labeled image was used. Final step to get exact OD margin it was necessary to apply morphological dilation operation with disk kernel size 4. Fig. (4) shows samples of the OD segment; furthermore fig. (5) shows the ROI after marking OD.

![Figure (3) Basic steps for OD segmentation](image)

![Figure (3) Basic steps for OD segmentation](image)

![Figure (4) samples of OD segment](image)
Figure (5) Samples of ROI after locating OD margin

Optic cup segmentation

Accurate segmentation of the optic Cup is surprisingly complicated. Because the depth is the best marker, which is missing in retinal image; furthermore, the OC has high variation in the appearance; In addition, the boundaries of OC are blurred and covered by blood vessels. Thus, classical segmentation algorithms such as thresholding, edge detection and region growing are not enough to accurately finding the OC because it does not incorporate clear edges. Thus the proposed procedure for OC segmentation contains the following stages.

a. Inpaint blood vessels

The retinal blood vessels are considered as noisy pixels which trap retinal features and hinder the feature extraction process; furthermore, causing problem in finding clear boundaries for OC. Hence an approach was used to inpaint the retinal blood vessels in the fundus images that yield promising result in OC segmentation. Initially the blood vessels must extracted to inpaint it, using the following steps.

- First step was normalizing the green plane of the fundus image, which was utilized for segmenting blood vessels, followed by applying adaptive histogram equalization to enhance the image after that store two copies from the equalized image.
- Blur the first copy from the equalized image using average filter with size (7×7).
- To exclude the entire fundus content and get only retinal vessels. The second copy will be subtracted from the blurred image Eq. (5)

\[
Faint_{img}(x,y) = Eq_{img}(x,y) - Avg_{img}(x,y)
\]  

(5)

Where \( Eq_{img}(x,y) \) is the adaptive histogram equalization for the green band of the retina image, \( Avg_{img}(x,y) \) is the blurred image, and \( Faint_{img}(x,y) \) is the image result from the subtraction operation. Fig. (6) Shows the subtracted image.
Then morphological open was applied to remove the noise from the image with disk structural element size 4. Followed by thresholding the image to get clear boundaries for the blood vessels Otsu’s thresholding method was employed for this purpose. Fig. (7) Shows the blood vessels network after Binarization.

The next step is get free from blood vessels image by subtracting blood vessels image from the original fundus Eq.(6), Fig. (8) Shows the fundus image without blood vessels.

\[
Free_{bv}(x, y) = cf_{img}(x, y) - bv_{img}(x, y)
\]  
(6)

Where \(Free_{bv}(x, y)\), is the image without blood vessels, \(cf_{img}(x, y)\) is the fundus image, \(bv_{img}(x, y)\) is blood vessels network image.
To replace low intensities pixel, which result from the deletion of the blood vessels, with neighbor pixels, a morphological dilation operator with disk kernel size 3 followed by median filter with size 7. These two consecutive operation were repeated times to get best result. Fig. (9) shows the original fundus and it’s free from blood vessels image; finally, crop ROI from inpainted image,

Figure (9) samples of inpainted image: on the left original fundus; on the right blood vessels free image

(b) Multilevel thresholding

To get the optic cup multilevel Otsu’s thresholding was applied, the input to the thresholding operation is the green band for the inpainted image as it shows the best discrimination for the OC, two threshold value were required to partition the input image into 3 regions Eq. (4), these values are automatically determined by using Otsu’s method, after that scan the image to label each object in it; by checking four neighboring for each pixel if they were the same color then they will belong to the same object otherwise they will belong to the other object, then each object will store in separate matrix fig. (10) Shows the different level of OC segmentation.

Figure (10) Basic steps for OC segmentation
(c) Parametric fit

To get accurate margin for OC circle shape was fit. Initially the center of OC, major axis length, minor axis length were determined, after that the diameter was calculated according to the following equation:

\[
dim_{len} = \frac{max_{axis} + min_{axis}}{2}
\]  

(7)

Where \( \dim_{len} \) the length of the cup diameter, \( max_{axis} \) is the length of major axis, and \( min_{axis} \) is the length of minor axis. Fig. (11) shows the optic cup segmentation before and after circle fit.

