ISSN No. 0976-5697

Volume 5, No. 6, July-August 2014

International Journal of Advanced Research in Computer Science

RESEARCH PAPER

Available Online at www.ijarcs.info

Retinal Vessel Extraction and Optic Disk Segmentation in Image Processing

Ms. S. Sathya
Asst. Professor, BCA & SS Dept.,
Sri Krishna Arts & Science College, Coimbatore

Mrs. C. Sunitha,
Professor and Head, BCA & SS Dept.,
Sri Krishna Arts & Science College, Coimbatore

Abstract: The main part of the human eye is retina which includes blood vessels, optic disc and fovea. It's possible to segment the parts, when there is any problem in the segmented parts it can be investigating extensively. Here the first step is the extraction of the retinal vessels and then finding the problematic vessels by using the image processing techniques. Principal part analysis (PCA) is one of the techniques that can be applied to phase the blind spot. In this paper, the retinal vessel extraction, segmentation of optic disk and fovea centralis victimization of PCA using the techniques canny edge detection, OD Localization Algorithm, fuzzy c-means segmentation.

Keywords: Segmentation, Retinal Vessel, PCA, Optic Disk (OD), OD Localization Algorithm, Fuzzy C-Means Segmentation.

I. INTRODUCTION

Diabetic Retinopathy (DR) is a retinal malady caused by the complications of diabetes that results in visual impairment. Before the onset of perceived visual loss, DR patients might not aware of any symptoms. If DR is detected in the early stage, the treatment is simpler and vital savings in care prices is realized. Automatic retinal image analysis guarantees to produce objective, fast, accurate, and consistent screening info to reinforce manual screening of the growing diabetic population. One of the primary necessities for automatic screening of DR is localization of anatomical landmarks like the point, fovea, and retinal vasculature.

The purpose is to develop a quick, economical and strong method for OD localization [1] in DR screening. We need to use vessel characteristics within the OD region to assist during this task. More identification of the OD location is enforced by directional matched filter within the inexperienced channel inside the OD candidates. This system not solely quickly exploits the high intensity, massive intensity variation and elliptical form of optic disk, however additionally utilizes vessel characteristics within optic disk. Temporal to the optic disk is that the pigmented macula that seems darker in color. The avascular area lies at the middle of the macula and is that the part of the tissue layer that's used for fine vision. The macula is associate some circular dark space, however the distinction is commonly quite low and it's going to be obscured somewhat by exudates and hemorrhages.

II. EXISTING SYSTEM

The OD localization and segmentation methodology given herein are often schematically delineate by the diagram. The tactic consists of 3 main process phases: 1) OD size estimation adaptive to totally different image resolution,2) OD localization, for deciding the situation of the disk centre; and 3) OD boundary segmentation.

A. OD Size Estimation:

An important parameter that has to be determined in our OD detection and segmentation rule is that the size of the OD [3].This approach is tedious and impractical for giant datasets. Victimization the FOV of the camera and image resolution, we have a tendency to developed a brand new approach to calculate the OD size. The MESSIDOR information pictures were no inheritable with a 45◦ FOV, which ends in an exceedingly retinal space of 124.8mm2 If the quantity of pixels within the FOV is NFOV, the image footprint is computed as wherever AFOV is that the imaging space of the particular FOV, during this case, AFOV = 124.8 mm2 . We have a tendency to calculate the OD radius in pixels rODimg based on the diameter of the common human optic tract head that has been reported to be about one.85mm.

Where AOD = π (DOD/2)2, DOD = 1.85mm.

