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Optic Disc Detection in Retinal Fundus Images Based on Saliency Map

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Abstract
The eye is one of the sensitive organs of the body that is affected by various factors. One of these diseases is glaucoma. Glaucoma is one of the most common ophthalmic diseases that affects the optic disc area and changes this area in terms of size, color and texture. For this reason, the detection of the optic disc area in retinal fundus images is one of the most basic steps in the process of automatic diagnosis of ocular diseases, including glaucoma. Due to the importance of eye diseases and their high incidence, the introduction of new methods in the process of automatic detection of optic disc area by analysis of retinal color images can reduce the volume and computational load, and it helps us to improve the process of early diagnosis of eye diseases. For the reasons mentioned, in this paper, a new method based on the graph-based visual saliency model, along with the watershed algorithm and region growing algorithm to detect optic disc area in retinal fundus images have been suggested to help diagnose eye diseases including glaucoma. According to the proposed method, in this paper, we were able to detect the optic disc area with a 99.1% standard success rate in DRIONS database.

Keywords: Optic Disc, Glaucoma, Retinal Fundus Images, Saliency Map.

1. INTRODUCTION

Today, the rapid development of eye diseases such as glaucoma is one of the most important challenges in the field of health and treatment. The number of people suffer from the disease is also increasing alarmingly. About 1.5 to 2 percent of the population has glaucoma, that almost 50 percent of them do not even know they have the disease.

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According to global statistics, the number of patients with glaucoma is estimated at 60.5 million by 2010 and 79.6 million by 2020.

As we know, medical images play an important role in providing information from different parts of the body, diagnosing diseases, medical research and education. In recent years, various researches in the field of image processing methods have been performed for automatic diagnosis diseases such as glaucoma. These systems provide the ability to process images in large volumes with minimal time and cost, and also do not include reduced efficiency, errors and other vulnerabilities that humans can suffer from.

The optic disc is a clear area in the retina that is almost circular in shape and has a normal diameter of 1.5 mm and has margins at the edge [1]. At the center of the optic disc is a yellow close to a white area called the optic nerve. The optic cup is somewhat deeper than the surrounding nerve tissue, so the optic nerve head has a donut-like appearance. The retinal vessels enter the eyeball through the optic nerve in the optic disc area and exit it [2]. Fig. 1 shows an image of an optic disc and optic cup.

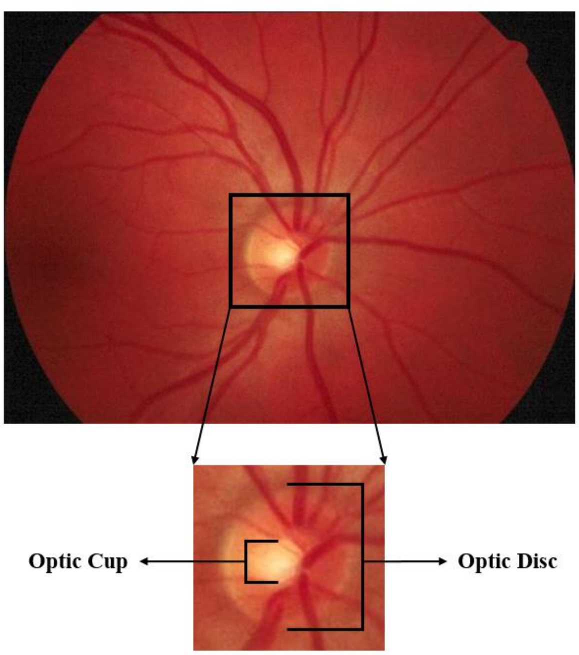


Fig. 1. Optic disc and optic cup in the retinal image.

In general, optic nerve damage in the form of cups of the nerve head and weakening and paleness of the optic nerve is characteristic of most cases of glaucoma. Due to the fact that the anterior part of the optic nerve is easily visible with fundus images, the diagnosis of early signs of optic disc and damage to the optic nerve is the best way to screen and diagnose glaucoma. Moreover, the Circular margin, such as the optic disc, is actually considered as the border between the optic nerve head and the surrounding retina. Therefore, by detecting and evaluating the optic disc area, the process of diagnosing optic nerve damage can be improved and prevented early glaucoma. According to the above explanations, various researches have been done in this field.

In this regard, Mittapalli et al. (2016) have used hybrid methods to detect the optic disc and help to diagnose glaucoma. In their method, first, the center of the optic disc is obtained by using the principal component analysis algorithm.Next, a certain size is cut around the desired point in the image to obtain the desired area. After that, the vessels are removed from the area with an adaptive filter. Finally, using interpolation methods, the value of the zeroed pixels is filled with the values of the neighboring pixels of those ones that are in the optic disc and optic cup. At this stage, the optic cup is determined using the fuzzy clustering method, and the optic disc area is obtained using the active contour model [3].

