Journal of Engineering Research and Applied Science
Available at www.journaleras.com
Volume 6 (1), June 2017, pp 543-555
ISSN 2147-3471 © 2017

A fast approach to human retina optic disc segmentation using fuzzy c-means level set evolution

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Accepted 15 May 2017

Abstract
The process of localization and segmentation of the optic disc (OD) plays a crucial role in automatic screening for eye disease. This paper presents a novel and simple iterative method for rapid, fully automatic localization and segmentation of the OD in retinal fundus images. Furthermore, this new method can find the boundary of the OD using the initial fuzzy clustering means algorithm. The proposed method employs a new level set evolution based on the fuzzy clustering algorithm. The proposed technique was compared, in terms of performance, with various methods in the literature, and the results were found to be conclusive and effective. The obtained results suggest that this OD segmentation technique is accurate in addition to being computationally inexpensive.

Keywords: Automatic screening for eye disease; fuzzy clustering; level set method; optic disc; localization; segmentation

1. Introduction

In addition to technological development, significant progress and a number of advances have been recorded in the computer techniques used in medical applications. Automatic image processing and analysis are extensively used in the area of medical diagnosis and treatment. Recent developments in the field of medical image processing in particular enable the automatic detection of various characteristics, changes, diseases and degenerative problems via retinal images. Retinal image analyses uses image processing techniques and is aimed at determining and monitoring diseases that can be detected via changes in the structure of the retina. Most retinal images have a high degree of resolution and when used in the clinical area offer features that can diagnose and treat many diseases [1]. The development of an automatic system could provide great convenience for doctors and practitioners in the field. The image processing methodology proposed in this study can contribute to more effective analysis and more accurate diagnosis, regardless of the individual levels of experience of the users or particular situations and conditions such as fatigue or image quality. Obtaining retinal images is extremely important in the diagnosis of retinal disorders that progress to blindness if not detected early. Blood vessels in this area and their functions are central factors in the diagnosis of retinal and macular diseases. A digital fundus angiography device is used for the display of retinal images. The pupil is first dilated for angiography, and then the images formed by the administered drug while passing through the blood vessels in the retina are recorded by the digital imaging device [2].

Optic disc (OD) localization is one of the many advantages of retinal image analyses. In most methods, the first step in the automatic detection of diseases passes from OD localization to the complex structure of the retinal image [3]. The automatic detection of retinal diseases has many benefits, such as early diagnosis, elimination of lost workforce time and prevention of detection discrepancies due to the individual experience of the practitioner. Thus, there is a need for automatic analysis of digital retinal images for purposes of detection and monitoring of the associated diseases [4] as well as for the development of a system to produce rapid, accurate results.

The determination of the OD and the measurement of retinal parameters are also extremely important for the automatic detection of retinal diseases. OD localization is capable of:

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- removing the vascular network, as it is a starting point for the vessel network
- determining the macula, due to the fixed distance to the macula
- simplifying detection of degeneration by eliminating the OD and its activation.

Moreover, the proposed method in this study offers advantages such as:

- providing a supporting tool for practitioners that will lighten their workloads
- preventing lost workforce time
- obtaining detailed statistical information from the images acquired
- positioning of the retinal images taken at different times, enabling segmentation and the opportunity for early detection and diagnosis by utilizing this information.

The focus of this study was the localization and segmentation of the OD, and is intended as a major first step for further studies aimed at the diagnosis and detection of many common retinal diseases.

2. Related work

Many studies have been conducted on the automatic localization and segmentation of the OD, which are of great importance for the diagnosis and treatment of retinal diseases at the primary stage. Their findings enable easy performance of procedures which would require quite a large number of trained and experienced practitioners if they were performed manually. Thus, due to the convenience of digital image processing techniques, the ability to analyze automatically based on objective criteria and evaluation is provided in the production of retinal images, their storage, and further improvement. Furthermore, the errors that doctors may make in segmentation due to the surrounding conditions or their own levels of experience and expertise are avoided with the use of these systems. Moreover, the reflection of such factors as fatigue on evaluation is prevented, and as a result, resources are saved to a large extent [5 - 7].

The methods used for OD localization and segmentation vary from morphological methods, in which brightness and geometric features are used, to statistical methods such as Bayesian-based methods, and on the other hand, to standard methods such as Hough transform and template matching. While some of the studies conducted on this subject take the vascular structure on the OD into account [8, 9], some methods monitor the boundary of the OD region [10, 11]. The method of template matching is used in some studies [12] and others use the method of active contour, or snake [13, 14]. Although a number of these studies have been conducted on OD detection [15, 16], applications have been performed on both the localization and segmentation of the OD in others [17, 18]. It has been reported that both the center and the edges of the OD were successfully detected without affecting the vessel structure using the method recommended in the study in which this classification was performed. Some examples from the literature in which determination of the OD and its segmentation are performed are given below. In the study conducted by Fleming et al. [19], the center of the OD was determined using a half ellipse and the success rate in the OD localization was reported as 98.4%.