The 1200 pictures from Messidor information have 3 different formats: 1440 ∗ 960, 2240 ∗ 1488 and 2304 ∗ 1536 pixels. Correspondingly, we've 3 totally different estimates of the ODradius: seventy, 100, and a hundred and ten pixels.

$$r_{\mathrm{OD\_img}} = \sqrt{\frac{(A_{\mathrm{OD}}/f_{\mathrm{img}})}{\pi}} = \sqrt{\frac{(D_{\mathrm{OD}}/2)^2}{f_{\mathrm{img}}}}$$

B. OD Localization Algorithm:

The first part is about realization of the OD candidate's victimization example matching in the CIE lab lightness image. The CIE lab color area is AN imaging device freelance color model. Its lightness element closely matches human perception of brightness variation [2]. In the CIE lab lightness channel, the image lightness is additional uniform and consistent in OD region than within the RGB red channel while the distinction of OD margin is high[3]. The red channel of a color retinal image additional tends to be saturated.

Step 1: Estimate Threshold.
Step 2: Apply Threshold and establish bright regions.
Step 3: choose candidate regions that satisfy space criterion.
Step 4: choose candidate region that satisfies density criterion.
Step 5: If no candidate region is chosen, scale back threshold.
Step 6: If threshold is bigger than zero, apply steps two through five.

Step 7: Stop.

The major steps within the algorithmic program area unit mentioned thoroughly here.

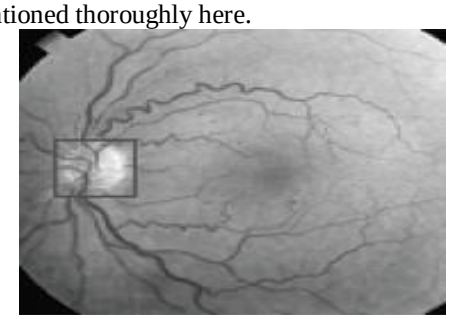

Figure: 1

C. OD Segmentation:

The segmentation failing once the pictures had pathological regions larger and brighter than the OD. They improved region-based active contour model by exploitation native red channel intensity and 2 texture feature areas within the neighborhood of the interested pixels. Quantitative analysis was created on 138 retinal pictures with 30◦ field of read (FOV)[4][5]. This methodology is computationally costly, as 2 native textural options square measure used. The segmentation was performed in parallel, exploitation each the red and inexperienced channel of down-sampled pictures.

The color channel with the upper score within the circular Hough remodel on the Prewitt edge map was hand-picked for OD boundary segmentation. AN overlapping space of eighty six with the reference normal was achieved. However, noise and spurious edge points as a result of non-uniformity in OD region will probably provide incorrect peak locations at parameter area within the Hough remodel. Our OD segmentation rule was developed employing a quick, hybrid level set model, which is able to be shown to supply a lot of correct delineation of the disk boundary than the Hough remodel, and was valid on 1200 pictures from the Revolutionary calendar month info. The rule is insensitive to curve low-level formatting. The vessels and bright region distracters within the per papillose region square measure removed exploitation alternating successive filtering (ASF) and morphological reconstruction. The fast, hybrid level set model deforms the evolving curve supported the region and native edge data, that performs well on the blurred disk margin. The brink worth is adaptively computed exploitation image dependent statistics. Improvement of model parameters ensures the most effective segmentation performance.

A. Disadvantages Of Existing System:

a. Automated analysis of fundus images requires segmentation of the image into regions such as optic disk, fovea, vessels, and background retina. The technique described here can form part of this segmentation process.
b. The proposed algorithm processes images 80% of the time with considerable accuracy
c. The future automatic eye disease screening system will have to be robust. Existing method eye disease not found automatic.
d. Advantage of providing up to 10 times faster speed with sufficient accuracy to meet automatic analysis system requirements. But existing method time period is not efficient.

III. PROPOSED SYSTEM

In the proposed system we need to extract the retinal vessels, evaluating the OD segmentation algorithmic rule for the detection of optic disk (OD)[9], finding out the diseased region of fovea using fovea centralisis. For segmenting the optic disk we have used the following algorithm.