Khalid et al. (2014) used a morphological operator and a fuzzy C-Means algorithm to segment the optic disc region and suggested that fuzzy algorithm expansion and erosion could be used as a suitable segmentation for the optic disc. Given the favorable response of the fuzzy segmentation method with the morphological operator to the fuzzy segmentation without the morphological operator for the optic cup and optic disc, they stated that the expansion and erosion techniques could improve the quality of the fuzzy segmentation, and in general, the fuzzy segmentation method with the morphology operator gives better results than the fuzzy segmentation without the morphology operator [4].

Haleem et al. (2018) examined a novel adaptive region based edge smoothing model for automatic detection of optic disc and optic cup and segmented these areas to help diagnose glaucoma. In their method, a new region based edge correction model for optic disc and optic cup detection was proposed to assist in the process of glaucoma diagnosis [5].

Zilly and et al. (2016) conducted research on the diagnosis of glaucoma using entropy sampling and ensemble learning to automatically separate optic disc and optic cup. In their study, a new method for separating retinal images using convolutional neural network architecture (CNN) based on ensemble learning was presented and finally, a convex hull transformation was used to obtain the final segmentation of the optic disc area in retinal images [6].

Li et al. (2018) Conducted research on regulatory learning to detect the retinal optic disc. Their proposed method consisted of two main stages of optic disc localization and optic disc area segmentation. In this method, by training a series of monitoring directions for selection, they directly modeled the relationship between the optic disc area and local points [7].

Fu et al. (2018) have separated optic disc and optic cup by relying on a deep multilayer network and polar conversion. In their proposed method, a deep learning network is proposed that jointly examines the optic disc area and the optic cup in a multilayer system [8].

Kulkarni et al. (2015) proposed a computational saliency model for extracting the optic disc region from retinal images. In the pre-processing stage, we tried to eliminate the noise as much as possible and obtain clear images, and finally, the variables related to the color, brightness, and cases of the optic disc separator from the image using the transparency morphology operator. According to the saliency map method in this paper, it has been tried to differentiate the optic disc area based on more brightness than the surrounding areas by using the Itti-Koch saliency algorithm. The otsu’s operator has also been used to thresh and convert gray surfaces and transfer the image to the binary field to determine the bright areas from the dark background. Finally, by using the morphology operator, the interconnected points and subsequently the optic disc area has been tried to identify and remove scattered spots, yellow and white lesions and exudates from the retinal image [9].

Lu et al. (2011) in his proposed method used a circular lighting format, usually characterized by an optic disc. Due to the fact that the optic disc is a circular and brighter area, so with increasing distance from the optic disc, the intensity of the surrounding environment becomes constantly darker. To obtain this circular luminosity pattern corresponding to the optic disc area, a linear operator with minimum-maximum variation was used. The linear operator calculates the brightness changes along multiple lines and is finally determined according to the pattern of the optic disc area [10].

Dehghani et al. (2012) proposed a new method that uses histogram matching for localization of the optic disc and optic cup in the presence of other pathological lesions. In this method, four retinal images from the dataset are first used to create three histograms of color. RGB channel image components (red, blue and green) as a template by using a median filter, image noise is reduced. The next step involves extracting the optic disc for each retinal image using a normal-sized pattern of the optic disc. Then, by obtaining the histogram for the color component for each optic disc and computing the mean of the histogram, a corresponding pattern is created and finally,the optic disc is located [11].

Mithun et al. (2014) proposed an algorithm that could automatically detect optic discs and blood vessels in retinal imaging. In this method, the preprocessing step is done by a binary thresholding process. This threshold is using by otsu's operator. Most of the bright pixels in the base image are in the area of the optic disc, so morphological operations were used to obtain the full area of the optic disc. Finally, a circle with a specific radius was used to detect the area of the optic disc [12].

Weaknesses of the previous methods include the need for early learning, failure against noise, increasing the percentage of error in the presence of complications such as exudate and macular in the area of the optic disc, and noted the required processing with high volume and long-time duration.

In view of the above, this paper presents a new method based on the graph-based saliency map model for detecting the optic disc area to assist in the diagnosis of eye diseases such as glaucoma, which response quickly and efficiently. Optimally, it has a high performance in detecting the optic disc area from other regions of the retina. The flowchart of the proposed method is shown in Fig. 2.

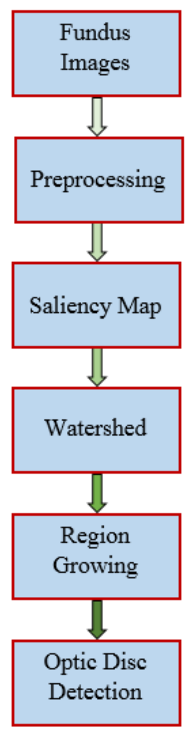
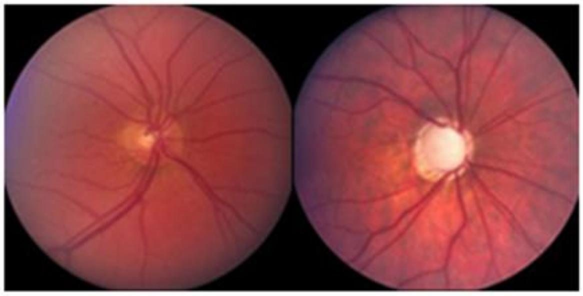


Fig. 2. Proposed method's flowchart.



