A Study on Automatic Segmentation of Optic Disc in Retinal Fundus Images

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Abstract
Diabetic Retinopathy (DR) is one of the main causes of vision loss in the world among patients suffering from diabetes. DR is a chronic eye disease, which can be controlled by regular checkup & treatment. If left untreated, loss of vision occurs gradually and become blind. The detection and diagnosis of DR is important. DR is characterized by its features like, micro aneurysms (MAs), hemorrhages, hard exudates, soft exudates and cotton wool sports. The presence of exudates is the distinguished sign of non-proliferative DR. For successful detection of exudates, it is necessary to localize the optic disc (OD) in the retinal image under study as a result, it appears in a similar bright pattern, color and contrast as exudates appear.
In this paper, we highlight the various techniques used for segmentation of OD and optic cup used by different authors performing experiments on standard and local database of fundus images.

Keywords— *Diabetic Retinopathy, Optic Disc, Microaneurysms, Hemorrhages, Exudates, Segmentation, Fundus Image.*

1. Introduction

Everywhere in the world ophthalmologists everywhere in the world depends on fundus images of the retina in order to diagnose and treat numerous diseases that have an effect on the retina. Therefore, experts have been applying digital image processing techniques to retinal images with the most aim of distinguishing, locating and analyzing the retinal landmarks which are the OD, macula, and blood vessels. This computer-aided image analysis, in turn, allows the detection of the retinal lesions and abnormalities which have an effect on the general appearance and semblance of the identification of retina. Hence, the early identification of irregularity which have an effect on the fundus image like MAs, exudates, hemorrhages, and change in shape and size of the blood vessels and / or the OD, leads to diagnosing and expectation of other major pathological problems that the eye might suffer from such as DR, macular edema, glaucoma (ocular hypertension), and blindness. Fundus, Latin word "bottom", is anatomical term referring to the portion of an organ opposite from its gap. Hence, the fundus of the attention is that the interior surface of the eye, opposite the lens, and includes the retina, OD, macula and fovea, and posterior pole [1]. The eye's fundus is the solely organ of the central system of the soma which will be imaged directly since it are often seen through the pupil [1, 2]. Therefore, numerous numbers of retina images are analyzed by the ophthalmologists all over the world, and over the past two decades researcher have applied digital image processing methods to ophthalmology with the aim of improving diagnosis of various diseases that affect the eye like DR, MAs, hemorrhages, glaucoma, neovascularization, etc. [1, 2]. Some of the functions performed by the inner surface of the human eye, along with their semblance and characteristics, are represented below:

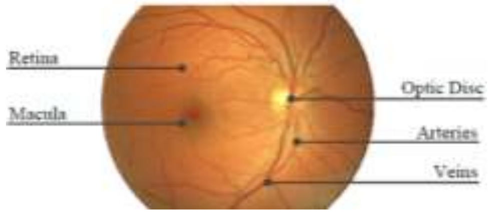

Fig. 1: Eye Fundus Image

- **Retina:** contains light sensitive cells referred to as cones and rods, which are responsible for day vision and night vision, respectively; the retina is the tissue wherever the image is projected since it receives the images generated by the lens and regenerate them into signals that reach the brain by the means that of the optic nerve. The color of the retina varies naturally in keeping with the color of the light employed; but, the color of the normal fundus are also represented as starting from orange to vermillion [2].
- **Optic Disc:** also referred to as the optic nerve head or papilla. This is a circular area wherever the optic nerve enters the retina; it doesn't contain receptors itself, and thus it is the blind spot of the attention. The shape of the OD is round or vertically oval, measuring about 2mm in diameter, and typically seems as a bright yellowish or white space. Also, large blood vessels are found in the neighborhood of the OD [2, 3].
- **Macula & Fovea:** macula is a part of the eye near the middle of the retina that allows us to clear visual. The fovea is a depression within the retina layer that contains only cones not rods, and that provides accurate eyesight focus. The fovea, which is at the middle of the area referred to as the macula, is an oval-shaped, blood vessel free reddish spot. It is approximately 5mm from the

middle of the OD (equal to 2.5 times the diameter of the OD [2].

