A comparative study of optic disc detection methods on five public available database

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Abstract. *Fundus images are valuable resources in eye diagnosis. Thus, processing and analysis of these images constitute a relevant task to aid eye specialists. Particularly, finding the Optic Disk (OD) in a retinal fundus image improves significantly the chances to detect eye diseases. In fact, the OD location can be input for algorithms that detect other retinal anatomical structures such as macula, blood vessels and some anomalies, such as exudates, hemorrhages and drusen. And these anomalies indicate the presence of retinal diseases. This paper compares and evaluate the performance of seven different automatic OD detection algorithms using five public benchmark image database.*

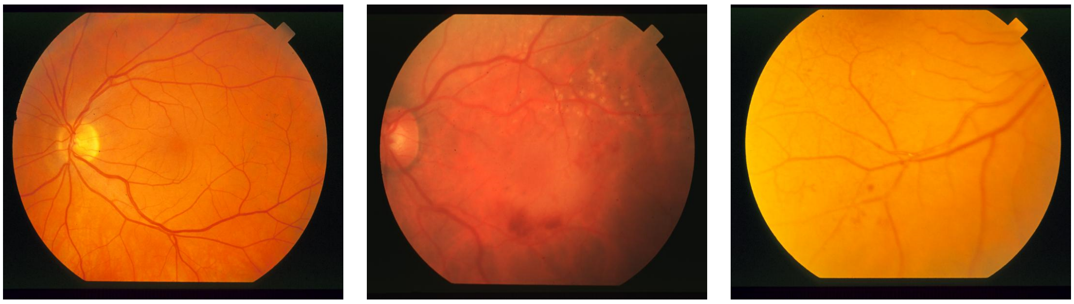
1. Introduction

Recent advances in digital imaging and processing have provided the use of medical images in new and revolutionary ways. Indeed, these advances have also led to considerable interest in the development of automatic medical diagnosis systems to improve the services provided by the medical community [Trevisan et al. 2007]. These systems aid physicians to diagnose, measure important anatomical structures, monitor changes by comparing sequential images and furthermore plan and develop the best treatment. They also the repetitive task, reduce fatigue and increase efficiency.

In clinical ophthalmology, color retinal images acquired from digital fundus camera are widely used for the detection and diagnosis of diseases related to eye, hypertension and various vascular disorders [Bernardes et al. 2011]. The location of the Optic disk (OD) is an important issue in retinal image analysis. The OD is a significant landmark and its localization is a prerequisite for the identification of other anatomical structures in retinal images. For example, in blood vessel tracking, the positions of vessels in the neighborhood of the OD are used as seeds for vessel detection [Gagnon et al. 2001]. In macula localization, the approximate distance between OD and the macula is used as a priori knowledge for locating the macula [Veras et al. 2013]. During the exudates lesion identification, many false positives arise due to other pale objects including light reflections, cotton wool spots, and most significantly, the OD [Giancardo et al. 2012].

OD segmentation is also relevant for automated diagnosis of other ophthalmic pathologies. One of them and maybe the most noteworthy is Glaucoma. Glaucoma is identified by recognizing changes in shape, color, or depth in the OD caused by this disease [Ho et al. 2011]. OD segmentation and analysis can be used to automatically detect early evidence of Glaucoma, and thus increase the chances of a successful treatment.

Figure 1 shows three sample images of STARE database [Hoover et al. 2000] and Figure 1(a) shows the contour of the OD well defined, which enables an easier detection of it. However, Figure 1(b) depicts a very heterogeneous background and a central region with color intensity very close to the region of the OD. Figure 1(c) presents an image where it is not possible to identify the OD.



(a) (b) (c)

Figure 1. Examples of STARE database.

Automatic OD detection can be hard to achieve using fundus image. Actually, there are variations of OD shape, size, and color features and some additional difficulties to take into account to develop OD detection algorithms. The contrast around the OD boundary is usually not constant or high enough due to outgoing vessels that produce "shadows" and partially obscure portions of the OD rim. Additionally, the presence of peripapillary atrophy produces bright areas just outside the OD rim and therefore it distorts the OD shape. It is worth noting that the eye movement at the moment of retinography capture may also lead to slightly blurred images and thus the automated analysis becomes more difficult [Aquino et al. 2010].

There are several algorithms for retinal image processing and analysis in the literature, however, different groups of researchers tend to use different metrics and image databases to compare the performance of these algorithms. Thus, it is difficult to draw meaningful comparisons among them. Despite using the same evaluation measures, different implementations of the metrics may influence the final results [Faust et al. 2012]. In this paper, we apply a simple rule introduced in [Tobin et al. 2007] to evaluate the performance of OD detection algorithms, for improving the proposed comparison approach among techniques.