(a) (b)

Fig. 3. Retinal fundus images (a) healthy, (b) glaucoma.

According to the flowchart in the proposed method, after receiving the database images, the preprocessing operation is performed. In the next step, after applying the saliency map model and improving the model output, the results obtained are used to determine the center of the image by the watershed algorithm. Finally, by using the region growing algorithm and the watershed output, the optical disc area will be detected.

2. MATERIALS AND METHODS

Glaucoma is a disease in which the optic nerve is damaged by factors such as increased intraocular pressure. Because the optic nerve is responsible for transmitting visual information to the brain, its damage gradually causes the visual field to fail, and it is left untreated, the disease can eventually progress to complete blindness. It should be noted that early treatment can prevent the progression of the disease and reduce the patient's vision. Fig. 3 shows an example of a healthy eye with glaucoma.

Due to the importance of glaucoma and the widespread use of automatic diagnostic methods in medical imaging, in this article a new method is presented to help improve the diagnostic process of the optic disc area to facilitate the diagnosis of glaucoma.

2.1. Database

The database used in this paper is DRIONS-DB data which has completely standard data. This database contains 110 digital color images of the retina that belong to the ophthalmology department of Miguel Servet Hospital, Saragossa (Spain).

The average age of patients was 53 years, 46.2% were male and 53.8% were female, and they were all of the same ethnicity. 23.1% of patients had simple glaucoma and 76.9% had chronic glaucoma.

Reference contours were also collected by two ophthalmologists with the help of a software tool for contouring images. In each image, each specialist automatically identified a specific contour by selecting the most important points with a circular curve. For this reason, in this article, as a reference in each image, we have used the average of the lines identified by specialists. Some images in the database have visual characteristics that may distort the optic disc contour detection process. Table 1 shows the number of images with different visual characteristics.

2.2. Pre-Processing

Preprocessing is an important step in retinal image analysis. Many factors can affect the quality of images. Some of the things seen in the retina include low contrast, noise, lack of uniform brightness, changes in light reflection and diffusion, differences in retinal pigments, differences in focal length or camera sensor are some of the factors that reduce image quality. And ultimately reduce the efficiency of retinal image analysis. Therefore, for a system with proper processing and analysis, image enhancement should be considered first. In this paper, color images derived from RGB channels and histogram equalization algorithm were used to improve the image quality in the preprocessing step.

2.2.1. Image Enhancement Using Histogram Equalization

One of the image enhancement methods is histogram equalization. This algorithm is suitable for improving local brightness and increasing the sharpness of edges in the image. Due to the detail and quality of the database images, there was no need for sophisticated image filtering methods to enhance and improve their quality. The only weakness in the images used in the database was the change in brightness in some of the images while capturing them; histogram equalization as a suitable preprocessing was used to improve the images and improve their quality.

In image processing, the histogram is a graphical image that determines the frequency of the pixels of each brightness level in the input image. The horizontal axis of the histogram shows gray levels, which are usually between zero (darkness) and 255 (brightness), and the vertical axis is the number of pixels with a gray level specified in the image [13].

Histogram equalization can be used to improve image quality. It is also very useful in applications such as image compression and segmentation. The histogram operation of digital images with intensity levels in the range [0, L-1] is defined as equation (1):

$$h(r_k) = n_k \tag{1}$$

In this equation, L is the number of gray levels, r_k, k is the value of intensity, and n_k is the number of pixels of the image with brightness r_k.

In general, in histogram normalization, each component in the histogram is divided by the total number of pixels in the $M \times N$ image, and a normalized histogram is obtained from equation (2). It can easily be said that $P(r_k)$ is a probability of occurrence of the intensity r_k level.

Table 1. ***Visual characteristics of database.***

Characteristic	Number of images
Cataract (severe or moderate)	0
Light artifacts	3
Some of rim blurred or missing	15
Moderate peripapillary atrophy	16
Concentric peripapillary atrophy/artifacts	20
Strong pallor distractor	6

$$P(r_k) = \frac{r_k}{MN} \qquad k = 0,1,2,\dots,L-1 \qquad (2)$$

Due to the symmetrical form of light in the image pixels at all color levels, we have used a linear histogram equalization. For this reason, the highest degree of brightness in the image is mapped to 255 and the lowest degree of brightness in the image is mapped to 0, and by obtaining the equation and the required linear mapping angle coefficient, all pixels of the image are mapped to a number between 0 and 255 have been transferred. Fig. 4 shows an example of a database image before and after the histogram equalization step along with its curve.

