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Automatic localization and segmentation of optical disk based on faster R-CNN and level set in fundus image

Defeng Zhang, Weifang Zhu, Heming Zhao, Fei Shi, Xinjian Chen*
Soochow University, Suzhou, Jiangsu Province, 215006, China

ABSTRACT

The processing and analysis of retinal fundus images is widely studied because many ocular fundus diseases such as diabetic retinopathy, hypertensive retinopathy, etc., can be diagnosed and treated based on the corresponding analysis results. The optic disc (OD), as the main anatomical structure of ocular fundus, its shape, border, size and pathological depression are very important auxiliary parameters for the diagnosis of fundus diseases. So the precise localization and segmentation of OD is important. Considering the excellent performance of deep learning in object detection and location, an automatic OD localization and segmentation algorithm based on Faster R-CNN and shape constrained level set is presented in this paper. First, Faster R-CNN+ZF model is used to locate the OD via a bounding box (B-box). Second, the main blood vessels in the B-box are removed by Hessian matrix if necessary. Finally, a shape constrained level set algorithm is used to segment the boundary of the OD. The localization algorithm was trained on 4000 images selected from Kaggle and tested on the MESSIDOR database. For the OD localization, the mean average precision (mAP) of 99.9% was achieved, with average time of 0.21s per image. The segmentation algorithm was tested on 120 images randomly selected from MESSIDOR database, achieving an average matching score of 85.4%.

KEYWORDS: Optic Disc(OD), Deep Learning, Faster R-CNN, OD localization and segmentation

1. PURPOSE

The optic disc (OD) is a bright, yellow and approximately elliptic region in the fundus image, in which the vessels are thick and dense. At present, the works related to OD processing in fundus images can be classified into two categories: localization and segmentation. The OD localization is mainly depending on the appearance (shape and intensity) of OD, vascular structure, spatial scale and position information. H. Li et al¹ located the OD according to its appearance characteristics based on clustering and principle component analysis. T. Walter et al² detected the OD by means of morphological filtering techniques and the watershed transformation. Because of mainly based on intensity information, these two methods are not robust in case of co-existence of hard exudates. M. Foracchia et al³ detected the OD center based on the shape of vessels and a geometrical parametric model. G.A. Hoover et al⁴ proposed a method based on fuzzy convergence of the blood vessels to locate the OD. The technique of locating optic disk with vascular features has greatly improved the accuracy, while it is slower due to the detection of blood vessels. A. P. Rovira et al⁵ achieved 91.4% localization accuracy by fusing multi-features of the OD, including the distance and angle between the OD and the macula. S. Ravishankar⁶ used the intersection of the major blood vessels and the color properties to localize the optic disk and yielded 97.1% success rate. A.E. Mahfouz et al⁷ presented a fast technique that is based on image features such as retinal vessels orientation and the OD brightness and shape and dimension reducing method, and the average OD detection was 0.65 seconds per image. Aquino et al⁸ designed three candidate regions and voted according to the intensity characteristics of OD and blood vessels.

Segmentation of the OD is the key step for calculating the size and area of the OD. Aquino et al⁸ used morphological operation and edge detection techniques followed by the circular Hough transform (CHT) to obtain a circular OD boundary approximation. Zhou et al⁹ used ellipse fitting and gradient vector flow (GVF) snake model to segment the OD. Lalonde et al¹⁰ segment the OD using Hausdorff-based template matching and pyramidal decomposition. Sekhar et al¹¹ considered the OD as a circular region and segmented it by the CHT. Yin¹² combined edge detection, the CHT and a statistical deformable model to segment the OD with the average absolute area error of 10.8%.

This paper presents a method for automatic localization and segmentation of optic disc in fundus images. Because of the excellent performance of Faster R-CNN in natural image localization, it is adopted in our OD localization and achieved a localization accuracy of 99.9% in the test. After the localization of the OD, the Hessian matrix is used to remove the vascular disturbance. Then, the segmentation of the optic disc is achieved using the shape constrained level set algorithm.

2. METHOD AND MATERIALS

The proposed method includes three parts: OD localization based on Faster R-CNN, blood vessels exclusion based on morphological operation and Hessian matrix, and OD segmentation based on shape constrained level set algorithm. Figure 1 shows the flowchart of the proposed method.

