Journal of Computers Vol. 29 No. 5, 2018, pp. 66-79
doi:10.3966/199115992018102905006

Optic Disk Detection and Segmentation for Retinal Images Using Saliency Model Based on Clustering

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Received 6 June 2017; Revised 9 October 2017; Accepted 1 December 2017

Abstract. Optic disk (OD) is considered one of the main features of a retinal image. OD detection plays an important role in retinopathy analysis. In this study, a new OD detection method using saliency model based on clustering is presented to simulate the human filtering mechanism of visual system for OD detection of fundus images. First, the candidates of OD regions are extracted from fundus images using k-means clustering. Second, two saliencies of sub-regions are computed, and the maximum saliency region from the image is selected as the OD region. Third, the original OD contour can be extracted by ellipse fitting after detecting the convex hull of the OD. Finally, the OD contour can be accurately segmented by active contour. A test is performed with 1422 colored fundus images from four different colored fundus image databases. Experimental results indicate that the detection accuracy for OD is up to 94%, and the segmentation accuracy is up to 88% for Drishti-GS database. The proposed method effectively overcomes the influence of large bright lesions on OD detection and is applicable to incomplete ODs. The method also does not rely on vessel segmentation, which results in short computation time. This study also confirms the effectiveness and robustness of the proposed algorithm.

Keywords: active contour, convex hull detection, ellipse fitting, k-means cluster, optic disk detection, saliency model

1 Introduction

Retinal fundus images are widely used in diagnosing various retinal diseases, and this diagnosis is a key technique for the early screening of diabetic retinopathy and glaucoma. Optic disk (OD) is the main physiological structure of a fundus image and is the bright, approximately circular area in yellow or white color [1]. Automatic OD detection is the prerequisite and main step in the analysis of retinal fundus images and computer-aided diagnosis of retinal diseases. The roles of OD in fundus images can be divided into the following five aspects: (1) OD is the convergence of retinal vessels, where it can be used as the starting seed of vessel tracking. (2) Insufficient luminance equalization on the region near the OD affects the detection of lesions, such as hemangioma and hemorrhage. Thus, OD should be removed before these lesions are recognized. (3) Cup-to-disk ratio is an important index in assessing glaucoma. (4) The distance between OD and macula is fixed, and this distance can be used for quantifying lesion index (e.g., arteriovenous or vein diameter) in fundus images. (5) The measuring region of interest (ROI) can be obtained from the center of the OD and optic diameter [1-2].

Various OD detection algorithms have been proposed by domestic and foreign researchers, and these algorithms can be divided into three categories [3]. The first category consists of methods for retinal vascular structure. These methods are accomplished through convergence localization of retinal vessels [4]. The second category comprises methods for OD characteristics. These methods detect OD by analyzing its characteristics. The third category is a combination of the two previous methods.

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OD segmentation algorithms are also grouped into three categories, namely, template-, morphology-, and deformable model-based techniques.

The accuracy of OD detection is high in normal fundus images with high quality depending on the appearance of features. OD detection error occurs when the shape of OD changes or with the interference of other lesions in pathological images. OD has a relatively high detection accuracy based on retinal vessels. However, the retinal vessel network should be extracted accurately in advance. OD detection algorithm based on retinal vessel is complicated and time-consuming. Retinal vessel is extremely difficult to extract in pathological image with poor quality. The algorithm combining various characteristics of OD frequently adopts supervised learning. This algorithm can improve the robustness of OD detection but also increase the complexity of OD detection. The algorithm is not suitable for real-time applications. At present, research on OD detection has achieved significant progress but several challenges remain. The discontinuity of OD edge produced by overlapping vessels influences OD segmentation. Numerous main vessels are found in the OD region, which segment the OD region into many small regions. These vessels also affect the complete and accurate segmentation of OD.

A novel algorithm is proposed to locate and segment OD to solve the limitations of the aforementioned algorithms. The main contributions of the proposed algorithm are described as follows.

- OD detection does not depend on vessel extraction, and the accuracy of OD detection will not be affected due to the change of OD appearance.
- The influence of segmentation caused by the discontinuity of OD edge can be solved using convex hull detection.

OD is the salient region in fundus images, which is the bright, approximately circular area in yellow or white color. The saliency characteristic based on clustering can emphasize the saliency in images and remove noises, thereby providing a good basis for saliency detection. The proposed method incorporates the saliency model based on clustering. First, the candidate OD regions are extracted from fundus images using k-means clustering. Second, two saliencies are computed among the sub-regions, and the maximum saliency region is selected as the OD region. OD can be detected without extracting the vessel network in advance. Finally, the OD contour can be segmented accurately based on ellipse fitting and active contour after convex hull detection. The influence of segmentation caused by the discontinuity of OD edge can be solved. The algorithm does not extract the retinal vessel, which is difficult and requires considerable calculation. The proposed algorithm is completely automated. Thus, the process is accelerated, which is suitable for real-time processing. Fig. 1 shows the flowchart of the proposed algorithm.