A. The fuzzy c-means segmentation algorithm:

Fuzzy C-Means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. This method is frequently used in pattern recognition. It is based on minimization of the following objective function: (1) where, m :Any real number greater than 1, it was set to 2.00 by Bezdek (1981) u_{ij}: The degree of membership of x_i in the cluster j x_i: The i^{th} of d-dimensional measured data c_j:

The d-dimension centre of the cluster ||*||:Any norm expressing the similarity between any measured data and the centre Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership u_{ii} and the c_i

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{m}\left\|x_i - c_j\right\|^2$$

where, m Any real number greater than 1, it was set to 2.00 by Bezdek (1981) u_{ij}: The degree of membership of x_i in the cluster j x_i: The i^{th} of d-dimensional measured data c_j: The d-dimension centre of the cluster ||*||:Any norm expressing the similarity between any measured data and the centre Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership u_{ii} and the c_i cluster centres by:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\left\|x_i - c_j\right\|}{\left\|x_i - c_k\right\|}\right)^{\frac{2}{m-1}}} \qquad (1)$$

$$c = \frac{\sum_{i=1}^{N} u_{ij}^{m}.x_i}{\sum_{i=1}^{N} u_{ij}^{m}}$$

This iteration will stop when:

$$\max_{ij}\left\{u_{ij}^{(k+1)} - u_{ij}^{(k)}\right\} < \varepsilon$$

(2 and 3)

Whereas, a termination criterion between 0 and 1 k: The iteration steps of this procedure converge to a local minimum or a saddle point of J_m. The algorithm is composed of the following steps:

• Initialize $U = [u_{ij}]$ matrix, $U(0)$ (4)

• At k-step: calculate the centres vectors $C(k) = [c_j]$ with $U(k)$

$$c = \frac{\sum_{i=1}^{N} u_{ij}^{m} . x_i}{\sum_{i=1}^{N} u_{ij}^{m}} \quad (5)$$

• Update U(k), U(k+1)

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}} \quad (6)$$

If $\|U(k+1) - U(k)\| < \varepsilon$ then STOP; otherwise return to step 2.

In Fuzzy K-C-Means the interest is on creating the quantity of iterations capable that of the fuzzy c means that associated still get an optimum result [9][10]. This suggests that regardless of the lower range of iteration, we are going to still get an ideal result. The algorithmic rule has the subsequent steps:

a) Browse the image into the Mat laboratory surroundings
b) Get input from hybrid technique
c) Cut back range of iteration with distance check
d) Get the dimensions of the image
e) Calculate the gap attainable size victimisation continuance structure
f) Concatenate the given dimension for the image size
g) Repeat the matrix to come up with giant information things in finishing up probably distance calculation
h) Cut back continuance once attainable distance has been earned
i) Iterations begin by distinguishing giant part of knowledge via the worth of the constituent
j) Iteration stops once attainable identification elapses
k) Time is generated.

B. PCA and fovea centralis Localization:

The primary step within the application of PCA to find foveae within the input retinal pictures is to decide on foveae regions from retinal pictures for coaching functions. Localization of foveae exploitation the PCA in associate input retinal image is longer overwhelming computationally compared with localization of the point. are often} as a result of the PCA can be applied to given regions once localising the point by selecting candidate regions as clusters of the brightest pixels in a very retinal image or by applying the PCA solely at thick vessel points exploitation the binary vessel tree of the retinal image. The fovea centralis is that the darkest region in a very retinal image with nearly constant intensity because the blood vessels. The centre of the fovea centralis is sometimes settled from the centre of the point at regarding two.5 times the diameter of the point. The PCA may be applied to the candidate regions that are clusters of the darkest pixels excluding the blood vessels (using info from a binary vessel tree). This method then provides the simplest way resolute curtail the computation time in locating the fovea centralis by the PCA.

The retinal pictures in the image will have their darkest areas at the sides, that aren't a part of the tissue layer and may be full of intensities from adjacent regions.