This paper is structured as follows: Section 2 describes the evaluated algorithms. Section 3 presents the image database and assessment methodology applied to the algorithms. In Section 3.3, we discuss and compare the experimental results. Section 4 draws the conclusions and summarizes the future work.

2. OD Detection Methods

Previous works for OD detection generally assumed that the grey level variation in the OD region was higher than in any other part of the retinal image [Chaudhuri et al. 1989].

The algorithms localized the OD by identifying the largest cluster of bright pixels. Moreover, algorithms which relied solely on intensity variation proved to be simple, fast and reasonably robust for OD localization in normal retinal images with negligible variation between images. However, an OD obscured by blood vessels or only partially visible may be misidentified using methods based solely on identifying the brightest regions.

OD characteristics including intensity, morphology and color have been investigated to localize the disk in the presence of distractors [Sinthanayothin et al. 1999]. In [Vimala and Mohideen 2013], Vimala and Mohideen used a fuzzy c-means clustering and the line operator technique to detect the optic disc. The image is preprocessed by using LAB color space technique. Differently, Krishnan et al. in [Krishnan et al. 2012] used Attanassov intuitionistic fuzzy histon (A-IFSH) based segmentation technique. Then, the algorithm applied an intensity based and neighborhood operation to search for the optic disc on the segmented image. This strategy achieved good results in images of the same database. However, the aforementioned characteristics differ widely among different image databases.

A number of authors have investigated the Hough transform (HT) for the the OD localization [Sekhar et al. 2008, Zhu et al. 2010]. This transform is highly tolerant of gaps in feature contour descriptions and it is relatively unaffected by image noise. This is an useful aspect when attempting to isolate the OD, which often does not present a clearly defined edge and furthermore vessels break the OD edge. However, edge detection algorithms often fail to provide an acceptable solution due to the fuzzy boundaries. The seven implemented OD detection algorithms are described in the following.

2.1. Method of Liu et al.

Liu et al. [Liu et al. 1997] used the Hough transform to develop a methodology capable of identifying the OD and fovea. They applied the OD detection algorithm to the red color component, considering that the blood vessels in the OD do not appear in this component and may interfere with the edge detection in the green channel. The algorithm searched for the candidate area which is a region of 180×180 pixels that includes the highest 2% gray levels. Then, it calculated the candidate area's gradient and detected its edge points by applying the Sobel operator. Finally, it estimated the size and position of the OD with the Hough transform technique and the detected edge points. According to Liu et al., tests were conducted on a set of 20 images collected at the Singapore Tan Tock Seng Hospital and the experimental results showed that two retinal images failed to be properly identified due to the blurred OD.

2.2. Method of Akram et al.

Akram et al. introduced in [Akram et al. 2010] an automatic method for OD detection on retinal images. The algorithm converted the image to the green channel and then it applied an averaging filter on the green channel to remove noise from the image background. As OD was considered as the brightest portion of retina, the authors localized the maximum gray level pixels in an image histogram. And these pixels were named ROI (region of interest). From this region, the method extracted the OD by applying the Hough transform and furthermore a Canny operator was used for edge detection and to plot a circle where the OD was detected. Akram et al. conduced the tests on DRIVE

(40 images) [Staal et al. 2004], STARE (20 images) [Hoover et al. 2000], DIARETDB0[1] (130 images), and DIARETDB1[2] (89 images) database. The algorithm achieved an overall success rate was 96.7%. The authors assessed the detection results as success or failure based on human eye observation.

2.3. Method of Rajaput et al.

Rajaput et al. [Rajaput et al. 2011] introduced a method for fovea center localization in digital color eye fundus images. Thismethod is based on prior knowledge of OD center and diameter. For OD detection, they applied a histogram equalization to the red channel for contrast enhancement and then inverted the image result. Then, the authors identified the areas with minimal intensities using the extended minima transform (EMT). The EMT is the regional minima of h-minima transform. The authors empirically set the h-value (threshold height) to 20. The output was a binary image with the white pixels representing the regional minima in the original image. Regional minima are connected pixels with the same intensity value, whose external boundary pixels all have a higher value. To eliminate falsely detected regions, the authors applied a morphological opening with a disk shaped structuring element of size 8. Finally, the algorithm computed the mean intensities of the identified areas and selected the region with the lowest mean intensity as the OD region.