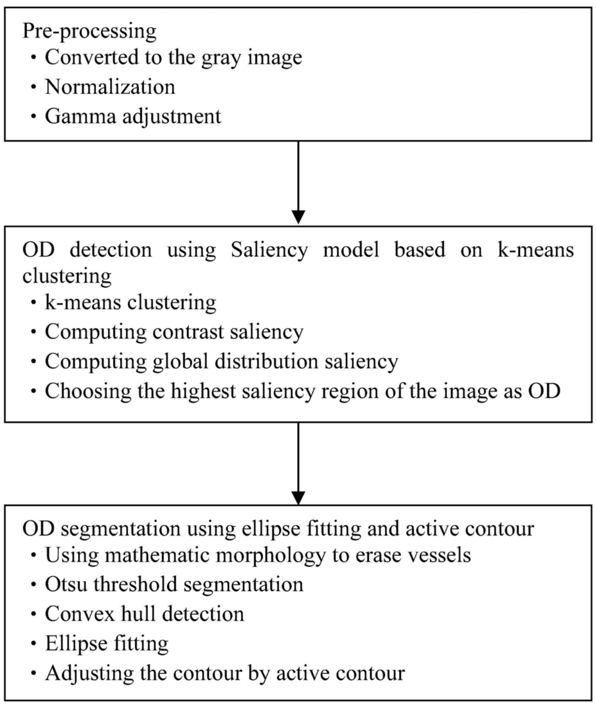


Fig. 1. Flow chart of the proposed technique

The remainder of this paper is organized as follows. Section 2 describes the related works. Section 3 introduces the proposed algorithm, including preprocessing, OD detection using saliency model based on clustering, and OD segmentation using ellipse fitting and active contour. Section 4 discusses the experimental results. Section 5 presents the conclusion and future works.

2 Related Works

2.1 OD Detection

Various OD detection algorithms have been proposed by domestic and foreign researchers, and these algorithms can be divided into three categories [3].

The first category consists of methods for retinal vascular structure. These methods are accomplished through convergence localization of retinal vessels [4]. Ma and Chen [5] proposed a method for rapid OD detection by initially extracting the main vessel in H-channel and confirmed the orientation of the main vessel by using weighted matching filtering to obtain the OD area. Zou et al. [2] proposed a novel method by integrating morphology, ellipse fitting, and gradient vector flow. These methods initially extract the retinal vessel; thus, they are suitable for fundus images with clear vessels.

The second category comprises methods for OD characteristics. These methods detect OD by analyzing its characteristics. Padmanaban and Kannan [6] proposed a novel method based on fuzzy C-means clustering combined with median filtering. Zhao et al. [3] proposed a rapid method for automatic OD detection. In this method, the vertical coordinate of OD is determined according to the distribution structure of the retinal blood vessel network, and the horizontal coordinate is located based on OD brightness information and the relationship between OD and blood vessels. OD region is restricted in a small window with a rough OD center, and the center is confirmed through Hough transform. Zheng et al. [1] adopted directional local contrast to extract the local brightness area and selected the exact OD ROI by considering the local vessel features of the OD region. These methods do not require prior extraction of the vessel, and they rely on the structure of the vessel. Although the detection accuracy of these methods is high, they require considerable calculation.

The third category is a combination of the aforementioned methods. Zhao et al. [23] proposed a novel algorithm. In this method, the candidate OD locations are identified by gradient and intensity information. Then, the OD center are located according to the main vasculature characteristics that converge in the OD region and spread vertically.

The proposed algorithm belongs to the second category. OD is the salient region in fundus images, which is the bright, approximately circular area in yellow or white color. The saliency characteristic based on clustering can emphasize the saliency in images and remove noises, thereby providing a good basis for saliency detection.

2.2 OD Segmentation

OD segmentation algorithms are also divided into three categories, namely, template-, morphology-, and deformable model-based techniques.

Template-based techniques are based on the shape of the OD. Chaichana et al. [27] investigated the areas of OD using Hough transform, which detected several straight lines and approximated them as a circular line. OD center was identified with the center of the circle. Template-based methods rely on the boundaries of OD. Several parts of actual OD boundaries are missed or several parts of wrong information are contained when the boundaries of OD are not exact circles.

Morphology-based techniques are based on the brightness and shape characteristics of OD. Welfer et al. [7] proposed an OD segmentation algorithm based on adaptive morphology algorithm. Saleh et al. [8] adopted region growing to segment OD. Morales et al. [28] extracted OD contour based on mathematical morphology along with Principal Component Analysis. In this method, PCA was adopted to obtain gray images to distinguish different structures of a fundus image. Several operations based on mathematical morphology are used to locate OD. Aquino [26] used morphological and edge detection techniques followed by circular Hough transform to obtain a circular OD boundary. These methods, however, are limited by other lesions and cannot obtain good results in poor images.

Deformable model-based techniques can obtain an accurate boundary of OD. Narasimhan et al. [9]

employed iterable k-means clustering combined with ellipse fitting to segment OD. Cheng et al. [10] presented a novel algorithm based on superpixel and SVM to segment OD. Yu et al. [11] adopted different template matchings to obtain the center of OD and a hybrid level set to segment OD. Zhao et al. [12] proposed a fast, automatic OD segmentation algorithm. The vessels were erased by Gabor filtering and filled by interpolation arithmetic. The OD boundary could be obtained based on the method of CV model and level sets. These methods can obtain high accuracy. However, the discontinuity of OD edge produced by overlapping vessels influence OD segmentation. Numerous main vessels are found in the OD region, which segments the OD region into many small regions. These vessels also affect the complete and accurate segmentation of OD. Thus, the convex hull detection is implemented before OD segmentation using ellipse fitting and active contour in the proposed segmentation algorithm.

3 Proposed Method

3.1 Retinal Image Preprocessing

Given the characteristics of OD detection, the normalization and gamma curve are adjusted to extend the dynamic range of images and enlarge the contrast for clustering and saliency detection. First, the gray image is normalized according to Eqs. (1) and (2). Then, the image is adjusted by a gamma curve. The processing is defined by Eqs. (1), (2), and (3).