In contrast, in the study conducted by Lupascu et al. [16], the geometric location and boundary determination for the OD were performed. The success rates for determining the OD and its boundary were reported as 95% and 70%, respectively, in this study. Their attempts to find the most suitable boundary of the OD employed tissue identification and regression-based methods.

Tobin et al. [20] recommended a method based on regional filtering and Bayesian-based classification for identifying features in the retinal veins. In the tests conducted using this method, in which the center of the OD was detected according to the highest value in the reliability image map, the success rate was 90%. It is obvious that the success of this method was connected to correctly determining the vein structure.

Muramatsu et al. used the active contour model, the fuzzy c-means clustering model and the model of artificial neural networks (ANNs) for OD segmentation and then compared them. The results made possible the automatic calculation of the cup/disc ratio used in the diagnosis of glaucoma [21].

In their study, Lowell et al. [22] recommended a technique for OD localization and segmentation in images with low resolution (approximately 20 μ/pixel). The OD localization was performed using a specialized template matching method. Segmentation was carried out via a deformable contour model using global elliptical and local variable models.

A deformable model-based methodology was proposed by Xu et al. [14] utilizing retinal images for the detection of the OD and cup boundaries. The original snake model was developed and extended from the standpoint of knowledge-based clustering and from that of smoothing update. With the deformation of the snake, the energy is minimized, and then the snake self-clusters and divides into the edgepoint and uncertain-point groups. Local information and global information are combined to determine these two groups. The aforementioned improvements enable the contour flexibility needed to become more active and accurate in blocking out noise, blood vessels, poorly defined edges and fuzzy outlines. Results of the experiments conducted on 100 images showed a 94% success rate for the technique, in comparison with those obtained via GVF-snakes (12%) and modified ASM (82%).

A novel fast and robust OD localization and segmentation technique for retinal image screening was developed by Yu et al. [18], in which the template size was changed by OD localization methodology in an adaptive way which hinged on the OD radius estimation via image resolution and camera FOV. Initially, identification of the candidates for OD location was performed by means of template matching. The template was created with the capability of adapting to various image resolutions. Subsequently, the location of the OD was determined by examining the vessel features or patterns on the OD. A rapid hybrid model which combined gradient information, both regional and local, was then employed to achieve the disc boundary segmentation. This levelset model was initialized through the detection of the OD center and the estimation of the OD radius. Both the appearance characteristics of the OD and the orientation of the major vessels inside the OD were exploited by the methodology in order to improve its robustness. In order to exclude distractors, e.g., vessels and interference from the bright region, while maintaining the contour of the papillary region, the OD segmentation method employs ASF and morphological reconstruction.

In this study, the retinal image analysis was carried out using the method developed by Kim et al. [23]. The brightest point was selected as the center of the OD, and an imaginary circle was drawn around this point. This circle was then converted into a rectangle. Afterwards, the model was again converted into an inverse circle. In the study, 91% sensitivity and 78% positive prediction was achieved upon examination of 30 images showing disease and 40 normal images.

In Section 3, the important qualities associated with the retinal image are described. Section 4 explains retinal image preprocessing and retinal image OD localization and segmentation. Finally, Section 5 concludes the paper.

3. Important features of the retinal image

The retina is a network layer covering the back wall of the eyeball like wallpaper and consisting of optic cells. The retina layer includes light-sensitive cells, that allow us to see, and nerve fibers. The nerve layer in the retina takes the light from the eye lens and converts it into nerve impulses. These impulses are transmitted via the optic nerve to the brain, where they are converted into the images we perceive.

Diseases that occur in the retina directly threaten our eyesight. Moreover, specialists claim that most diseases can be diagnosed from the retina.

The interior surface of the eye, represented by its retinal image, incorporates the blood vessels, the macula, the optic disc (OD) and the optic cup. The colored illustration of a retinal image showing several important characteristics such as the OD, macula, fovea and retinal blood vessels can be seen in Figure 1.

The OD or optic nerve head has a very important place in the detection of retinal diseases and is the point of exit for the optic nerve endings leaving the eye. The OD, in which over one million nerve fibers are collected, is the place where optic nerves are connected to the retina, and, as seen in Figure 1, is observed as an area forming a bright disc at the point where the veins are united.