2.4. Method of Dehghani et al.

Dehghani et al.[Dehghani et al. 2012] used a number of retinal images to create a template of OD. However, instead of creating an image as model, they constructed three histograms as templates, each corresponding to one color component. The algorithm applied an average filter to decrease the effect of noise in processing images. Then, it extracted from each retinal image a window with the typical size of the OD (80×80). In the next step, it separated the color channels (red, blue, and green) of each OD to obtain the histogram of each color component. Finally, it calculated the mean histogram of each color component for all retinal image samples to form the template. After calculating the three histograms and setting them as templates, the algorithm then computed the correlation between the histogram of each channel in the moving window and the histograms of its corresponding channel in template to detect the OD in the retinal image. Dehghani et al. used the OD of the first four retinal images in DRIVE database to obtain their histograms as templates. The authors applied the proposed method on a dataset including 40 retina images from DRIVE dataset, 81 retinal images from STARE database, and 273 retinal images from a local database. The success rate was 100%, 91.36%, and 98.9% for these three datasets, respectively.

2.5. Method of Sekar and Nagarajan

Sekar and Nagarajan [Sekar and Nagarajan 2012] proposed a method for OD localization based on clustering and histogram approaches. This method determined the candidate regions by clustering the brightest pixels in the red plane of the fundus image. Then, it identified three OD candidate pixels within the candidate region of the green plane by using three independent methods namely maximum difference method, maximum variance method and Gaussian low pass filtering method. And the method selected three sub

[1] Available in http://www2.it.lut.fi/project/imageret/diaretdb0/index.html
[2] Available in http://www2.it.lut.fi/project/imageret/diaretdb1

images inside these three candidate regions. After finding the histogram of each of the sub images, the method located the center of the OD by selecting a sub image with a large number of bright pixels in the blue plane. The method was validated on MESSIDOR [Messidor 2008] database and successfully found the OD in 1194 cases out of 1200 images. The authors reported that the results produced a success rate of 99.50%. Actually, the authors did not clearly explain the strategy adopted in the evaluation methodology.

2.6. Method of Punnolil

Punnolil [Punnolil 2013] presented an automated system for maculopathy severity grading and detection. This approach detected the centre of OD and the fovea region by using superior and inferior vascular arcades within the retina. This automated system for macula localization is based on the OD detection and therefore its detection is a crucial step for this approach. Initially a morphological closing operator is applied to the green channel with a flat, octagonal structuring element of fixed radius fifteen to eliminate the blood vessels that may remain in the OD region. Then, a columnwise neighborhood operator was applied to set each output pixel of the image to the variance value of the input pixel's using 11-by-11 sliding neighborhood. The resulting image was binarized with a threshold value of 0.95 based on iterative estimation.

2.7. Method of Zubair et al.

Zubair at al. [Zubair et al. 2013] proposed a method to detect the OD on the basis of its high intensity value by applying image contrast enhancement, contrast stretching and morphological operations. The contrast limited adaptive histogram equalization was used to enhance image features and increase significantly the contrast between background and foreground. Hereafter, Zubair at al. applied the contrast stretching transform to improve the image contrast. After this step, the OD region was enhanced and thus detected taking into account the information of its highest intensity value and its relatively large size among the other non OD candidate regions. Finally, morphological operations were applied to remove all non optic disc candidate regions.

3. Experiments

3.1. Image Database

To perform the evaluation of the algorithms, we have selected five public retinal image databases: STARE [Hoover et al. 2000], DRIVE [Staal et al. 2004], ARIA [Damian 2006], MESSIDOR [Messidor 2008] and DRIONS_DB [Carmona et al. 2008]. Tests of retinal image processing algorithms are usually conducted on subsets of images instead of using the whole image database. Differently, our tests include the whole image databases and furthermore we have excluded only those images whose ground-truth are not available.

Regarding the STARE database, we used a subset of 103 images. In fatc, this subset consists of 36 images of healthy retinas and 67 images that exhibit a wide variety of lesions and other disease symptoms. The DRIVE database contains 40 fundus images from subjects with diabetes.

Members of St Paul's Eye Unit and the University of Liverpool collected all images from the ARIA database as part of the ARIA project. Thus, our tests were conducted on 116 images of ARIA database, 61 images of healthy patients and 55 images of diabetic patients who have some kind of pathology in their retinas. Another database named MESSIDOR has a total of 1200 images. Medical experts provided two diagnoses for each image of the MESSIDOR database: retinopathy grade and risk of macular edema. In total, this database includes 660 healthy images and 540 pathological images. The DRIONS_DB database consists of 110 color digital retinal images from an eye fundus image base which belongs to the Ophthalmology Service at Miguel Servet Hospital, Saragossa (Spain).