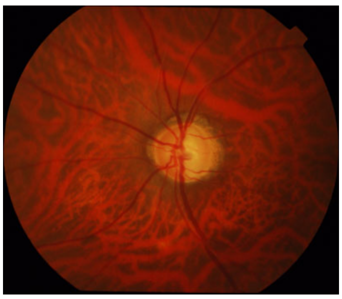
The formulas are expressed as follows:

$$f_{gout} = (f_{gin} - f_{gin\_mean}) / f_{gin\_std} \tag{1}$$

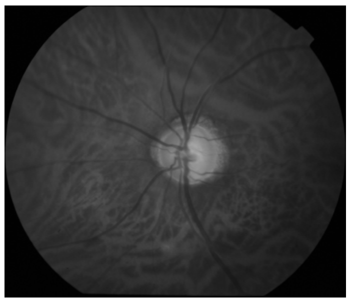
$$f_{normalized} = \frac{f_{gout} - f_{gout\_\min}}{f_{gout\_\max} - f_{gout\_\min}} * 255 \tag{2}$$

$$f_{out} = 255 * \left(\frac{f_{normalized}}{255}\right)^{\frac{1}{\alpha}} \tag{3}$$

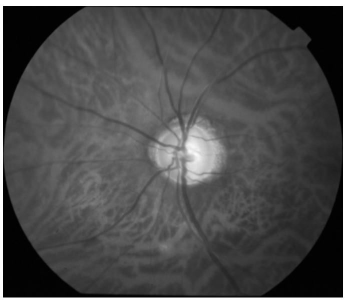
where *fgin* is the gray image, *fgin_mean* is the average of the image, *fgin_std* is the standard deviation of the image, and *fnormalized* is the normalized image. *fout* is the image after adjusting the gamma curve, α=0.25. The processing results are shown in Fig. 2.



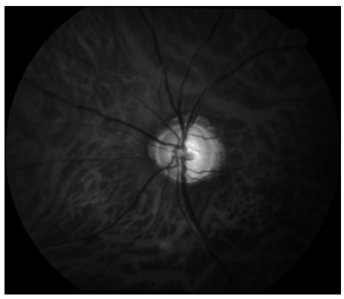
(a) The original image



(b) The gray image



(c) The normalized image



(d) The adjusting image by Gamma curve

Fig. 2. The results of preprocessing

The processing result shows that the vessel along the OD is diluted after adjusting, thereby reducing the influence of vessel on clustering and benefitting the following detection.

3.2 OD Detection Using Saliency Model Based on K-means Clustering

This study adopts k-means clustering in gray space to extract the target for coarse segmentation of fundus images [13-15].

3.2.1 K-means Clustering

In this study, the distance function is used as the mean square Euclidean distance function, and the error square sum criterion is selected as the clustering criterion function [13].

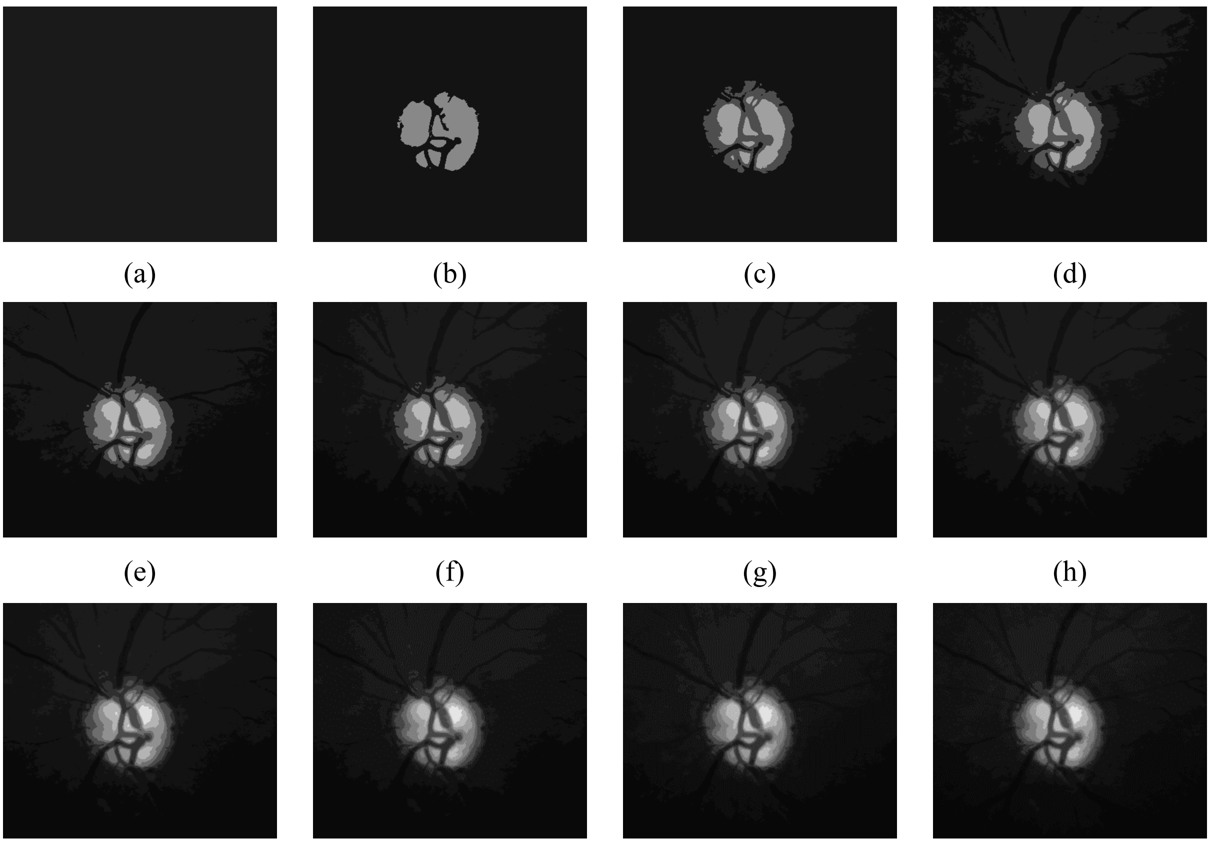
The algorithm is described as follows [14]:

(1) k-Data points from all pixels in a fundus image are selected as initial cluster centers.