- **Blood Vessels:** like the remainder parts of the human body, arteries and veins are the two main parts of blood vessels responsible for the blood supply. Arteries carry fresh blood from the heart and lungs to the eye, whereas veins take away the blood that has been used by the eye and return back it to the lungs and heart to be refreshed with oxygen and different nutrients [4]. The major branches of the retinal vasculature originate from the center of the OD to the four quadrants of the retina. In the macular region, all the vessels are arch shape surrounding retina, sending only part of a vessels towards the vascular fovea regions. The arteries appear with the illumination of red color and are slightly thinner than the veins [2].

Detecting the OD and analyzing its spatial structure help us to indicate the various pathologies such as DR and glaucoma. As because of confusing between exudates and the OD (Fig. 2-b), DR can be diagnosed by identifying and removing the OD which in turn improves the identification of exudates, which is one of the main abnormalities in DR [3, 5,6].

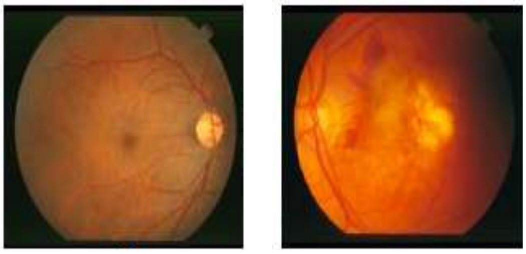

Fig. 2. (a) Normal retina (b) DR (with Exudates)

Also, the cup-to-disc ratio (CDR) is an important structural that indicate the presence of glaucoma. The glaucoma is characterized by the cupping of the OD which changes in ischemic due to the imbalance between the intraocular pressure and the perfusion pressure in the vessels of the retina [2], as shown in Fig. 3.

Fig. 3. (a) Normal O.D (b) Glaucomatous O.D.

2. Ophthalmology Image Processing

Majority of works managing ophthalmology image processing is divided into two broad types [2, 7]:

2.1. Automated Detection of Abnormalities

This part helps in identification of the abnormalities in the retina. Ophthalmologists used to diagnose, predict and monitor the progress of the disease that a patient is suffering.

- **Disease diagnosis:** specify to detecting the abnormal symptoms in the retina like exudates, MAs and hemorrhages in order to diagnose diseases that affect the retina like DR, glaucoma, macular edema, etc.
- **Disease prediction:** refers to observing the retinal disorders which might result in different pathological conditions or vision loss.
- **Disease progress monitoring:** referred with comparing the movement of the states in the eye at explicit intervals of time to observe the development or deterioration of some sickness.

2.2. Automated Segmentation of Landmarks

The eye fundus is being divided so as to find and isolate the retinal landmarks, namely the OD, macula, fovea, veins and arteries.

- **Optic disc segmentation:** the OD is the landmark in retinal images, and shows changes related to diseases including diabetic retinopathies and glaucoma. The OD is a landmark so as to find different fundus features like the macula and blood vessels [3].
- **Macula and fovea segmentation:** locating the macula is necessary in detecting diseases like macular degeneration and macular edema [6].
- **Vascular segmentation (veins & arteries):** analyzing the blood vessels in the retina is vital for detection of diseases of blood circulation like DR.

3. Retinal Image Datasets

The retinal images are considered as the raw material to be enhanced, segmented and evaluated. Image datasets are naturally accompanied with a ground truth which acts as a benchmark for checking and estimating the experimental results using the results provided by ophthalmologists on an image dataset. Below table 1 shows a list of the most widely used datasets of retinal images employed for OD image processing, in particular.

Database	Data base Size	Image Size (Pixel)	FOV Field of View	Image Format	Ground Truth
STARE [24] Structured Analysis of Retina	81	700 * 605	35 degree	PPM	Blood Vessels
DRIVE [25] Digital Retinal Images for Vessel Extraction	40	565 * 584	45 degree	TIFF	Blood Vessels
DIARETDB0 [26]	130	1500 * 1152	50 degree	PNG	Microanerusym, Hemorrages, Hard & Soft Exudates
DIARETDB1[27]	89	1500 * 1152	50 degree	PNG	Microanerusym, Hemorrages, Hard & Soft Exudates
MESSIDOR [28] Methods to Evaluate Segmentation and Indexing Techniques in the Field of Retinal Ophthalmology	1200	1440 * 960 2240 * 1488 2304 * 1536	45 degree	TIFF	Retinopathy Grading, Hard Exudates

Table 1: Retinal images datasets [Accessed 20 May 2016]

Other publicly available databases, such as REVIEWdb, HRF, ONHSD, ARIA, CMIF, JRD, ROC and LEDGE, which are not described here as they are not commonly used by researchers in OD segmentation.