All vessels that nourish the retina enter from this point and exit from this point. The vessels approaching this point gain a certain thickness. In order to examine the OD effectively and successfully, the retinal image must first be examined, and its physical properties such as brightness, width, etc., will form the basis for the careful analyzation of the program.

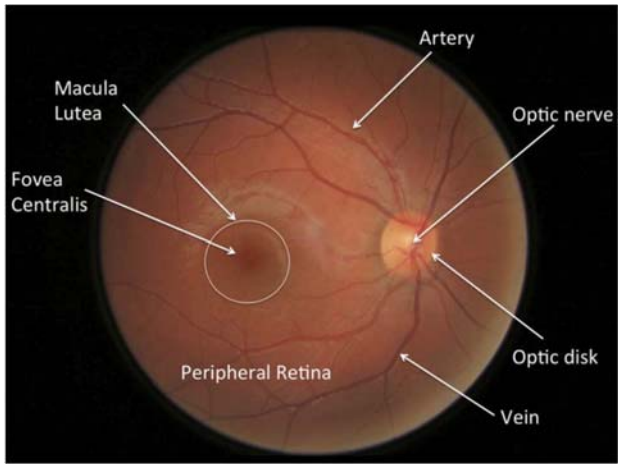

Figure 1. Retinal image: Important features.

4. Proposed methods

The objective of this study was focused on the automatic localization and segmentation of the OD, both of which are of great importance in the early detection and diagnosis of the retinal diseases which threaten a significant part of the world population. A dependable and efficient OD detection and segmentation process plays a crucial role in automatic screening for eye disease. This paper presents a simple, quick and powerful automated technique for OD localization and segmentation. The method proposed here includes three main stages:

- The location of the OD is found conjecturally according to different image resolutions.
- The fuzzy clustering algorithm is applied to the OD location.
- The boundary of the OD is determined with the level set algorithm.

At the second stage, the OD segmentation is performed with the clusters formed by the modified fuzzy c-mean algorithm. After this stage, the level set contour model is applied to the image obtained. The level set algorithm used at this stage is the edge-based level set algorithm. After applying these processes, the OD boundary is found.

The iteration numbers, working periods and segmentation quality will be examined according to the method used in the study.

4.1. Optic disc localization

The first step required in OD localization makes the subsequent OD segmentation a much simpler operation. As seen in Figure 2, the location of the OD does not remain the same all the time within the retinal images. Thus, the OD can be anywhere within a retinal image due to the fact that the OD does not have a fixed position in the retina. Therefore, before the boundary is definitely identified, the approximation of the OD location is extremely important.

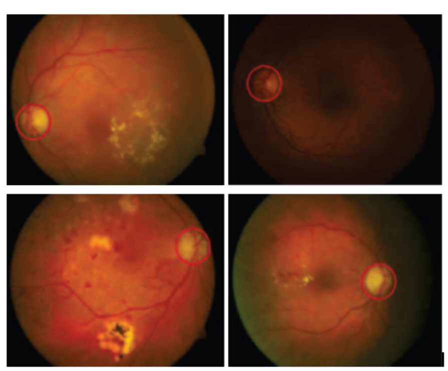
Figure 2. Location of optic disc in retinal images

The OD appearance may vary considerably as a result of retinal pathologies. Accordingly, the automatic localization of the OD is not a direct process. Therefore, when attempting to locate the OD, the difference in appearance, size, and position in diverse images must be taken into account.

The first step of the proposed algorithm is to eliminate the blood vessels in the red channel band by means of a combination of morphological operations as well as by using anisotropic diffusion. The red channel includes the largest information content required for the identification of the center of the OD and significantly exceeds the obtained threshold. Thus, having clearly defined borders, the red channel is considered as the blood intensity region and is removed from the color retinal image.

The proposed OD segmentation algorithm is conducted in the red channel. The saturation of the red channel around the OD occurs in some images, and thus is responsible for a significant reduction in the efficient functioning of the algorithm. In order to eliminate this, first, the detection of the saturation level in the red channel is carried out based on the red channel ROI data. The area of the ROI exceeds the OD area by about 10 times. When the saturation of the red channel is observed, a great many bright pixels will be present in the ROI. This leads to the rule for detecting saturation of the red channel: The red channel is considered to be saturated when half (50th percentile) of the ROI pixels are brighter than 80% of the maximum ROI intensity value.