(2) Each pixel in the fundus image is divided in the adjacent cluster center to calculate the mean Euclidean distance between each data point and clustering center.

(3) The belongingness of each pixel, which is determined by previous iteration, is not preserved. All data points should be divided again. A new cluster center is obtained, in which its familiarity is redistributed until it remains constant, which implies that the algorithm has reached convergence.

A smaller k indicates faster clustering. However, the results are irregular. A larger k indicates slower clustering is but with good results. The clustering results by different k from 1 to 12 are shown in Fig. 3. The number of gray level in the clustering image is the same as the number of clustering. The gray value of each region should be multiplied by 30 to distinguish the difference among the clustering regions. Subsequently, the gray difference among the regions is expanded. The final results from the map indicate that the pixels with collectively similar gray group achieve the effect of clustering. Compared with the results in Fig. 3, a good clustering effect is produced when k is more than 9. To compute the eigenvalues of the sub-region in the clustering image, k=10 is confirmed to produce a good effect.



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

(e) (f) (g) (h)

(i) (j) (k) (l)

Fig. 3. The results by k-means clustering (k=1,2...12)

The sub-area information is obtained after separating the image using the region information based on the clustering results. There are 10 sub-regions in Fig. 4.

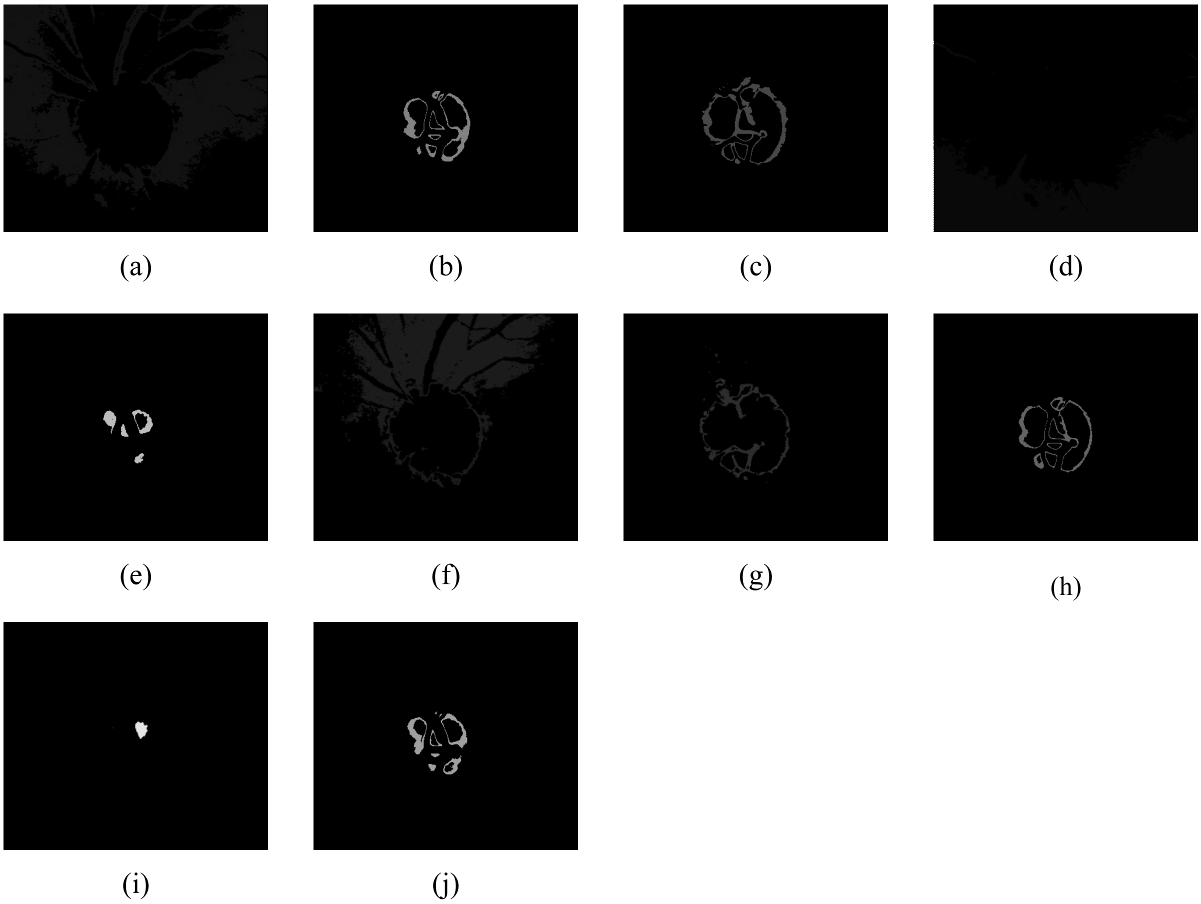


Fig.4. The sub-regions of clustering

3.2.2 OD Detection Using Saliency Feature Based on Clustering

The OD region is significant in fundus images, where at least one feature of OD region differs from other regions in the image. OD features the saliency of an image, in which it differs from other regions in terms of color, contrast, and global distribution. This study adopts the contrast and global distribution cues as saliency based on clustering [15-16].