Low contrast in the image means that the difference between the minimum and maximum brightness of the image is low. Histogram equalization increases the contrast of the input image as much as possible. In dark images, the important components of the histogram are concentrated in low light intensity, just as the important components of the histogram are concentrated in a bright image in areas of high brightness.

2.2.2. RGB to Grayscale Conversion

Due to the color difference in the optic disc area compared to other areas in the retina color images, using a color recognition filter before entering the edge extraction step can improve the correctness of the proposed algorithm and the processing of the next steps. According to the description given and the structure of the optic disc, we can use RGB (red, green and blue) channels of images. As previously stated, most of the important pixels are in the brightest area of the binary form of the image, or the center of the optic disc. Therefore, we must select a point as the most appropriate choice in the center of the bright area as the center of the cup and the optic disc in the next steps consequently, we can approximate the area of the optic disc with a circle having an average radius.

For this process, images in the form of RGB channels are derived from the color images of the database, and due to the fact that the green channel component of the fundus image has more structural information from the optic disc area, from the green channel as the base image, used for later steps.

Fig. 5 shows an example of a grayscale image taken from the green channel space of a database image.

2.3. Graph-Based Saliency Map

The saliency is a feature of an area of the image related to the surrounding points throughout the image. In other words, the main purpose of the saliency map criterion is to determine the amount of attention in one area of the image related to other areas in the image. which distinguishes the prominent and important area from other areas of the image.

Generally, the views that exist in determining the saliency of the image fall into two categories: bottom-up and top-down. Bottom-up methods work based on features such as color, brightness and direction. Top-down methods, on the other hand, use features such as semantic information on faces, text, or geometric structures and symmetries.

