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Automatic Detection of the Optic Disc of the Retina: A Fast Method

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Submission: 11-12-2015 Accepted: 17-01-2016

ABSTRACT

Localizing the optic disc (OD) in retinal fundus images is of critical importance and many techniques have been developed for OD detection. In this paper, we present the results obtained from two fast methods, correlation and least square, to approximate the location of optic cup. These methods are simple and are not complex, while most of the OD detection algorithms are. The methods were tested on two groups of data (a total of 100 color fundus images) and were 98% successful in the detection of the optic cup. An algorithm using the vessel mask of fundus images is proposed to be run after correlation to ensure that the localization of OD in all images is successful. It was tested on 40 of the test images and had a 100% rate of success.

Key words: *Correlation, denoising, least square, optic disc, vessel mask*

INTRODUCTION

The optic disc (OD) or optic nerve head (ONH) represents the beginning of the optic nerve and is also where the major blood vessels enter the retina. It is usually a round or elliptical-shaped object appearing in the right or left side of the normal fundus images and can be detected as a brighter region than its neighborhood. In addition, the convergence of major retinal vessels is outstanding in the area of the OD.[1] Despite its circular shape, it does not have a distinguishable boundary, while its edge is destroyed by the vessels going out from it to the retinal region.[2]

Localizing the OD has clinical importance in automatic algorithms, as it is very similar to hard exudates in color and brightness, which can cause miss-detection of exudates. However, knowing the position of ONH can prevent false diagnosis of exudates by masking the OD area.[3]

In addition, localization of OD can help detecting macula, while it is usually in a standard distance of OD.[4,5] Since macula has a low contrast with its neighbor region, the correlation algorithms are not successful to detect it. However, its usual distance of 2.5 times the OD's diameter from OD can help detecting the macula.[5]

In addition, as above mentioned, the OD is the convergence area of major vessels, therefore it can be used as the starting point in vessel extraction algorithms.[4] There are different methods to detect ONH. Here, we will bring a short review on some of the previous related works.

In Lalonde *et al*.[4] using Hausdorff-based template matching, a method is proposed to detect OD area. Testing the method on 40 fundus images, an average error of 7% is reported.

The method of Faracchia *et al*.[3] needs a preliminary extraction of major blood vessels. A geometrical parametric

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How to cite this article: Jamshidi M, Rabbani H, Amini Z, Kafieh R, Ommani A, Lakshminarayanan V. Automatic Detection of the Optic Disc of the Retina: A Fast Method. J Med Sign Sence 2016;6:57-63.

model is proposed to detect the general direction of vessels at any position, where two of the parameters of the model are the coordinates of the center of the ONH. These model parameters were identified by means of a simulated annealing optimization technique. Testing their method on 81 images of STARE (Structured Analysis of the Retina) database, the success rate of 97.53% is achieved. Note that, STARE database includes both normal and pathological images.

In Kaur and Sinha[2] by thresholding the OD is estimated, based on Otsu's method and the prior information of standard diameter of ONH in normal fundus images. Using snake model, an estimation of OD boundary is achieved, after eliminating the vessels of OD area with morphological closing and opening. Within 148 images tested with thresholding method, 99.32% of success is reported. Furthermore, 90.68% of 74 images were successful in detecting the boundary of OD with active contour. The authors reported that snake model has a better performance with gray-scale images than color ones.

Lowell *et al*.[5] proposed a method to locate the OD with the help of template matching and detect its boundary in low resolution images along with an active contour model. The methods are tested over a randomly selected 100 images from a diabetic screening program; note that 10 of them were classified as "unusual" images. The template-matching algorithm was successful in all the images and the snake model achieved the success rate of 83%.

Osareh *et al*.[6] have localized the OD with the help of a pattern obtained by averaging the OD area of 25 fundus images. Using 75 images for test, the pattern-matching technique achieved a good result even with the images containing large exudates.

According to the high brightness and circular shape of OD, Park *et al*. have proposed a method[7] which consists of thresholding and detecting the circles. A success rate of 90.25% for 40 images of DRIVE (Digital Retinal Images for Vessel Extraction) database is reported.