Contrast cue. Contrast is the key factor that determines whether an object can be observed. Contrast reflects the difference between one region and the surrounding region, and the difference can be in terms of color, texture, or shape. Contrast represents the visual uniqueness of a single image or multiple images. Contrast cue based on clustering is more consistent than that based on pixels or pixel regions. The contrast of cluster C_k is defined by comparing the center of cluster C_k and those of other clusters.

$$\omega^{c}(k)=\sum\nolimits_{i=1,i\neq k}^{K}\left(\frac{n_i}{N}\left\|c_k-c_i\right\|_2\right) \tag{4}$$

where N is the pixel number of the image, and ni is the pixel numbers in the ith region of the image.

Global distribution cue. Compared with contrast and spatial cues, global distribution cue is used to measure the distribution of each cluster in the image. This study employs the variance of clusters to measure the wide distribution of the cluster approximately among input images.

The global distribution of cluster C_k can be described as follows:

$$\omega^{s}(k)=\frac{1}{\operatorname{var}(\widehat{q}^{k})+1} \tag{5}$$

where $var(\hat{q}^k)$ denotes the variance of histogram $\hat{q}^k$ of cluster C_k.

Ten clustering regions obtained from cluster computing are used as the candidate of OD regions. The saliency images are obtained by calculating the corresponding saliency. Each saliency map of the images plays a distinct role in different images. Thus, the weight of each saliency should be adaptive during fusion. Fixed or null weight is unacceptable. This study employs the reciprocal of salient information entropy as the weighted coefficient to compute the two saliencies of all sub-regions. The high saliency of the image is shown in Fig. 5. This study also adopts luminosity to represent saliency. The region with high saliency is identified as OD, as shown in Fig. 6.

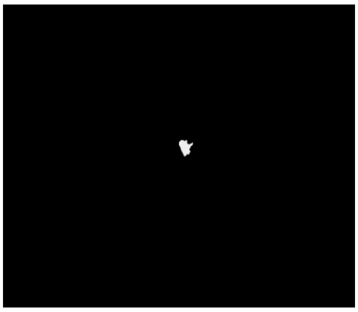


Fig. 5. The region which has the highest saliency

Fig. 6. The OD region

The experiment results show that saliency detection based on clustering can emphasize the significant region in the images and remove noises.

The OD segmentation region is cut from the fundus image. The size of the rectangular centers on the center of the salient region is about one-fifth of the fundus image. The OD segmentation region is shown in Fig. 7(a).

3.3 OD Segmentation Using Ellipse Fitting and Active Contour

OD segmentation is confirmed based on the result of OD detection. Numerous retinal vessels are found, which is unsuitable for OD segmentation. The OD is segmented after processing, as described as follows.

(1) The retinal vessels based on open-closing operators are erased in mathematical morphology. The preprocessed image is shown in Fig. 7(c).

(2) OTSU thresholding method is used for image segmentation. The binary image is shown in Fig. 7(d).

(3) Convex hull exists in the OD after segmentation influenced by vessel erasure, which is detected to correct the defects for all contour points. The contour of binary image is found, as shown in Fig. 7(e). Several closed curves exist in the image. One closed region is one contour. Corresponding smoothing curves are found considering that each contour implements convex hull detection. Thus, all contours found in the image are synthesized into one contour. This condition is accomplished by summing all the pixels of each contour. Convex hull detection [17] is implemented after obtaining the entire contour. The formula is defined as follows:

$$P=\sum_{i=1}^{n} p_i \tag{6}$$

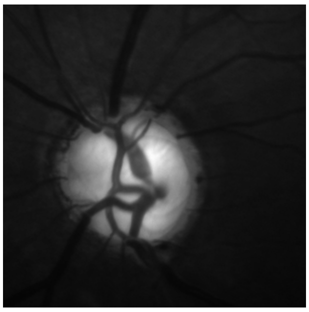
where p_i is the pixel set of the ith contour, n is the number of contour in the image, and P is the pixel set of the entire contour. After convex hull detection, the defects caused by vessel erasure will be filled, which is good for ellipse fitting. The result is shown in Fig. 7(f).

(4) OD region is approximated using an elliptical shape. Ellipse fitting [18] is constructed using contour points extracted from the detected convex hull, which is the initialized contour of the active contour model. The fitting result is shown in Fig. 7(g).

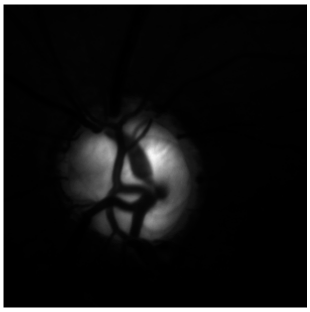
(5) The active contour model is used to adjust the initialized contour to obtain a considerably accurate OD contour. The active contour model will be deformed under its internal force curve and external binding. The internal force plays a role in smoothing and constraint, whereas the external force guides the model to move into the characteristics of the image. The contour of OD can independently converge to

minimum energy state. The ultimate contour of OD is shown in Fig. 7(h).

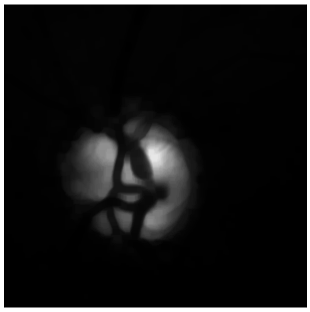
The process of OD segmentation is shown in Fig. 7. After convex hull detection, the defects caused by the vessels are filled, which is good for accurate fitting. The edge of OD is obtained accurately by ellipse fitting and active contour.