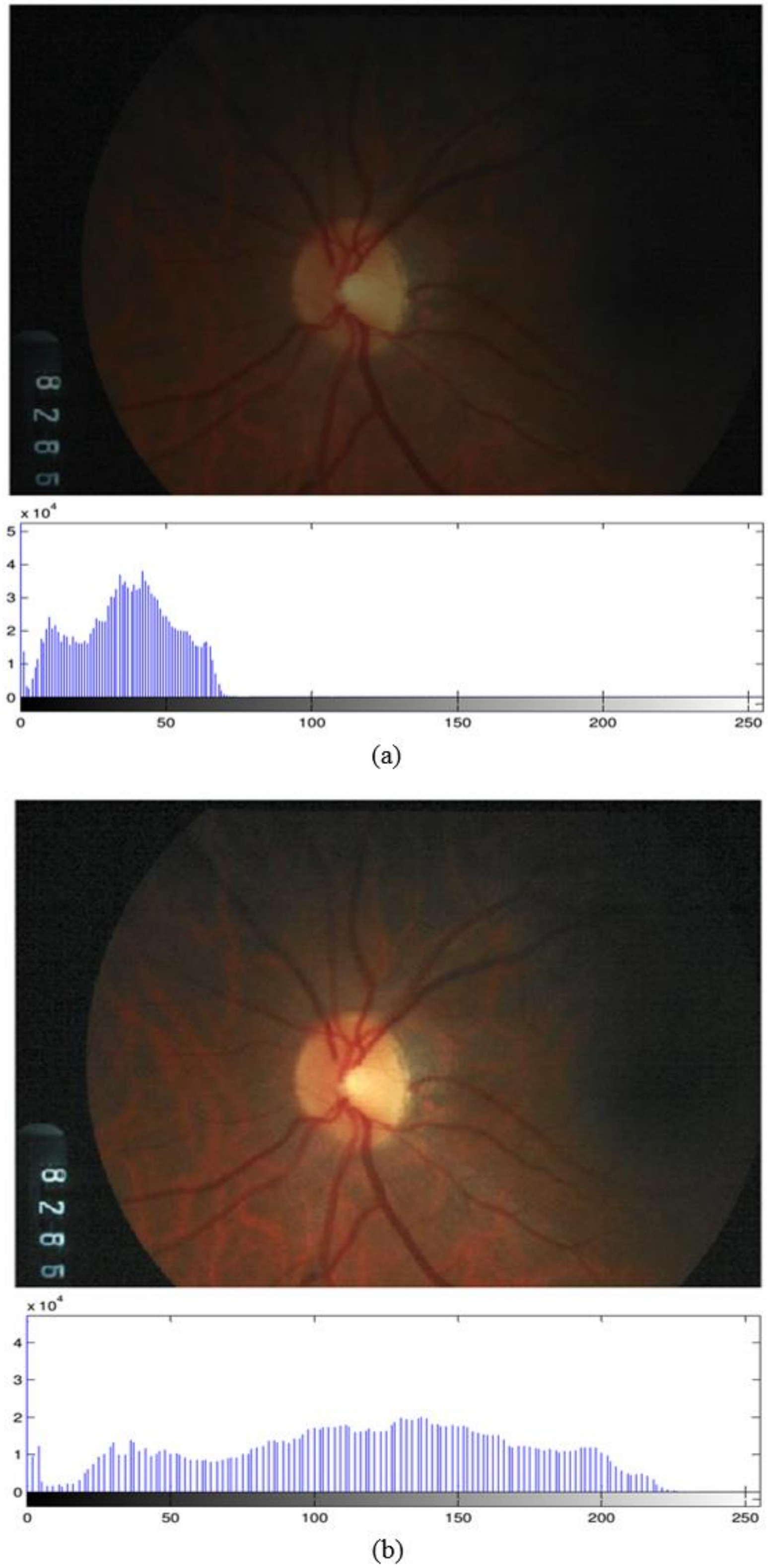


Fig. 4. Histogram equalization method along with its curve. (a) Database image, (b) After histogram equalization.

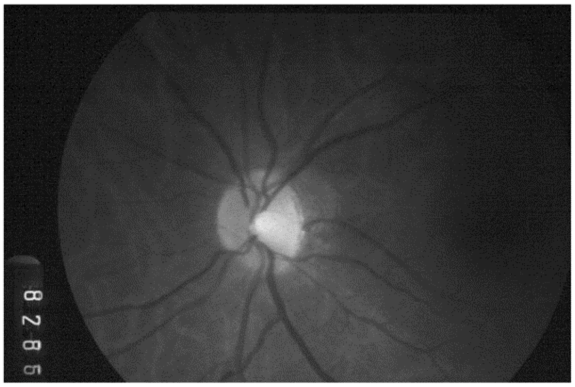


Fig. 5. An example of a grayscale image from the green channel space.

Graph-based saliency map model uses a bottom-up view that assigns a relative logarithmic formula to each pixel of the numerical image and then applies a linear filter to remove the minor points of the image. At this stage, the important points compared to other parts of their neighborhood are identified.

The purpose of the proposed model is to show the features in each location in the field of view with a scalar value. Locations are also guided by the spatial distribution of features.

Obtaining a saliency map based on a secondary graph is generally done in three steps:

1. Feature vectors are extracted at locations throughout the image.
2. An active map is formed using feature vectors.
3. By combining the active map with other maps, a final normalization map is obtained.

During this process, important parts of the image are highlighted. The saliency maps are then combined. This model is relatively simple and is biologically close to human vision [14].

This approach is to define a Markov chain on different maps of the input image and apply an equilibrium distribution to the values of the activation map. In this step, an approach to the second and third steps of the saliency calculation is defined using the dissimilarity and weight of the edges in the graph, which is interpreted as the Markov chain.

The proposed algorithm for graph-based visual saliency by receiving an input image allows us to finally have a limited number of sections in that image, prominent with specific information.

2.3.1. Activation Map Creation

Suppose we are given a feature map $M: [n]^2 \to \mathbb{R}$. The goal is to create an activity map A where $A: [n]^2 \to \mathbb{R}$ so that, the position $(i,j) \in [n]^2$ in $M(i,j)$,somehow unusual in its neighborhood, will correspond to high values of activation map A [15].

Of course, there is no limit to the definition of the word "unusual", and different definitions can be chosen for it. "Improbable" would lead one to the formulation of Bruce [16], where a histogram of $M(i,j)$ values is computed in some region around (i,j), subsequently normalized and treated as a probability distribution, so that $A(i,j) = -\log(p(i,j))$ is clearly defined with $p(i,j) = \Pr\{M(i,j)|\text{neighborhood}\}$. Another approach compares the local distribution of the "center" to broader "surround" distributions and calls the Kullback-Leibler tension between the two "surprise" [17].

2.3.2. Markovian Algorithm

Here, we propose a state of art approach in which the dissimilarity between M (p,q) and M (i,j) is defined as equation (3) [15].

$$d\big((i,j)||(p,q)\big) = \left|\log\frac{M(i,j)}{M(p,q)}\right| \tag{3}$$

This is a natural definition of dissimilarity: simply the distance between one and the ratio of two quantities, measured on a logarithmic scale.

In some experiments, instead of equation (3), we used $|M(i,j) - M(p,q)|$ and finally, both functions have a good response. In this step, a fully connected graph G_A is considered by connecting all nodes of the network called M, where each node $(i,j) \in [n]^2$ is connected to all other $n-1$ nodes and the directional edge is weighted from the node (i,j) to the node (p,q) with equation (4) [15].

$$w_1\big((i,j),(p,q)\big) = d\big((i,j)||(p,q)\big),F(i-p,j-q) \tag{4}$$

where

$$F(a,b) = \exp\left(-\frac{a^2+b^2}{2\sigma^2}\right) \tag{5}$$

In this algorithm σ is a free parameter. The weight of an edge from a node (i,j) to a node (p,q) is proportional to its dissimilarity and proximity to the domain M. That is, if the similarity between the node (i,j) and the node (p,q) is high, the value of the dissimilarity goes to zero and the weight of the edge that connects the two nodes is low. Furthermore, if the similarity between the node (i,j) or the node (p,q) is high, the amount of dissimilarity will be high and also the weight of the edge that connects the two nodes will be high [14].