4. Evaluation Metrics

Although the evaluation of an algorithm comes at the final stage of a detection and segmentation technique, although the metrics used for evaluation are reviewed here prior to, in order to provide a concrete understanding of the results achieved by the segmentation algorithms within the literature review.

In diagnosing, the region of interest ROI (i.e. landmark or lesion) is typically classified into two classes: present or absent; during which the response given by ophthalmologists or a computer process is: positive or negative.

Therefore, the detection of the ROI is generally depicted using the terms given in table 2 [8]. The evaluation of the medical imaging test is typically determined by the indexes for the true positive (TP), true negative (TN), false positive (FP), false negative (FN).

	Present ROI	Absent ROI
Positive Response	Hit (T_P)	False alarm (F_P)
Negative Response	Miss (F_N)	Correct rejection (T_N)
	SENS=$\frac{T_P}{T_P+F_N}$	SPEC=$\frac{T_N}{T_N+F_P}$

Table 2: Signal detection indices and derived evaluation metrics

The TP and TN indices refer to the successful response to find and reject region of interests, respectively. The true positive index (TP) refer to the positive response of a human or computer for the ROI that is present in the retina, where as the true negative index (TN) refer to the negative response to the abnormality that is not present. On the other hand, the FP and FN indices refer to unsuccessful rejection and detection, respectively. The false positive index (FP) indicates the positive response to the ROI that is not present, whereas the false negative index (FN) indicates the negative response for the ROI that is present.

Derived from the four aforesaid indices as shown in table 2, four statistical metrics are computed in order to find the detection of landmarks or abnormalities that are: sensitivity, specificity, positive predictive value, and negative predictive value.

4.1. Sensitivity and Specificity

Sensitivity is a measure that reflects the probability of a positive response for the cases during which the landmark or abnormality present, whereas specificity is the probability of negative response for the cases during which the abnormality is absent. Both, sensitivity and specificity are expressed either by a proportion or a percentage find by the equation shown in table 2, in which sensitivity and specificity are typically referred to as true positive rate and true negative rate, respectively. Moreover, the term false positive rate (FPR) is used for the calculation of specificity, computed as (1 − specificity) [9].

5. Survey of Methodologies used for Optic Disc and Optic Cup Segmentation

To calculate the vertical cup to disc ratio (CDR), the optic cup and OD first have to be divided from the retinal images. Its segmentation are carried out only on retinal fundus images. OD segmentation is mostly applied in the red channel attributable to higher contrast between OD and non OD region. Region of interest is mostly located in several cases because it reduces the size of the image and makes the computation quick and accurate. Problems in the disc segmentation is mainly due to vessels present and are overcome by pre-processing image using the morphological operations like opening and closing. Optic cup segmentation is tougher as compared to OD segmentation attributable to cup's interweavement with blood vessels and surrounding tissues. Optic cup segmentation is sometimes applied in green channel due to less visibility of vessels during this channel. Some of the approaches used so far for OD and optic cup segmentation are as follows:

5.1. Property-based methods

This type of methods is directly based on the above mentioned property of the OD (e.g. location, size, color and shape). In the early work of the OD detection, Goldbaum et al. [16] utilized most of these properties so as to collectively find the OD. They combined three properties of the OD: the convergence of blood vessels at the OD, the appearance of the OD as a bright region, and entrance of large vessels above and below the OD.

Sinthanayothin et al. [14] located the OD by identifying the area with highest variation in intensity of adjacent pixels using a window whose size equal to that of the OD. Their approach correctly detected the OD with sensitivity and specificity of 99.1% on a local dataset composed of 112 images of the fundi patients.

Walter and Klein [17] approximated the centroid of the OD as the largest at the center and brightest connected object in the fundus image. Their method successfully detected OD in all images of a local dataset composed of 30 color images, and achieved a success rate of 90%.