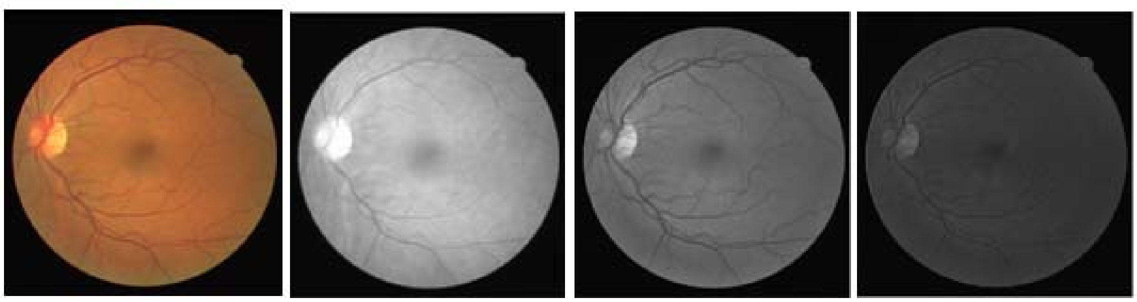

Figure 3. a) Original retinal image, b) the red channel, c) the green channel, d) the blue channel.

As seen in Figure 3(b), the red channel shows the OD more clearly and distinctly. Therefore, the red channel was chosen for the determination of the OD.

The segmentation of the OD contour may be complicated by the blood vessels obscuring the OD region. Therefore, a morphological approach is proposed in which the vascular tree convergence is used as a reference for the location of the OD in the fundus images.

The application of this structuring element on the red color band of the fundus image is performed as a closing operation, which includes the morphological processes of dilation and erosion. The median filter is then applied to the red channel to eliminate unwanted data such as small capillaries and hemorrhages, thus improving the image. At this stage in particular, the use of the median filter is necessary, as it maintains the edges while eliminating noise from the image without negatively affecting the shape of the OD boundary. Furthermore, the median filter can perform the filtering operation without blurring sharp edges in the retina endings. The median filter essentially changes the f pixel (x, y) value with the average of all pixels around it, as seen Equation 1.

$$f_{med}(x,y) = median\{f(s,t)\}, \quad (s,t) \in W_{xy} \tag{1}$$

where: W represents neighbor center locations (x,y) in the image. Figure 4 shows the light intensity of the retinal image before and after the application of the median filter

In this study, after applying the median filter, Otsu's method was used for binarization. Otsu's method enables the gray-level image threshold to be decided automatically by recognizing the background and the foreground areas as the two sets. The method then seeks out a global threshold. The intra-class variance is minimized by this global threshold. The weighted sum of variances of the two classes (the intra-class variance) is presented in Equation (2):

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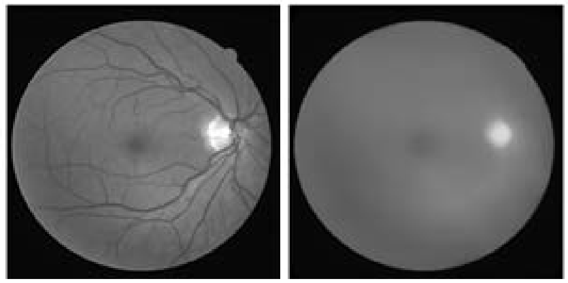


(a) (b)

Figure 4. a) Original retinal image (gray level image), b) Final image after the filter application.

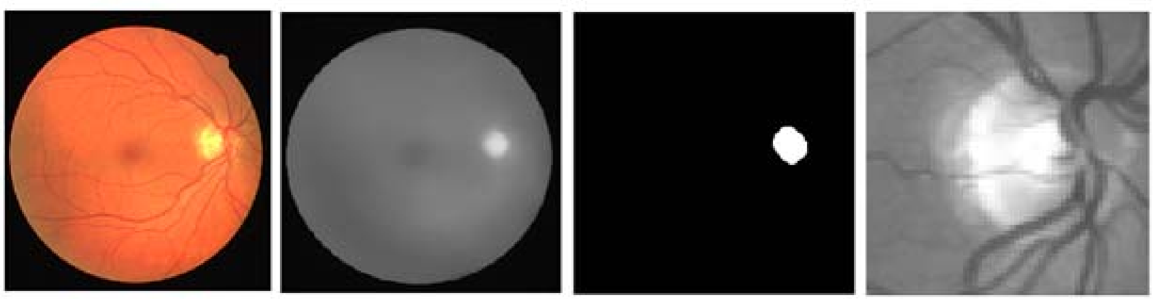
$$\sigma_{\omega}^{2}(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t) \tag{2}$$

where: ω_i represent the probabilities of the two classes, t is the threshold which separates them, and σ_i^2 represents class variances. An empirical formula that combines the threshold value decided by Otsu's method and the standard deviation-based threshold demonstrates an optimal threshold value (Eqs. 3-4).

$$T = T_{OTSU} + \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(I_m(i) - \mu I_m\right)^2 * 10} \tag{3}$$

$$T = \begin{cases} 135 & if\ T \geq 135 \\ T & otherwise \end{cases} \tag{4}$$

Following this operation, the prediction of the OD location is found. This procedure is shown in Figure 5.