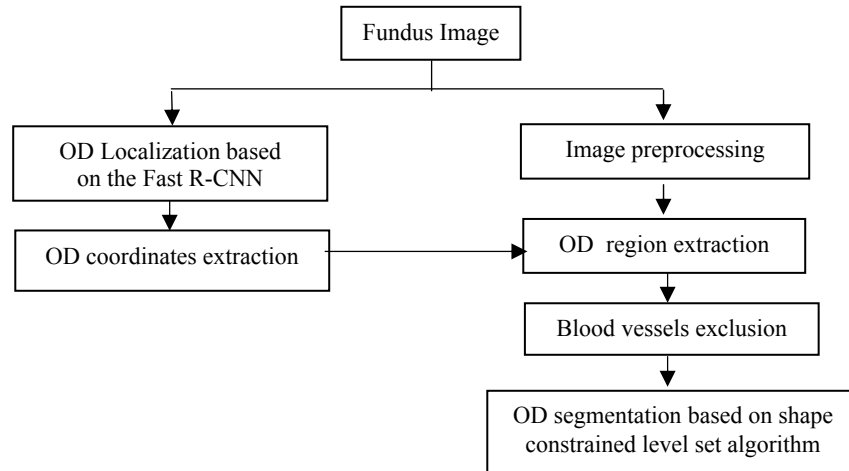


Figure 1. Flowchart of the proposed method

2.1 OD localization based on Faster R-CNN

The classic Faster R-CNN+ZF model is used as the network, in which region proposal networks (RPN) is adopted to extract the candidate area by CNN, replacing the traditional selective-search algorithm¹³. Therefore, the speed of OD detection is improved greatly. In this paper, 4000 images were randomly selected from the Kaggle Diabetic Retinopathy Detection database as training samples, in which the OD regions were marked manually. The OD localization model was tested on MESSIDOR dataset, which included 1200 pictures. The average time for OD localization was 0.21s per image and the accuracy achieved 99.4%. The results shows that the trained Faster R-CNN model can accurately mark the position of the OD in almost any retinal color images. Figure 2 shows the results of the disc localization. No matter the relatively high contrast disk area (as shown in Figure 2. (a)) or the more fuzzy disk area (as shown in Figure2. (b)), this method can accurately locate the disc.

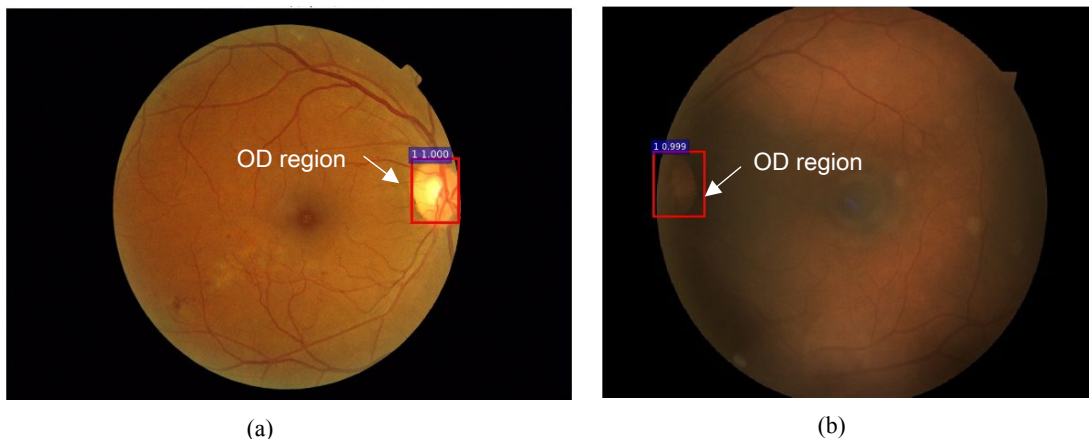


Figure 2. Example of localization of optic disc used FAST R-CNN. (a) Fundus image under good illuminations. (b) Fundus image with low contrast between optic disc and background

Bright lesions may interfere with the localization of the OD and cause false positives, because of the higher the brightness of the lesion area and the lower the brightness of the OD. As shown in the Figure 3, two candidate regions, the false bright lesion region and the OD were detected, the probability of which were 0.893 and 0.999, respectively.

Because of the uniqueness of the disc, only the B-box corresponding to the maximum probability was taken as the OD. After the exclusion of false positives, the OD localization accuracy could reach 99.9%.