In Zhu and Rangayyan[8] a method based on Hough transform and edge detection is proposed to detect the OD. A sensibility of 92.5% was achieved on the DRIVE database, while the performance on STARE database was poor.

Although many of these methods have achieved good and excellent success rates, however most of them have complexity.

In Ravishankar *et al*.[9] the authors have localized the OD using the detection of blood vessels and their intersection to find an approximation of the OD area. Evaluation of the algorithm on a database of 516 images with varied contrast, illumination, and disease stages yielded 97.1% success rate for OD localization.

Due to the brightness and the circular shape of OD, its optic cup (the brightest region of OD) can be approximated with a white circle. Since the blue band of the color fundus image contains no information of ONH, an image obtained from averaging the red and green bands is used. We have implemented two methods of approximating, correlation and least square, and tested them on the 40 images of DRIVE database and 60 other images. Least square was successful with all of 40 DRIVE images, while correlation failed on one of them. However, a short algorithm is proposed to be run after correlation to make sure of locating OD in all the 40 images of DRIVE; however, both methods failed with one image from 60 images of second database.

A recent clinical review summarizes various cup and disk segmentation methods available in the literature.[10]

In the following section, part 2 includes the methods, part 3 belongs to introducing the data set, part 4 is about the results, and the conclusion comes in the part 5.

METHODS

To estimate the optic cup with a circle, according to its higher brightness in comparison with other regions in its neighborhood, white seems to be the best choice for color of the circle. In this way, we will have a black image, called estimated image, with the same size as the original fundus image, which has a white circle in the location of optic cup. The center of this circle can locate the optic cup.

Two approaches are proposed here: Estimating the optic cup using correlation and least square.

Correlation

Assuming two images A and B of size n × m, the correlation of them will be computed from Eq. 1.

$$C_{A,B} = \sum_{i=1}^{n} \sum_{j=1}^{m} a_{ij} \times b_{ij} \tag{1}$$

Two different parameters should be identified in our case: The position of the circle on the original image (which gives the location of optic cup) and the radius of the circle.

To identify the position of the circle (suppose with the known radius r), the white circle must be shifted on the estimated image, while it will be correlated with the original gray-scaled fundus image. In this way, there will be a vector of correlation coefficients, whose maximum relates to the shift of the white circle, which can locate the optic cup in the best way.

To identify the circle radius, the above-mentioned algorithm should be done for different radii. Here, we have assumed that the optic cup's radius is not larger than 30 pixels and the image estimation algorithm is done for circles with radius varying from 10 to 30 pixels. For each radius, the fundus image is estimated as mentioned, while along with each of these estimated images, there is a correlation coefficient. The maximum among these coefficients relates to the best radius.

To ensure the truth of localization of the OD, even the cases that correlation fails, a short algorithm using the vessel mask of the fundus image has been proposed, which uses the correlation coefficient vector to guarantee the localization of OD.

As described before, the ONH is the convergence area of the major retinal vessels. Therefore, it seems that the "density" of the pixels relating to vessels is higher in this area than other parts of the fundus image. Now, assuming to have the vessel mask, the below algorithm is implemented after computing the correlation coefficient vector relating to different radii (for example, suppose that the correlation vector is called c).

- Find the estimated image relating to the maximum correlation factor in c and assume the area within the white circle as optic cup
- In the area of optic cup in step 1, evaluate the portion of the number of pixels marked as "vessel pixel" in the vessel mask to the number of background pixels
- If the portion evaluated in step 2 is larger than 0.1, the detected area is in the ONH, else the maximum element of c is omitted and the algorithm backs to step 1, having the new vector as the correlation vector. (Note that, 0.1 is found through experimenting the images of DRIVE database).

Note that, the algorithm in Esmaeili *et al*.[11] and Esmaeili *et al*.[12] are used to extract the vessel mask.