![Figure (11) circular fit for OC: (a) original mask for cup, (b) ROI after drawing boundaries of original mask, (c) circle mask for cup segment, (d) ROI after drawing boundaries of circle mask](image)

IV. Results

To measure the adequacy of the proposed segmentation procedures. Simple comparison operation was performed between the segmented parts result from the previous steps and the ground truth provided with the dataset. Each image in the dataset provided with two text files contains coordinates for the boundary of the OD and its OC; to be able to measure the accuracy of the segmentation, binary masks for disk and its cup were constructed from the set of coordinates provided with data. The following steps clarify the mask construction steps.

a. At the beginning the text file provided with the dataset was stored it in an array, then false array with a size equal to the size of the fundus image corresponding to that text file was made, after that a comparison between the coordinate of the ground truth and the coordinate of the false mask was implemented. If they were equal, then the zero in the false mask was replaced with one; otherwise, it will stay zero. The next step had dilated the boundary of the ground truth to fill the holes in the margin of the OD with disk structural element size 3. Finally, the result OD boundary filled with white color to create binary mask fig. (12) shows the groundmask construction steps.
b. The first step in handling the dataset was resizing it to standardize the different sizes of images in the data set as mentioned earlier. Hence to make comparison between ground truth and segmented part they must be at the same size; therefore, resizing the ground mask to be at the same size for fundus image was necessary step; after that, get the center coordinate for the ground truth mask; final step was crop a window with size (100×100), which is equal to the size of ROI.

c. For Optic Cup ground truth the previous steps must be repeated.

d. To measure the accuracy of the segmentation, the number of true positive, true negative, false positive, false negative pixels must be counted. To count the number of pixels which is correctly classified as optic disk, which is also known as true positive \( tp \), simple intersection operation between ground truth mask and OD mask Eq. (8) clarify the operation, on the other hand the \( fp \) that is the pixels segmented as part of OD; but, in fact it does not belong to the OD, which result from the intersection of segmented part and the negation of ground truth Eq. (9) clarify the operation; moreover, \( fn \) is the number result from the and operation between the ground truth and the negation of the segmented part as it clarify in Eq. (10); finally, the \( tn \) is defined as the region owned by an image which is not segmented but belongs to ground truth. It is calculated as given in Eq. (11)

\[
\begin{align*}
    tp &= \sum_{i=0}^{n} (G_{mask} \land S_{mask}) \\
    fp &= \sum_{i=0}^{n} (S_{mask} \land \neg G_{mask}) \\
    tn &= \sum_{i=0}^{n} (\neg S_{mask} \land \neg G_{mask}) \\
    fn &= \sum_{i=0}^{n} (G_{mask} \land \neg S_{mask})
\end{align*}
\]

Where \( tp \) is the true positive, \( G_{mask} \) is the ground truth mask , \( S_{mask} \) is the mask of the segmented OD, \( tn \) is the true negative, \( fp \) is false positive, \( fn \) is false negative, \( (\land) \) is the and logical operation symbol and \( (\neg) \) is the symbol of negative image.

e. The \( (tp, tn, fp, fn) \) were calculated using Eq. (8) to (11) respectively; as a result, the accuracy sensitivity and specificity of Optic Disc segmentation are calculating using Eq. (12), (13), (14) respectively. Table (1) clarify the
segmentation results; furthermore, table (2) that shows comparison between the proposed system and the related work in this field. Moreover, to fig. (13) that shows samples for the OD segmentation result after marking OD margin. In addition, to fig. (14) that shows samples for the result of Optic Cup segmentation after marking OC margin.

Accuracy = \frac{TN + TP}{TN + FN + FP + T} \times 100 \quad (12)

Sensitivity = \frac{TP}{TP + FN} \quad (13)

Specificity = \frac{TN}{TN + FP} \quad (14)

Table (1) OD&OC segmentation performance

| Segmentation   | Accuracy  | Sensitivity | Specificity |
|----------------|-----------|-------------|-------------|
| Optic Disc     | 94.7549   | 95.058      | 95.93       |
| Optic Cup      | 94.3254   | 0.7877      | 0.9848      |

Figure (13) ROI after marking OD margin: red line is the proposed margin; yellow line is the ground truth line
Figure (14) ROI after marking OC margin: yellow line is the proposed margin; white line is the ground truth line