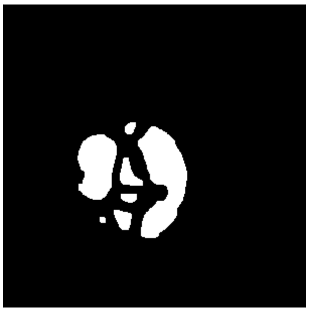
(a) The OD segmentation region



(b) The OD segmentation region after gamma adjusting

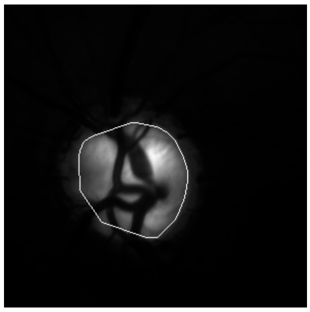


(c) The image after open and close operation



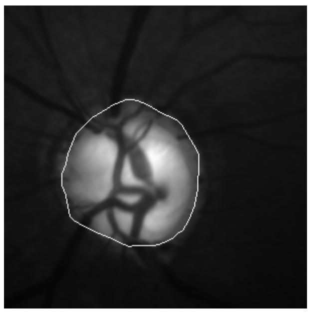
(d) The binary image

(e) The contour of the binary image



(f) Convex hull detection

(g) The ellipse fitting



(h) The segmentation of OD by active contour

Fig. 7. The process of OD segmentation

4 Experimental Results and Discussion

4.1 Data Collection

To develop and examine the OD detection algorithm, four publicly available datasets, namely, DRIVE [19], STARE [20], MESSIDOR [21], and Drishti-GS [24], are employed. These datasets contain healthy and pathological retinas.

Drive database is established from a diabetic retinopathy screening program in Netherlands. A total of 400 subjects are patients with diabetes who are between 25 and 90. The retinal images have a 568×584 resolution, which are captured using a Cannon CR5 non-mydriatic 3CDD camera with a 45° field of view.

Stare database is created for retinal vessel segmentation. The retinal images have a 605×700 resolution. Each image corresponds to two manual markings by experts.

Messidor database is used for fundus image segmentation (i.e., microaneurysm, hemorrhage, and diabetic retinopathy). A total of 1200 color images at different sizes (i.e., 1440×960, 2250×1488, and 2304×1536) are found in Messidor database. The database obtains OD segmentation via manual labeling for the comparative analysis of experimental results.

Drishti-GS database is built for glaucoma detection. It consists of 50 training images and 51 testing images. The retinal images have a 2896×1944 resolution with a 30° field of view. Each image has four manual labeling results for OD and cup region from four experts.

4.2 OD Detection

OD detection is accurate when the coordinates of detected OD are among OD boundaries. An OD detection accuracy of 94% is obtained from 1422 retinal images within the four datasets. The average time of detection within the four datasets is 0.35, 0.54, 1.24, and 1.03 s. The detection accuracy within four datasets is shown in Table 1.

Table 1. Detection accuracy of proposed method in four different datasets

Datasets	Healthy images	Pathological images	Accuracy	Average Time(s)
Drive	33	7	100%	0.35
Stare	31	50	90.1%	0.54
Messidor	540	660	94.1%	1.24
Drishti-GS	-	-	94%	1.03

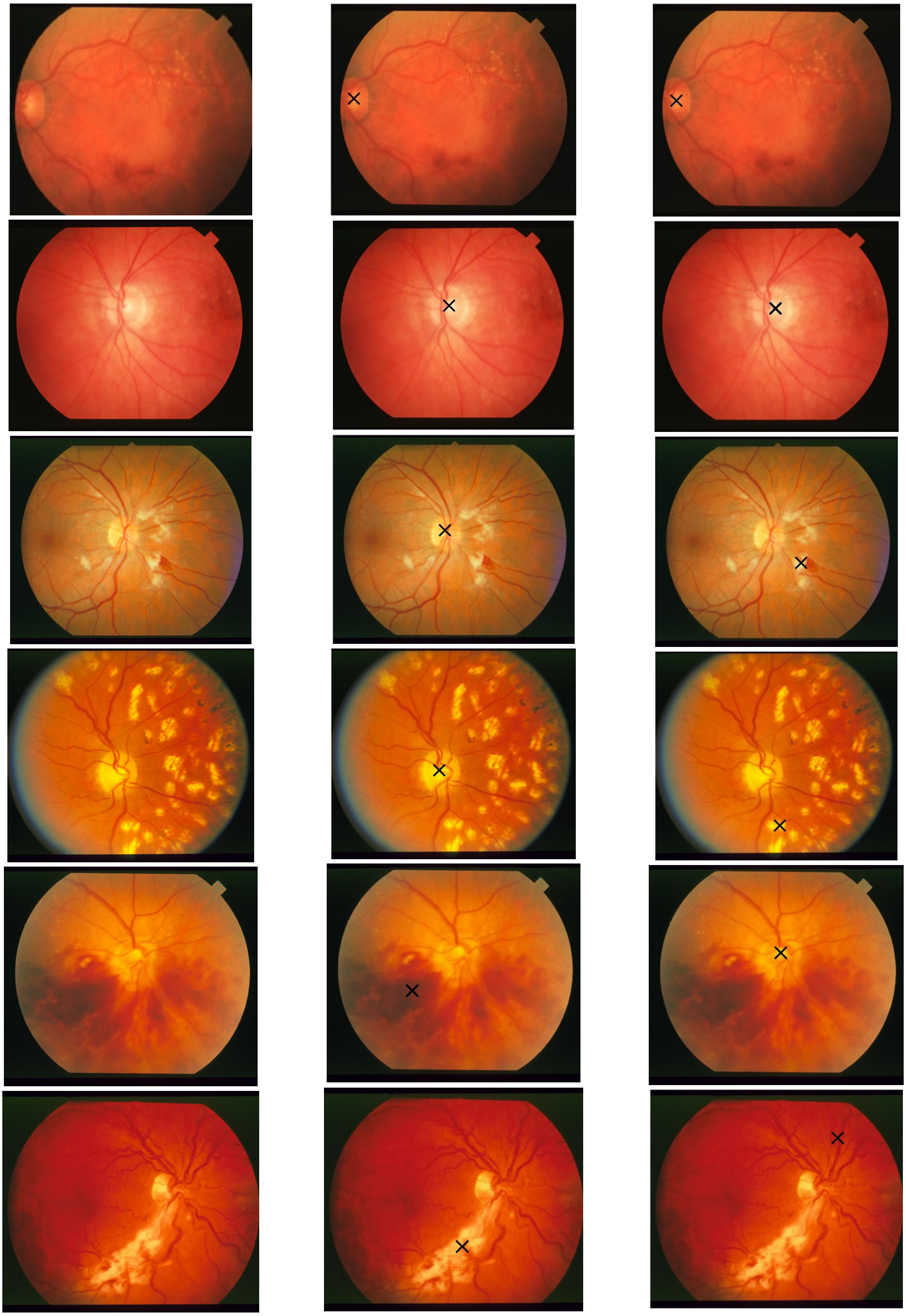
A total of 85 images incur errors in detection. These errors are caused by the following three aspects. (1) Many lesions exist in pathological retinal images. (2) The appearance of OD changes because of the lesions around the OD or the position deviated from the ROI boundary. (3) The image quality is poor; the OD is dark compared with other regions.