Least Square

Least square is one of the known estimation methods. In this method, the sum of squares of the deviations of data points from the points of the candidate estimation is computed (for example, suppose the desired signal $A = [a_i]_{1\times n}$ and $B = [b_i]_{1\times n}$ to be an estimation candidate for it. Eq. 2 shows the sum of squares of deviations of A from B).

$$S = \sum_{i=1}^{n} (a_i - b_i)^2 \tag{2}$$

This sum will be evaluated for all the approximation candidates, the one with the least sum will be the best estimation, as Eq. 3 represents.

$$\text{Best Estimation} = \operatorname{argmin}(S) \tag{3}$$

This method is extended to the images. For example for $A = [a_{ij}]_{n\times m}$ and $B = [b_{ij}]_{n\times m}$ with the same role as above, S is computed from Eq. 4.

$$S = \sum_{i=1}^{n} \sum_{j=1}^{m} (a_{ij} - b_{ij})^2 \tag{4}$$

Now for our case of estimation, the approximation candidate is the same as in correlation method. S must be computed for all of them and the least one stands for the best image. The same as in correlation method, this algorithm should be repeated for different radiuses.

DATA SET

In this work, two groups of data sets were used:

1. DRIVE: This database includes 40 color fundus images along with their vessel masks. The images were obtained from a diabetic retinopathy screening program in the Netherlands. From these 40 images, 33 do not show any sign of diabetic retinopathy and 7 show signs of mild early diabetic retinopathy.[13]
   The size of images of this database's is 584 × 565 × 3 pixels.
2. A set of 60 color fundus images described in Hajeb Mohammad Alipour *et al*.,[14] from which 35 were abnormal cases. These images are available at http://www.misp.mui.ac.ir/en/Angio-fundus.[15] We call this data set as "Medical Image and Signal Processing Research Center (MISP) database" in the remaining part of the paper, since the data images are included in the website of this research center.
   This database's images have the size of 576 × 720 × 3 pixels.

RESULTS

To lower the simulation time, the images obtained from averaging the red and green bands of the color fundus images are split, such that the ONH falls in the half image used in simulation. This can also eliminate the areas far from ONH.

Correlation

As it is described in Methods section, the estimated images are produces by creating a black image, the same size as the half fundus image, with a white circle shifted 1 pixel-1 pixel on them.

In the following section, the results on DRIVE and MISP database are explained.

DRIVE database

This method was successful with 39 of the 40 images of DRIVE database. Figure 1 shows one of these 39 images. Note that, in the images, the center of the circle area is

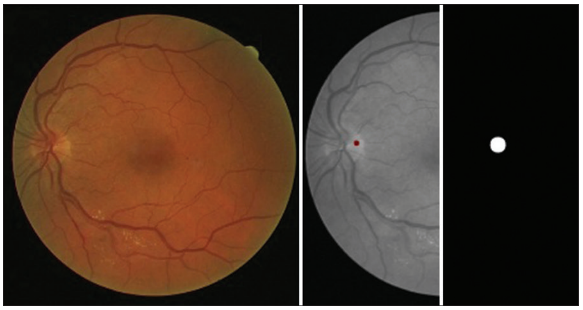

Figure 1: The detected areas using correlation method. The left side image is the original color fundus image from DRIVE (image number 3), the middle one is the image used in the simulation with the detected optic cup marked with a red point, and the right most image is the related estimated image

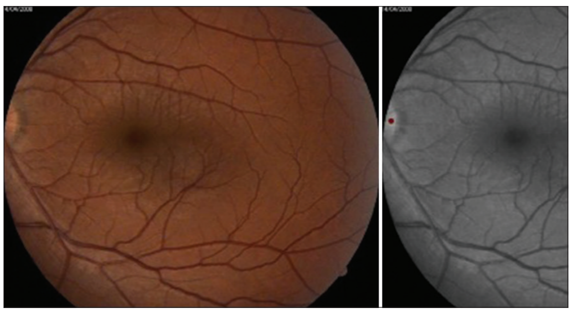

Figure 3: An example where correlation was successful on Medical Image and Signal Processing Research Center normal images. The left image is image number 2 of Medical Image and Signal Processing Research Center normal images and the right one is the detected optic cup marked with a red point