Table(2) Comparison for the proposed algorithm with other methods

| Segmentation approach | Dataset    | Method                                                                 | Accuracy percentage |
|----------------------|------------|------------------------------------------------------------------------|---------------------|
|                      |            |                                                                       | Optic Disc | Optic Cup |
| (Guo et al.,2016)[III] | Drishti GS | convolutional neural networks(CNNs)                                    |           | 93.73     |
| (Xue, Lin, Cao, Zheng, & Yu, 2018)[XIII] | Drishti GS | Saliency based approach and active contour                             | 88        |           |
| (Thakur & Juneja, 2019)[XI] | Drishti GS | Hybrid approach                                                       | 93.23     | 92.6      |
| Proposed algorithm   | Drishti GS | ROI extraction followed by thresholding red band then inpainting blood vessels | 94.7549   | 94.3254   |

V. Discussion

An easy, fast and fully automatic OD and OC segmentation procedures for retinal image screening were developed. Without excluding any images for poor quality. The proposed algorithm successfully segmented the OD with accuracy percentage 94.7549%. Even with existence of blurred OC margin or different retinal pathologies, the method successfully segmented OC with accuracy percentage 94.3254%. Moreover, this paper suggested new method for segmentation blood vessels network in addition to simple fast method for inpaint the blood vessels from fundus images.
References

I. Bhat SH, Kumar P. Segmentation of Optic Disc by Localized Active Contour Model in Retinal Fundus Image. Smart Innovations in Communication and Computational Sciences: Springer; 2019. p. 35-44.

II. Eladawi N, ElTanboly A, Elmogy M, Ghazal M, Fraiwan L, Aboelfetouh A, et al., editors. Diabetic Retinopathy Early Detection Based on OCT and OCTA Feature Fusion. 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019); 2019: IEEE.

III. Guo Y, Zou B, Chen Z, He Q, Liu Q, Zhao R. Optic cup segmentation using large pixel patch based CNNs. 2016. Available from: https://ir.uiowa.edu/omia/2016_Proceedings/2016/17/ DOI: 10.17077/omia.1056

IV. Ho H, Tham Y-C, Chee ML, Shi Y, Tan NY, Wong K-H, et al. Retinal nerve fiber layer thickness in a multiethnic normal Asian population: the Singapore epidemiology of eye diseases study. 2019;126(5):702-711.

V. Jonas JB, Bergua A, Schmitz–Valckenberg P, Papastathopoulos KI, Budde WMJIO, Science V. Ranking of optic disc variables for detection of glaucomatous optic nerve damage. 2000;41(7):1764-1773.

VI. Lindeberg T, Li M-XJCv, Understanding I. Segmentation and classification of edges using minimum description length approximation and complementary junction cues. 1997;67(1):88-98.

VII. Stein SK, Barcellos A. Calculus and analytic geometry: McGraw-Hill New York; 1992.

VIII. Sivaswamy J, Krishnadass S, Joshi GD, Jain M, Tabish AUS, editors. Drishti-gs: Retinal image dataset for optic nerve head (onh) segmentation. 2014 IEEE 11th international symposium on biomedical imaging (ISBI); 2014: IEEE.

IX. Spaeth GL, Henderer J, Liu C, Kesen M, Altangerel U, Bayer A, et al. The disc damage likelihood scale: reproducibility of a new method of estimating the amount of optic nerve damage caused by glaucoma. 2002;100:181.

X. Suha Dh. Athab NHS. Localization of Optic Disc in Retinal Fundus Image Using Appearance Based Method and Vasculature Convergence. IJS. 2020;61(1).
XI. Thakur N, Juneja MJESwA. Optic disc and optic cup segmentation from retinal images using hybrid approach. 2019;127:308-322.

XII. Weinreb RN, Bowd C, Moghimi S, Tafreshi A, Rausch S, Zangwill LM. Ophthalmic Diagnostic Imaging: Glaucoma. High Resolution Imaging in Microscopy and Ophthalmology: Springer; 2019. p. 107-134.

XIII. Xue L-Y, Lin J-W, Cao X-R, Zheng S-H, Yu LJJoC. Optic Disk Detection and Segmentation for Retinal Images Using Saliency Model Based on Clustering. 2018;29(5):66-79.

XIV. Yin F, Liu J, Wong DWK, Tan NM, Cheung C, Baskaran M, et al., editors. Automated segmentation of optic disc and optic cup in fundus images for glaucoma diagnosis. 2012 25th IEEE international symposium on computer-based medical systems (CBMS); 2012: IEEE.

XV. Yu D-Y, Cringle SJ, Morgan WH. Glaucoma Related Ocular Structure and Function. Medical Treatment of Glaucoma: Springer; 2019. p. 1-31.