The results of OD detection are shown in Fig. 8. The results from the first to fourth images are accurate because these images overcome the lesions and are suitable for only half disk, such as in Fig. 8(a). OD is detected when it is salient, even though OD is incomplete. The results between the fifth and sixth images are incorrect because of the changes in OD appearance or lesions, which is the saliency of the image. The results in the third, fourth, and sixth images are incorrect, which adopts a method proposed in the literature [1]. However, the result in the fifth image is correct. Thus, the proposed algorithm can detect the OD accurately for images with salient OD.

Compared with other available datasets, STARE dataset possesses poor quality; the images display many severe lesions and OD is covered partially or fully. Therefore, many studies have selected this dataset to examine their proposed algorithm. The accuracy of the reported algorithms is shown in Table 2. The accuracy of the proposed algorithm in the present study is not high. However, the algorithm with high accuracy can extract the retinal vessel accurately but can make the calculation relatively complex. The saliency model based on clustering is proposed for OD detection, which does not rely on vessel segmentation. With simple computation, this model can achieve high accuracy without removing the vessels.

Table 2. OD detection results for the proposed and literature reviewed methods

reference	algorithm	accuracy
Youssif et al. [22]	Vessel direction Matching filter	98.8%
Zhao et al. [23]	Edge gradient, shape and luminosity	93.8%
Zheng et al. [1]	DLC and local vessel feature	90%
The proposed algorithm	Saliency based on clustering	90.1%