Using the Circular Hough remodel, Abdel-Ghafar et al. [18] were able to notice the OD by finding the most important circular object. Similarly, Zhu et al. [19], [2] also used the Hough Transform method to notice the circles in that the best-fitting circle for the OD was chosen by employing a technique of intensity-based choice. They achieved a successful detection rate of 90% on the DRIVE dataset.

S. Lu [11] a circular transformation was designed to capture each of the circular forms of the OD similarly because the image variation across the OD boundary, simultaneously. The variation of each pixel within the retinal image was measured on multiple evenly-oriented radial line segments of specific length. The pixels with the maximum variation on all radial line segments were determined, which were then exploited to find each the center and therefore the boundary of the OD. Experimental results showed that the OD was detected accurately in 99.75%, 97.5%, and 98.77% of the STARE, ARIA and MESSIDOR datasets, respectively. Also, the OD was accurately segmented in 93.4% and 91.7% of the STARE and ARIA datasets, respectively.
Carmona *et al.* [20] proposed a genetic algorithm in order to obtain an ellipse that approximated the OD. First, they obtained a set of hypothesis points that exhibited the geometric properties and intensity levels similar to the OD contour pixels. The genetic algorithm was used to find an ellipse that contains the maximum number of hypothesis points in an offset of its perimeter. The result of their algorithm was 96% of the 110 retinal images had less than five pixels of discrepancy.

5.2. Convergence of blood vessels
Instead of counting on the properties of the OD, an various approach to notice the OD is to use the data provided by the tube-shaped structure tree of the membrane, since the OD takes into account because the convergence OD of the few major blood vessels that split into several smaller vessels throughout the membrane [3].

Taking advantage of this spatial relationship between the OD and blood vessels, Hoover and Goldbaum [13] developed a voting-type algorithm referred to as fuzzy convergence in order to notice the origination of the blood-vessel network (i.e. convergence OD) which was thought of as the center of the OD during a bodily structure image. The input to their algorithm was a binary segmentation of the blood vessels, in which every vessel was sculptured by a fuzzy section that contributed to the additive option image. The output of the algorithm was a convergence, image that was thresholded to determine the strongest OD(s) of convergence. This technique successfully detected 89% of the conventional and abnormal images within the STARE dataset.

Fleming et al. [21] detected the approximate region of the OD using elliptical shape of the major retinal vessels that was formed uses the Generalized Hough Transform. The approximate location of the OD was then refined via the Circular Hough Transform achieving successful rate of 98.4% of the 1056 retinal images, in which the OD accuracy was higher than 50% of the diameter of the OD.

In the work of Rangayyan et al. [22, 2] the blood vessels were first detected using Gabor filters, and then phase portrait, modeling was applied to detect the convergence ODs of the vessels, in which the best-fitting circle for the OD was chosen by using an intensity-based condition. This approach achieved success rates of 100% and 88.9% for the DRIVE and STARE datasets, respectively.

5.3. Model-based methods (template-matching)
This type of methods is based on comparing a template image (model) with a set of candidates in order to determine the best-matching candidate. Lalonde et al. [10] implemented a Hausdorff-based template matching method using edge maps, guided by pyramidal decomposition for large-scale object tracking where small bright lesions (e.g. exudates) disappear, creating fewer OD candidates. The edge map regions were matched to a circular template with completely different radii using the Hausdorff distance, region having the large number of overlapped template pixels was considered the OD. This approach properly detected the center of the OD in 93% of a dataset of 40 images.

Osareh et al. [23] proposed a model-based approach that created a gray-level template image by averaging the OD region of 25 images whose colors were normalized by histogram specification. The center of the OD was located using the generated template with gray-scale morphological filtering and active contour modeling in which the normalized coefficient of correlation was used to find the most similar match between the template and all the candidate pixels, with an average accuracy of 90.32% in detecting the boundary of the OD of 75 images of the retina.

Youssif et al. [3] proposed a model-based method of matching the expected directional pattern of the retinal blood vessels found within the neighborhood of the OD. They obtained a vessels direction map of the retinal vessels that were segmented using 2D Gaussian matched filter. The low difference between the matched filter and the vessels directions in the surrounding area of each of the OD candidates achieved a successful detection rate of 100% on the DRIVE dataset and 98.77% on the STARE dataset.