By normalizing the weight of the output edges of each node to one, a definition of the Marco chain in graph G_A is obtained as an equivalence between nodes & states, and edges weights & transition probabilities are drown. Over time, the equilibrium distribution of the chain changes, assuming that the passer-by crosses the graph paths. And naturally, significant regions accumulate in the surrounding nodes, that have high dissimilarity, to the extent that the probability of transmission equilibrium in these subgraphs increases and the nodes with similar values are less likely. The result of this operation is an activation map obtained from the pairwise contrast [14].

2.3.3. Activation Map Normalizing

The purpose of the normalization step in the proposed algorithm is to focus on the important areas in the activity map. If areas of the initial activity map were previously concentrated in the composition, the original map may become too uniform and worthless. Although this may seem trivial, the spirit of any activation mapping algorithm is to focus the activity on several more valuable points [14].

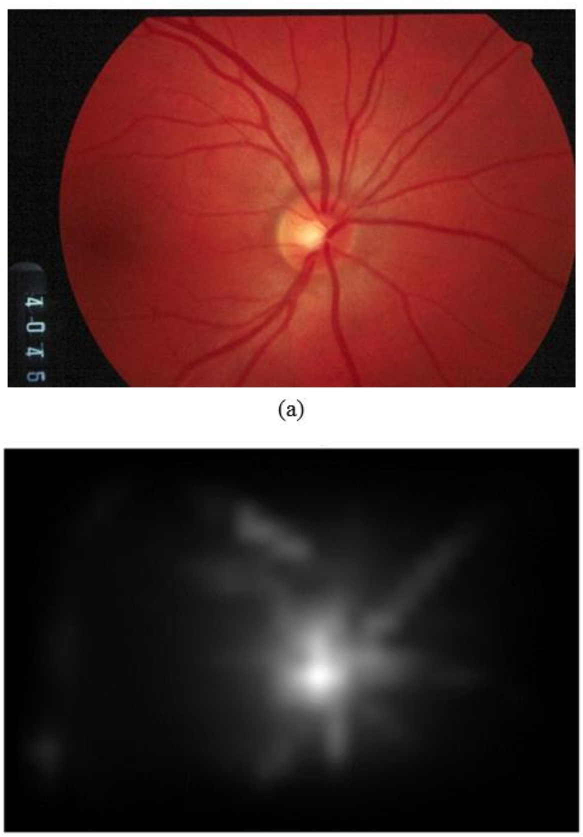
By defining the concentration of valuable areas, another Markovian algorithm is proposed as follows. There is an activation map in which the expression A: [n] ^ 2 → R needs to be normalized, then a graph G_A with n ^ 2 nodes, labeled with indices [n] ^ 2, is created. For each node (i,j) and any other nodes (p,q) even itself (i,j), that are connected, thereis an edge from (i,j) to (p,q), with a weight defined in equation (6), has been allocated [14].

$$w_2\big((i,j),(p,q)\big) = A(p,q),F(i-p,j-p) \tag{6}$$

Then, the weight of the outbound edges for each node is normalized again so that they all become one. The resulting graph behavior as a Markov chain allows to calculate the equilibrium distribution on the nodes.

After that, the important areas go to those nodes having high activity. This is an algorithm for concentrating areas of prominence in a structure and has many advantages [14].

Finally, the image, obtained in these steps, is an image equal to the input image of the database, which in important areas of the input image, pixels with high brightness, and in low importance parts of the pixel image have zero brightness. This model is called an image saliency map.



(a)

(b)

Fig. 6. (a) Database image (b) Saliency map output.

Fig. 6 shows the output of the graph-based saliency map model on an image of the database.

2.4. Watershed Algorithm

Watershed transformation considers an image with grayscale as a topographic image. In the order that the minimum degree of gray is equal to the height (value) zero and the maximum degree of gray will be one height. Each point of the image will be evaluated as a point with height-based on this algorithm [18].