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

Figure 5. a) Original retinal image, b) after applying the filter, c) the result of the Otsu's method, d) the estimated location of the optic disc.

4.2. Optic disc segmentation

Following the localization of the OD region, the segmentation scheme should accurately demarcate the boundary of the OD in order to trace the progression of eye diseases. A novel OD segmentation method based on the fuzzy clustering algorithm has been proposed. In order to increase the success of segmentation and shorten the processing time, the fuzzy c-means algorithm is preferred. In this algorithm:

- Cluster centers are generated randomly.
- A neighborhood matrix is created and neighborhood levels are assigned randomly.
- Until the termination condition is reached:
    - The objective function is calculated.
    - Cluster centers are recalculated.
    - A member function is created.

The median filter is applied on the OD location on the image, the image is converted into a one-dimensional array, and then the fuzzy c-means algorithm is applied to this array. Thus, the member function is obtained. The number of clusters is determined by the user, and in this study, the number of clusters was determined as 8 (Fig. 6). After the member function is obtained, the standard deviation is calculated. The standard deviation is indicated as the cluster that shows the biggest OD most clearly.

With the fuzzy c-means algorithm which was used in this study, the cluster programs that best represented the boundaries of the OD varied each time it was run. When the program was run for the first time, No: 3 index showed the boundaries of the OD the most clearly (Fig. 6), while for the second time, No: 5 index showed most prominently the boundaries of the OD (Fig. 7). The standard deviation was calculated after the member function was obtained in order to find the cluster which represented the best the boundaries of the OD.

4.3. Proposed level set model

The idea of the level set model emerged for the first time with Osher and Sethian, who used the Hamilton–Jacobi approach for the numerical solution of the time-dependent moving objects' functions [24]. There are many studies in the field of image segmentation which report achieving successful results by using the level set algorithm [25-28].

According to the basic idea, the zero level set for the higher dimensional function φ (t, x, y) is curve C:

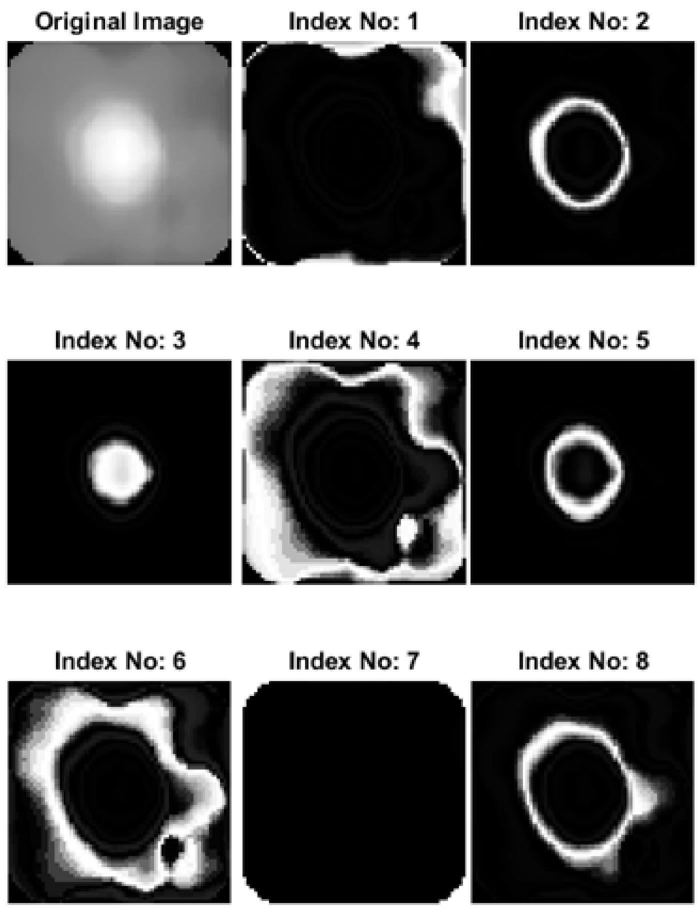


Figure 6. The results obtained for 8 sets..