Aquino et al. [12] presented another template-based methodology that used morphological and edge detection techniques followed detection of circular OD boundary approximate by the Circular

Hough Transform. Their methodology needs an initial pixel located within the OD, and for this process, a location based methodology used in a voting-type formula and succeeded in 99% cases. The algorithms were evaluated on 1200 images of MESSIDOR dataset; achieve a success rate of 86%.

Lu [24] proposed a method for detection of the OD this method completely differs from that of one he used. In the proposed method, the retinal background surface was first evaluated by an iterative Savitzky-Golay smoothing procedure. Afterwards, multiple OD candidates were identified through the difference between the retinal image and the calculable retinal background surface. Finally, the real OD was selected through the combination of the difference image and the directional retinal blood vessel which was based on the observation that the retinal blood vessels were mostly oriented vertically as they exit the OD. The proposed technique was evaluated over 4 different datasets and achieved success rate of 98.88%, 99.23%, 97.50% and 95.06% for DIARETDB0, DIARETDB1, DRIVE and STARE respectively.

Creating an image and using it as a template, Dehghani et al. [15] constructed 3 histograms as a template for localizing the center of the OD using 4 retinal images from the DRIVE dataset, each histogram shows one color channel. Then, an 80×80 window was moved on the retinal image of each channel to obtain the histogram. Lastly, they evaluated the correlation between the histogram of each channel in the moving window and the histograms of its corresponding channel in the template. The DRIVE, STARE, and a local dataset is used which composed of 273 images to evaluate their proposed algorithm, and calculated the success rate of 100%, 91.36% and 98.9%, respectively.

6. Discussion and Conclusion

The performance of the segmentation methods were usually compared via evaluation metrics such as sensitivity and specificity. The algorithms are conjointly classified into 3 categories: vessels convergence ways, property-based methods, and template-based methods.

Moreover, the following conclusions are determined from the angle of every stage of the OD image processing:

Image Datasets

From the perspective of the datasets employed to phases the OD and value their results, the STARE and DRIVE datasets were considered as the gold normal for many of the planned segmentation algorithms. However, other additional datasets such as MESSIODOR and DIARETDB0, and DIARETDB1 were also used sometimes by some of the algorithms. It was observed that segmentation algorithms accomplish higher results victimization the DRIVE dataset compared thereto achieved with the STARE dataset. This is due to the good-quality images within the DRIVE dataset compared to the scanned images within the STARE dataset, as well because the presence of bright lesions within several of the STARE images.

Image Preprocessing

Preprocessing techniques potentially lead to accurate and faster results at the segmentation stage. For instance, the fundus images in most of the presented algorithms were initially masked out via a binary image in order to discard the dark background from more gratuitous process. Also, in order to produce the best contrast for a picture, most algorithms extensively exploited the green channel of the image, whereas alternative fewer ones used the red channel, whereas the blue channels are not used. Also, some algorithms exploited the intensity channel in the HSI color model. Moreover, this contrasted-image was re-enhanced using techniques such as bar chart feat and its variations (e.g. AHE and CLAHE), as well as other methods that increase the sharpness of the ridges, such as unsharp masking, wavelet, contourlet, and curvelet transforms. These latter sharpening techniques proved to be additional helpful in enhancing the distinction of retinal vessels, however they were compared in enhancing the distinction of the OD.

Image Segmentation

The OD segmentation approaches, in this survey, were categorized into: property-based ways, blood vessels convergence methods, and template-matching methods. As a concluding observation, it is obvious that the methods supported the properties of the OD (e.g. its circular shape, brightness, size, etc.) achieved best results in local datasets, images that contained no abnormalities, but such approaches sometimes failing to discover the OD in pathological images wherever abnormalities, such as large exudates, were confused with the OD due to their similar appearance.

As a result, alternative approaches were followed by researchers in order to discover the OD while not entirely looking forward to the properties of the OD. These approaches exploiting the information provided by the tube tree of the tissue layer, since the OD takes into account because the convergences OD of the foremost blood vessels. Moreover, other primarily based approaches relied on making a template image (model) on the OD properties at the side of the blood vessels, properties (e.g. orientations, convergence, width, etc.), in order to see the best-matching OD candidate. These approaches based on vessels-convergence and template matching tried to attain higher sensitivity rates than that achieved by the property-based ways, since the number of false responses were greatly reduced within the presence of alternative similar abnormal artifacts. But, on the other hand, such approaches obviously take additional processing time than property-based methods.