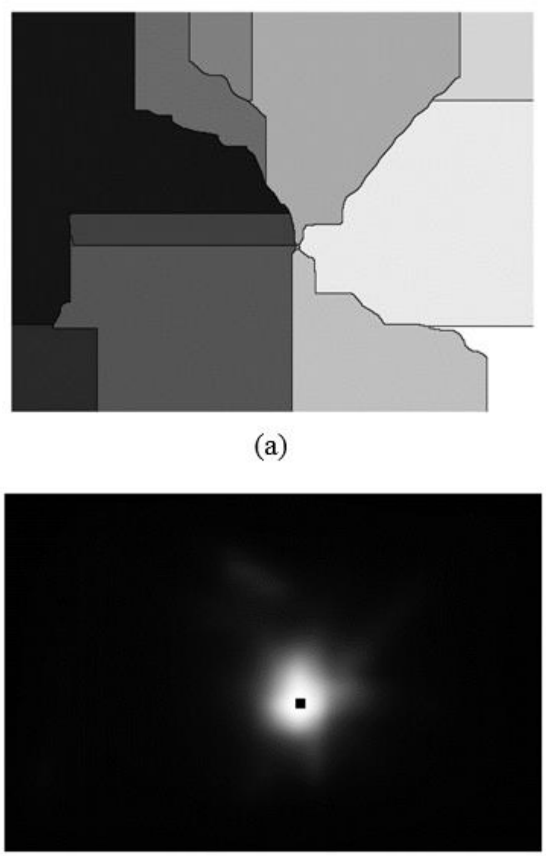
Watershed transformation is mainly applied to the image gradient because the image gradient has large values at the edges and small values in homogeneous areas. Since the components, generated by the watershed algorithm, are not meaningful, the main idea of using a gradient is to convert the image in such a way that its watershed segmentation eventually leads to the production of meaningful and correct edges in the image. Otherwise, the watershed segmentation leads to the production of an image that still contains additional image parts that result from the detection of some additional minimums. For this reason, it is better to use filtering or another algorithm in the step before applying the watershed segmentation to optimize and prepare the image so that the watershed transformation has the desired response in the best case.

According to the image segmentation process by the watershed algorithm, it is determined that the center of the optic disc can be easily found in the image. Although it moves on the line of contact in the precise position of this center, this reduction of possible candidates in finding the exact center of the optic disc helps a lot in advancing the response to find the optic disc area in the retinal image.

Fig.7 shows an example of the output of the watershed algorithm.

2.5. Region Growing Algorithm

Region growing segmentation methods work better than edge-based methods in images that have destructive spots and are difficult to detect. The region growing algorithm examines the neighboring pixels from the initial designated points and determines whether the neighboring pixels can be added to the target area. As a result, finding the correct point or points, which are called seed points, is important in this algorithm [19].



(a)

(b)

Fig. 7. (a) Primary output of watershed transformation, (b) Detection of optic disc center by watershed transformation.

Seed points can be selected manually or automatically based on the points with the highest brightness. The region growing of an area starts from the selected seed points and then the adjacent pixels are compared according to different criteria such as brightness, color or texture or seed point, and if as a seed point. If they are or the difference with the seed point is less than the specified threshold value, they are connected to the seed point [20].

Determining the appropriate connection criteria and the threshold is ofgreat importance in the proper operation of the region growing method. The region growing algorithm also has advantages. For example, its parameters can be set by the user. It is also possible to have several criteria for connecting neighboring points to starting points, but when the image has a non-uniform brightness or the brightness between areas is low, using a single threshold and a connection criterion such as the brightness of the pixels is not enough. [21].

In general, it can be said that after finding the center of the optic disc, the last step of the proposed method is to apply the region growing algorithm and find the area of the optic disc. In this part, the feature of the difference in the brightness of the optic disc with other parts and the geometric shape of a circle such as an optic disc have been used to help the method. For this operation, a circle was grown to the center of the selected point in the center of the optic disc so that the brightness of the area enclosed in the circle was less than a certain threshold level relative

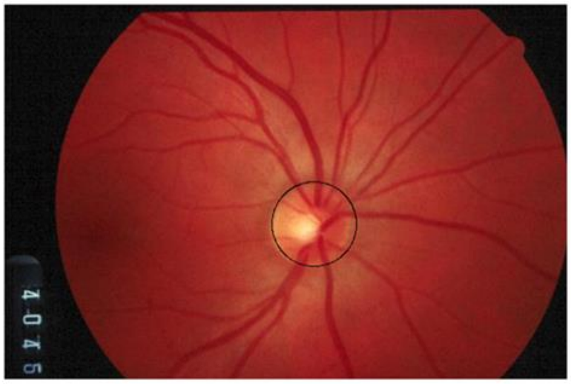


***Fig. 8. Final detection of the optic disc area as a corresponding contour*.**

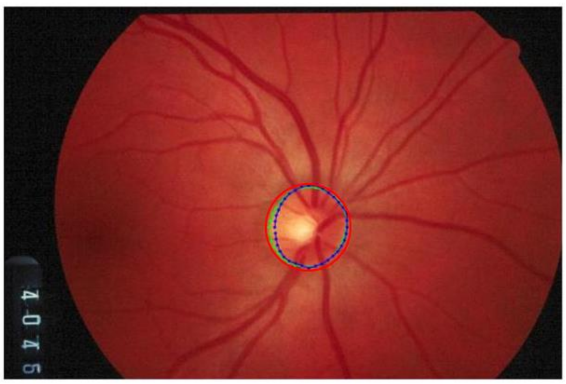


Fig. 9. Optic disc area detection by corresponding contour*. *Blue & Green: reference contours, Red: proposed method's contour.

to the center to reach the desired area of the optic disc with normal diameter. Finally, the extracted area of the optic disc is identified as a corresponding modified contour.