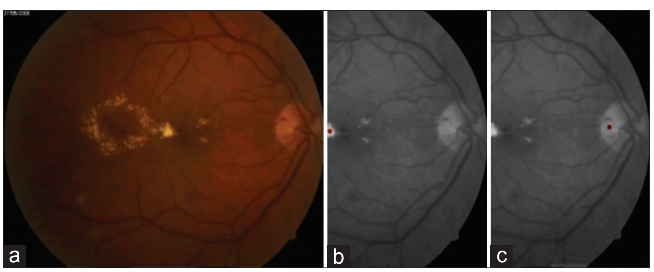

Figure 5: (a) Image number 23 of Medical Image and Signal Processing Research Center abnormal images. (b) The correlation algorithm failed to detect its optic disc. (c) Result of running the algorithm using vessel mask

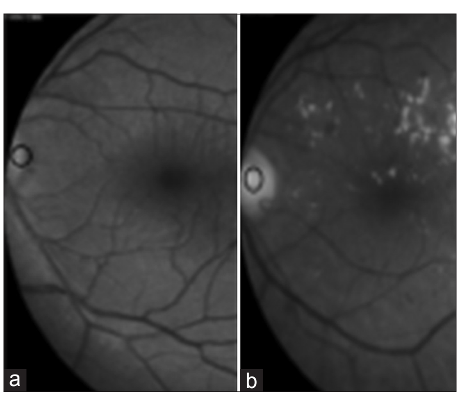

Figure 7: (a) Least square on Medical Image and Signal Processing Research Center normal images on Figure 3. (b) Least square on Medical Image and Signal Processing Research Center abnormal images on Figure 4

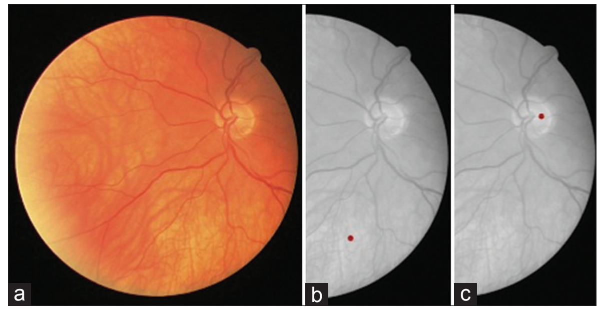

Figure 2: (a) Number 23 of DRIVE. (b) The correlation algorithm failed to detect its optic disc. (c) Result of running the algorithm using vessel mask

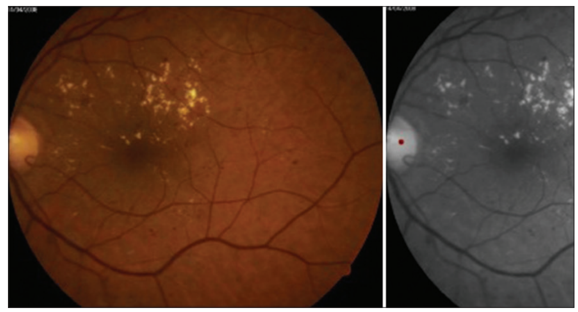

Figure 4: An example where correlation was successful on Medical Image and Signal Processing Research Center abnormal images. The left image is image number 2 of Medical Image and Signal Processing Research Center abnormal images and the right one is the detected optic cup marked with a red point

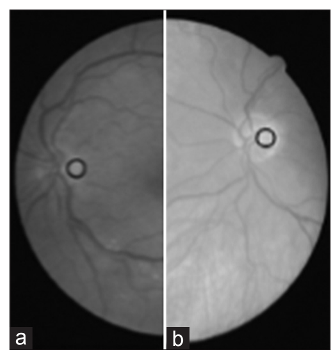

Figure 6: (a) Least square on images number 1 of DRIVE, with the detected marked with a circle (the original images are shown in Figure 1). (b) Least square on image number 23 of DRIVE. (The original image is in Figure 2)

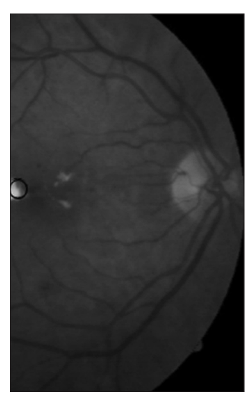

Figure 8: Result of least square on Medical Image and Signal Processing Research Center abnormal image on Figure 5

marked. Figure 2 is the image number 23 of DRIVE, for which the correlation cannot detect the optic cup (b).