Evaluation Metrics
From the perspective of calculating the segmentation techniques, all the proposed segmentation algorithms were evaluated in terms of the sensitivity (i.e. the true positive rates of detecting the OD). A few of those algorithms also provided the accuracy share of the divided OD, while the specificity were seldom provided due to its insignificance as a result of it is the likelihood of a negative response of the cases wherever the OD was absent, or more exactly, not apparent.

This survey reviewed the process of detection work and segmenting the OD, showing the techniques and methodologies that were followed for that purpose. It started by showing the public on the local databases of retinal images. The paper then checks the techniques used to enhance the raw fundus images, such as the contrast improvement, illumination correction, mask generation, etc. At the end, the survey categorized the ways used for segmenting the OD, which was classified into property-based, vessels-convergence, and template-matching methods.

7. References

1. K. Mahesh K. and K. Nilesh S., "Review on Fundus Image Acquisition Techniques with Database Reference to Retinal Abnormalities in Diabetic Retinopathy," International Journal of Computer Applications, vol. 68, no. 8, pp. 17-27, April 2013.
2. X. Zhu, R. M. Rangayyan and A. L. Ells, "Digital Image Processing for Ophthalmology: Detection of the Optic Nerve Head," in Synthesis Lectures on Biomedical Engineering, Morgan & Claypool Publishers, 2011.
3. A. A. A. Youssif, A. Z. Ghalwash and A. A. S. A. Ghoneim, "Optic Disc Detection From Normalized Digital Fundus Images by Means of a Vessels' Direction Matched Filter," IEEE Trans. Med. Imag., vol. 27, no. 1, pp. 11-18, 2008. DOI: 10.1109/TMI.2007.900326
4. Royal National Institute of Blind People (RNIB), "Retinal vessel occlusion," 7 Aug 2013. [Online]. Available: http://www.rnib.org.uk/eyehealth/ eyeconditions/eyeconditionsoz/Pages/ retinal_ vessel _occlusion.aspx. [Accessed 19 Aug 2013]
5. Mohammed Shafeeq Ahmed, Dr. B. Indira, “A Survey on Automatic Detection of Diabetic Retinopathy” International Journal of Computer Engineering and Technology, Volume 6, Issue 11, Nov 2015, pp. 36-45, ISSN Print: 0976-6367.
6. G. Schaefer and A. Clos, "Image Analysis for Exudate Detection in Retinal Images," in Biocomputation and Biomedical Informatics: Case Studies and Applications.: Medical Information Science Reference, 2010, pp. 198-203.
7. N. Patton, T. M. Aslam, T. MacGillivray, I. J. Deary, B. Dhillon, R. H. Eikelboom, K. Yogesan and I. J. Constable, "Retinal image analysis: Concepts, applications and potential," Progress in Retinal and Eye Research, vol. 25, pp. 99-127, 2006. DOI: 10.1016/j.preteyeres.2005.07.001
8. E. M. Beytas, J. F. Debatin and R. A. Blinder, "Accuracy and predictive value as measures of imaging test performance," Invest. Radiol., vol. 27, no. 5, pp. 374-378, May 1992.
9. P. Macaskill, C. Gatsonis, J. Deeks, R. Harbord and Y. Takwoingi, "Analysing and Presenting Results," in Cochrane Handbook for Systematic Reviews, J. Deeks, P. Bossuyt and C. Gatsonis, Eds., The Cochrane Collaboration, 2010.
10. M. Lalonde, M. Beaulieu and L. Gagnon, "Fast and Robust Optic Disc Detection using Pyramidal Decomposition and Hausdorff-Based Template Matching," IEEE Trans. Med. Imag., vol. 20, no. 11, pp. 1193-1200, Nov 2001. DOI: 10.1109/42.963823
11. S. Lu, "Accurate and Efficient Optic Disc Detection and Segmentation by a Circular Transformation," IEEE Trans. Med. Imag., vol. 30, no. 12, pp. 2126-2133, Dec 2011. DOI: 10.1109/TMI.2011.2164261