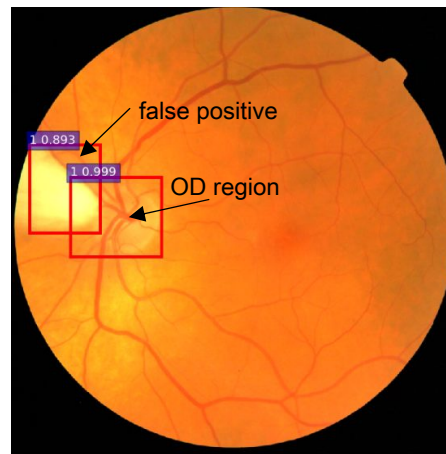


Figure 3. Localization of optic disc lesions with interference of the bright lesions.

2.2 Image preprocessing

Influenced by light, instruments, and fundus diseases, etc, the retinal fundus images may differ a lot in contrast and color, which increases the difficulty of OD segmentation. In order to improve the contrast between the OD and the background, a high quality fundus image is selected as a template for histogram matching algorithm, and a histogram-matching algorithm is used for each RGB channel of the fundus images. The method can effectively improve the image quality of the retina, as shown in Figure 4.

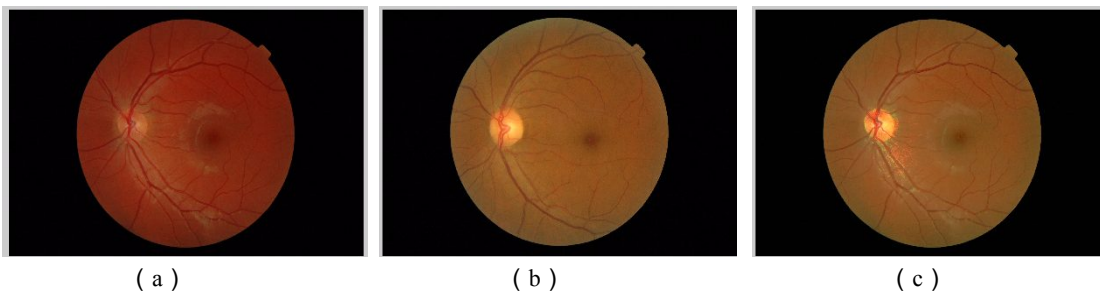


Figure 4. Example of contrast enhancement by matching histogram equalization (a) Original image (b) Template for histogram matching algorithm (c) Enhanced image

2.3 Blood vessels exclusion

To segment full and precise OD boundary, the B-box, which contains the OD, is expanded 20 pixels in four directions. According to the brightness of the fundus image, different channels are selected in the vessels exclusion. In most cases (the average intensity value is not larger than 225 in red channel), the contrast between blood vessels and the background is low and the contrast between OD and the background is high in red channel image of the B-box. In these cases, the red channel is selected and the blood vessels are excluded by using morphological close operation (structure element is set as disk with size of 10 pixels). The Fig.5 (a) shows the B-box and Fig.5(b) shows the corresponding red channel after vessels exclusion. If the average intensity value is larger than 225 (as shown in Fig.5 (b)), the contrast between the OD and the background is very low and the OD boundary is blurry in the red channel. In these cases, the green channel is selected. But in the green channel, the contrast between the blood vessels and the background is high (as shown in Fig.6 (c)). In this paper, the Hessian matrix is used to extract the blood vessel and the vessel regions are filled with the average intensity value of the neighborhoods. Finally, in order to preserve the edge information of the optic disc, a nonlinear edge preserving smoothing filter (Kuwahara filter) based on local statistical characteristics¹⁴ is adopted. Fig.6 (d) shows the green channel after vessel exclusion and smoothing filtering.

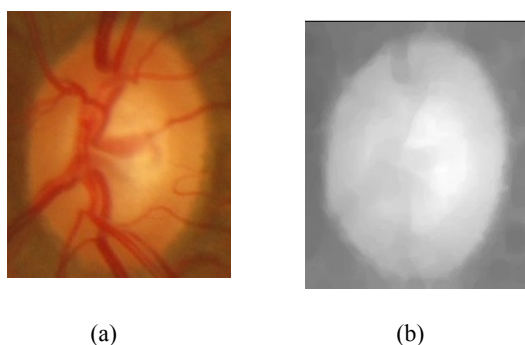


Figure 5. Example of excluding the blood vessels in the red channel. (a) An original image. (b) An image after Blood vessels exclusion in the red channel