A short algorithm was proposed in part 2.1 using the vessel mask of the fundus images, running which after the correlation algorithm will guarantee the detection of the ONH.

Although the only failure of correlation is the image in Figure 2b, for 7 of the 40 DRIVE images the portion in step 2 of above-mentioned algorithm is <0.1 in the first run of the algorithm. However, the area in the output of the algorithm again lies in the ONH for all of them. Figure 2c is the output of above algorithm for image in Figure 2a.

To detect the ONH by means of correlation and vessel mask, the simulation time was in average 3.65 s for each DRIVE image.

Medical Image and Signal Processing Research Center database

Correlation was successful with all 25 normal images of this data set, while the result for one of the 35 abnormal cases was not true. Figure 3 shows one of the successful cases of normal images, Figure 4 illustrates one example of successful cases of abnormal images. The proposed algorithm, which exploited the information of vessel mask is then run after the correlation algorithm and the only failure of correlation algorithm on MISP abnormal images was therefore corrected. Figure 5 shows this failed image along with the detected optic cups before and after vessel mask algorithm.

The average simulation time for each normal image of MISP database was 3.11 s, while for each abnormal image this time was 2.89 s.

Least Square

As mentioned before, the estimated images are the same as in correlation method (Part A) for this part. Although in regular form the circle should be shifted 1 pixel-1 pixel, as in Part A, to speed up the algorithm and since the accuracy does not change in overall, the white circle is shifted 10 pixel-10 pixel in least square method. In addition, to make the program faster, and due to the prior information of optic cup (that its radii are not larger than 15 pixels), the simulation is done only for a circle with a radius of 15 pixels.

In the following section, the results for the two databases are presented.

DRIVE database

This method was 100% successful with the DRIVE database. Figure 6 depicts the results of this method on the images in Figures 1 and 2. The average simulation time of least square is 5.55 s for each DRIVE image.

Medical Image and Signal Processing Research Center database

The performance of least square on MISP images was the same as correlations. It failed on the same image that correlation did. Figures 7 and 8 are the results on the images in Figures 3-5, respectively.

The average simulation time was 9.17 and 8.52 s for each normal and abnormal image of this database, respectively. (Comparing with DRIVE, these are higher values, which are due to the larger dimensions of MISP database).

CONCLUSION

In this paper, we compared the performance of two methods of detecting OD on 100 color fundus images. We implemented correlation and least square to localize the OD's brightest region. In addition, an algorithm using the vessel mask of images was proposed, which guaranteed the localization of ONH after correlation.

As explained, the least square method had a success rate of 100% on DRIVE, while correlation failed in 1 of 40 images, which could be solved with the help of the vessel mask of the fundus image. On the MISP data set, both methods failed only with one of abnormal images (98.33% success).

Looking at the average simulation time of the methods, correlation along with vessel mask has a better performance in comparison with least square, while it does need the vessel mask to insure about the truth of the algorithm's output.

The methods proposed and implemented in this paper are simple and accurate in localizing the OD in comparison with the algorithms reviewed in the introduction (an average error of 2% can be seen in the reviewed methods). If more accurate location of ONH was needed, the result of these methods can be used as the initial contour of active contour algorithms[16-17] which can estimate OD's boundary.

The major difference of this paper with the prior works in this field is that almost all of them have focused on the ONH contour. However, in many applications, it is only important to determine the location of OD and it is not needed to use complex methods to approximate the boundary of ONH. The previous works to localize the OD have a high computational complexity and their background theories were never based on simple methodologies. However, our method uses a very simple mathematical theory with lowest possible complexity in implementing and can compete the results of the previous works in detecting the location of ONH.

Although at the first glance, it may seem that our proposed method does not have a specific application by itself alone, many of the fundus image processing algorithms only need an approximation of the area, where the ONH locates and our simple and low-complexity method can give them a good approximation of what they need.

Financial Support and Sponsorship

Nil.

Conflicts of Interest

There are no conflicts of interest.

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