$$C\{t\}=\{(x ,y) \mid \varphi \{t, x, y\}=O\} \quad (5)$$

The general form of the evolution equation for calculating the level set function φ is given in Equation 6:

$$\frac{\partial \varphi}{\partial t}+F|\nabla\varphi|=0 \quad (6)$$

Function F (the speed function) depends on the image and φ and controls the development of curve C. Re-initialization is recommended for the prevention of sharp discontinuities during the process. The standard re-initialization method is expressed in Equation 7:

$$\frac{\partial \varphi}{\partial t} = sign(\varphi_0)(1 - |\nabla \varphi|) \quad (7)$$

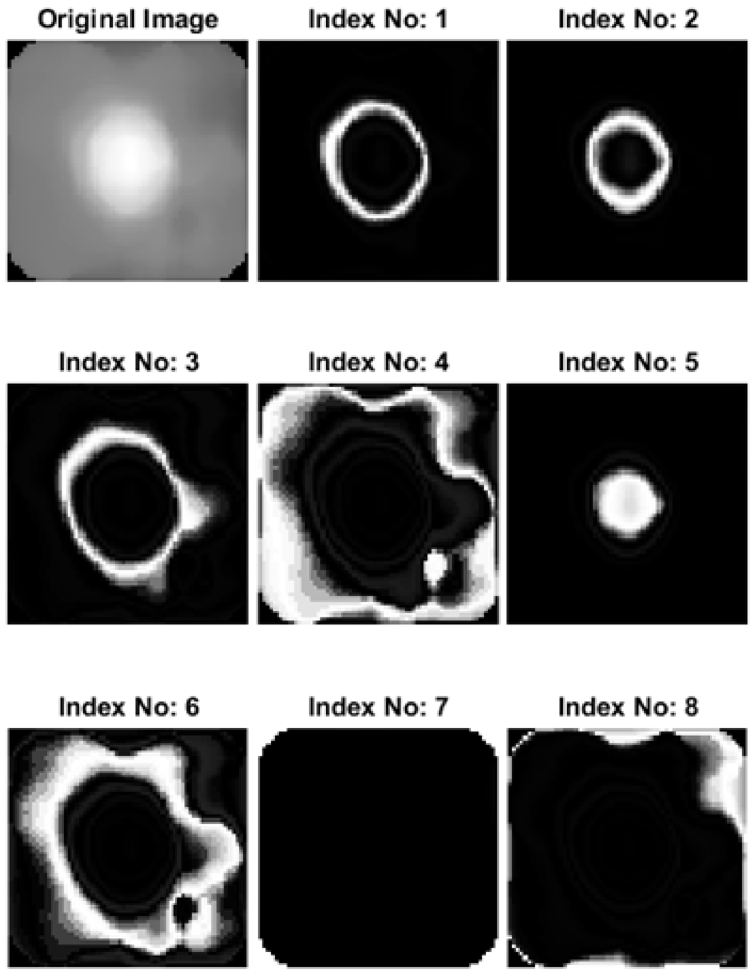


Figure 7. 8 sets obtained after running for a second time.

where: φ_0 represents the function that will be re-initialized and the sign (φ_0) is the sign function. The level set function is assumed as a signed distance function of the re-evolution by the re-initialization scheme. The energy function is expressed in Equation 8, and the level set regularization term in Equation 9:

$$E = mP(\varphi) + E_{ext} = m\int_{\Omega} p|\nabla\varphi|dxdy + E_{ext} \quad (8)$$

$$P(\varphi) = \int_{\Omega}^{\frac{1}{2}} |\nabla\varphi - 1|^2\, dxdy \quad (9)$$

The level set regularization term is important for the formulation of variations. It determines the distance between the level set function and a signed distance function, thus making φ satisfy ∇φ =1. An edge indicator function must be calculated in order to determine the external energy capable of moving the zero level curve to the boundary of the object. Equation 10 is used to determine the edge indicator function:

$$g = \frac{1}{1 + |\nabla G_\sigma * I|^2} \quad (10)$$

where: G_σ represents the Gaussian kernel with standard deviation σ, and I represents an image. Therefore, the energy term is expressed as follows:

$$E = mP(\varphi) + \lambda L_g(\varphi) + \alpha A_g(\varphi) \quad (11)$$

$$L_g(\varphi) = \int_\Omega g\delta(\vec{\varphi})|\nabla_\varphi| dxdy \tag{12}$$

$$A_g(\varphi) = \int_\Omega gH(-\varphi)dxdy \tag{13}$$

when: λ >O and α is constant and, according to the relative position of the original contour to the object of interest, can be positive or negative. Here, the length of the zero level set curve is calculated by L_g, and the weighted part of the region, calculated by A_g, is inside the zero level set.