B. Advantages of proposed system:

A new, fast, and strong OD localization and segmentation methodology for retinal image screening has been developed. The OD localization methodology adaptively changes the guide size supported the OD radius estimation, mistreatment the camera FOV and also the image resolution [5][6]. The methodology not solely exploits the looks options of the OD, however additionally main vessel orientation within the OD, to extend strength. The OD segmentation technique uses ASF and morphological reconstruction to get rid of vessels and bright region distracters whereas retentive the form of the outgrowth region. The fast, hybrid level set model uses each region info and native edge vector with easy Automatic format to attain strong, fast, and correct segmentation. The model parameters square measure optimized for the most effective segmentation performance

The blind spot (OD) centre and margin area unit generally requisite landmarks in establishing a frame of reference for classifying retinal and nervusopticus pathology. Reliable and economical OD localization and segmentation [8] area unit vital tasks in automatic disease screening. This paper presents a brand new, fast, and absolutely automatic OD localization and segmentation rule developed for retinal malady screening. First, OD location candidates area unit known victimization guide matching. The guide is meant to adapt to totally different image resolutions. Then, vessel characteristics (patterns) on the OD area unit won't to verify OD location. Initialized by the detected OD centre and calculable OD radius, a fast, hybrid level set model, which mixes region and native gradient data, is applied to the segmentation of the disk boundary.