Fig. 8 shows the extracted area of the optic disc as a corresponding contour in the center of one of the database images.

3. RESULTS

Our proposed method was tested on the standard DRIONS database. In this collection, 110 images of the retina with a size of 400 × 600 pixels were taken by two ophthalmologists. Moreover, in this database, reference contours were collected by two ophthalmologists. For this reason, as a reference in each image, we used the contours identified by the ophthalmologists in the evaluation process of the proposed method.

In general, in the proposed method, after receiving the database images, preprocessing operations were performed on the database. At this stage, histogram equalization was used to improve the images. In the next step, the images were transferred to RGB channels. According to the structure of the optic disc area, the best result was obtained in using the grayscale images of the green channel space. Then, after preprocessing the image, a graph-based saliency map model is applied on them, and finally, by determining the center of the optic disc in the watershed algorithm, by obtaining the value of the pixels and their neighborhood by the region growing algorithm, the area of the optic disc is detected with its corresponding contour. The results show that the proposed algorithm has a desirable response in the automatic detection of the optic disc area in retinal fundus images. Fig. 9 shows an example of the exposed area of the optic disc as a corresponding contour with reference contours on the database image.

We used standard success rate and overlap (OLA) criteria to evaluate the proposed method. In the success rate criterion, after determining the optic disc center, we specified the optic disc area and used the corresponding contour to obtain the success rate of the proposed method in all database images, and then we calculated the correct optic disc area detection values in the

Table 2. ***Proposed Method Result (Percentage).***

Area	Standard Success Rate	Overlap Average
Optic Disc	99.1	94.3
Optic Cup	100	100

Table 3. ***Comparison Proposed Method Results with Previous Methods (Percentage).***

Authors	Year	Method	Database	Success Rate
Proposed Method	2019	Saliency Map, Whatershed, Region Growing	DRIONS	99.1
Khalid et. Al.	2014	Morphology Operations, Fuzzy C-Means (FCM)	HRF	93.7
Haleem et. Al	2018	Region Based Edge Smoothing Model (ARESM)	RIM-One	91
Zilly et. Al	2016	Entropy Sampling, Ensemble Learning	RIM-One	94.1
Lu et. Al	2011	Linear Operator, Circular Contour	STARE 81	96.3
Kulkarani et. Al	2014	Saliency Map, Morphology, Otsu's Method	STARE 81	72.8
Dehghani et. Al	2012	Histogram Matching	STARE 81	91
Mithun et. Al	2014	Morphology Operations, Edge Detection	STARE 81	91.3

database images. In the next criterion for obtaining the area of overlap, we compared the subsidence and community of the identified area with the specified area of reference. Table 2 shows these results quantitatively.

4. DISCUSSION

The eye is one of the most important organs of human communication with the environment and plays an important role in perceiving and maintaining the safety of people in different environments. For this reason, one of the most essential parts of medicine is the study of a person's visual characteristics. Due to the recent progress of artificial intelligence and automated methods of medical image processing, in this paper, a new method for detecting the optic disc area of the eye was presented to help the diagnosis of eye diseases such as glaucoma using the saliency map model.

Given that this method uses region information to detect the optic disc, even if there are false edges in the image, the proposed method can provide the desired result and this can improve another algorithm, which is used in detecting the optic disc area in these conditions. In addition, since blood vessels exit the optic disc area, the proposed method can integrate vascular information into area information and use them in the area detection process.

According to the explanations given in the previous sections, our proposed method can use the studied algorithms, along with optimizing their implementation process, to a very desirable response in the detection of optic disc area in the DRIONS database.

The values obtained from the standard success rate criterion for the optic disc and optic cup area are 99.1% and 100%, respectively, and the average value of the overlap area in the optic disc is 94.3%.

Table 3 summarizes the results of previous research compared to the results of the proposed method.

Considering the comparison of the proposed method with others, while emphasizing the very favorable response of the proposed algorithm in the detection of optic disc area with 99.1% success rate, this method can be a great help to the treatment set for diagnosis, prediction and control of glaucoma diseases.

5. CONCLUSION

In this paper, a new method based on the saliency map model to detect the optic disc area in retinal images is presented to help the diagnosis of glaucoma.

In the proposed method, after preprocessing, a graph-based saliency map model with utilizing watershed and region growing algorithms was used to detect the optic disc area in the DRIONS database images.

The results show that the proposed method has a very desirable performance in detecting the optic disc area in retinal fundus images.

Finally, the use of more efficient methods for detecting the edge and boundary of the optic disc area in retinal fundus images can be suggested as future research.

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