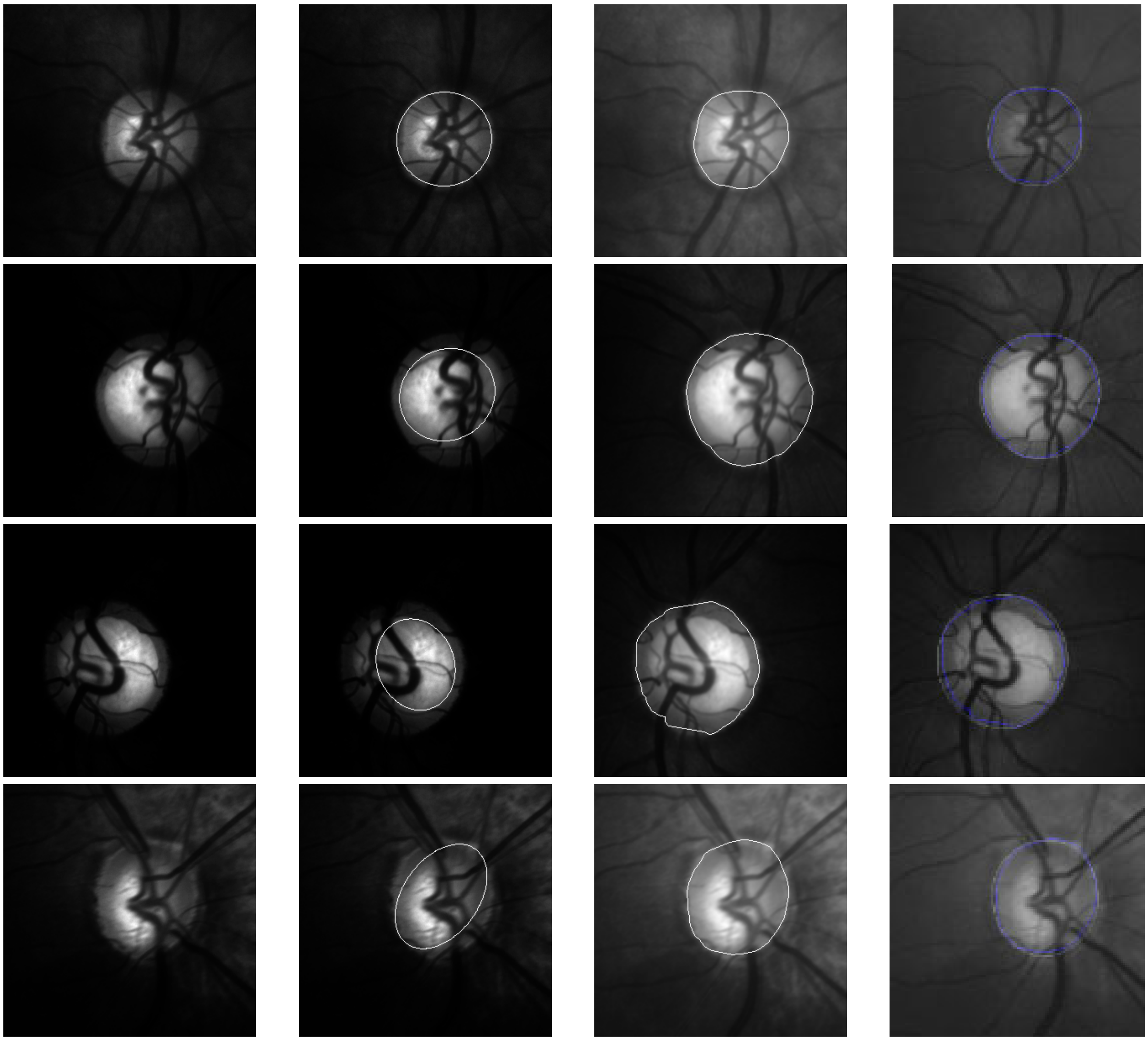


(a) The original image (b) The detection results by the proposed algorithm (c) The detection results by Zheng [1]

Fig. 8. OD detection results

4.3 OD Segmentation

OD segmentation after detection is achieved by ellipse fitting and active contour. The results of OD segmentation are shown in Fig. 9. Fig. 9(a) shows the OD segmentation region. Fig. 9(b) shows the segmentation result by ellipse fitting. Fig. 9(c) shows the segmentation result by ellipse fitting and active contour. Fig. 9(d) shows the comparison between the average segmentation result by expert labeling and the segmentation by the proposed algorithm. In Fig. 9(d), the white line denotes the result by expert labeling, and the blue line denotes the result by the proposed algorithm. From Fig. 9(b) and Fig. 9(d), significant differences are found between the results by ellipse fitting and manual results. The boundaries of OD are blurred in the second image. The vascular information is rich in OD in the third and fourth images. Thus, the results by ellipse fitting and manual results have a large difference. Convex hull detection should be completed before ellipse fitting and active contour in the proposed algorithm. This detection aids to eliminate vascular interference. Convex hull detection can find the actual boundary of OD using active contour. The results of the proposed algorithm are nearly consistent with the manual results.



(a) The segmentation region of OD (b) The results by ellipse fitting (c) The results by ellipse fitting and active contour (d) The results by expert labeling

Fig. 9. OD segmentation results

The algorithm is implemented in the training set of Drishti-GS database. A total of 50 training sets labeled by four experts is used. The segmentation results are compared with the average labeling result.

To evaluate the algorithm, *F_score* and *Acc* are calculated. Assume that *P* is precision, and *R* is recall. *S* is the proposed segmentation region, and *G* is the manual segmentation region. $S \cap G$ is the intersection of two regions, and $\cup G$ is the union of two regions. *Acc* is the ratio between two regions. *Acc* that is close to 1 indicates high accuracy.

The evaluation formulas are defined by Eqs. (7) and (8).

$$F\_score = 2P * R / (P + R) \tag{7}$$

$$Acc = Area(S \cap G) / Area(S \cup G) \tag{8}$$

The segmentation results are listed in Table 3 combined with the results of different algorithms. In these methods, Mahapatra and Buhmann [25] used a field of experts model to segment OD and obtained a large score of 0.895. Aquino et al. [26] used morphology and ellipse templates and obtained a small score of 0.873 because most of the OD boundaries were not strictly circular. Cheng et al. [10] used superpixel classification and obtained a small score of 0.868 because the boundaries of OD were blurred or irregularly illuminated, which resulted in the inaccuracy of prior knowledge. The segmentation accuracy of the proposed method in the present study is close to a high accuracy.

Tab1e 3. Comparison of performance between the recent studies

Method	*F_score*	*Acc*
Mahapatra and Buhmann [25]	0.959	0.895
Aquino et al. [26]	0.94	0.873
Cheng et al. [10]	0.932	0.868
Our method	0.947	0.88

5 Conclusion

OD is one of the most important structures of fundus images, and automatic OD detection plays an important role in analyzing fundus images. This study presents an automatic OD detection technique. A saliency model based on clustering is designed, and OD is detected by identifying the high saliency in a fundus image. Compared with previously reported algorithms, the proposed algorithm does not require the segmentation of retinal blood vessels and is suitable for incomplete OD. The proposed algorithm can also overcome the effect of lesions and poor image quality. The robustness and effectiveness of the proposed algorithm is tested in four publicly available datasets. The experimental results show that the detection accuracy is up to 94%. In addition, ellipse fitting and active contour are adopted after convex hull detection to achieve OD segmentation and to obtain better performance than other methods, which are in good agreement with manual labeling. The proposed algorithm can meet the requirements of clinical medicine and can be used in clinical diabetic retinopathy or macular disease screening. Our future study will focus on the segmentation of optic cup and the measurement of cup-to-disk ratio, which will provide intelligent diagnosis for eye disease screening.

Acknowledgements

The author thank the Editor and the anonymous reviewers for their valuable comments in improving the quality of this paper. This research was supported by the Natural Science Foundation of Fujian Province, China (No. 2016J0129), by the Educational Commission of Fujian Province of China (No. JAT170180).

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