3.2. Methodology for Performance Evaluation

The OD localization is usually related to the center identification of the disk either by specifying the center of the OD or placing a mask within a particular region of the retina.

Tobin et al. [Tobin et al. 2007] introduced a simple methodology to assess the performance of OD detection methods, which compares the estimated coordinates (x_E, y_E) to a coordinate pair that was manually labeled as the OD center (x_{OD}, y_{OD}). This approach labels the result as success if Equation 1 is valid

$$\sqrt{(x_{OD} - x_E)^2 + (y_{OD} - y_E)^2} \leq 1R, \tag{1}$$

where $1R$ means 1 OD radius.

In this paper, we have obtained the coordinates of the center and the maximum OD radius for each database using the outlined contour of the OD ground-truth images. For the DRIVE database the maximum radius was 40 pixels in length. Concerning the STARE and ARIA databases, we adopted 103 and 55 pixels for the OD radiuses, respectively. Particularly, we used three values, 70, 104 and 110 pixels for the MESSIDOR database.

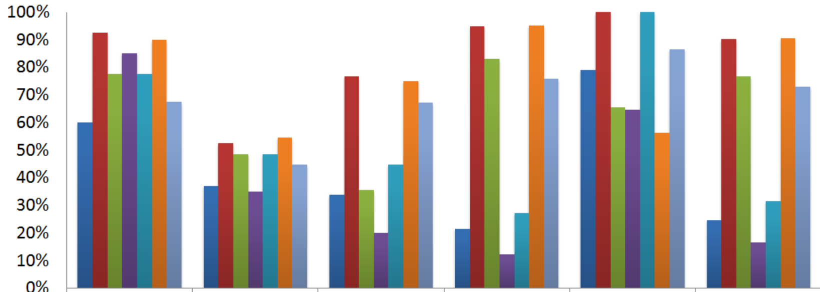
3.3. Experimental Results

In order to evaluate the algorithms, we have applied the algorithms to 790 healthy images and 779 images with pathologies, a total of 1569 images of five public database: 103 images from STARE database (36 healthy and 67 with pathologies), 40 images from DRIVE database (33 healthy and 7 with pathologies), 116 images from ARIA (61 healthy and 55 with pathologies), 1200 from MESSIDOR database (660 healthy and 540 with pathologies) and 110 images from DRIONS database(all with pathologies).

Figure 2 shows the overall evaluation result of the OD detection algorithms on five image databases. From the tests, we confirm that ARIA and STARE databases are more challenging than DRIVE and MESSIDOR. This fact is justified by the high diversity of diseases and damages caused by them.

The method of Akram et al. achieved the best results for DRIVE, ARIA and DRIONS databases with 90.27% of global success rate. Its best performance was in DRIONS database with 100.00% success rate, whereas the worst result was in STARE with 52.42%. Similarly, Punnolil's method achieved the best results for STARE and MESSIDOR databases with 90.47% of global success rate. Its best performance was in MESSIDOR database with 95.08% success rate.

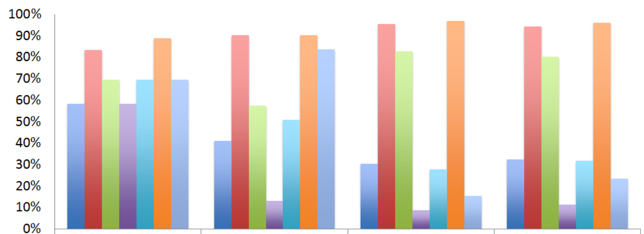
The worst performances of the methods are: Liu et al. method reached a success rate of 60.00% for ARIA, whereas Dehghani et al. reached success rates of 34.95%,



	DRIVE	STARE	ARIA	MESSIDOR	DRIONS	All images
Liu et al. (1997)	60.00%	36.89%	33.62%	21.50%	79.09%	24.61%
Akram et al. (2010)	92.50%	52.42%	76.72%	94.75%	100.00%	90.27%
Rajaput et al. (2011)	77.50%	48.54%	35.34%	83.00%	65.45%	76.63%
Dehghani et al. (2012)	85.00%	34.95%	19.82%	12.25%	64.54%	16.45%
Sekar and Nagarajan (2012)	77.50%	48.54%	44.82%	27.00%	100.00%	31.32%
Punnolil (2013)	90.00%	54.37%	75.00%	95.08%	56.36%	90.47%
Zubair et al. (2013)	67.50%	44.66%	67.24%	75.91%	86.36%	72.78%

Figure 2. Effectiveness of the algorithms in detecting the OD center.