12. A. Aquino, M. E. Gegúndez-Arias and D. Marín, "Detecting the Optic Disc Boundary in Digital Fundus Images Using Morphological, Edge Detection, and Feature Extraction Techniques," IEEE Trans. Med. Imag., vol. 29, no. 11, pp. 1860-1869, Nov 2010. DOI: 10.1109/TMI.2010.2053042
13. A. Hoover and M. Goldbaum, "Locating the Optic Nerve in a Retinal Image Using the Fuzzy Convergence of the Blood Vessels," IEEE Trans. Med. Imag., vol. 22, no. 8, pp. 951-958, 2003. DOI: 10.1109/TMI.2003.815900
14. C. Sinthanayothin, J. F. Boyce, H. L. Cook and T. H. Williamson, "Automated localisation of the optic disc, fovea, and retinal blood vessels from digital colour fundus images," British J. Ophthalmology, vol. 4, no. 83, pp. 902-910, 1999. DOI: 10.1136/bjo.83.8.902
15. A. Dehghani, H. A. Moghaddam and M. S. Moin, "Optic Disc Localization in Retinal Images using Histogram Matching," EURASIP Journal on Image and Video Processing, pp. 1-11, Oct 2012.
16. M. Goldbaum, S. Moezzi, A. Taylor, S. Chatterjee, J. Boyd, E. Hunter and R. Jain, "Automated diagnosis and image understanding with object extraction, object classification, and inferencing in retinal images," in Proc. IEEE Int. Congr. Image Process., 1996.
17. T. Walter and J. Klein, "Segmentation of Color Fundus Images of the Human Retina: Detection of the Optic Disc and the Vascular Tree Using Morphological Techniques," in Proc. 2nd Int. Symp. Medical Data Analysis (ISMDA '01), p.p 282-287, 2001. DOI: 10.1007/3-540-45497-7_43
18. R. A. Abdel-Ghafar, T. Morris, T. Ritchings and I. Wood,"Progress Towards Automated Detection and Characterization of the Optic Disc in Glaucoma and Diabetic Retinopathy," Med. Inform. Internet Med., vol. 32, no. 1, pp. 19-25 March 2007. DOI: 10.1080/14639230601095865
19. X. Zhu, R. M. Rangayyan and A. L. Ells, "Detection of the Optic Nerve Head in Fundus Images of the Retina Using the Hough Transform for Circles," Journal of Digital Imaging, vol. 23, no. 3, pp. 332-341, June 2010. DOI: 10.1007/s10278-009-9189-5
20. E. J. Carmona, M. Rincon, J. Garcia-Feijoo and J. M. Martinez-de-la-Casa, "Identification of the optic nerve head with genetic algorithms," *Artificial Intell. Medicine*, vol. 43, no. 3, pp. 243-259, Aug 2008. DOI: 10.1016/j.artmed.2008.04.005
21. A. D. Fleming, K. A. Goatman, S. Philip, J. A. Olson and P. F. Sharp, "Automatic detection of retinal anatomy to assist diabetic retinopathy screening," Physics in Medicine and Biology, vol. 52, no. 2, pp. 331-345, Jan 2007.
22. R. M. Rangayyan, X. Zhu, F. J. Ayres and A. L. Ells, "Detection of the Optic Nerve Head in Fundus Images of the Retina with Gabor Filters and Phase Portrait Analysis," J. Digital Imaging, vol. 23, no. 4, pp. 438-453, Aug 2010. DOI: 10.1007/s10278-009-9261-1
23. A. Osareh, M. Mirmehdi, B. Thomas and R. Markham, "Comparison of Colour Spaces for Optic Disc Localisation in Retinal Images," in Proc. 16th Int. Conf. Pattern Recognition, 2002. DOI: 10.1109/ICPR.2002.1044865
24. S. Lu, "Automatic Optic Disc Detection using Retinal Background and Retinal Blood Vessels," in 2010 3rd Int.

Conf. Biomedical Eng. Informatics, Yantai, 2010. DOI: 10.1109/BMEI.2010.5639660
25. http://www.ces.clemson.edu/~ahoover/stare
26. http://www.isi.uu.nl/Research/Databases/DRIVE
27. http://www.it.lut.fi/project/imageret/diaretdb0
28. http://www.it.lut.fi/project/imageret/diaretdb1
29. http://www.adcis.net/en/Download-Third-Party/Messidor.html **OR** Messidor.crihan.fr