The following gradient flow represents the sharpest downward progression for minimizing the functional E:

$$\frac{d\varphi}{dt} = mdiv(d_p(|\nabla_\varphi|)\nabla_\varphi) + \lambda\delta(\varphi)div(g\frac{\nabla\varphi}{|\nabla_\varphi|}) + \alpha g\delta(\varphi)$$
(14)

which is the equation for the evolution of the level set function in the rapid level set technique proposed in this article. After the accomplishment of these operations, the OD boundaries were respectively defined in this study.

The level set function gives the opportunity to make iterations with high time steps. This means that fewer iterations are needed to reach the edge of zero level. However, the reduction in the number of iterations remains slow for the segmentation process requiring high speed. In order to increase the segmentation speed, the aim was to decrease the number of iterations and therefore, to increase the speed by using the optimal cluster created via the fuzzy clustering algorithm instead of scanning the whole picture.

The proposed level set model defines an inner strength by using the curvature in order to correct the contour evolving during the deformation. Due to the effect of the large blood vessels, the final curve can still be seen as uneven. In order to ensure a proper contour, the segmentation of the OD boundary is formed into an ellipse by using the least squares optimization.

Figure 8. The result of the level set algorithm which was applied to the image

The red curve shown in Figure 9 is the preliminary curve of the level set, while the green curve is the finished curve. This result was obtained after 50 iterations. The segmentation of the OD was carried out in 3.054371 seconds with the level set algorithm applied to the retina images.

4.4. Summary of the proposed method

In Figure 9, a flowchart of the proposed method illustrates the order of the steps for obtaining the OD.

The algorithms used in the study were applied to 20 images randomly selected from the Messidor database. The applications used here were tested in the MATLAB 2015R version. The computer used for developing the applications was equipped with an Intel Core i5 processor, a 5GB Ram, a 64 bit Windows 8 operating system and a NVIDIA GeForce GT 520M graphic card.

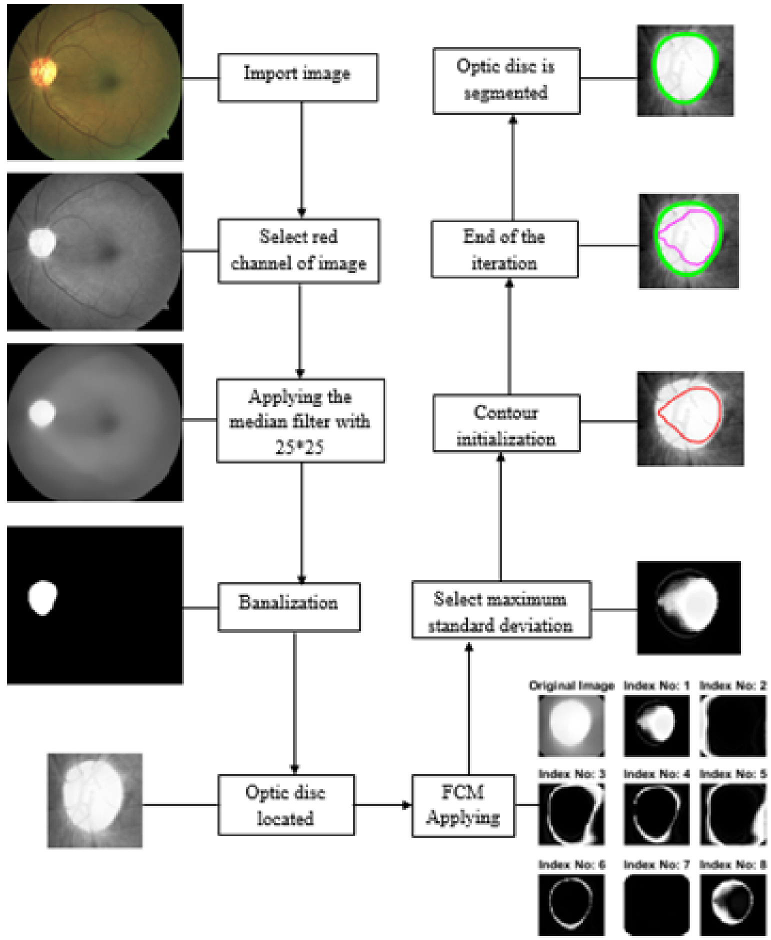


Figure 9 .Summarized steps to segment the optic disc.

4.5. Assessment of algorithm parameters

Algorithm parameters such as the true positive, the false positive, the true negative, the false negative and the accuracy rates were derived to measure the performance of the segmentation. The comparison between performances of the proposed method and alternative OD segmentation approaches were enabled by the application of these parameters.