19.82% and 12.25% for STARE, ARIA and MESSIDOR, respectively. Punnolil's method reached the worst results for DRIONS database. In general, the method of Dehghani et al. obtained the worst result with only 16.45% success rate. Although the images from the DRIVE and DRIONS database may include some pathological lesions, this information is not completely specified in the supplied dataset. On the other hand, the ARIA and the MESSIDOR databases contain the whole information about the retinal images status: healthy or pathological. In this paper, we use this information to identify methods that are more sensitive to the presence of pathologies. Therefore, Figure 3 presents the evaluation results for healthy images whereas Figure 4 shows the results for pathological ones.

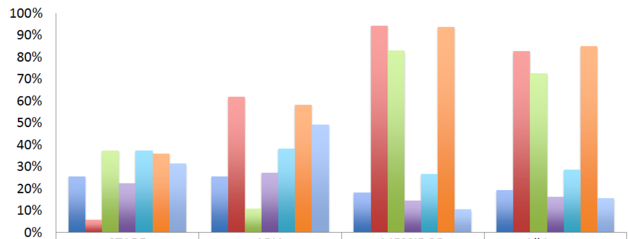


	STARE	ARIA	MESSIDOR	All images
Liu et al. (1997)	58.33%	40.98%	30.20%	32.41%
Akram et al. (2010)	83.33%	90.16%	95.36%	94.37%
Rajaput et al. (2011)	69.44%	57.38%	82.78%	80.10%
Dehghani et al. (2012)	58.33%	13.11%	8.60%	11.33%
Sekar and Nagarajan (2012)	69.44%	50.82%	27.81%	31.64%
Punnolil (2013)	88.89%	90.16%	96.85%	95.93%
Zubair et al. (2013)	69.44%	83.60%	15.37%	23.44%

Figure 3. Effectiveness in detecting the OD center in healthy images.

Regarding the subset of healthy images, the method of Akram et al. obtained the best global result (94.37%) with success rate of 83.33% in STARE, 90.16% in ARIA and 95.36% in MESSIDOR database. Liu et al. obtained the worst result for the STARE database (58.33%), whereas the method of Dehghani et al. performed badly for ARIA and MESSIDOR databases (13.11% and 8.6%).

For subsets of pathological images of ARIA and MESSIDOR databases, the method of Akram et al. outperformed the others and achieved the best results 61.82%



	STARE	ARIA	MESSIDOR	All images
Liu et al. (1997)	25.37%	25.45%	18.07%	19.42%
Akram et al. (2010)	5.82%	61.82%	94.38%	82.71%
Rajaput et al. (2011)	37.31%	10.91%	83.13%	72.49%
Dehghani et al. (2012)	22.38%	27.27%	14.45%	16.32%
Sekar and Nagarajan (2012)	37.31%	38.18%	26.51%	28.57%
Punnolil (2013)	35.82%	58.18%	93.64%	84.84%
Zubair et al. (2013)	31.34%	49.09%	10.45%	15.77%

Figure 4. Effectiveness in detecting the OD center in pathological images.

and 94.38%, respectively. Rajaput et al. achived the best results for STARE database. The worst performances (22.38%, 27.27% and 14.45%) were obtained by Dehghani et al. for STARE, ARIA and MESSIDOR databases, respectively.

4. Conclusion

In this paper, we have conducted experiments to evaluate the performance of seven methods on five different fundus image databases, simultaneously. We implemented OD detection algorithms, and addressed the difference among them, when considering normal and abnormal cases.

The importance of the OD detection algorithms is that they can provide inputs for automatic screening systems for glaucoma diagnosis, for example. Usually, automatic glaucoma grading systems require OD detection in both healthy and pathological retina images. In the former, the retina background is generally homogeneous, on the other hand, in unhealthy retinas the presence of artifacts impairs the search for the OD.

Our experiments have also showed that images with pathologies are more challenging to detect OD and therefore we can measure the robustness of the OD detection algorithms applying them to this kind of images. We conclude that the OD segmentation methods that encompass preprocessing steps that dealt with retina image degradation by illumination, lack of homogeneity in the optic disk region, blurring and pathological findings (hemorrhages, micro-aneurysms, etc.) were likely to succeed in the OD localization.

Moreover, we observed from this study that the development of algorithms capable of detecting many ocular diseases (e.g. macular edema, glaucoma, diabetic retinopathy) is still an open and wide research area that includes several challenges. Overall, we envision to combine information about other retina structures to provide more accurate automated diagnosis.

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