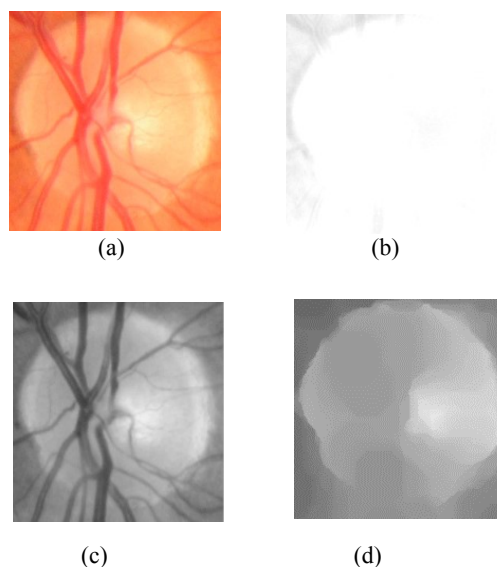



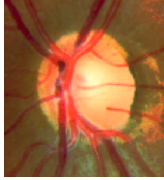
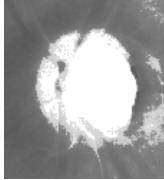
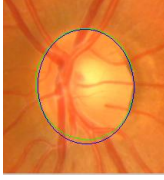
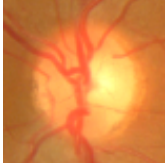

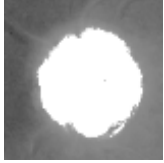

Figure 6. Example of excluding the blood vessels in the green channel.(a)An original image.(b) The red channel. (c)The green channel (d)The image after Blood vessels exclusion in the green channel

2.4 OD segmentation using level set algorithm based on shape model

Level set¹⁵ is a geometric deformation model, whose evolution of curve / surface can be used for image segmentation. Object segmentation based on prior shape is equivalent to adding a constraint in evolution, which makes the curve shape approximate to the prior model. In order to avoid falling into the local extremum, it is important to select the initial contour of the level set. A reasonable initial contour can greatly improve the evolution speed of the level set to convergence. The center of the OD is close to the center of the B-box. According to the shape characteristics of the OD, the initial contour is selected as a circle, whose center is set as the center of the B-box and diameter is set as $\min\{H, W\}$ (H represents the height of the B-box and W represents the width of the B-box). Table 1 shows the segmentation results of the OD boundary (blue curve) and the corresponding ground truth (green curve).

Table 1. Segmentation results of optic disc boundary

Localization	Preprocessing	Blood vessels exclusion	Segmentation	Matching score S
				0.97
				0.97

				0.95
				0.93

3. RESULTS

The proposed faster R-CNN + ZF model based OD localization method was tested on 1200 fundus images of MESSIDOR database. The average localization speed was about 0.2s, and the accuracy achieves 99.9% if the number of B-box was limited to 1. Table 2 showed the OD localization comparisons between the proposed method and some other methods.

Table 2. OD localization results comparisons on MESSIDOR database

Method	Accuracy	Computation time
Aquino ⁸	98.8%	1.67s
Zhou ⁹	98.7%	0.32s
Proposed method	99.9%	0.21s

As MESSIDOR database has the ground truth for OD boundary segmentation, the proposed OD segmentation method was tested on this database. For the objective evaluation, matching score S is adopted as the evaluation criteria¹⁰, which is defined as

$$S = \frac{Area(T \cap D)}{Area(T \cup D)} \quad (1)$$

in which matching score S equals to the common area between the true OD region T and the detected one D . Table 3 shows the performance measures of some reported methods.

Table 3. OD segmentation results comparisons on MESSIDOR database.

Method	S
Aquino ⁸	0.86
Lalonde ¹⁰	0.81
Proposed method	0.854

The accuracy of the proposed method is 85.4%, which is slightly lower than the one of Ref⁸(86%). In all, the proposed localization and segmentation method is efficient and fast.

4. NEW WORK

- Faster R-CNN is introduced into the optic disk localization for the first time, and the localization accuracy of the optic disk in the fundus image is improved.

- (b) According to the different characteristic of the fundus images, different vessels exclusion methods are adopted, which obviously improves both the OD segmentation speed and accuracy.

5. CONCLUSIONS

In this paper, we first propose an automatic method for the optic disc localization and segmentation. The shape constrained level set algorithm is used to segment the OD after located by Faster R-CNN. Although the preliminary results were not very good, they showed the feasibility and efficiency of the proposed method. We are working on improving the accuracy of the OD segmentation.

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