IV. IMPLEMENTATION RESULTS

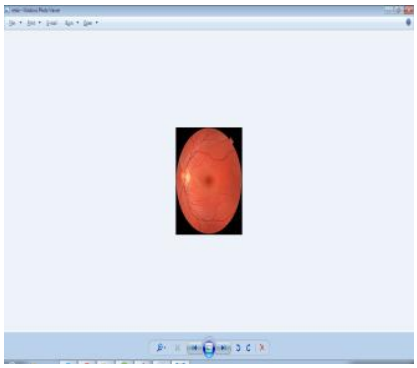

Figure: 2 Input image

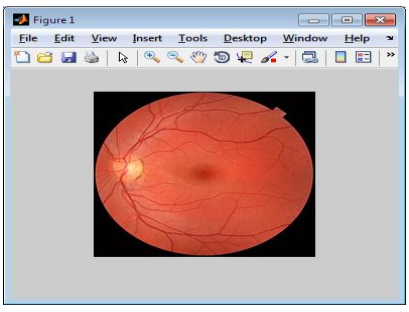

Figure: 3 Without red channel

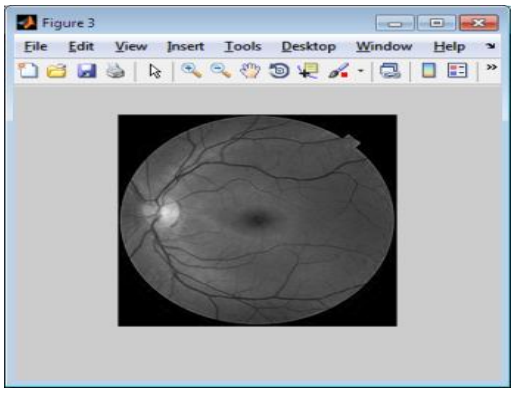

Figure: 4 Without green channel image

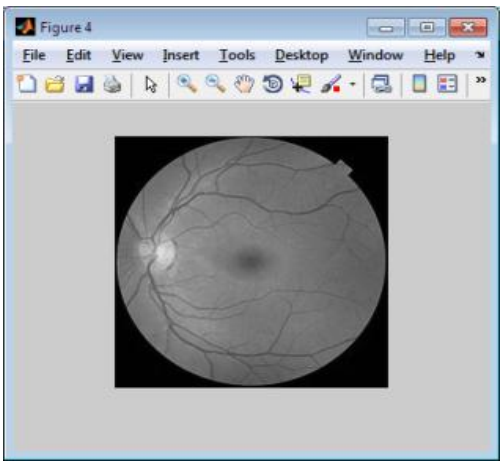

Figure: 5 Filtered image

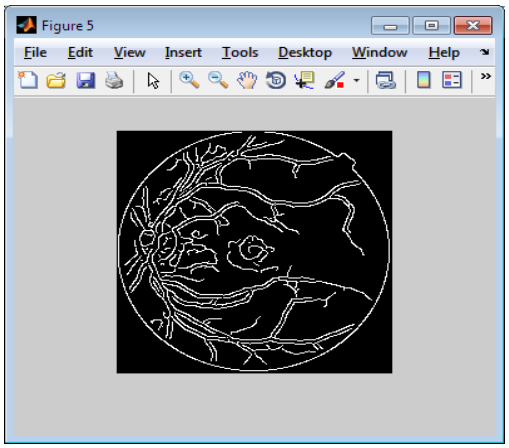

Figure: 6 Edge detection image

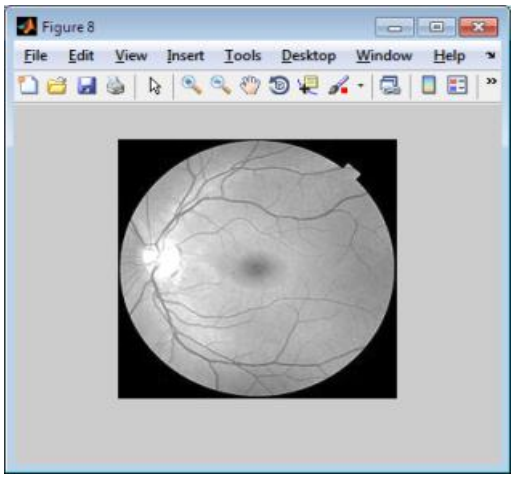

Figure: 7 Contrast enhanced image

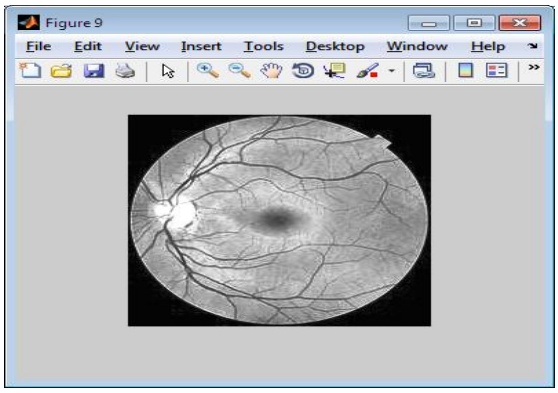

Figure: 8 Disease detection image

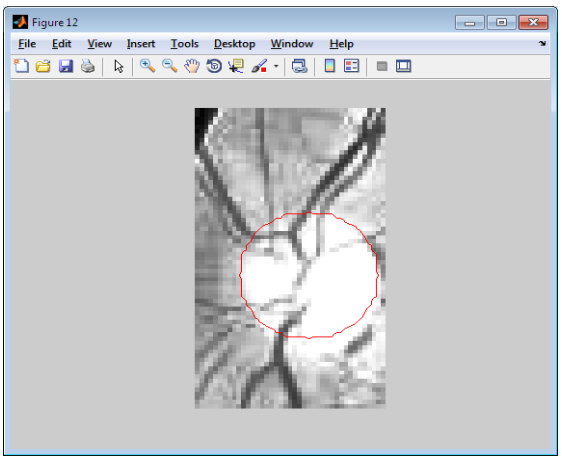

Figure: 9 Normal segmented image

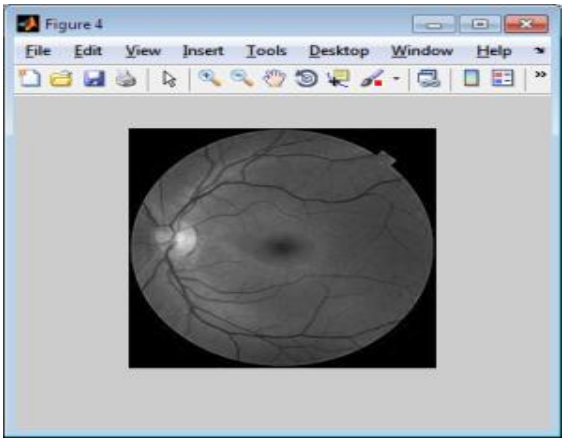

Figure: 10 Fovea in Retinal Images

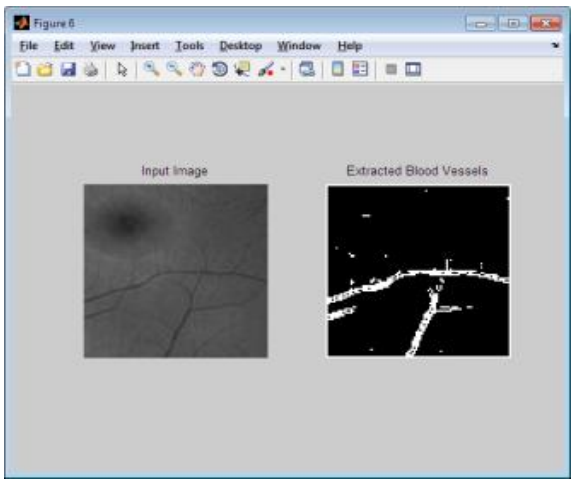

Figure: 11 Extracted images

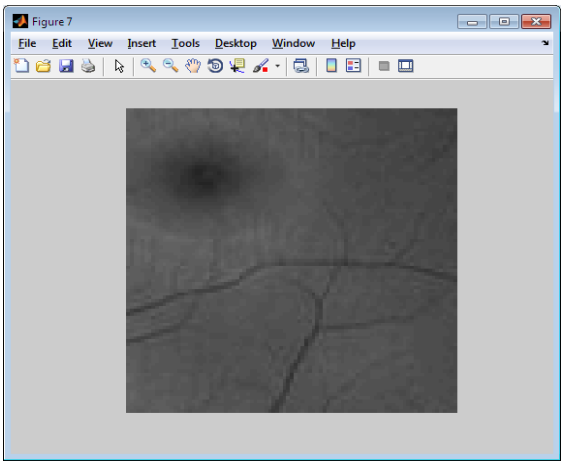

Figure: 12 Disease detection

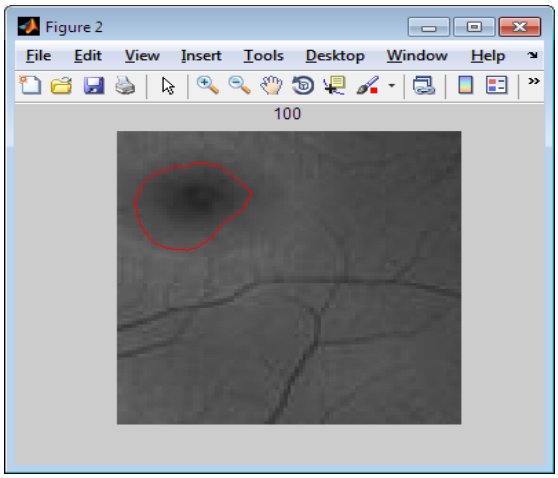

Figure: 13 Fovea disease detection

V. CONCLUSION

A new, fast, and sturdy OD localization and segmentation methodology for retinal image screening has been developed. The OD localization methodology adaptively changes the model size supported the OD radius estimation, exploitation the camera FOV and therefore the image resolution. The methodology not solely exploits the looks options of the OD, however conjointly main vessel orientation within the OD, to extend hardiness. The OD segmentation methodology uses ASF and morphological reconstruction to get rid of vessels and bright region distracters whereas holding the form of the appendage region. The fast, hybrid level set model uses each region info and native edge vector with easy automatic data format to attain sturdy, fast, and correct segmentation. The model parameters are optimized for the most effective segmentation performance; this paper has delineated the applying of Principal Element Analysis (PCA) to the localization of the blind spot and area during a retinal image. 