The sensitivity (SN), or true negative rate (TPR), defines the success rate of the segmentation algorithm in detecting image pixels as true OD pixels.

$$Sensitivity(SN) = \frac{TruePositives(TP)}{TruePositives(TP) + FalseNegatives(FN)} \quad (15)$$

The segmentation algorithm image pixels which are not OD pixels are rejected by the segmentation algorithm. The specificity (SP), or TNR, defines how well this is done.

$$Specificity(SP) = \frac{TrueNegatives(TN)}{TrueNegatives(TN) + FalsePositives(FP)} \quad (16)$$

The sum of pixels indicated as the OD in both the result and the ground truth images is the true positive (TP), while the sum of pixels shown as OD in the result image, but not in the ground truth image, is the false positive (FP). The sum of pixels indicated as background in the result image, but not in ground truth image, is the false negative (FN), whereas the sum of pixels denoted as background in both the result the ground truth images is the true negative (TN).

The sum of true positives and true negatives is divided by the total number of pixel in the images to give the accuracy rate (ACC).

$$Acc = \frac{TP + TN}{TP + FN + TN + FP} \quad (17)$$

Table 1 shows the algorithm evaluation parameters of the proposed method with regard to the true positive, true negative, false positive, false negative and accuracy.

Table 1.Performance results on MESSIDOR database images.

Image	TP	TN	FP	FN	Accuracy
1	0.9821	0.9897	0.0103	0.0179	0.9859
2	0.9397	0.9626	0.0374	0.0603	0.9511
3	0.9325	0.9690	0.0310	0.0675	0.9508
4	0.9604	0.9838	0.0162	0.0396	0.9721
5	0.9424	0.9717	0.0283	0.0576	0.9570
6	0.9228	0.9710	0.0290	0.0772	0.9469
7	0.9677	0.9816	0.0184	0.0323	0.9747
8	0.9636	0.9961	0.0039	0.0364	0.9799
9	0.8098	0.9141	0.0859	0.1902	0.8620
10	0.9980	0.9824	0.0176	0.0020	0.9902
11	0.9096	0.9880	0.0120	0.0904	0.9488
12	0.9901	0.9536	0.0464	0.001	0.9768
13	0.9621	0.9824	0.0176	0.0379	0.9723
14	0.9292	0.9816	0.0184	0.0708	0.9554
15	0.9629	0.9952	0.0048	0.0371	0.9790
16	0.9619	0.9914	0.0086	0.0381	0.9767
17	0.9502	0.9919	0.0081	0.0498	0.9711
18	0.9507	0.9736	0.0264	0.0493	0.9621
19	0.9655	0.9758	0.0242	0.0345	0.9706
20	0.9556	0.9758	0.0242	0.0444	0.9657
Average	**0.9478**	**0.9766**	**0.0234**	**0.0517**	**0.9625**

5. Conclusion

Retinal images are very important for the detection and diagnosis of retinal diseases which may lead to blindness without early detection and diagnosis. The detection of the OD via retinal image analysis has many advantages. In many methods the first step in detecting the diseases automatically in the retinal image is through the localization of the OD, which has a complex structure on the retinal image.

This study aimed to determine and segment the OD, which is the basic first step in the diagnosis of many common diseases. With the proposed system, mistakes made during segmentation due to the varied background and experience of the practitioners can be avoided. Furthermore, the influence of factors such as fatigue can be prevented from affecting the assessment. The method, as a result, can provide great savings in terms of resources.

The retinal fundus images used in this study were obtained from the database and from 20 randomly selected images from MESIDOR [29], where they are publicly available on the Internet. On the images in which the resolution differed from the MESSIDOR database, the OD location was found through estimation. In addition, OD segmentation was made with the clusters created by the modified fuzzy c-mean algorithm. After this step, the level set contour model was applied to the images. The algorithm used in this step was an edge-based level set algorithm. After applying these processes, the OD boundaries were determined.

The detection and segmentation of the OD are of great importance to on-going research in the field and for disease detection based on these analyses. Therefore, the methods developed for the detection of the OD should be constantly improved and made more effective. Successful methods should be developed for use in undesirable situations such as degeneration encountered on the retinal images and lower image quality. In order to obtain results more rapidly, the CPU and GPU speed performance of the algorithms used in the segmentation of the OD should be compared by testing in a GPU environment. In future studies, the CUDA technology implemented on GPU and research conducted on this issue should be examined in detail.

Acknowledgement

The authors are grateful to the publishers of the public MESSIDOR database for sharing their images.

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