10 optic discs and 10 foveae from a range of retinal pictures were chosen as coaching pictures[10][11]. The dimensions of the blind spot coaching pictures were a hundred. a hundred pixels which of the area was 70 pixels. PCA was then applied to seventy retinal pictures for localization of optic discs and foveae. The 2 cases were treated one by one.

The success rate was ninety seven within the case of blind spot segmentation and ninety four.3% just in case of area segmentation. PCA was found to be a promising technique, however it's a computationally time overwhelming approach. Strategies to create the technique quicker are known one by one for each the blind spot and therefore the area. The technique cannot be counselled for real time analysis; however it will be used in "batch processing" for the localization of optic discs and foveae in retinal pictures that are captured antecedent.

VI. REFERENCES

[1] Sinthanayothin, J. F. Boyce, H. L.Cook, andT. H.Williamson,"Automated localisation of the optic disc, fovea, and retinalblood vessels fromdigital colour fundus images," British Journalof Ophthalmology, vol. 83, no. 8, pp. 902–910, 1999.

[2] H. Li and O. Chutatape, "Automatic location of optic disk in retinal images," in Proceedings of the International Conference on Image Processing, vol. 2, pp. 837–840, 2001.

[3] M. Merickel, M. D. Abr`amoff, M. Sonka, and X. Wu,"Segmentation of the optic nerve head combining pixelclassification and graph search," Proc. of SPIE Image Processing **Vol. 6512**, 2007.

[4] M. Niemeijer, M. K. Garvin, B. van Ginneken, M. Sonka, and M. D. Abr`amoff, "Vessel segmentation in 3Dspectral OCT scans of the retina," in Proceedings of SPIE Medical Imaging 2008: Image Processing, **6914**, SPIE, 2008.

[5] J. Lowell, A. Hunter, D. Steel, A. Basu, R. Ryder, E. Fletcher, Optic nerve head segmentation, IEEE Trans. Med. Imaging 23 (2004) 256–264.

[6] J. Xu, H. Ishikawa, G. Wollstein, R.A. Bilonick, K.R. Sung, L.Kagemann, K.A. Townsend, J.S. Scbuman, Automated assessment of the optic nerve head on stereo disc photographs, Invest. Ophthalmol. Vis. Sci. 49 (2008) 2512–2517.

[7] M. D. Abr`amoff, W. L. M. Alward, E. C. Greenlee, L. Shuba, C. Y. Kim, J. H. Fingert, and Y. H. Kwon,"Automated segmentation of the optic disc from stereo color photographs using physiologically plausiblefeatures," Invest Ophthalmol Vis Sci **48**, pp. 1665–1673, Apr. 2007.

[8] T.Walter, J.-C. Klein, Segmentation of color fundus images ofthe human retina: detection of the optic disc and the vascular tree using morphological techniques, Int. Symp. Med. Data Anal. 2199 (2001) 282–287.

[9] M. Lalonde, M. Beaulieu, L. Gagnon, Fast and robust optic disc detection using pyramidal decomposition and Hausdorff-based template matching, IEEE Trans. Med. Imaging 11 (2001) 1193–1200.

[10] H. Li, O. Chutatape, Automated feature extraction in colorretinal images by a model based approach, IEEE Trans.Biomed. Eng. 51 (2004) 246–254.

[11] H. Li and O. Chutatape, "Automatic detection and boundary estimation of the optic disk in retinal images using a model based approach," Journal of Electronic Imaging, vol. 12, no. 1, pp.97–105,2003.